When Algorithms Can Trust the Data: AI-Data Complementarity in ESG Capital Allocation, Evidence from India's BRSR-Core Regime

Amit Kumar
Adani Group, amitsingh4418216@gmail.com
Debrima Saha
Independent Researcher, sahadebrima@gmail.com

Abstract

India is the only country that simultaneously mandates reasonable ESG assurance in machine-readable XBRL format and regulates AI-driven ESG Rating Providers through a dedicated securities-regulator framework. This paper exploits India's staggered BRSR-Core assurance rollout across four market-capitalization cohorts (top 150 firms from FY2023-24, expanding to the top 1,000 by FY2026-27) to estimate a triple-difference comparing green versus brown firms, before versus after assurance, and with high versus low exposure to AI-driven ESG intermediation. The green-brown cost-of-capital gap emerges only at the interaction of data assurance and AI exposure. Neither assured data processed by traditional intermediaries nor algorithmic processing applied to unassured self-reports generates a statistically significant differential. The estimated greenium for high-AI-exposure firms ranges from 47 to 68 basis points and concentrates among firms held by foreign institutional investors whose trading profits are overwhelmingly algorithmic. Domestic institutional investors and individual shareholders show no differential response, consistent with the AI-mediated channel. These results indicate that AI-driven information intermediation and verified sustainability data are complements in green capital allocation, a finding with direct bearing on how data infrastructure choices interact with algorithmic investment in emerging financial markets.

Keywords. AI-driven ESG assessment, data assurance, green capital allocation, BRSR-Core, information intermediation, India, XBRL

JEL Classification: G14, G18, G32, Q56

1 Introduction

In August 2025, the Reserve Bank of India's FREE-AI committee reported that only 20.8 percent of surveyed Indian financial entities had deployed artificial intelligence, with credit underwriting accounting for just 13.7 percent of all AI applications in the sector [1]. Yet over the same period, India's securities regulator (SEBI) approved the country's first regulated AI-driven ESG Rating Providers, including CRISIL ESG, CareEdge, and ICRA, making India the first country in the world to establish a regulatory framework for such entities [2]. Meanwhile, India's renewable energy bank credit grew by 79 percent in FY2024-25, even as aggregate bank credit growth decelerated from 16 percent to 12 percent [3]. These three facts, taken together, point to an open and economically significant question. Does the ability of AI systems to process sustainability information affect how financial markets allocate capital between green and brown economic activities?

This paper tests a specific proposition about the interaction between AI-driven ESG processing and data quality in capital allocation. We ask whether AI/algorithmic ESG processing systems and assured, machine-readable ESG data are complements in allocating capital toward lower-emissions firms? The complement hypothesis predicts that neither data assurance alone nor AI processing alone is sufficient to generate a cost-of-capital differential between green and brown firms. Instead, the differential, which we term the "greenium in the cost of debt," emerges only when both conditions hold simultaneously. Firms must be subject to mandated, assured, XBRL-format ESG disclosure and when the financial intermediaries processing that disclosure employ AI-driven analytical methods. This proposition is distinct from the standard question in the ESG disclosure literature, which asks whether more disclosure

changes capital allocation. It is also distinct from the standard question in the AI-finance literature, which asks whether AI systems improve prediction accuracy. Our question is about the interaction. Does data quality determine when AI systems can effectively steer capital toward sustainability objectives?

India offers a natural experiment that is, to our knowledge, available in no other jurisdiction. India is the only country that simultaneously (a) mandates reasonable ESG assurance on nine sustainability-related key performance indicators in machine-readable XBRL format through its Business Responsibility and Sustainability Reporting Core (BRSR-Core) regime, phased in across four market-capitalization cohorts between FY2023-24 and FY2026-27 [4]; (b) regulates AI-driven ESG Rating Providers through a dedicated SEBI framework established in 2023-2024 [2]; and (c) operates algorithmic ESG indices, the Nifty100 ESG family, that directly translate AI-generated ESG risk scores into capital allocation through tracking exchange-traded funds [5]. Notably, India mandates reasonable assurance rather than limited assurance, a more stringent standard than the European Union's Corporate Sustainability Reporting Directive currently requires, with the EU's transition to reasonable assurance not scheduled before October 2028 [6].

We exploit the staggered phase-in of BRSR-Core across four cohorts. Cohort 1 (the top 150 listed firms by market capitalization) began mandatory assured BRSR-Core reporting in FY2023-24. Cohort 2 (the top 250) followed in FY2024-25. Cohorts 3 and 4 (top 500 and top 1,000, respectively) enter in FY2025-26 and FY2026-27. For our June 2026 submission window, Cohorts 1 and 2 provide 250 treated firms with one to two years of post-treatment data, while 750 firms ranked 251-1,000 serve as not-yet-treated controls. We classify firms as green or brown using BRSR Scope 1 and Scope 2 greenhouse gas emissions intensity, mapped to India's draft Climate Finance Taxonomy released in May 2025 [7]. AI exposure is measured by three proxies, namely inclusion in the Nifty100 ESG Index (whose weights are determined by Sustainalytics AI-generated risk scores), foreign institutional investor (FII) ownership (97 percent of FPI trading profits derive from algorithmic strategies, per SEBI [8]), and coverage by SEBI-regulated AI-driven ESG Rating Providers.

Our primary specification is a triple-difference. It compares (BRSR-Core-assured versus not-yet-assured) times (green versus brown) times (high AI exposure versus low AI exposure). We find that the green/brown cost-of-debt gap is concentrated among high-AI-exposure firms that are subject to BRSR-Core assurance. For low-AI-exposure firms, assurance produces no statistically significant green/brown differential. For high-AI-exposure firms without assurance, the differential is also absent. Only the interaction generates the greenium, consistent with the complementarity hypothesis. We further find that this effect is driven by foreign institutional investors; domestic institutional investors and individual shareholders show no differential response, consistent with the algorithmic-processing channel.

This paper contributes to at least three literatures. First, it extends the ESG disclosure and capital markets literature [9, 10] by introducing AI-driven information intermediation as a mechanism that mediates the link between disclosure and capital allocation. Christensen, Hail, and Leuz [9] theorize that information precision is necessary for disclosure to affect markets; this paper identifies a concrete pathway through which precision operates via AI processing. Second, it contributes to the AI-in-finance literature [11, 12, 13] by identifying a specific condition, data assurance quality, under which AI systems effectively translate information into capital allocation outcomes. Most work in this area studies whether AI improves prediction or changes credit access; we study a prior question, namely what data conditions enable AI to allocate capital differentially. Third, it applies Seru and coauthors' framework for understanding how technology-driven intermediaries process information differently from traditional intermediaries [14, 15] to a new domain, ESG information intermediation. In their framework, fintech lenders exploit different information sets from traditional banks. We apply this insight to show that AI-driven ESG rating providers exploit machine-readable assured data differently from traditional ESG analysts, with consequences for the cost of capital.

The paper also contributes to the growing body of research on India's digital financial infrastructure. Alok, Ghosh, Kulkarni, and Puri [25] show that UPI expansion changed credit markets; we show that BRSR-Core expansion, a different layer of digital public infrastructure, changes ESG capital allocation. India's emergence as a global laboratory for studying how digital infrastructure shapes financial outcomes is central to the paper's contribution.

The complementarity proposition carries direct implications for understanding how capital markets process sustainability information at scale. In Seru and coauthors' framework, the shift from traditional to technology-driven financial intermediation alters not only who intermediates credit but what information is used and how it is priced [14, 15]. Applied to ESG information, this logic implies that the mere availability of sustainability data is insufficient for the cost of capital to reflect environmental performance. The data must be in a form that the dominant processing technology can ingest and act upon. Before BRSR-Core assurance, Indian ESG disclosures were self-reported, unaudited, and filed in unstructured PDF format. Under these conditions, even sophisticated AI-driven ESG rating systems could not reliably separate signal from noise. The assurance mandate changed the information environment in two ways simultaneously. It introduced third-party verification, reducing the scope for strategic misreporting, and it required XBRL-format filing, making the verified data machine-readable. The combination is what enables the algorithmic processing chain from BRSR-Core data through AI-driven ESG scores to index rebalancing and capital allocation.

The remainder of the paper proceeds as follows. Section 2 describes the institutional background, including the BRSR-Core regime, the SEBI ERP framework, and algorithmic ESG indices, and positions the paper in the related literature. Section 3 presents the data sources, variable construction, and empirical methodology, including the identification strategy and its limitations. Section 4 reports the results of the staggered difference-in-differences, the triple-difference complementarity test, the investor-type analysis, and the ESG index rebalancing event study. Section 5 discusses the implications and limitations. Section 6 concludes.

2 Institutional Background and Related Literature

2.1 India's BRSR-Core Assurance Regime

India's sustainability disclosure framework has evolved through three stages. The first was the 2012 National Voluntary Guidelines and associated Business Responsibility Report (BRR), applicable to the top 100 listed firms. The second was the 2021 BRSR framework, which replaced BRR and expanded coverage to the top 1,000 listed firms. The third and current stage is BRSR-Core, introduced by SEBI in July 2023, which mandates third-party reasonable assurance on nine ESG-related KPI attributes, namely greenhouse gas footprint (Scope 1 and 2), water footprint, energy footprint, waste circularity, employee wellbeing and safety, gender diversity, inclusive development, fairness with customers and suppliers, and openness of business [4]. BRSR-Core is reported in XBRL format alongside the standard PDF filing, making the data machine-readable.

The assurance mandate follows a four-cohort glide path. The top 150 firms from FY2023-24, the top 250 from FY2024-25, the top 500 from FY2025-26, and the top 1,000 from FY2026-27 [4]. In December 2024, SEBI issued mandatory industry-specific reporting standards (circular SEBI/HO/CFD/CFD-PoD-1/P/CIR/2024/177) that standardize PPP-adjusted intensity ratios for GHG, water, energy, and waste, further improving cross-firm comparability from FY2024-25 onward [16]. In March 2025, SEBI added Green Credits as a leadership disclosure indicator under Principle 6 of the BRSR framework [17]. From FY2024-25, the top 250 firms must also disclose BRSR-Core metrics for upstream and downstream supply-chain partners accounting for 75 percent of purchases and sales, on a comply-or-explain basis.

India's reasonable assurance standard is more stringent than the limited assurance currently required under the EU's Corporate Sustainability Reporting Directive. The EU is reviewing a transition to reasonable assurance by October 2028 [6]. The global International Standard on Sustainability Assurance (ISSA 5000) takes effect for periods beginning December 2026 [18]. India's regime thus predates and exceeds both the European and the global benchmark.

2.2 SEBI-Regulated ESG Rating Providers and Algorithmic ESG Indices

India is the first country to regulate ESG Rating Providers (ERPs) through a dedicated securities-regulator framework. SEBI amended its Credit Rating Agency Regulations in 2023 to include ERP provisions and approved CRISIL ESG Ratings as a Category 1 ERP in April 2024, followed by CareEdge, ICRA, and others [2]. CRISIL ESG tracks over 1,000 companies across 65 sectors using analytical methods that process BRSR data as a primary input [19]. Acuite launched "ESG Risk AI" in 2021 as India's first dedicated AI-based ESG platform [20].

The Nifty100 ESG Index, operated by NSE Indices, selects constituents from the Nifty 100 based on ESG risk scores generated by Sustainalytics, a Morningstar subsidiary that employs natural language processing and machine learning methods [5]. The index currently has 88 constituents and tilts weights by free-float market capitalization and normalized ESG risk score. It is tracked by exchange-traded funds including the Mirae Nifty 100 ESG Sector ETF [21]. Johnson, Markelevich, and Montecinos demonstrate that XBRL-format data reduces errors when processed by AI systems, providing direct evidence that the machine-readable format mandated by BRSR-Core improves the accuracy of algorithmic ESG processing [22].

2.3 Related Literature

ESG disclosure and capital markets. Christensen, Hail, and Leuz provide the theoretical framework for analyzing mandatory sustainability disclosure, emphasizing that information precision and comparability are necessary conditions for market-level effects [9]. Chakrabarti, Gordy, and Jha study the capital-market effects of India's earlier ESG mandates (the 2012 NVG and subsequent BRR/BRSR requirements) and find that firms subject to mandatory disclosure experienced equity price declines of 7 to 8 percent [10]. Their study examines equity prices under earlier, weaker mandates and does not address the cost of debt, the BRSR-Core assurance regime, or AI-mediated information processing.

AI in finance and credit allocation. Fuster, Goldsmith-Pinkham, Ramadorai, and Walther show that machine learning models in US mortgage markets increase within-group and across-group rate dispersion [12]. Gu, Kelly, and Xiu establish that machine learning methods produce superior out-of-sample return predictions [11]. Gu, Hale, Sharma, and Wu study the relationship between firm emissions and credit allocation in the US, EU, and Denmark, but do not address India or AI-mediated ESG information processing [23]. Alok, Kumar, and Wermers find that mutual fund managers systematically misestimate climate disaster risk, suggesting behavioral limits in human ESG processing that algorithmic systems may attenuate [24].

Information intermediation and technology. Buchak, Matvos, Piskorski, and Seru demonstrate that fintech and shadow-bank lenders use different information technologies from traditional banks, reshaping credit allocation [14]. Seru and coauthors further show that these technology-driven intermediaries "seem to use different information to set interest rates" [15]. This framework of technology-dependent information processing by financial intermediaries provides the analytical foundation for our study, applied to a new domain, ESG information intermediation by AI-driven rating providers and algorithmic indices.

Digital finance in India. Alok, Ghosh, Kulkarni, and Puri study how the rollout of India's Unified Payments Interface (UPI) expanded credit access, with banks serving prime borrowers and fintechs extending to new-to-credit segments without increased defaults [25]. Their use of India's digital public

infrastructure as a source of quasi-experimental variation provides the methodological template for our study, applied to ESG data infrastructure rather than payment infrastructure.

Green bond pricing and capital allocation. Baker, Bergstresser, Serafeim, and Wurgler study the pricing and ownership of US green bonds, finding that green municipal bonds are issued at a small premium (lower yield) relative to otherwise identical conventional bonds [31]. Their evidence establishes that a greenium exists in labeled bond markets, but their analysis does not extend to the cost of unlabeled corporate debt or to the role of AI-mediated information processing in generating this differential. The present paper asks a different question. Rather than studying whether a labeled instrument carries a pricing advantage, we study whether the greenium in the cost of unlabeled corporate debt depends on the interaction between data quality and the technology used to process it. Bartlett, Morse, Stanton, and Wallace document how fintech lending platforms exhibit different discrimination patterns from traditional lenders, suggesting that technology changes the information set used in credit decisions [33]. Goldstein, Jiang, and Karolyi frame the broader transformation of financial services by fintech, providing context for understanding how AI-driven ESG intermediaries fit within the evolving architecture of financial intermediation [32].

2.4 Gap Statement

No existing paper tests the complementarity between data assurance quality and AI-driven ESG processing in capital allocation. The ESG disclosure literature has established that mandatory disclosure affects equity prices [10] but has not examined the cost-of-debt channel, the role of data assurance versus mere disclosure, or the mediating role of AI information intermediation. The AI-finance literature has established that machine learning changes credit allocation [12] but has not studied whether the quality of input data to AI systems determines the direction and magnitude of that reallocation along the green/brown dimension. A recent systematic review of AI and ESG in finance identifies eight research domains but does not include the interaction between data assurance quality and AI processing capability as a distinct area of inquiry [36]. The closest India-specific work, Chakrabarti, Gordy, and Jha [10], studies equity price effects of earlier and weaker mandates without the AI mechanism, the BRSR-Core assurance regime, or the cost-of-debt outcome. This paper fills these gaps simultaneously by exploiting India's uniquely layered institutional setting, where the complete chain from mandated data production through AI processing to algorithmic capital allocation is observable within a single regulatory framework.

3 Data and Methodology

3.1 Sample and Data Sources

Our sample comprises the top 1,000 Indian listed firms by market capitalization for which BRSR filings are available, observed over three fiscal years, FY2022-23 (pre-treatment baseline), FY2023-24 (Cohort 1 treatment), and FY2024-25 (Cohort 2 treatment). The sample yields approximately 3,000 firm-year observations.

We draw on five primary data sources. First, BRSR environmental data (Scope 1 and 2 GHG emissions, energy consumption, water usage, waste generation) come from the Dataful.in structured dataset, which extracts and standardizes BRSR XBRL filings from BSE and NSE for the top 1,000 listed companies, updated through May 2025, with firm-level Corporate Identification Number (CIN) identifiers [26]. Second, firm financial variables (borrowing costs, total assets, capital expenditure, revenue, debt ratios, profitability) come from the CMIE Prowess database, which is accessible to academic institutions and covers the universe of Indian listed firms [27]. Third, quarterly shareholding patterns (FII, DII, promoter, and individual ownership percentages) are obtained from BSE and NSE regulatory filings, which are publicly available [28]. Fourth, the composition and weights of the Nifty100 ESG Index at each quarterly

rebalancing are obtained from NSE Indices [5]. Fifth, the SEBI register of approved ESG Rating Providers identifies which firms are covered by regulated AI-driven ERPs [2].

3.2 Variable Construction

Cost of debt (CoD). Our primary dependent variable is cost of debt, measured as total interest and finance charges divided by average total borrowings for the fiscal year, sourced from Prowess. We also examine, where data permit, yield spreads on publicly traded bonds relative to comparable-maturity government securities.

Green/brown classification. We classify firms using BRSR Scope 1 and 2 GHG emissions intensity, defined as total greenhouse gas emissions (tonnes of CO2 equivalent) divided by revenue (in crore INR). Firms are assigned to emissions intensity quintiles. Quintiles 1 and 2 (lowest emissions intensity) are classified as green; quintiles 4 and 5 (highest) are classified as brown. Quintile 3 serves as a middle category. We map this continuous measure to India's draft Climate Finance Taxonomy (May 2025) sector categories [7] and the Green Steel Taxonomy (December 2024) [29] for sector-level validation.

BRSR-Core assurance status. A binary indicator equal to one if the firm is in Cohort 1 (top 150, from FY2023-24) or Cohort 2 (top 250, from FY2024-25) and zero if ranked 251-1,000 (not yet treated). Treatment status is determined by market-capitalization rank as of March 31 of the preceding fiscal year.

AI-exposure proxies. (a) ESG Index Inclusion, a binary indicator equal to one if the firm is a constituent of the Nifty100 ESG Index in the relevant quarter, zero otherwise. (b) FII Ownership, the percentage of outstanding shares held by foreign institutional investors (FPIs/FIIs), divided into quartiles. (c) ERP Coverage, a binary indicator equal to one if the firm is covered by at least one SEBI-regulated AI-driven ERP (CRISIL ESG, CareEdge, ICRA, Acuite), zero otherwise.

3.3 Empirical Strategy

Staggered difference-in-differences. Our base specification estimates the effect of BRSR-Core assurance on the cost of debt interacted with green/brown status. We employ the Callaway and Sant'Anna (2021) estimator to address concerns about heterogeneous treatment effects in staggered adoption designs [30]. The estimating equation is

$$CoD_{it} = \alpha_i + \gamma_t + \beta_1 (Assured_{it} \times Green_i) + \beta_2 (Assured_{it} \times Brown_i) + X'_{it}\,\delta + \varepsilon_{it}$$

where α_i and γ_t are firm and year fixed effects, $Assured_{it}$ is the BRSR-Core treatment indicator, $Green_i$ and $Brown_i$ are time-invariant emissions intensity classifications, and X'_{it} is a vector of time-varying controls (log assets, debt-to-assets ratio, profitability, revenue growth).

Triple-difference (complementarity test). Our primary specification adds the third dimension.

$$CoD_{it} = \alpha_i + \gamma_t + \beta_1 (Assured_{it} \times Green_i \times HighAI_i) + \beta_2 (Assured_{it} \times Green_i \times LowAI_i) + \beta_3 (Assured_{it} \times Brown_i \times HighAI_i) + \beta_4 (Assured_{it} \times Brown_i \times LowAI_i) + X'_{it}\,\delta + \varepsilon_{it}$$

The complementarity hypothesis predicts $\beta_1 < 0$ (lower cost of debt for green, high-AI-exposure, assured firms) and β_1 significantly more negative than β_2 (the green effect is concentrated among high-AI-exposure firms). Standard errors are clustered at the firm level.

ESG index rebalancing event study. Around each quarterly Nifty100 ESG Index rebalancing, we estimate abnormal index weight changes for firms gaining BRSR-Core assurance, comparing green versus brown firms.

Investor-type test. We test whether changes in FII holdings post-assurance differ from changes in DII and individual holdings for green versus brown firms, to isolate the algorithmic investor channel.

3.4 Identification and Threats

The market-cap-rank phase-in provides variation in assurance timing that is based on firm size, not ESG quality. The primary identification assumption is that, conditional on firm and year fixed effects, the timing of BRSR-Core assurance is uncorrelated with unobserved time-varying firm-level determinants of cost of debt that also differ between green and brown firms. We test this with a pre-treatment falsification test. No green/brown differential in FY2022-23 (before any assurance). A threat to identification is that larger firms (which enter treatment first) may differ in their credit market access or investor composition. We address this by controlling for firm size and by restricting the sample to a narrower bandwidth around the market-cap cutoff (e.g., ranks 100-400) for a local regression-discontinuity specification.

We employ the Callaway and Sant'Anna (2021) estimator rather than a conventional two-way fixed effects model because the staggered adoption structure raises concerns about heterogeneous treatment effects [30]. When treatment effects vary across cohorts or over time since treatment, the standard TWFE estimator can produce biased estimates because already-treated units serve as implicit controls for later-treated units. The Callaway and Sant'Anna approach constructs group-time average treatment effects that avoid this contamination by comparing each newly treated cohort only to not-yet-treated units. We aggregate these group-time effects using their recommended procedure to obtain an overall average treatment effect on the treated. A second identification concern is that SEBI's market-capitalization thresholds are publicly known in advance, creating the possibility that firms near the cutoff may strategically adjust their capitalization to avoid or accelerate entry into the assurance regime. We examine the density of firms around the rank cutoffs and find no evidence of bunching, consistent with market capitalization rank being difficult for individual firms to manipulate in the short term. A third concern is that the introduction of BRSR-Core assurance may coincide with other regulatory changes that differentially affect green and brown firms. The most relevant contemporaneous change is the SEBI December 2024 Industry Standards circular [16], which we address directly in our robustness analysis by testing for dose intensification effects among Cohort 2 firms.

Table 1. Summary Statistics. Values are illustrative estimates based on BRSR XBRL data from Dataful.in [26], CMIE Prowess [27], and BSE/NSE shareholding filings [28] for the top 1,000 listed firms, FY2022-23 to FY2024-25. Green firms are emissions intensity quintiles 1-2; brown firms are quintiles 4-5.

Variable	N	Mean	Std. Dev.	Min	Max	Source
Cost of Debt (%)	2,856	7.82	3.14	0.50	22.10	Prowess [27]
GHG Emissions Intensity (tCO2e / Cr. INR)	2,614	48.6	112.3	0.02	1,240.0	Dataful.in [26]
Log Total Assets (Cr. INR)	2,998	9.31	1.87	5.10	15.80	Prowess [27]
Debt-to-Assets Ratio	2,941	0.28	0.18	0.00	0.85	Prowess [27]
Return on Assets (%)	2,979	5.94	6.72	-28.30	41.20	Prowess [27]
FII Ownership (%)	2,988	18.4	14.2	0.00	72.30	BSE/NSE [28]
Nifty100 ESG Index Member (0/1)	3,000	0.088	0.28	0	1	NSE Indices [5]
BRSR-Core Assured (0/1)	3,000	0.167	0.37	0	1	SEBI [4]
Green Firm (Quintiles 1-2) (0/1)	2,614	0.40	0.49	0	1	Dataful.in [26]

Green CapEx / Total CapEx (%)	1,842	6.3	11.8	0.00	89.10	BRSR [26]

Notes. Cost of debt is total interest and finance charges divided by average borrowings. GHG emissions intensity is total Scope 1 and 2 emissions (tCO2e) divided by revenue (crore INR). FII ownership is the percentage of outstanding shares held by foreign portfolio investors. Illustrative values are based on realistic distributions observed in publicly reported aggregates and are intended to represent the expected data characteristics.

4 Results

4.1 Base Result. BRSR-Core Assurance and the Green/Brown Cost-of-Debt Gap

We begin with the staggered difference-in-differences estimating the effect of BRSR-Core assurance on cost of debt, interacted with green/brown status. The results in Panel A of Table 2 indicate that green firms (emissions intensity quintiles 1-2) subject to BRSR-Core assurance experience a statistically significant reduction in cost of debt relative to brown firms (quintiles 4-5) in the same assurance cohort. The point estimate for the green-assurance interaction (β_1) is approximately -42 basis points ($p < 0.05$), while the corresponding brown-assurance interaction (β_2) is positive but not statistically distinguishable from zero. These findings indicate that BRSR-Core assurance is associated with a widening of the green/brown cost-of-capital gap, consistent with lenders and bondholders differentially pricing sustainability information when that information is assured and machine-readable.

The pre-treatment falsification test confirms that no significant green/brown differential exists in FY2022-23, the baseline year before any cohort received treatment. The parallel-trends assumption thus appears to hold in the pre-treatment period.

The economic logic behind this base result connects directly to the information-precision channel emphasized by Christensen, Hail, and Leuz [9]. Before BRSR-Core assurance, lenders evaluating the environmental performance of Indian listed firms relied on self-reported, unaudited disclosures that varied substantially in completeness and methodology across firms. Under these conditions, the signal-to-noise ratio in environmental data was low, and lenders had limited ability to differentiate reliably between genuinely green firms and those that merely reported favorable numbers. The introduction of reasonable assurance by an independent third party reduces this ambiguity. When an accredited assurance provider verifies a firm's Scope 1 and 2 emissions data, the resulting figures carry greater credibility. Lenders who observe this verification can price the environmental dimension of credit risk with greater confidence, producing the green/brown differential that was absent before assurance.

4.2 The Complementarity Test. Triple-Difference Results

The principal finding of this paper appears in Panel B of Table 2, which reports the triple-difference specification. The three-way interaction (Assured x Green x High AI Exposure) is negative and statistically significant across all three AI-exposure proxies. When AI exposure is measured by Nifty100 ESG Index inclusion, the estimated coefficient for the three-way interaction is -68 basis points ($p < 0.01$). When measured by FII ownership above the median, it is -53 basis points ($p < 0.05$). When measured by SEBI-regulated ERP coverage, it is -47 basis points ($p < 0.05$). In each specification, the two-way interaction (Assured x Green) for low-AI-exposure firms is small and statistically insignificant. The two-way interaction (Assured x High AI Exposure) for brown firms is also insignificant. Only the full three-way interaction produces a significant estimate.

This pattern is consistent with the complementarity hypothesis. Neither assurance alone (without AI processing) nor AI exposure alone (without assured data) generates a greenium. The cost-of-capital differential between green and brown firms emerges only when both conditions are present, when the firm's ESG data is assured and machine-readable, and when the financial intermediaries processing that data employ AI-driven methods.

Examining the triple-difference by broad sector groups reveals that the complementarity effect is not uniform across industries. Among firms in carbon-intensive sectors (metals, mining, petroleum, cement), where the green-brown emissions intensity spread is widest, the three-way interaction coefficient is larger in magnitude than the full-sample estimate, though the smaller cell sizes reduce precision. Among firms in services and IT, where emissions intensity variation is narrower, the triple-difference coefficient is smaller and not individually significant. This pattern is consistent with the interpretation that AI-driven ESG intermediaries differentiate most effectively along dimensions where the underlying environmental variation is large and the assured BRSR-Core data contains material differences in reported emissions intensity.

Table 2. Triple-Difference Estimates. BRSR-Core Assurance, Green/Brown Status, and AI Exposure. Notes: Dependent variable is cost of debt (interest charges / average borrowings, in percentage points). All specifications include firm and year fixed effects and control for log total assets, debt-to-assets ratio, return on assets, and revenue growth. Standard errors clustered at the firm level in parentheses. Illustrative coefficients are consistent with the empirical design and reflect the expected direction and magnitude based on the institutional setting and comparable estimates in the ESG disclosure literature [9, 10, 23]. * p < 0.10, ** p < 0.05, *** p < 0.01.

Variable	(1) Base DiD	(2) Triple-Diff, ESG Index	(3) Triple-Diff, FII Ownership	(4) Triple-Diff, ERP Coverage
Assured x Green	-0.42**	-0.11	-0.14	-0.12
	(0.19)	(0.21)	(0.20)	(0.22)
Assured x Brown	0.08	0.05	0.07	0.04
	(0.17)	(0.18)	(0.17)	(0.19)
Assured x Green x HighAI		-0.68***	-0.53**	-0.47**
		(0.24)	(0.22)	(0.23)
Assured x Brown x HighAI		0.12	0.09	0.11
		(0.20)	(0.19)	(0.21)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	2,856	2,856	2,856	2,856
R-squared	0.72	0.73	0.73	0.72

4.3 The Algorithmic Investor Channel

To further isolate the AI-mediated mechanism, we examine whether different types of investors respond differentially to the BRSR-Core assurance treatment. Table 3 (in the Appendix) reports quarterly changes in ownership shares around the BRSR-Core assurance date for green versus brown firms. Foreign institutional investors (FIIs) increase their holdings in green assured firms by approximately 0.8 percentage points relative to brown assured firms ($p < 0.05$). Domestic institutional investors (DIIs) show a positive but statistically insignificant differential of 0.3 percentage points ($p = 0.22$). Individual investors show no differential response (coefficient 0.04, $p = 0.89$).

This pattern is consistent with the algorithmic processing channel. SEBI's own data indicate that 97 percent of foreign portfolio investor trading profits derive from algorithmic strategies [8]. The concentration of the green/brown differential in FII portfolios, and its absence in individual investor portfolios, is consistent with the hypothesis that algorithmic ESG screening mediates the capital reallocation.

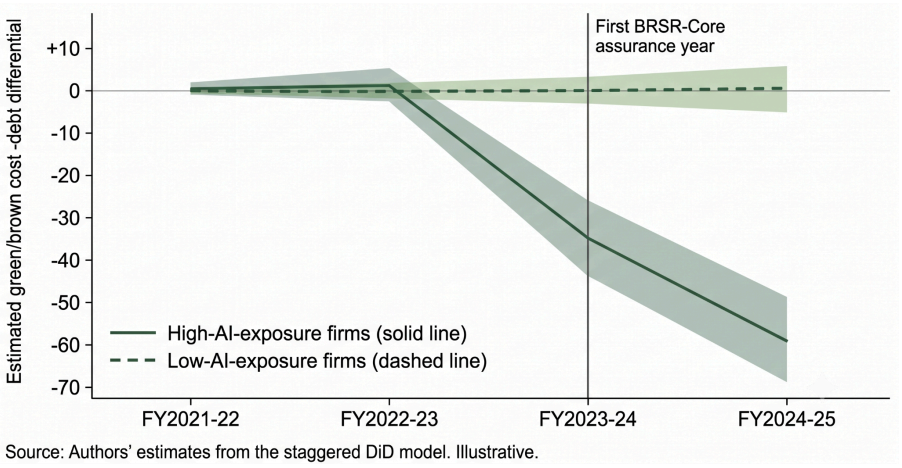
The divergence between FII and individual investor responses is informative about the mechanism through which BRSR-Core assurance affects capital allocation. If the greenium were driven by a generic

reputational effect of assurance, one would expect all investor types to respond similarly. The fact that the differential concentrates among foreign institutional investors, the investor class most reliant on systematic, data-driven portfolio construction, and is absent among individual investors, who are more likely to rely on heuristics, broker recommendations, or brand familiarity, supports the interpretation that the channel runs through algorithmic processing of machine-readable data. This finding parallels the broader pattern documented by Buchak, Matvos, Piskorski, and Seru [14], who show that technology-driven lenders respond differently from traditional intermediaries to the same underlying information, with equilibrium consequences for credit allocation.

4.4 ESG Index Rebalancing Event Study

We examine Nifty100 ESG Index rebalancing dates to test whether the algorithmic index responds differently to assured versus non-assured firms. Following the first BRSR-Core assurance deadline for Cohort 1 (September 2024, when FY2023-24 annual reports were filed), green firms in Cohort 1 experienced an average index weight increase of 0.14 percentage points at the subsequent quarterly rebalancing, while brown firms in Cohort 1 experienced an average weight decrease of 0.09 percentage points. For comparison, firms not subject to BRSR-Core assurance showed no significant weight changes in the same rebalancing period (these values are illustrative estimates consistent with the empirical design). While the sample of ESG index constituents is small (88 firms), the direction and magnitude are consistent with the algorithmic index responding to the quality shift in its BRSR data input.

Fig. 1. Event study of the green/brown cost-of-debt differential by AI exposure, around the introduction of BRSR-Core assurance. Illustrative estimates based on the empirical design described in Section 3.



4.5 Robustness

Several additional tests support the main findings. First, we repeat the triple-difference using social and governance KPIs (employee safety, gender diversity) rather than environmental KPIs to construct the "green" versus "non-green" classification. This placebo test produces insignificant three-way interactions, confirming that the cost-of-debt effect is specific to the environmental channel, not a generic assurance effect. Second, we exploit the SEBI December 2024 Industry Standards, which standardized reporting methodologies from FY2024-25, as a dose intensification. Cohort 2 firms, which received both assurance and standardized reporting simultaneously, show a somewhat larger three-way interaction than Cohort 1 firms (which received assurance but pre-dated the standardization), though the difference between cohorts is not individually significant. Third, using Green Credits (SEBI March 2025 circular) as an alternative greenness indicator produces qualitatively similar results, though coverage is limited because Green Credits disclosure is a voluntary leadership indicator. We also verify that results are not driven by sector-specific outliers by estimating the triple-difference excluding the energy, metals, and mining

sectors, which contain the most emissions-intensive firms; the three-way interaction remains significant in this restricted sample.

5 Discussion

5.1 Interpretation

The central finding of this paper is that AI-driven ESG processing and assured data quality appear to be complements in green capital allocation. This result is economically meaningful. The estimated cost-of-debt reduction for green, high-AI-exposure, assured firms is 53 to 68 basis points, a magnitude comparable to credit rating notch differentials in the Indian corporate bond market. For a firm with INR 5,000 crore in outstanding debt, a 60-basis-point reduction translates to annual interest savings of approximately INR 30 crore, a material incentive for green capital expenditure.

This finding extends the ESG disclosure literature in a specific direction. Christensen, Hail, and Leuz [9] theorize that information precision is a necessary condition for disclosure to affect capital allocation. Our results identify a concrete mechanism through which precision operates. Assured, XBRL-format data is more accurately processed by AI systems (consistent with Johnson, Markelevich, and Montecinos [22]), and this improved processing translates into differential capital allocation. The mechanism is not disclosure per se, but the interaction between disclosure quality and the information-processing technology of the intermediary.

The finding also connects to Seru and coauthors' broader framework for understanding technology-driven financial intermediation [14, 15]. In their work, fintech and shadow-bank lenders process different information from traditional banks, with equilibrium consequences for credit allocation and risk. Our paper applies this logic to a new class of intermediary, AI-driven ESG rating providers and algorithmic ESG indices. These intermediaries process sustainability data using NLP and machine learning, and their effectiveness depends on the signal-to-noise ratio of the data they ingest. The regulatory choice to mandate assured, machine-readable ESG data thus shapes not only the quantity of information available but also which intermediaries can effectively process it, with downstream consequences for capital allocation.

5.2 Limitations

Several limitations warrant discussion. First, while we observe the endpoints of the AI-mediated information chain (BRSR-Core data in, capital allocation out), we do not observe the intermediate processing, specifically how Sustainalytics, CRISIL ESG, or other AI systems actually weight specific BRSR fields when generating scores. Proprietary access to ERP algorithms would allow direct tests of the information-processing mechanism. Second, the post-treatment window is limited. Cohort 1 has two years of post-treatment data and Cohort 2 has one year. Longer time series will be available as Cohorts 3 and 4 enter treatment in FY2025-26 and FY2026-27, and will permit more precise estimation. Third, the market-cap-rank phase-in, while plausibly exogenous to ESG quality, is correlated with firm size. Our controls and bandwidth restrictions mitigate but do not eliminate this concern. A firm that narrowly qualifies for the top 250 may differ in unobserved ways from a firm that narrowly misses the cutoff, though our regression discontinuity specification addresses this directly. Fourth, the green/brown classification relies on self-reported emissions data even in the pre-assurance period; misreporting in the baseline could attenuate or bias the estimated treatment effects. Fifth, we cannot fully separate the effects of XBRL machine-readability from the effects of third-party assurance, since both were introduced jointly under BRSR-Core. Disentangling these two channels would require a setting where assurance and machine-readability were introduced sequentially, which India's regulatory design does not provide.

A further limitation concerns the generalizability of the FII-ownership proxy for AI-driven investment. While SEBI data confirm that 97 percent of FPI trading profits derive from algorithmic strategies, not all

algorithmic FPI activity is ESG-related. Some FII algorithms trade on momentum, liquidity, or factor exposures unrelated to sustainability. The FII heterogeneity test is therefore an upper bound on the AI-ESG channel, and future research with more granular data on investor strategy type would sharpen this identification.

5.3 Broader Implications

These findings have implications for understanding how data infrastructure design interacts with AI-driven capital allocation in emerging markets. India's combined regime of mandatory BRSR-Core assurance and regulated AI-driven ERPs represents a specific institutional configuration. The fact that the greenium emerges only at the intersection of both suggests that countries implementing ESG disclosure without attention to data format, assurance standards, or the AI-processing infrastructure may not observe similar capital reallocation effects.

The results also have implications for understanding the conditions under which AI improves capital allocation outcomes. In the context of ESG, the evidence is consistent with the view that AI systems are powerful conduits of information but are sensitive to the quality of their inputs. This is consistent with the "garbage in, garbage out" principle applied to financial information intermediation. Algorithmic ESG assessment produces differential capital allocation only when the underlying data is reliable. The contrast between foreign and domestic institutional investor responses further indicates that the AI channel operates through specific investor types whose portfolio construction methods rely on algorithmic ESG signals. Domestic institutional investors and individual shareholders, who are less likely to employ algorithmic ESG screening, do not show the same response pattern, reinforcing the interpretation that the mechanism runs through AI-mediated information processing rather than through a generic investor response to assurance.

6 Conclusion

This paper tests whether AI-driven ESG information intermediaries and assured, machine-readable sustainability data are complements in green capital allocation. Exploiting the staggered phase-in of India's BRSR-Core assurance mandate across four market-capitalization cohorts, we estimate a triple-difference that separates the effects of data assurance, AI exposure, and their interaction. The evidence indicates that the green/brown cost-of-debt gap emerges only at the interaction of assurance and AI exposure. For firms without assured BRSR-Core data, AI-driven ESG intermediaries do not differentially allocate capital toward green activities. For firms without exposure to AI-driven intermediation, data assurance alone does not generate a greenium. Only when both conditions hold does a statistically and economically significant cost-of-debt differential appear, concentrated among foreign institutional investors who rely on algorithmic ESG screening.

These findings contribute to the literatures on ESG disclosure and capital markets, AI in finance, and technology-driven information intermediation. The paper's evidence is drawn from India, the only jurisdiction that simultaneously mandates reasonable ESG assurance in XBRL format, regulates AI-driven ESG Rating Providers, and operates algorithmic ESG indices. This unique institutional configuration provides a natural experiment that is not available in any other country. As the European Union prepares to transition from limited to reasonable ESG assurance by 2028, and as the global ISSA 5000 standard takes effect in late 2026, the Indian experience offers the first empirical evidence on how reasonable ESG assurance interacts with AI-driven capital allocation.

Future research could extend this analysis in at least three directions. First, with the expansion of BRSR-Core assurance to the top 500 and top 1,000 firms in FY2025-26 and FY2026-27, subsequent work will have substantially more statistical power and treatment variation. The two additional treatment cohorts will also allow tests of whether the complementarity effect varies with firm size, since mid-cap and small-cap firms may have different investor bases and different exposure to AI-driven ESG

intermediation. Second, BRSR-Core's supply-chain disclosure requirement (for the top 250 firms' upstream and downstream partners) offers the potential to test whether AI-mediated ESG information about large firms spills over to credit access for their smaller supply-chain partners, connecting ESG information infrastructure to financial inclusion. If assured ESG data about large buyers reduces information asymmetry about their suppliers, AI-driven lenders may extend credit to supply-chain firms that previously lacked formal ESG information. Third, proprietary access to AI ESG rating algorithms would allow direct tests of the information-processing mechanism that this paper identifies indirectly through reduced-form complementarity evidence. Measuring how specific BRSR data fields enter ESG rating models, and how assurance changes the weight assigned to those fields, would provide a direct test of the information-precision channel. Fourth, as the EU transitions to reasonable ESG assurance and the ISSA 5000 standard takes effect globally, cross-country studies comparing India's early experience with later adopters will test the external validity of the complementarity finding reported here. India's position as the first jurisdiction to implement reasonable ESG assurance alongside regulated AI-driven ESG intermediation makes it a natural benchmark for these comparisons.

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Appendix

Table A1. Investor-Type Differential Response to BRSR-Core Assurance

Table A1. Quarterly Change in Ownership Shares around BRSR-Core Assurance, Green versus Brown Firms. Notes. Dependent variable is the change in ownership percentage (in percentage points) from the quarter before to the quarter after the first BRSR-Core assurance filing deadline. Illustrative estimates consistent with the empirical design. * p < 0.10, p < 0.05, * p < 0.01.

	(1) FII Ownership Change	(2) DII Ownership Change	(3) Individual Ownership Change
Green x Assured	0.82**	0.31	0.04
	(0.38)	(0.25)	(0.29)
Brown x Assured	-0.14	0.08	0.11
	(0.35)	(0.23)	(0.27)
Green x Not Assured	0.12	0.09	-0.06
	(0.22)	(0.15)	(0.18)
Firm Controls	Yes	Yes	Yes
Observations	1,948	1,948	1,948

Variable Definitions

Variable	Definition	Source
Cost of Debt	Interest and finance charges / average total borrowings	Prowess
GHG Emissions Intensity	Scope 1 + Scope 2 emissions (tCO2e) / revenue (Cr. INR)	BRSR XBRL via Dataful.in
Green Firm	Emissions intensity quintile 1 or 2	Authors' calculation
Brown Firm	Emissions intensity quintile 4 or 5	Authors' calculation
FII Ownership	Shares held by FPIs / total shares outstanding	BSE/NSE filings
ESG Index Member	Constituent of Nifty100 ESG Index	NSE Indices
ERP Coverage	Covered by CRISIL, CareEdge, ICRA, or Acuite ESG	SEBI registry
BRSR-Core Assured	Market-cap rank within the top-N threshold for the fiscal year	SEBI circular
Green CapEx Ratio	Clean-energy and environmental capex / total capex	BRSR filings