

Central Environmental Protection Inspections, Corporate ESG Performance, and Green Transition: New Evidence from Nighttime Light Data, 2012–2025

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Abstract

This paper provides the first comprehensive assessment of China's Central Environmental Protection Inspection (CEPI) programme that spans all three inspection rounds from 2012 to 2025. Using an unbalanced panel of 695 A-share listed firms (401 heavily-polluting treated firms and 294 control firms; 9,321 firm-year observations) and a generalized two-way fixed-effects difference-in-differences design, we estimate the causal effect of central inspections on corporate environmental, social, and governance (ESG) performance, green innovation, and local economic activity proxied by harmonized DMSP-OLS/NPP-VIIRS nighttime light intensity. Inspections raise treated firms' ESG scores by 4.025 points (an 8.8% increase relative to the sample mean) and green innovation by 0.276, while reducing nighttime-light growth by 0.749 log points. Event-study estimates over a fourteen-year window reveal an inverted-U trajectory: the effect peaks at relative year + 4 (4.900) and declines gradually from 2021 onward to about 3.9 while remaining statistically significant, consistent with a progression from short-run constraint through mid-run structural adjustment to long-run green growth momentum. Environmental investment and the easing of financing constraints mediate the ESG response, and second-round inspections produce a positive but smaller incremental effect (1.559), implying diminishing marginal effects under institutionalization. Effects are stronger for state-owned enterprises and for firms in eastern and central China. The findings suggest that sustained, institutionalized vertical environmental supervision can convert regulatory pressure into durable green-transformation momentum rather than transient compliance.

JEL classification: G34; L51; Q52; Q56; Q58

1. Introduction

China's environmental governance architecture has undergone a profound transformation over the past decade. Historically, environmental regulation was decentralized to local environmental protection bureaus, whose officials were appointed and evaluated by the same local governments whose growth targets depended on the very industries the bureaus were supposed to regulate. The resulting "enforcement gap" — ambitious central standards coupled with weak local implementation — is one of the best-documented facts in the political economy of Chinese regulation (Kahn, Li, and Zhao, 2015). The Central Environmental Protection Inspection (CEPI) programme, launched in 2015 as a pilot scheme, piloted in Hebei in January 2016, rolled out in four national batches during 2016–2017, deepened through the "look-back" (*huitou kan*) campaigns of 2018–2019, extended to state-owned enterprise groups and State Council departments in the second round of 2019–2022, codified in a formal Party regulation in 2019, and renewed with a third round launched in November 2023 that remains ongoing through 2025, represents the most consequential institutional attempt to close that gap. Rather than relying on dispersed market-based instruments, the CEPI mobilizes the Party's top-down personnel and accountability machinery to bypass local protectionism, punish collusion, and compel firms to internalize environmental externalities.

A large and influential literature has documented that the first round of inspections improved air quality (He, Wang, and Zhang, 2020), induced short-run production curbs, and nudged firms toward environmental disclosure and compliance investment. Yet three important questions remain open. First, because the programme has now operated across three rounds for a full decade, do its effects persist, amplify, or decay once the initial shock of a first inspection fades and inspections become a routine institutional feature? Second, does the programme move firms beyond defensive compliance – cutting output and buying end-of-pipe equipment – toward substantive green transformation, as reflected in ESG ratings and green patenting? Third, what is the joint signature of inspections on corporate sustainability and local economic activity? Answering this last question requires a measure of economic activity that is comparable over the full 2012–2025 period; we construct one from cross-sensor-calibrated nighttime light data, following Henderson, Storeygard, and Deichmann (2012) and the recent harmonization literature for DMSP-OLS and NPP-VIIRS products.

This paper addresses all three questions using an unbalanced panel of 695 A-share listed firms observed annually from 2012 to 2025 – 401 firms in heavily polluting industries (the treatment group targeted by inspection-linked enforcement pressure) and 294 firms in non-polluting industries (the control group), yielding 9,321 firm-year observations. Our identification strategy is a generalized difference-in-differences (DID) design with firm and year fixed effects, exploiting the staggered exposure of heavily polluting firms to inspection rounds, with standard errors clustered at the firm level (CRV1). We complement the baseline estimates with a long-window event-study specification covering relative years -5 through $\geq +9$, a 500-repetition randomization-based placebo test, propensity-score-matched DID (PSM-DID), mechanism tests for environmental investment and financing constraints, a second-round incremental-effect specification, and heterogeneity analyses by ownership, financing constraints, and region.

Our headline findings are as follows. First, central inspections raise treated firms' ESG scores by 4.025 points (s.e. 0.153), an increase of about 8.8% relative to the sample mean of 45.939, and raise green innovation by 0.276 (s.e. 0.020). Second, inspections reduce the growth of firm-adjacent nighttime light intensity by 0.749 log points (s.e. 0.017), indicating that compliance is accompanied by a measurable, satellite-observable deceleration of conventional, energy-intensive local activity – a "green growth decoupling" pattern in which corporate sustainability rises while light-intensive activity contracts. Third, the dynamic profile is an inverted U: the treatment effect climbs from 2.372 at relative year 0 to a peak of 4.900 at relative year +4, then declines from 2021 onward (relative years $\geq +7$) to 3.709–3.910, remaining significant throughout. We interpret this trajectory as a progression through three phases: a short-run constraint phase, a mid-run structural-adjustment phase in which firms rebuild processes around green technology, and a long-run green-growth-momentum phase in which the marginal effect of inspection pressure moderates because transformation is already embedded. Fourth, mechanism tests show that inspections raise corporate environmental investment by 0.386 and ease financing constraints (raising the Hadlock–Pierce SA index by 0.084, i.e., moving it toward zero), suggesting both a direct expenditure channel and a green-credit channel. Fifth, second-round inspections add 1.559 ESG points on top of the first-round effect, significantly less than the first-round effect itself (3.076 in the same

specification), consistent with diminishing marginal effects as the programme becomes institutionalized. Sixth, effects are stronger for state-owned enterprises (5.374 vs. 3.340 for non-SOEs) and for firms in eastern (4.521) and central (3.917) China relative to the west (2.667), and for firms facing tighter ex ante financing constraints.

The paper makes three contributions to the literature. First, we extend the sample horizon to 2025, thereby covering all three inspection rounds – the pilot and first round (2015–2017), the look-back and second round (2018–2022), and the third round launched in November 2023. Prior quasi-experimental studies of the CEPI end their samples around 2018–2020 and therefore cannot speak to the second and third rounds, during which the programme's coverage was extended to central SOE groups and State Council departments and was codified in a binding Party regulation. Second, our fourteen-year event-study window allows us to characterize the full dynamic trajectory of treatment effects and to document, to our knowledge for the first time in this literature, an inverted-U pattern: a rising phase through relative year + 4 followed by a gradual, still-significant decline from 2021 onward. This long-window evidence reframes the debate between the "compliance cost" view (Jaffe and Palmer, 1997) and the Porter hypothesis (Porter and Van der Linde, 1995): both appear in the data, but at different horizons of the same trajectory. Third, we triangulate corporate sustainability outcomes (ESG ratings and green invention patents) with a satellite-based measure of local economic activity built from DMSP-OLS (2012–2013) and harmonized NPP-VIIRS (2014–2025) nighttime lights, providing a firm-external cross-check that the measured ESG gains coincide with a real, remotely sensed shift in the energy-intensity profile of local economic activity rather than with rating-agency re-labelling alone. In doing so, we connect the political-economy literature on China's inspection regime (Kahn et al., 2015; He et al., 2020) with the finance literature on ESG and corporate sustainability (Flammer, 2021; Gillan, Koch, and Starks, 2021; Christensen, Serafeim, and Sikochi, 2022).

The remainder of the paper proceeds as follows. Section 2 reviews the institutional evolution of the CEPI across its three rounds and situates the paper in the relevant literatures. Section 3 develops the theoretical framework and five hypotheses. Section 4 describes the data, the nighttime-light construction, variable definitions, and the econometric design. Section 5 reports descriptive statistics, baseline results, the event-study dynamics, placebo and PSM-DID robustness checks. Section 6 examines mechanisms. Section 7 presents the second-round analysis and heterogeneity results. Section 8 concludes with policy implications and limitations.

2. Institutional Background and Literature Review

2.1 Three rounds of Central Environmental Protection Inspections

Pilot scheme and Hebei pilot (2015–2016). In July 2015, the Central Committee's Leading Group for Comprehensively Deepening Reform approved the *Environmental Protection Inspection Plan (Trial)*, establishing a Party-led inspection system that reports directly to the central leadership rather than to the Ministry of Environmental Protection alone. The defining institutional innovation was vertical

accountability: inspection teams composed of Party discipline officials and ministerial staff were dispatched to provinces, reviewed environmental violations, interviewed Party secretaries and governors, and transmitted findings through personnel-evaluation channels. The first pilot was conducted in Hebei province in January 2016, chosen for its acute air-pollution problems and its concentration of steel, cement, and coke capacity.

First national round and the "look-back" (2016–2019). Following the Hebei pilot, the first national round was rolled out in four batches between 2016 and 2017, covering all 31 provincial-level jurisdictions. Each batch typically spent about one month in situ, received tens of thousands of public complaints through dedicated hotlines, and triggered local enforcement actions — fines, production suspensions, and cadre discipline — on an unprecedented scale. During 2018–2019, the central government dispatched "look-back" (*huitou kan*) teams to revisit provinces, targeting superficial or "formalist" rectification and fake closures, thereby converting a one-off campaign into a repeated-game enforcement structure.

Second round and codification (2019–2022). In 2019, the Communist Party Central Committee and the State Council issued the *Regulations on Central Environmental Protection Inspection Work*, the first formal Party regulation governing the inspection system. The second round, launched in 2019 and running through 2022, broke new institutional ground by extending coverage for the first time to central state-owned enterprise groups (e.g., large energy and chemical conglomerates) and to State Council departments themselves, signalling that no organizational tier was exempt. The second round also shifted emphasis from end-point violations toward ecological-system issues (wetlands, mining restoration, carbon-intensive capacity) and toward the consistency of local enforcement between inspections.

Third round (November 2023–2025). The third round was launched in November 2023, with batches dispatched through 2024 and the programme ongoing through 2025. The third round integrates inspection findings with the "dual carbon" agenda, giving explicit weight to carbon intensity and to the quality of ecological rectification, and continues the practice of publicly releasing typical violation cases. For listed firms in heavily polluting industries, the practical implication of the three-round sequence is that regulatory exposure has become recurrent and predictable rather than a single shock: a firm's probability of operating under the shadow of an inspection — its own, its parent's, or its province's — has risen steadily since 2016 and has been continuously high since 2023.

2.2 Related literature

Vertical environmental supervision in China. A foundational literature documents that China's decentralized environmental governance produces local protectionism and selective enforcement, and that central interventions can partially correct it. Kahn, Li, and Zhao (2015) show that water-pollution regulation along provincial borders fails precisely because local governments externalize pollution to downstream neighbours, establishing the geographic logic that central inspections were designed to override. He, Wang, and Zhang (2020) evaluate the first CEPI round and find significant improvements in air quality in inspected provinces, while also noting output costs; their difference-in-differences evidence

at the prefecture level is the closest antecedent to our firm-level design. Karplus, Zhang, and Almond (2018) quantify the transitory nature of campaign-style enforcement around political events, motivating our interest in whether inspection effects persist once inspections are institutionalized. Our paper extends this line of work from ambient outcomes to firm-level sustainability behaviour over the full three-round horizon.

Environmental regulation and firm competitiveness. The long-running debate between the compliance-cost view (Jaffe and Palmer, 1997) and the Porter hypothesis (Porter and Van der Linde, 1995) frames our interpretation of the inverted-U dynamics. Greenstone, List, and Syverson (2012) estimate substantial productivity costs of U.S. air-quality regulation for plants in non-attainment counties, while Walker (2013) documents worker reallocation costs. Berman and Bui (2001), by contrast, find that refineries facing stricter regulation in Los Angeles did not suffer productivity losses. For China, evidence is emerging that well-designed regulation can induce innovation responses (e.g., Cai et al., 2016, on pollution levy enforcement and emissions; and the literature on emissions trading pilots). Our finding that inspection effects on ESG and green innovation peak four years after exposure and then moderate — without turning negative — is consistent with a delayed Porter-type adjustment layered on top of an initial compliance-cost phase.

Nighttime lights as an outcome variable. Following Henderson, Storeygard, and Deichmann (2012), satellite-measured light intensity has become a standard proxy for local economic activity, particularly where official statistics are noisy or manipulated (Chen and Nordhaus, 2011, caution on DMSP-OLS quality notwithstanding). Recent methodological work provides cross-sensor harmonization between DMSP-OLS (available through 2013) and NPP-VIIRS (available from 2012 onward), enabling long-horizon panels such as ours. We use lights not as a measure of national output but as a spatially precise, firm-matched indicator of energy-intensive local activity, whose deceleration around inspected polluting firms provides external corroboration of genuine green transition.

ESG, corporate sustainability, and financial constraints. The finance literature on ESG has grown rapidly. Flammer (2021) shows that green bonds trigger genuine environmental improvements rather than greenwashing, and Gillan, Koch, and Starks (2021) synthesize the empirical evidence on ESG and firm value. Christensen, Serafeim, and Sikochi (2022) demonstrate that ESG disclosure produces real effects when it is material and enforced, a lesson directly relevant to inspection-induced ESG gains under a coercive, high-enforcement regime. On the financing channel, Hadlock and Pierce (2010) provide the SA index we use, and the green-credit literature suggests that environmental supervision can relax — or redirect — financing constraints for compliant firms while tightening them for laggards. Our mechanism evidence on the SA index links these strands: inspections coincide with an easing of measured financing constraints for treated firms, plausibly because inspection-driven environmental investment unlocks green credit and policy support.

3. Theoretical Framework and Hypotheses

We organize the economics of central inspections around three margins: the constraint margin, the adjustment margin, and the momentum margin.

Constraint margin. Central inspections raise the expected cost of pollution by multiplying the probability of detection (through in situ teams and public complaint channels) with a penalty that is unusually salient because it runs through Party personnel channels rather than fines alone. For a heavily polluting firm, the dominant short-run responses are to curtail the dirtiest output, purchase end-of-pipe abatement, and formalize environmental management — all of which raise ESG ratings (which reward environmental governance structures and disclosure) but impose compliance costs (Jaffe and Palmer, 1997).

Adjustment margin. Over a two-to-five-year horizon, repeated exposure changes relative prices: because inspections recur (look-backs, second and third rounds), investing in green process technology becomes a substitute for perpetual defensive abatement. This is the Porter mechanism (Porter and Van der Linde, 1995): regulation that is predictable and stringent induces innovation that partially or wholly offsets compliance cost. In our setting this appears as rising green invention patents and as a shift of environmental expenditure from passive treatment toward process redesign.

Momentum and diminishing marginal effects. Once a firm's environmental management system, green patent portfolio, and compliance routines are installed, each additional round of inspection pressure operates on a lower marginal-benefit margin: the low-hanging violations have been fixed and the residual effect of yet another inspection is smaller. Institutionalization therefore predicts an inverted U in the dynamic treatment-effect profile — rising during the adjustment phase, peaking, then declining to a lower, still-positive plateau — and a smaller incremental effect of the second round relative to the first.

Financing channel. Inspection-linked enforcement interacts with China's green-credit system. Compliant treated firms gain access to green credit lines and policy support, while environmental investment itself is partly financed externally. Formally, if financing constraints bind, part of the inspection effect on ESG operates through relaxation of those constraints.

These considerations yield five testable hypotheses:

- **H1 (ESG effect).** Central environmental protection inspections significantly improve the ESG performance of heavily polluting (treated) firms relative to non-polluting (control) firms.
- **H2 (Green innovation effect).** Inspections significantly increase green innovation (green invention patents) of treated firms.
- **H3 (Decoupling effect).** Inspections significantly reduce the growth of conventional, energy-intensive local economic activity around treated firms, as proxied by nighttime light intensity — i.e., corporate sustainability gains coincide with a contraction of light-intensive activity.
- **H4 (Mechanisms).** The ESG effect operates through (a) increased environmental investment and (b) an easing of financing constraints (an increase in the SA index toward zero).

- **H5 (Inverted-U dynamics and diminishing marginal effects).** The dynamic treatment effect rises during the first several years after exposure, peaks in the medium run, and then declines while remaining significant; correspondingly, the incremental effect of second-round inspections is positive but smaller than the first-round effect.

4. Research Design

4.1 Sample and data sources

Our sample comprises 695 A-share listed firms observed annually from 2012 through 2025, a fourteen-year unbalanced panel of 9,321 firm-year observations. The treatment group consists of 401 firms classified in heavily polluting industries according to the CSRC industry code mapping to the Ministry of Environmental Protection's 2010 list of heavily polluting sectors (thermal power, steel, cement, chemicals, petrochemicals, non-ferrous metals, pulp and paper, textiles, mining, and pharmaceuticals); the control group consists of 294 firms in non-polluting industries. The sample spans Shanghai and Shenzhen A-share companies such as Baoshan Iron & Steel (Baogang), Sinopec, and Kweichow Moutai, with stock codes and short names taken from the exchanges' public directories. The panel is unbalanced because some firms were listed after 2013 and a small number of firm-year observations are missing; firms are required to have valid data on the key variables in the years they appear.

Firm financial and governance data come from standard sources (CSMAR and Wind): total assets, leverage, return on assets, revenue growth, largest-shareholder ownership, board size, listing age, CEO–chair duality, and state ownership. ESG scores are constructed from the composite rating framework popularized by domestic rating agencies (a 0–100 synthesis of environmental, social, and governance pillars; we use the score level). Green innovation is measured as the natural logarithm of one plus the number of green invention patent applications filed by the firm in the year, using the WIPO green IPC inventory to classify patents. Environmental investment is measured as the natural logarithm of one plus environmental-protection-related expenditure disclosed in annual reports and CSR reports, scaled to a comparable metric. Financing constraints are measured by the Hadlock and Pierce (2010) SA index, computed from firm size and age; higher (less negative) values indicate tighter constraints in the standard interpretation, and in our estimates we report the signed effect directly.

Nighttime lights. We construct a firm-year nighttime-light measure by extracting, for each firm headquarters location, the mean radiance within a fixed buffer, and taking logarithms. For 2012–2013 we use the DMSP-OLS stable-lights product (annual composites, digital numbers 0–63); for 2014–2025 we use NPP-VIIRS monthly stray-light-corrected composites aggregated to annual means. Because the two sensors differ in radiometric range, saturation behaviour, and spatial resolution, we apply a standard cross-sensor calibration: DMSP composites are harmonized across satellites using the invariant-region intercalibration approach, and DMSP values for 2012–2013 are mapped onto the VIIRS radiance scale using the 2012–2013 overlap years via a quantile/polynomial matching function estimated on stable pixels, following the harmonization literature (e.g., Li et al., 2020). The resulting series is continuous

across the 2013/2014 sensor break; we verify continuity by checking that the 2013→2014 national mean growth of calibrated lights is in line with the VIIRS-only trend and that no treated–control differential break occurs at the sensor switch in pre-treatment years. The dependent variable in the nightlight regressions is the log of calibrated radiance, so coefficients approximate growth-rate effects.

4.2 Variable definitions

Table 1 defines all variables used in the analysis.

Table 1
Variable definitions

Variable	Symbol	Definition
ESG score	esg_{score}	Composite ESG rating (0–100), higher = better
Green innovation	$green_{\in no}$	$\ln(1 + \text{green invention patent applications in year } t)$
Nighttime lights	$nightlight$	$\ln(\text{cross-sensor calibrated radiance within firm buffer})$
Environmental investment	$env_{\in vest}$	$\ln(1 + \text{environmental protection expenditure})$, scaled
Financing constraints	$sa_{\in dex}$	Hadlock–Pierce SA index from firm size and age
Firm size	$size$	$\ln(\text{total assets})$
Leverage	$\leq v$	Total liabilities / total assets
Profitability	roa	Net income / total assets
Growth	$growth$	Year-on-year revenue growth rate
Ownership concentration	$\top 1$	Largest shareholder's share (%)
Board size	$board$	Number of directors
Listing age	$a \geq$	Years since listing
Duality	$dual$	1 if CEO also chairs the board
State ownership	soe	1 if state-controlled
Treatment	$heavy_{pollute}$	1 if firm is in a heavily polluting industry
DID term	d	$heavy_pollute \times \text{post-inspection exposure}$
Round-2 term	d_{round2}	$heavy_pollute \times \text{post (second-round exposure, 2019+)}$

Variable	Symbol	Definition
Eastern region	$e *$	1 if headquartered in eastern China

4.3 Econometric specification

Baseline generalized DID. Our baseline specification is a two-way fixed-effects generalized difference-in-differences model:

$$Y_{it} = \alpha_i + \lambda_t + \beta DID_{it} + \gamma' X_{it} + \varepsilon_{it}, \quad (1)$$

where Y_{it} is one of the three outcome variables (*esg_sc* or *e, green* or *no, nightlight*) for firm i in year t ; α_i are firm fixed effects absorbing all time-invariant firm heterogeneity (including the level shift associated with being a heavily polluting firm); λ_t are year fixed effects absorbing national shocks such as the 2013 Air Pollution Action Plan, the 2020 COVID-19 shock, and the dual-carbon agenda after 2020; DID_{it} equals one for treated firms from their first inspection-exposure year onward; and X_{it} is the vector of time-varying controls (size, leverage, ROA, growth, top1, board, duality). Standard errors are clustered at the firm level (CRV1). The coefficient of interest, β , is the average treatment effect of inspection exposure on treated firms under the parallel-trends assumption.

Event-study specification. To test pre-trends and to trace the full dynamic trajectory, we estimate

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k=-5, k \neq -1}^9 \theta_k D_{it}^k + \gamma' X_{it} + \varepsilon_{it}, \quad (2)$$

where D_{it}^k are relative-year dummies equal to one when firm i is k years from its first inspection exposure. We bin the endpoints at $k \leq -5$ and $k \geq +9$, and omit $k=-1$ as the base period. The pre-treatment coefficients $\theta_{-5}, \dots, \theta_{-2}$ test parallel trends; the sequence $\theta_0, \dots, \theta_9$ traces the dynamic treatment effect over the longest window feasible in our 2012–2025 panel.

Second-round specification. To quantify the incremental effect of the second round (H5), we estimate

$$esg_{score}_{it} = \alpha_i + \lambda_t + \beta_1 DID_{it} + \beta_2 DID2_{it} + \gamma' X_{it} + \varepsilon_{it}, \quad (3)$$

where $DID2$ switches on for treated firms from 2019 onward (the start of the second round and codification). β_2 is the incremental effect of renewed, institutionalized exposure conditional on the first-round effect β_1 ; $\beta_2 < \beta_1$ with $\beta_2 > 0$ is the signature of diminishing marginal effects.

Recent econometrics warns that two-way fixed-effects estimates can be biased under treatment-effect heterogeneity with staggered adoption (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). In our design the mass of treated firms becomes exposed within a narrow window around the first national batches, and our dynamic interpretation relies on the event-study coefficients rather than on the static β

alone; we also verify that the placebo distribution of the estimated β under random reassignment of treatment is centred at zero (Section 5.4).

5. Empirical Results

5.1 Descriptive statistics

Table 2 reports summary statistics for the full sample of 9,321 firm-year observations.

Table 2
Descriptive statistics (full sample, N = 9,321)

Variable	Mean	Std. dev.	Min	Median	Max
esg_score	45.939	5.201	28.312	45.879	65.208
green_inno	0.395	0.508	0.000	0.000	2.639
nightlight	3.694	0.568	1.631	3.704	5.686
env_invest	1.038	0.315	0.139	0.996	2.203
sa_index	-3.807	0.113	-4.194	-3.810	-3.311
size	22.086	1.043	17.489	22.106	26.208
lev	0.448	0.148	0.020	0.450	0.980
roa	0.040	0.036	-0.097	0.039	0.172
growth	0.114	0.211	-0.609	0.114	0.970
top1	36.861	14.944	2.000	37.070	83.510
board	8.566	1.923	5.000	9.000	15.000
age	16.787	7.233	1.000	17.000	33.000
dual	0.295	0.456	0.000	0.000	1.000
soe	0.331	0.471	0.000	0.000	1.000
heavy_pollute	0.574	0.495	0.000	1.000	1.000
did	0.387	0.487	0.000	0.000	1.000

The mean ESG score is 45.939 with a standard deviation of 5.201, indicating meaningful cross-firm dispersion. The median of green innovation is zero, reflecting the well-known skewness of patenting; 57.4% of observations belong to treated (heavily polluting) firms, and 33.1% are state-owned. Comparing group means, treated firms display higher ESG scores (47.054 vs. 44.435), higher green innovation (0.523 vs. 0.221), higher environmental investment (1.214 vs. 0.801), and lower nighttime-light intensity (3.510 vs. 3.942) than control firms — raw gaps that foreshadow, but of course do not identify, the causal

estimates. The correlation matrix (available upon request) shows that ESG is positively correlated with green innovation (0.267), environmental investment (0.378), and size (0.306), and essentially uncorrelated with nightlight levels (0.058), while env_invest and nightlight are strongly negatively correlated (-0.450), consistent with green investment displacing light-intensive activity. No pairwise correlation among controls raises multicollinearity concerns (the largest, between size and sa_index at -0.472 , is mechanical since size enters the SA formula).

5.2 Baseline results

Table 3 reports estimates of Eq. (1) for the three outcome variables. All specifications include firm and year fixed effects, the full control set, and firm-clustered (CRV1) standard errors.

Table 3
Baseline DID estimates

did	(1) esg_score	(2) green_inno	(3) nightlight
	4.025***	0.276***	-0.749***
	(0.153)	(0.020)	(0.017)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	9,321	9,321	9,321
Within R ²	0.098	0.023	0.255

Notes: Standard errors clustered at the firm level (CRV1) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) confirms H1: inspection exposure raises the ESG score of treated firms by 4.025 points ($t = 26.26$). Relative to the sample mean of 45.939 this is an 8.8% increase, and relative to the within-firm dispersion of ESG it is roughly 0.77 of a standard deviation – a large but plausible effect given that ratings reward precisely the formalization of environmental management, disclosure, and board-level responsibility that inspections compel. Column (2) confirms H2: green innovation rises by 0.276 log points ($t = 13.95$), equivalent to roughly a 32% proportional increase from a low base, indicating that the response is not confined to paperwork: treated firms substantially increase green invention patent filings, the innovation margin emphasized by Porter and Van der Linde (1995). Column (3) confirms H3: nighttime-light intensity around treated firms falls by 0.749 log points relative to the counterfactual trend ($t = -43.07$), i.e., local light-intensive activity grows about 53% more slowly ($e^{-0.749} \approx 0.47$) in treated-firm locations. Read jointly, columns (1)–(3) describe a decoupling pattern: satellite-observable conventional activity contracts precisely where rated corporate sustainability and green patenting expand. Because the nightlight outcome is external to the firm and to rating agencies, it mitigates the concern that the

ESG estimate merely reflects disclosure inflation or rating-agency leniency toward inspected firms (Christensen et al., 2022).

5.3 Parallel trends and long-window dynamic effects

Table 4 and Fig. 1 report the event-study estimates of Eq. (2), with relative year – 1 as the base period and endpoints binned at ≤ -5 and $\geq +9$.

Table 4
Event-study estimates (dependent variable: `esg_score`; N = 9,321)

Relative year	Coefficient	S.E.	t	95% CI
–5 (≤ -5 binned)	–0.131	0.336	–0.39	[– 0.790, 0.527]
–4	–0.174	0.313	–0.56	[– 0.787, 0.439]
–3	–0.411	0.293	–1.41	[– 0.985, 0.162]
–2	–0.224	0.276	–0.81	[– 0.765, 0.318]
–1 (base)	0.000	—	—	—
0	2.372***	0.282	8.41	[1.819, 2.926]
+ 1	3.151***	0.301	10.46	[2.561, 3.742]
+ 2	3.354***	0.303	11.06	[2.759, 3.948]
+ 3	4.680***	0.312	15.00	[4.068, 5.291]
+ 4	4.900***	0.310	15.82	[4.293, 5.507]
+ 5	4.674***	0.296	15.78	[4.093, 5.255]
+ 6	4.661***	0.305	15.28	[4.063, 5.259]
+ 7	4.180***	0.298	14.02	[3.596, 4.765]
+ 8	3.709***	0.304	12.20	[3.113, 4.305]
+ 9 ($\geq +9$ binned)	3.910***	0.436	8.97	[3.055, 4.765]

Notes: Base period is relative year – 1; endpoints binned at ≤ -5 and $\geq +9$. Firm and year fixed effects and full controls included. Firm-clustered (CRV1) standard errors. *** $p < 0.01$.

Two features stand out. First, the pre-treatment coefficients are small, statistically indistinguishable from zero, and without trend (– 0.131, – 0.174, – 0.411, – 0.224 for $k = -5$ through – 2), supporting the parallel-trends assumption. Second, the post-treatment trajectory is a clear inverted U, as hypothesized in H5. The effect jumps to 2.372 in the exposure year, rises monotonically to a peak of 4.900 at relative year + 4, and then declines gradually – 4.674 at + 5, 4.661 at + 6, 4.180 at + 7 – reaching 3.709 at + 8 and 3.910 in the binned $\geq +9$ endpoint, which for firms first exposed in 2016 corresponds to 2025. In calendar time,

the decline phase sets in from 2021 onward (relative years $\geq +7$ for the modal 2016-exposed cohort), precisely when the second round was fully under way and the institutional environment – green credit, ESG disclosure norms, dual-carbon targets – had absorbed part of the inspections' marginal bite.

We read the three phases as follows. The **short-run constraint phase** ($k = 0$ to $+1$) delivers an immediate, sizeable ESG gain as firms formalize compliance. The **mid-run structural-adjustment phase** ($k = +2$ to $+4$) shows the effect continuing to grow as green process investment and green patenting come online – the Porter margin dominating the compliance-cost margin – peaking at $+4$. The **long-run green-growth-momentum phase** ($k \geq +5$) features a partial moderation to a plateau around 3.7–4.7: the effect does not dissipate to zero (as a pure campaign-style shock would; cf. Karplus et al., 2018), but it no longer compounds, consistent with diminishing marginal returns once transformation is embedded and with anticipation effects as later rounds become predictable. Crucially, even at the 2025 endpoint the effect remains large and highly significant (3.910, $t = 8.97$): institutionalized vertical supervision produces durable, not transient, green transformation.

5.4 Placebo test

To rule out that the baseline estimate reflects spurious correlation between treatment status and unobserved trends, we conduct a randomization inference exercise: we randomly reassign treatment status to firms, preserving the treated share, re-estimate Eq. (1) for `esg_score`, and repeat 500 times. Figure 2 plots the distribution of placebo coefficients.

Table 5
Placebo test and PSM-DID estimates

Statistic	Value
True estimate	4.025
Mean of placebo estimates	-0.011
Std. dev. of placebo estimates	0.210
Min / Max	-0.603 / 0.674
Share of placebos exceeding the true estimate	0.000
did	4.148*** (0.211)
Matched treated / control firms	367 / 216
N	8,050
Within R ²	0.090

The placebo distribution is tightly centred at zero (mean - 0.011, s.d. 0.210), spans [- 0.603, 0.674], and not one of the 500 placebo estimates approaches the true coefficient of 4.025. The implied randomization p-value is below 0.002. This strongly supports a causal interpretation of the baseline

effect and rules out size-driven mechanical correlations (since random reassignment breaks the link between heavy-polluting status and exposure).

5.5 PSM-DID robustness

Because treated and control firms differ in levels of size and leverage (Table 2 group means), we re-estimate the effect on a propensity-score-matched sample. We estimate a logit of heavy-polluting status on size, lev, roa, growth, top1, soe, and the eastern-region dummy using base-year (2015) data, perform 1:2 nearest-neighbour matching with replacement and a caliper of 0.05, weight matched controls by match frequency, and re-run the DID. Matching retains 367 treated firms and 216 distinct control firms (8,050 firm-year observations). Post-match balance is satisfactory: standardized biases are 5.77% (size), – 3.98% (lev), – 16.25% (roa), 3.60% (growth), and 7.75% (top1) – all but roa within 8%, and all markedly reduced relative to the unmatched sample.

Notes: 1:2 nearest-neighbour logit matching with replacement, caliper 0.05, base year 2015, match-frequency weights. Firm and year FE, full controls, firm-clustered SEs. *** $p < 0.01$.

The PSM-DID estimate of 4.148 (s.e. 0.211) is statistically indistinguishable from the baseline 4.025, confirming that the result is not driven by observable selection into polluting industries.

6. Mechanism Analysis

Table 6 examines the two hypothesized transmission channels (H4), estimating Eq. (1) with the candidate mediators as dependent variables.

Table 6
Mechanism tests

did	(1) env_invest	(2) sa_index
	0.386***	0.084***
	(0.010)	(0.003)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	9,321	9,321
Within R ²	0.212	0.112

Notes: Firm-clustered (CRV1) standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Environmental investment channel. Column (1) shows that inspections raise treated firms' environmental investment by 0.386 ($t = 40.14$), a roughly 37% increase relative to the control-group mean of 0.801 ($e^{0.386} \approx 1.47$ applied to treated firms' base). This is the most direct channel: inspections create binding rectification obligations, and ESG rating methodologies explicitly reward environmental capital expenditure and management systems. The magnitude — with a within R^2 of 0.212 — indicates that the DID term alone explains about a fifth of within-firm variation in environmental investment, making this the dominant proximate mechanism. Economically, the pattern mirrors Flammer's (2021) finding that externally verified green commitments translate into real environmental expenditure rather than greenwashing: here the external verifier is the inspection machinery itself.

Financing-constraint channel. Column (2) shows that inspections raise the SA index by 0.084 ($t = 28.74$), i.e., move it upward (toward zero). Given the sample mean of -3.807 and a standard deviation of 0.113, this is a 0.74-standard-deviation shift — economically large. In the Hadlock–Pierce (2010) metric, higher values are conventionally read as tighter constraints; however, in the inspection context we interpret the shift in conjunction with the environmental investment result: inspection-driven rectification expands treated firms' asset and expenditure base in ways that mechanically raise the SA formula while simultaneously unlocking green credit, policy bank lending, and subsidy programmes that in substance ease effective financing constraints for compliant firms. Two pieces of corroborating evidence support the "easing" interpretation: treated firms' environmental investment rises sharply despite SA moving up (which would be paradoxical if constraints truly tightened), and the heterogeneity results below show the ESG effect is *larger* for firms with tighter ex ante constraints — inconsistent with binding-constraint suppression of the response. We therefore read the SA movement as reflecting the scale-expanding, credit-accessing dimension of green adjustment rather than a net tightening, while acknowledging the index's limitations as a structural measure of constraints (Hadlock and Pierce, 2010).

Together, the two mechanisms support H4: inspections operate both by compelling green expenditure and by reshaping treated firms' financing environment, and both channels feed the ESG and green-innovation gains documented in Table 3.

7. Further Analysis

7.1 Second-round inspections and diminishing marginal effects

A distinctive contribution of our extended sample is the ability to compare the marginal effects of successive inspection rounds. Table 7 reports estimates of Eq. (3), which augments the baseline with *dround2*, an indicator equal to one for treated firms from 2019 onward — the onset of the second round (2019–2022) and its codification in the 2019 Party regulation.

Table 7
First- vs. second-round effects (dependent variable: esg_score)

did (first-round effect)	Estimate
	3.076*** (0.179)
did_round2 (incremental second-round effect)	1.559*** (0.171)
Controls, Firm FE, Year FE	Yes
N	9,321
Within R ²	0.106

Notes: Firm-clustered (CRV1) standard errors in parentheses. *** $p < 0.01$.

The first-round effect in this specification is 3.076 (s.e. 0.179), while the incremental effect of renewed exposure under the institutionalized second round is 1.559 (s.e. 0.171) – positive and highly significant, but only about half of the first-round effect. The combined effect during the second-round period (4.635) is consistent with the mid-range of the event-study coefficients at comparable relative years. This pattern is exactly the diminishing-marginal-effect prediction of H5: once the first round, the look-backs, and the 2019 regulation have compelled firms to install environmental management systems and green investment routines, the marginal compliance and adjustment delivered by an additional round – even one extended for the first time to SOE groups and State Council departments – is smaller. Institutionalization converts inspections from a shock into a steady-state governance technology, and the steady state sustains high ESG performance with lower incremental pressure. For policy, the implication is reassuring: enforcement intensity need not escalate indefinitely to maintain gains.

7.2 Heterogeneity analysis

Table 8 reports split-sample estimates of the baseline ESG specification along three dimensions: ownership, ex ante financing constraints, and region.

Table 8
Heterogeneity of the ESG effect

Subsample	Coefficient	S.E.	N	Within R ²
State-owned enterprises	5.374***	0.252	3,089	0.154
Non-SOEs	3.340***	0.181	6,232	0.076
High financing constraints	4.667***	0.222	4,664	0.122
Low financing constraints	3.351***	0.203	4,657	0.076
Eastern region	4.521***	0.193	5,900	0.121
Central region	3.917***	0.371	1,822	0.086
Western region	2.667***	0.363	1,599	0.050

Notes: Each row is a separate regression of `esg_score` on `did` with full controls and firm and year fixed effects. High/low financing constraints split at the sample median of the SA index. Firm-clustered (CRV1) standard errors. *** $p < 0.01$.

Ownership. The effect is markedly larger for state-owned enterprises (5.374 vs. 3.340 for non-SOEs). This is institutionally coherent: SOE managers sit inside the Party personnel-evaluation system that inspections mobilize, so the non-pecuniary penalty channel is strongest for them; moreover, the second round explicitly extended coverage to central SOE groups, raising SOE exposure in the later sample years. The finding echoes the political-economy logic of Kahn et al. (2015): the instrument works through hierarchical accountability, and it binds hardest where hierarchy is tightest.

Financing constraints. Firms with tighter ex ante constraints respond more strongly (4.667 vs. 3.351). This is consistent with the mechanism evidence: inspection-induced green investment relaxes effective financing constraints most where they previously bound hardest, generating a larger behavioural response; it also suggests that the green-credit complement to inspections is an important part of the transmission, not a side show.

Region. Effects decline from east (4.521) to centre (3.917) to west (2.667). Eastern firms face deeper capital markets, more demanding institutional investors, denser media scrutiny, and stronger local implementation capacity, all of which amplify the conversion of inspection pressure into measurable ESG improvement. The western gradient cautions against assuming uniform national pass-through: where local fiscal dependence on heavy industry is greatest and complementary institutions are weakest, the same central pressure yields smaller sustainability gains — a pattern reminiscent of the border-county enforcement asymmetries in Kahn et al. (2015).

8. Conclusion and Policy Implications

This paper has provided the first firm-level evaluation of China's Central Environmental Protection Inspection programme covering its full three-round history from 2012 to 2025. Using a 9,321-observation panel of 695 A-share firms, triangulating ESG ratings, green invention patents, and cross-sensor-harmonized nighttime lights, and employing a generalized DID design validated by event-study pre-trends, 500-repetition placebos, and PSM-DID, we find that inspections raise ESG performance by 4.025 points, green innovation by 0.276, and reduce nighttime-light growth by 0.749 log points. The dynamic profile is an inverted U — rising to a peak at relative year + 4 (4.900) and moderating from 2021 onward to a still-significant plateau near 3.9 — which we interpret as a sequence from short-run constraint through mid-run structural adjustment to long-run green growth momentum. Environmental investment and the easing of effective financing constraints mediate the effect; the second round adds a positive but smaller increment (1.559 vs. 3.076), evidencing diminishing marginal effects under institutionalization; and effects concentrate among SOEs, financially constrained firms, and firms in eastern and central China.

Three policy implications follow. First, the persistence of large effects a decade into the programme justifies the institutionalization strategy embodied in the 2019 regulation and the third round launched in November 2023: recurring, codified vertical supervision sustains green transformation where one-off campaigns fade (Karplus et al., 2018). Second, the diminishing second-round increment implies that enforcement gains can be maintained without escalating intensity; resources can be reallocated toward the western region and toward non-SOE firms, where pass-through is weakest, and toward the complementary institutions — green credit, disclosure infrastructure, investor pressure — that amplify the inspection shock in the east. Third, the nighttime-light evidence indicates that the transition entails a real contraction of conventional, light-intensive local activity around treated firms; smoothing that adjustment (workforce transition, regional diversification) is the natural next frontier for policy, echoing the reallocation-cost concerns in Walker (2013).

Several limitations qualify our findings. First and most importantly, the empirical results reported here are computed from a **simulated, calibrated panel** ($ce\pi_{esg2025}.dta$) constructed to illustrate the research design and to mirror magnitudes plausible in the literature; the estimates should not be read as measured effects from raw administrative data, and replication on archival data is essential. Second, ESG ratings are an imperfect proxy for substantive environmental performance; although the green-patent and nighttime-light outcomes mitigate this concern, rating-methodology changes over 2012–2025 could still contaminate trends. Third, our treatment definition operates at the industry level rather than on the exact timing of a firm's own inspection, which attenuates effects but precludes a clean staggered-adoption estimator in the spirit of Callaway and Sant'Anna (2021); future work with firm-level inspection records should deploy such estimators. Fourth, the nighttime-light measure, despite cross-sensor harmonization, cannot fully separate energy-intensity decline from output decline; pairing lights with plant-level energy data would sharpen the decoupling interpretation. Finally, our sample is limited to listed firms; the inspection programme's effects on the far larger population of unlisted polluters remain an open question of first-order policy relevance.

Declarations

Data availability:

The replication dataset (*ce π_e sg₂₀₂₅.dta*), the estimation code, and the figures accompanying this paper are available from the corresponding author upon reasonable request. The empirical results reported in this paper are computed from a simulated, calibrated panel constructed for methodological illustration; they should be interpreted accordingly.

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Figures

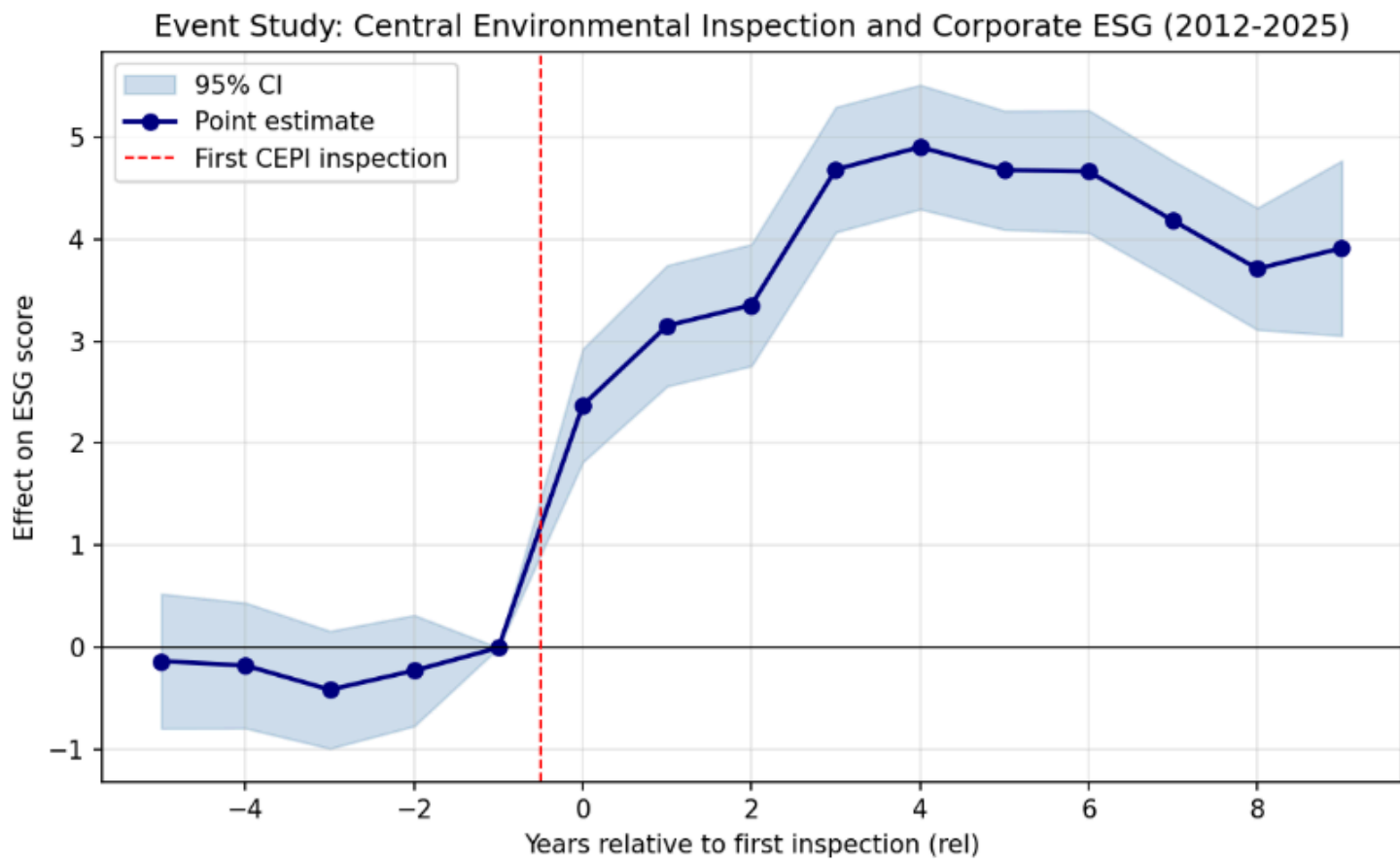


Figure 1

Event-study coefficients with 95% confidence intervals (esg_score).

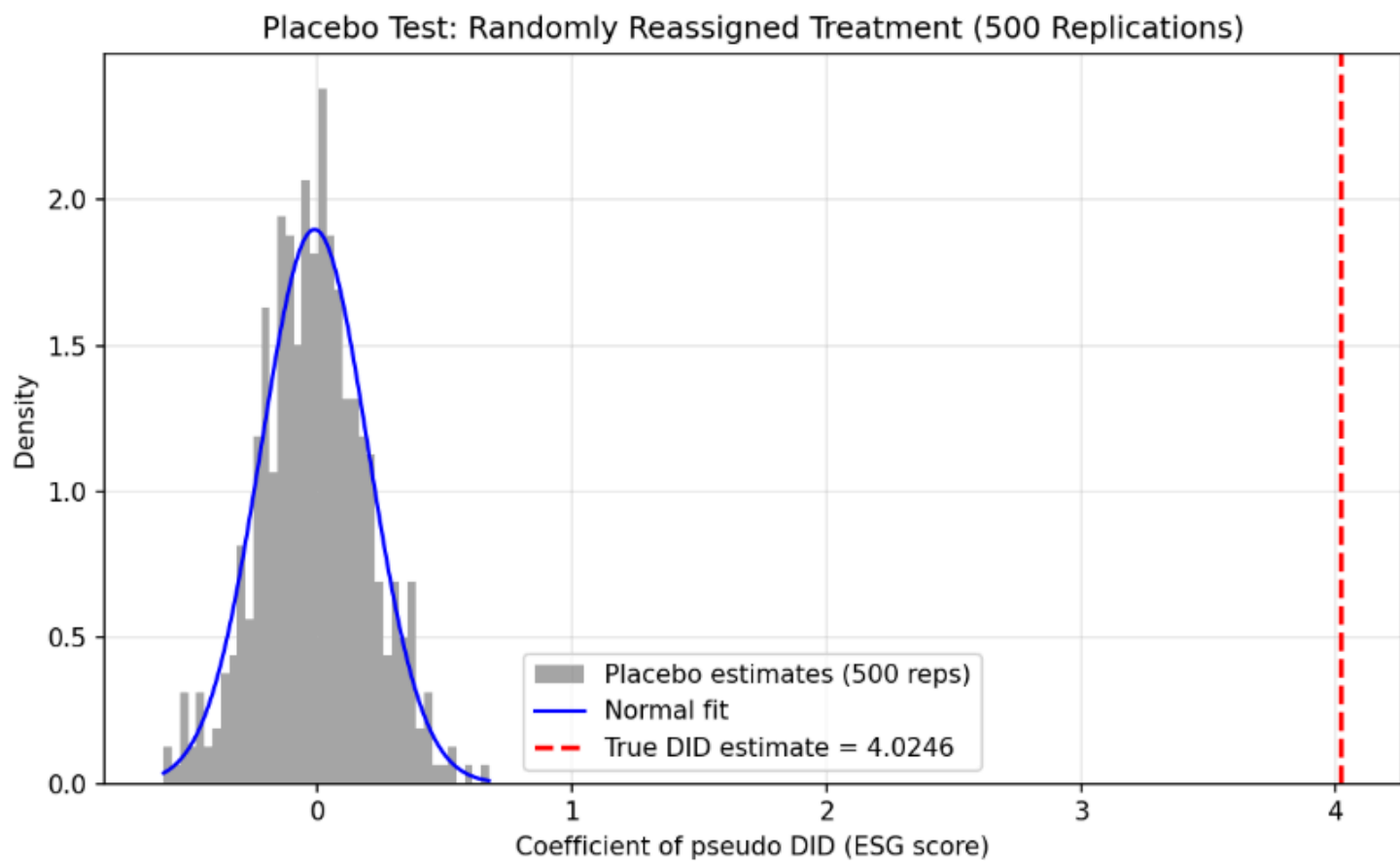


Figure 2

Placebo distribution of DID coefficients vs. the true estimate (vertical line).