Indonesian Journal of Sustainability Accounting and Management
ISSN 2597–6214 | e–ISSN 2597–6222
DOI: 10.20448/ijsam.v10i2.9776

Above-Benchmark Greenhouse Gas Emissions and Corporate Green Innovation in Chinese Listed Companies

Penghui Zhang[1]*

[1]*College of Business and Law, Adelaide University, Adelaide, SA 5005, Australia*

*Correspondence to: Penghui Zhang, College of Business and Law, Adelaide University, Adelaide, SA 5005, Australia.
E-mail: penghui.zhang@student.adelaide.edu.au

Abstract: Drawing on a resource-based perspective, this study examines whether firms whose reported greenhouse gas emissions exceed an operating benchmark undertake less green innovation. The sample comprises 2,559 firm-year observations from 1,379 Chinese A-share listed companies during 2020–2024. Reported emissions are benchmarked against operating characteristics using pooled ordinary least squares with industry and year fixed effects. The resulting residual is separated into the non-negative magnitudes of deviations above and below the benchmark. Both components enter regressions of green patenting that control for firm characteristics and R&D intensity. Inference uses standard errors clustered by firm and a bootstrap that re-estimates the emissions benchmark and outcome model. Larger deviations above the benchmark are associated with fewer green patent applications. The coefficient for deviations below the benchmark is not statistically significant, and formal tests reject equality of the two coefficients. The negative association is also observed for invention applications and application volume among current applicants, while evidence on patenting participation remains inconclusive. Supplementary analysis links larger deviations above the benchmark to lower commercial resource commitment, which is positively associated with green patenting. These findings extend emissions benchmarking by showing that the direction of a deviation carries information about inventive activity. They suggest that managers and analysts should assess the commercial resources supporting green invention alongside emissions positions and research spending when evaluating transition plans.

Keywords: Emissions benchmarking, environmental management, green innovation, greenhouse gas emissions, resource commitment.

Article info: Received 14 September 2026 | revised 4 November 2026 | accepted 10 November 2026 | published 16 November 2026

Recommended citation: Zhang, P. (2026). Above-Benchmark Greenhouse Gas Emissions and Corporate Green Innovation in Chinese Listed Companies. *Indonesian Journal of Sustainability Accounting and Management*, *10*(2), 615–632. https://doi.org/10.20448/ijsam.v10i2.9776

INTRODUCTION

Corporate decarbonisation requires firms to adapt production assets while developing cleaner products and processes. Current policies remain far from the emission pathways required to meet the Paris Agreement's temperature goals (United Nations Environment Programme, 2025). Green innovation can support this transition (Truong, 2025), but firms must finance uncertain inventive projects alongside changes to existing operations. For managers and providers of finance, the resulting allocation problem concerns whether firms facing greater operational adjustment also sustain the inventive activity needed for future change. Emissions disclosures make these positions visible, yet an emissions total alone does not establish how a firm compares

Copyright © 2026 by the author(s). This article is published under the Creative Commons Attribution (CC BY 4.0) license. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial & non-commercial purposes), subject to full attribution to the original publication and author(s). The full terms of this license may be seen at http://creativecommons.org/licenses/by/4.0/legalcode

with businesses operating under similar conditions. This study asks whether firms with greenhouse gas (GHG) emissions above the level predicted by their operating fundamentals undertake more or less green innovation.

A growing body of research links environmental demands to innovation through both incentives and access to resources. Environmental regulation can stimulate cleaner invention (Calel, 2020; Liu & Li, 2022), and Sun, Sun, and Dong (2024) find that negative environmental performance feedback induces substantive green innovation. Cecere, Corrocher, and Mancusi (2020) link eco-innovation in European small and medium-sized enterprises (SMEs) to the availability and mix of funding. Chang and Wang (2024) identify financing constraints as a channel connecting environmental, social, and governance (ESG) ratings to green innovation in China. Studies that focus on emissions levels report different adjustment responses. Cui, Ding, Han, and Suardi (2023) find that higher emissions accompany weaker research and development (R&D), whereas Ma (2024) reports a positive relationship with low-carbon innovation. Because these studies adopt different reference points and examine different outcomes, it remains unclear how green invention varies with emissions relative to firms' operating characteristics.

Answering this question requires a measure that distinguishes the scale of emissions from a firm's position relative to its own operations. Large emitters may also have larger resource bases, while a smaller producer can emit less in total yet lie further above the level predicted by its operating characteristics. Following Gipper, Sequeira, and Shi (2026), this study benchmarks reported emissions against observable fundamentals. The authors use the absolute size of these deviations to assess carbon accounting quality. Retaining the sign instead allows the present study to distinguish firms on opposite sides of the same operating reference point. Two deviations of equal magnitude can then be examined separately, allowing their relationships with green invention to differ. The benchmark describes a conditional emissions position rather than a regulatory target. This distinction is central to interpreting the measure and separates the comparison from the managerial aspirations examined by Sun et al. (2024).

A resource-based perspective helps to explain why firms in these emissions positions may differ in their levels of green invention. Established carbon-intensive assets can make operational change costly (Goldstein, Neimark, Garvey, & Phelps, 2023), while environmental strategies depend on organisational resources and capabilities (Hart, 1995; Qin, Muskat, Ambrosini, Mair, & Chih, 2026). When changes to existing operations compete for these resources, stronger incentives to innovate need not translate into more invention. Evidence that high-emitting firms acquire green assets while reducing R&D illustrates the range of responses available to them (Cui et al., 2023). Examining firms' own green patent applications therefore addresses a distinct aspect of adjustment: the development of patentable environmental technologies. Separating invention applications from utility-model applications and participation from application volume further clarifies which part of inventive activity accompanies an above-benchmark position.

The resource argument also extends to activities that connect invention with markets. Customer engagement and product introduction can support the commercial use of new technologies (Richey, Musgrove, Gillison, & Gabler, 2014; Teece, 2018). These complementary activities merit attention because differences in research spending alone may not describe the support available to inventive projects. The analysis therefore examines commercial resource commitment alongside green patenting while controlling for R&D intensity. This links the emissions comparison to a managerial allocation question: whether firms with larger above-benchmark gaps also commit fewer resources to the commercial activities that accompany invention. Selling expenses provide an observable measure of this broad commitment.

China offers an informative setting because carbon-intensive production, clean-technology manufacturing and uneven access to innovation finance coexist within the same economy. Meeting China's commitments to peak carbon emissions before 2030 and to achieve carbon neutrality by 2060 requires extensive changes to industrial and energy systems while development continues (World Bank Group, 2022). China also plays a prominent role in manufacturing and trading clean energy technologies (International Energy Agency, 2024). Prior evidence from Chinese listed firms documents financing obstacles to green innovation, with private firms more vulnerable than state-owned firms (Yu, Wu, Zhang, Chen, & Zhao, 2021). Together, these conditions make the relationship between operational adjustment and inventive resources relevant even

in an economy with substantial clean-technology capabilities. The setting allows the analysis to examine differences among firms that national emissions totals or manufacturing strengths cannot reveal.

The analysis draws on 2,559 firm-year observations from 1,379 Chinese A-share companies over the period 2020–2024. Above-benchmark emissions are negatively associated with green patent applications, whereas the below-benchmark estimate is statistically insignificant and differs from the above-benchmark coefficient. The association persists across alternative benchmarks and industry-year controls. Further analyses support the pattern for invention applications and output among current applicants, with inconclusive evidence for participation. Larger above-benchmark gaps also coincide with lower commercial resource commitment, which is positively related to patenting.

The study examines whether deviations above and below predicted emissions have different associations with green patenting and whether these associations coincide with differences in commercial resource commitment. In doing so, it extends the use of benchmarked carbon-accounting information to the assessment of inventive activity and its organisational support. The Chinese evidence also provides a basis for examining the same allocation problem in other economies where carbon-intensive production and clean-technology development coexist.

THEORETICAL FOUNDATION AND HYPOTHESIS DEVELOPMENT

Corporate Carbon Emissions and Conditional Benchmarks

Corporate carbon research examines both the economic consequences of emissions and the information conveyed by their disclosure. Choi and Luo (2021) find a negative relationship between emissions and firm value after accounting for voluntary disclosure selection. Bui, Houqe, and Zaman (2020) show that climate governance is associated with closer alignment between carbon disclosure and carbon performance. He, Luo, Shamsuddin, and Tang (2022) organise carbon accounting research around disclosure, management, performance, and assurance, illustrating why a reported emissions number can serve different decision purposes. More recently, Gipper et al. (2026) assess carbon accounting quality through deviations from emissions predicted by production-related fundamentals. These studies show why it is important to distinguish carbon performance from its reporting and measurement. They leave open the question of how relative emissions positions relate to the development of cleaner technologies.

Absolute emissions describe aggregate exposure, while intensity ratios use a selected denominator such as sales. A regression benchmark, by contrast, accommodates several operating characteristics at once. It therefore compares relative emissions positions across firms whose operations differ. Research on reporting boundaries and disclosure sources also explains how firms construct reported emissions (Klaaßen & Stoll, 2021).

Green Innovation, Incentives and Resource Capacity

Research on green innovation has identified a range of conditions that encourage firms to develop environmentally beneficial products and processes. Zhang, Liang, Feng, Yuan, and Jiang (2020) link environmental regulation to green product and process innovation through external knowledge adoption. They document a positive relationship between environmental regulation and green patenting among Chinese listed firms. Alongside these incentives, financing constraints restrict green innovation (Yu et al., 2021). Overall, this literature indicates that inventive activity requires both motivation and resources. Evidence on policy and organisational conditions, however, leaves open the question of whether firms with greater carbon adjustment needs have the capacity to respond through invention.

The natural-resource-based view links environmental strategy to organisational resources and capabilities (Hart, 1995). It helps explain why incentives alone may not be sufficient to sustain cleaner invention. Evidence from European SMEs (Cecere et al., 2020) and Chinese firms (Chang & Wang, 2024) connects green innovation to the availability of finance. Across emerging markets, De Haas, Martin, Muûls, and Schweiger (2025) show that credit constraints and weak green management impede investment in green technologies

embodied in equipment. This perspective links inventive capacity to the resources that remain available alongside existing production commitments.

Green patent applications capture attempts to develop patentable environmental technologies. Firms can also improve environmental performance by purchasing abatement equipment, adopting existing processes or reducing production. Cui et al. (2023) distinguish innovation expenditure from the acquisition of green assets, illustrating how firms can respond without producing their own inventions. In French manufacturing, Colmer, Martin, Muûls, and Wagner (2025) find that carbon trading induces targeted investment that lowers the emissions intensity of production. This distinction motivates the focus of this study on firms' own green inventions, within the broader range of environmental adjustment activities available to them.

Carbon Emissions and Green Innovation

Collectively, these strands of literature give rise to competing expectations. Ma (2024) finds that higher emissions encourage low-carbon innovation, consistent with emissions pressure stimulating inventive effort. The innovation-compensation perspective explains this response through opportunities to improve efficiency and offset environmental costs (Dechezleprêtre & Sato, 2017; Porter & van der Linde, 1995). Yet higher emissions also accompany lower R&D and greater reliance on acquired green assets in Chinese firms (Cui et al., 2023). Firms can therefore respond to emissions pressure by acquiring technologies rather than by producing green inventions of their own.

Performance-feedback research explains inventive responses through the gap between environmental performance and managerial aspirations. Sun et al. (2024) find that performance below aspirations stimulates substantive green innovation, with external regulation and internal incentives shaping the response. Yin and Gao (2026) examine the intensity and duration of environmental underperformance using ESG ratings. A shortfall relative to aspirations can trigger organisational search. The operating benchmark used in this study compares emissions conditional on production-related characteristics. This reference point shifts attention towards the resource demands that accompany different emissions positions, while leaving pressure-induced search as a competing explanation.

When an above-benchmark position reflects carbon-intensive production commitments, adjustment can compete with invention for resources. Long-lived fossil-fuel-based equipment and costly process changes entrench these commitments and sustain emissions (Goldstein et al., 2023). Adjusting such commitments requires changing assets and capabilities that reinforce existing production systems. Accumulated technological knowledge can also direct subsequent innovation towards established rather than cleaner technologies (Aghion, Dechezleprêtre, Hémous, Martin, & Van Reenen, 2016). Green invention then requires resources beyond those needed to modify existing operations, while acquiring cleaner equipment provides an alternative route to adjustment. Firms that have inherited cleaner assets, or that have adopted cleaner technologies in the past, can sustain low relative emissions at different levels of current inventive effort.

Financing constraints are likely to make this allocation problem more acute. Evidence from R&D grants shows that early-stage funding can support patenting, with larger effects among financially constrained firms (Howell, 2017). Regulation-related expenditure also competes with R&D for finance (Cui et al., 2023). In China, where such constraints impede green innovation (Yu et al., 2021), firms facing substantial operational adjustment can prioritise immediate production and compliance needs over inventive projects with uncertain returns.

This reasoning extends beyond the level of R&D spending. Customer engagement and new-product introduction connect inventive effort to commercial opportunities (Richey et al., 2014; Teece, 2018). Resources committed to these activities can support the eventual commercial use of inventions. Research on green practices in SMEs identifies market orientation and relational motives alongside regulation as relevant drivers. Firms that direct resources towards existing operations may therefore have less support available for research and for its commercial complements. Where these competing demands outweigh pressure-induced search, an above-benchmark position should be associated with weaker green patenting. This reasoning leads to H1.

H_1: Above-benchmark GHG emissions are negatively associated with corporate green innovation.

METHODS

Sample Selection

The sample comprises Chinese A-share listed companies from 2020 to 2024. Firm-level GHG disclosures before 2020 were too sparse in the assembled sources to support the analysis. The required data for 2025 had not been fully released at the time of collection. Data come from the China Stock Market & Accounting Research (CSMAR) database, the China Research Data Service Platform, and the Wind Financial Terminal. This study matches financial statements, ownership, patents, research reports, and GHG disclosures by firm and year. For 2024, emissions records were checked against available company reports, and values were revised where documentary evidence supported a correction. Industries follow the China Securities Regulatory Commission's 2012 industry classification. The initial panel contains 27,630 firm-years. Observations from 2019 serve only to construct lagged variables.

The sample excludes financial-sector firms, firms designated for special treatment (ST), delisted firms, and observations missing emissions, model, patent, or control data. Zeros in the source files that denote GHG non-disclosure are coded as missing. The baseline comprises 2,559 firm-years from 1,379 firms with disclosed positive GHG emissions. The emissions benchmark is estimated on this same sample. Baseline continuous inputs are winsorised at the 1st and 99th percentiles before residualisation, and the resulting gap components are not winsorised again. The subsection 'Disclosure Selection' assesses disclosure selection using inverse-probability weighting.

Variable Measurement

Green patent measures are widely used to examine corporate environmental innovation (Hong, Drakeford, & Zhang, 2020; Liu & Li, 2022). This study measures green innovation (GI) as the natural logarithm of one plus the annual number of green invention and green utility-model patent applications, consistent with application measures used by Cui, Dai, Wang, and Zhao (2022) and He and Wang (2023). Applications record inventive activity at the filing stage and avoid the additional examination delays associated with patent grants.

The explanatory variables measure deviations from emissions predicted by operating characteristics. This study adapts the regression-residual approach of Gipper et al. (2026) to the fundamentals available for the Chinese sample. The benchmark in Equation 1 is estimated by pooled ordinary least squares (OLS), with separate industry and year fixed effects.

$$LnGHG_{i,t} = \alpha_0 + \alpha_1 Size_{i,t} + \alpha_2 PPE_{i,t} + \alpha_3 Lev_{i,t} + \alpha_4 ROA_{i,t} + \alpha_5 Employee_{i,t} + \text{Industry FE} + \text{Year FE} + \mu_{i,t} \quad (1)$$

Where i indexes firms, t indexes years, FE denotes fixed effects, and LnGHG is the natural logarithm of reported GHG emissions in tonnes of CO_2. The residual, defined in Equation 2, is the difference between observed and fitted log emissions.

$$GHGGap_{i,t} = \hat{\mu}_{i,t} \quad (2)$$

Equations 3 and 4 separate this residual into the non-negative magnitudes of deviations above (PosGHGGap) and below (NegGHGGap) the benchmark.

$$PosGHGGap_{i,t} = \text{Max}(GHGGap_{i,t}, 0) \quad (3)$$

$$NegGHGGap_{i,t} = \text{Max}(-GHGGap_{i,t}, 0) \quad (4)$$

Selling expenses are used as a broad proxy for commercial resource commitment. The interpretation draws on research on resources devoted to green marketing and on complementary assets in commercialisation (Richey et al., 2014; Teece, 2018). The measure does not isolate spending on green projects.

The supplementary financing analysis uses analyst and research-report attention to capture external information coverage. Research links analyst coverage to green innovation (Fiorillo, Meles, Mustilli, & Salerno, 2022; Wang & Cao, 2024). This study combines the number of analysts following the firm with the number of research reports to construct the attention measure. The absolute size–age score summarises financing-related firm characteristics by adapting the functional form of Hadlock and Pierce (2010).

The control variables follow prior Chinese studies of green innovation and account for differences in firm scale, financial resources, research intensity and organisational characteristics (Cui et al., 2022; He & Wang, 2023; Hong et al., 2020). Table 1 reports the complete variable definitions and calculation rules.

Table 1: Variable definitions

Variable type	Variables	Symbol	Measurement
Dependent variable	Green innovation	GI	ln(1 + green invention patent applications + green utility-model patent applications)
Emissions benchmark	Disclosed GHG emissions	LnGHG	ln(GHG emissions in tonnes of CO_2)
	GHG emissions deviation	GHGGap	Actual minus predicted log GHG emissions from Equation 1
Independent variable	Above-benchmark GHG deviation	PosGHGGap	max(GHGGap, 0)
	Below-benchmark GHG deviation	NegGHGGap	max(−GHGGap, 0)
Control variable	Firm size	Size	Natural logarithm of total assets
	Leverage	Lev	Total liabilities divided by total assets
	Return on assets	ROA	Net profit divided by total assets
	Sales growth	Growth	Growth rate of operating revenue
	Fixed-asset intensity	PPE	Fixed assets divided by total assets
	Operating cash flow	Cashflow	Operating cash flow divided by total assets
	R&D intensity	RD	R&D expenditure divided by operating revenue
	Employee size	Employee	ln(1 + number of employees)
	State ownership	SOE	One for state-owned enterprises; zero otherwise
	Firm age	Age	ln(1 + sample year − establishment year)
Pathway variables	Commercial resource commitment	MRC	ln(1 + annual selling expenses)
	Analyst and report attention	ReportAttention	ln(1 + analysts following + research reports)
	Size–age score	FC_SA	Absolute value of −0.737SizeSA + 0.043SizeSA² − 0.040FirmAge

Note: ln denotes the natural logarithm. GHG denotes greenhouse gas, R&D denotes research and development, and RMB denotes renminbi. SizeSA is the natural logarithm of total assets in RMB millions, and FirmAge is the number of years since establishment. These are inputs to FC_SA, which adapts the functional form of Hadlock and Pierce (2010), and are not additional baseline controls. Age = ln(1 + FirmAge).

Empirical Models

To test H1, Equation 5 includes both directional components in the baseline model. H1 predicts a negative β_1.

$$GI_{i,t} = \beta_0 + \beta_1 PosGHGGap_{i,t} + \beta_2 NegGHGGap_{i,t} + \beta_3 Controls_{i,t} + \text{Industry FE} + \text{Year FE} + \varepsilon_{i,t} \quad (5)$$

The baseline model includes both emissions-gap components and the ten variables listed as controls in Table 1, namely Size, Lev, ROA, Growth, PPE, Cashflow, RD, Employee, SOE and Age. All ten are reported in Table 3. The model is estimated by OLS with separate industry and year fixed effects, and standard errors are clustered by firm. Because R&D intensity is a control, the estimate concerns patenting conditional on observed research spending intensity. To account for the fact that GHGGap is itself estimated, a 2,000-replication, firm-

clustered bootstrap re-estimates both the emissions benchmark and the outcome model. Each replication samples firms with replacement, retaining all observations for each selected firm, and fits both stages to the same resampled panel.

Comparing β_1 and β_2 tests whether equally sized above- and below-benchmark deviations have the same association with GI.

EMPIRICAL RESULTS AND ANALYSIS

Descriptive Statistics

Table 2 reports variation in green patenting and conditional emissions positions. PosGHGGap and NegGHGGap have the same full-sample mean of 0.887. For each observation, the positive component minus the negative component equals the estimated residual. Because the emissions benchmark is estimated by OLS with an intercept on the same sample, its residuals sum to zero up to numerical precision, giving the two components equal means. Equal means do not imply identical distributions, equal numbers of observations on either side of the benchmark, or equal associations with green innovation. NegGHGGap is more dispersed, with a standard deviation of 1.852 compared with 1.289 for PosGHGGap.

Table 2: Descriptive statistics

Variables	N	Mean	SD	Min.	Max.
GI	2,559	1.671	1.579	0.000	6.059
PosGHGGap	2,559	0.887	1.289	0.000	8.339
NegGHGGap	2,559	0.887	1.852	0.000	12.039
Firm size	2,559	23.468	1.452	20.806	27.488
Leverage	2,559	0.459	0.190	0.071	0.882
Return on assets	2,559	0.039	0.059	−0.163	0.220
Sales growth	2,559	0.081	0.281	−0.546	1.419
Fixed-asset intensity	2,559	0.212	0.159	0.004	0.666
Operating cash flow	2,559	0.062	0.066	−0.144	0.258
R&D intensity	2,559	0.058	0.079	0.000	0.507
Employee size	2,559	8.463	1.368	5.606	12.201
State ownership	2,559	0.460	0.498	0.000	1.000
Firm age	2,559	3.151	0.299	2.197	3.738

Note: Variable definitions appear in Table 1. N denotes firm-year observations, SD denotes standard deviation, and Min/Max denotes the minimum/maximum. Continuous inputs are winsorised at the 1st and 99th percentiles before residualisation, with no further winsorisation of the gaps.

Baseline Results

Table 3 shows a negative association between above-benchmark emissions and green innovation, supporting H1. An above-benchmark gap that is one standard deviation larger is associated with a value of GI that is approximately 0.082 points lower, conditional on the included controls and fixed effects. The estimate remains statistically significant when the bootstrap re-estimates the emissions benchmark and the outcome model, which accounts for the uncertainty in the generated emissions measure.

The coefficient on NegGHGGap is −0.0010 and is not statistically distinguishable from zero. Both components measure the magnitude of a deviation in the same log emissions units, so comparing their coefficients concerns deviations of equal size on opposite sides of the benchmark, conditional on the same controls and fixed effects. Because their standard deviations differ, this comparison differs from comparing a change of one standard deviation in each component. The coefficient-equality tests reject the null of equal coefficients, with a Wald p-value of 0.002 and a bootstrap p-value of 0.003. The negative association above the benchmark is consistent with the resource argument in the subsection 'Carbon Emissions and Green Innovation'.

Table 3: Baseline regression results

Variables	GI
PosGHGGap	−0.0634*** (0.0215)
NegGHGGap	−0.0010 (0.0159)
Firm size (Size)	0.5200*** (0.0441)
Leverage (Lev)	0.3771** (0.1883)
Return on assets (ROA)	−0.5977 (0.6794)
Sales growth (Growth)	−0.0162 (0.0830)
Fixed-asset intensity (PPE)	−0.4539** (0.2203)
Operating cash flow (Cashflow)	0.1228 (0.5185)
R&D intensity (RD)	0.9010* (0.4716)
Employee size (Employee)	0.1260*** (0.0442)
State ownership (SOE)	0.2528*** (0.0702)
Firm age (Age)	−0.0103 (0.1111)
Industry fixed effects	Yes
Year fixed effects	Yes
Firm-clustered standard errors	Yes
Observations	2,559
Firm clusters	1,379
R-squared	0.6131
Root MSE	0.9990
Two-stage bootstrap p-value for PosGHGGap	0.005
Coefficient-equality p-value (Wald)	0.002
Coefficient-equality p-value (two-stage bootstrap)	0.003

Note: Variable definitions appear in Table 1. Parentheses contain firm-clustered standard errors. MSE denotes mean squared error. The coefficient-equality tests compare the two gap coefficients. The 2,000-replication firm-cluster bootstrap re-estimates the emissions benchmark and outcome model. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Robustness Tests

Green Invention Applications

The first check restricts the outcome to green invention applications to assess whether combining patent types obscures the relationship. Prior research uses both combined application measures (He & Wang, 2023) and separate measures of invention and utility-model applications (Cui et al., 2022; Huang, Cao, & Pan, 2024). Liu and Li (2022) also distinguish patent types using grant data. The invention-only estimate remains negative and statistically significant, with little change in magnitude (Table 4, column 1). The subsection 'Patent Composition and Participation' examines both patent types, participation, and output among applicants while accounting for benchmark-estimation uncertainty.

Count-Data Estimation

Green patent applications are non-negative counts, and transforming outcomes that include zeros affects interpretation (Chen & Roth, 2024). This study therefore estimates a negative binomial model, which accommodates counts and permits overdispersion, as in the robustness analysis of Jiang (2025). Modelling the patent counts directly preserves the negative and statistically significant association (Table 4, column 2).

Within-Industry-Year Permutation

The permutation exercise compares the observed association with the distribution obtained when the gap is reassigned among firms in the same industry and year. Using regression permutation inference, the exercise

uses a studentised statistic (D'Haultfœuille & Tuvaandorj, 2024; DiCiccio & Romano, 2017). Both directional components are reconstructed after each reassignment of the signed gap. The observed association remains significant under this reference distribution within the disclosure sample (Table 4, column 3).

Alternative Clustering and Industry-Year Effects

Following MacKinnon, Nielsen, and Webb (2023), a wild cluster bootstrap is used to assess the sensitivity of the firm-clustered inference. The negative association remains statistically significant under this alternative reference distribution (Table 4, Panel C).

Industry-specific changes in demand, technology, or regulation could affect emissions and patenting together. Industry-by-year fixed effects are therefore added to absorb these common developments, following recent green innovation research (Huang, Chen, & Cheng, 2025). The original emissions benchmark is retained, and standard errors are clustered by firm and by industry-year. The estimate remains negative and significant, and it is close to the baseline. This result reduces the concern that common annual industry developments account for the association.

Table 4: Robustness tests

Panel A. Outcome specification and inference				
Variables	**(1)** **Green invention**	**(2)** **Negative binomial**		**(3)** **Permutation inference**
PosGHGGap	−0.0641***	−0.1036***		−0.0634**
SE / p-value	(0.0215)	(0.0273)		(Empirical *p* = 0.015)
Dependent variable	ln(1 + green invention applications)	Raw green patent applications		GI
Estimator	OLS	Negative binomial		OLS
Baseline controls	Yes	Yes		Yes
Industry fixed effects	Yes	Yes		Yes
Year fixed effects	Yes	Yes		Yes
Observations	2,559	2,559		2,559
Panel B. Alternative emissions benchmarks				
Benchmark	Above-benchmark coefficient	Clustered SE		p-value
Additional revenue and fixed-asset predictors	−0.0628***	0.0212		0.0031
Expanded benchmark with year-varying coefficients	−0.0624***	0.0210		0.0030
Revenue-scaled emissions relative to industry-year median	−0.0484**	0.0198		0.0149
Panel C. Alternative inference and industry-by-year effects				
Specification	Coefficient	SE	p-value	Observations
Firm-level wild cluster bootstrap	−0.0634***	—	0.0034	2,559
Industry-by-year fixed effects	−0.0571**	0.0229	0.0134	2,491

Note: Variable definitions appear in Table 1. All models retain both gaps and baseline controls. Industry and year effects are separate except in the final row. OLS denotes ordinary least squares, and SE denotes standard error. Panel A columns (1)–(2) report firm-clustered SEs. Column (3) uses 1,999 joint-gap permutations within industry-year and a two-sided studentised statistic. Panel B uses 2,559 observations and firm-clustered SEs. Panel C retains the original benchmark. The wild bootstrap uses 9,999 firm-cluster replications. The industry-by-year model clusters by firm and industry-year and drops 68 singletons. These checks condition on the estimated benchmark. ***, ** denote significance at 1%, 5%, respectively.

Alternative Emissions Benchmarks

An emissions residual depends on the characteristics used to construct its benchmark (Gipper et al., 2026). Panel B of Table 4 first adds the natural logarithm of operating revenue and the natural logarithm of one plus fixed assets, both winsorised at the 1st and 99th percentiles. It then allows the expanded benchmark's operating coefficients to vary across years. Both estimates remain negative and statistically significant, with magnitudes close to the baseline. These checks address the concern that omitted measures of output scale drive the results. They also relax the assumption that operating relationships remain constant over the sample period.

The final specification subtracts log operating revenue from log emissions and measures the deviation from the industry-year median of this log intensity. This provides a reference point that does not require an estimated operating equation. The above-benchmark association remains negative and statistically significant despite the change in measurement scale and benchmark construction. The tests also continue to distinguish the two directional coefficients under all three alternative benchmarks. Taken together, these comparisons indicate that the main pattern is not confined to a single definition of relative emissions.

Endogeneity and Sensitivity Analyses

Disclosure Selection

Firms with usable emissions disclosures may differ in characteristics that also relate to innovation. A logit model estimates disclosure probabilities using the baseline controls and industry and year effects. The estimation weights each disclosure observation by the sample disclosure rate divided by its predicted disclosure probability and caps extreme weights (Seaman & Vansteelandt, 2018). The balance diagnostic compares the two disclosure groups, with both groups weighted after adjustment. Balance improves, although some imbalance remains after weighting. The weighted estimate remains negative and statistically significant (Table 5), and alternative caps preserve the finding.

Table 5: Disclosure-selection and temporal-ordering analyses

Variables/statistic	(1) Stabilised IPW	(2) Lagged PosGHGGap
PosGHGGap / L.PosGHGGap	−0.1002***	−0.0560*
Firm-clustered SE	(0.0270)	(0.0309)
p-value	<0.001	0.0698
Maximum absolute SMD before weighting	0.899	—
Maximum absolute SMD after weighting	0.150	—
Baseline controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2,559	1,305

Note: Variable definitions appear in Table 1. Both models retain both gap components. IPW denotes inverse-probability weighting, SE denotes standard error, and SMD denotes the standardised mean difference between disclosure groups. L. indicates a one-year lag. The propensity model uses 20,579 observations after removing perfect-prediction cases. Disclosure weights are capped at the 1st and 99th percentiles; non-disclosure weights used for balance are uncapped. *** and * denote significance at 1% and 10%, respectively.

Lagged Emissions Deviations

The lagged specification places emissions before patenting, following the temporal ordering examined in recent green innovation research (Bendig, Schäper, Strehlow, & Foege, 2026). It matches current outcomes and controls to prior-year gaps from the baseline sample. The design does not require current-year emissions disclosure. Continuous variables, including the lagged gaps, are winsorised at the 1st and 99th percentiles

within the resulting sample. The lagged estimate remains negative and similar in magnitude to the baseline (Table 5). It is less precise in the smaller sample and receives statistical support only at the 10% level. The estimates are consistent with the association extending beyond the current year.

Higher-Moment Instrumental Variables

Panel A of Table 6 uses the higher-moment instruments of Dagenais and Dagenais (1997) to examine measurement-error sensitivity under their distributional and exclusion assumptions. The second-stage coefficient is negative and significant at the 10% level under conventional inference. Following Keane and Neal (2024), Anderson–Rubin inference is also reported for this estimate. The Anderson–Rubin test does not reject a zero coefficient, indicating weaker statistical support under this procedure. Table 6 reports the instrument diagnostics.

Coefficient Sensitivity

Oster (2019) proportional-selection approach assesses sensitivity to omitted variables using changes in coefficients and in explanatory power. Huang et al. (2024) apply this approach in a recent study of green strategies. In Panel B of Table 6, the preferred restricted model retains the below-benchmark component and fixed effects. Adding firm controls moves the above-benchmark coefficient from near zero to a negative estimate and increases explanatory power. Under the maintained assumptions, the negative selection parameter implies that unobservables would need to select in the opposite direction from the included controls to eliminate the estimate. The alternative restricted model shows how the result depends on the choice of control comparison and on the assumed maximum explanatory power.

Table 6: Higher-moment IV and coefficient-sensitivity analyses

Panel A. Higher-moment instrumental-variable analysis				
Statistic	**First stage / PosGHGGap**	**Second stage / GI**	**Identification diagnostic**	**Value**
Instruments / Coefficient	Durbin and Pal	−0.0438*	KP rk Wald F	4,035.82
Joint p-value / Clustered SE	<0.001	(0.0234)	KP rk LM	180.83
Second-stage p-value	—	0.0608	AR F-test p-value	0.1689
Observations	2,559	2,559	Hansen J p-value	0.9770
Panel B. Oster coefficient-stability analysis				
Statistic	Preferred restricted	Preferred controlled	Without Neg restricted	Without Neg controlled
PosGHGGap coefficient	0.0016	−0.0634	−0.0265	−0.0627
R-squared	0.3547	0.6131	0.3528	0.6131
Rmax = min (1, 1.3 × controlled R^2)	—	0.7970	—	0.7970
δ for β = 0	—	−1.3461	—	−2.4325

Note: Variable definitions appear in Table 1. IV denotes instrumental variables, and SE denotes standard error. The Durbin and Pal instruments are cP^2 and $cP^3 - 3\mu_2 cP$, where cP is mean-centred PosGHGGap and $\mu_2 = E(cP^2)$. KP denotes Kleibergen–Paap, AR Anderson–Rubin, rk rank testing, and LM Lagrange multiplier. Panel A retains NegGHGGap, baseline controls, and industry and year effects, with firm-clustered SEs. Panel B retains these fixed effects. Restricted models omit firm controls. The preferred pair retains NegGHGGap; the alternative omits it. Rmax is the assumed maximum R^2, and δ is selection on unobservables relative to observables when β = 0. * denotes significance at 10%, respectively.

Patent Composition and Participation

The robustness analyses strengthen the evidence for H1 across alternative emissions benchmarks, patent measures and model specifications. The next question is which dimensions of inventive activity underlie the

observed pattern. Table 7 separates patent type, participation and application volume among current applicants. Nearly three in ten firm-years have no green applications. A lower combined log outcome may therefore reflect either a smaller number of applicants or lower output among those that do apply. Chen and Roth (2024) explain why these dimensions matter when outcomes include zeros. The separate models retain the baseline controls and fixed effects. In each resampled panel, the bootstrap re-estimates the emissions benchmark before fitting the outcome models.

The results support the negative association for green invention applications and for output among current applicants, with both bootstrap confidence intervals excluding zero. Evidence for utility-model applications is weaker, while the participation estimate is statistically insignificant. The evidence therefore points to lower application volume among current applicants. These findings link H1 to the scale of current inventive activity and draw attention to the resources that support it.

Table 7: Patent composition, participation and output among applicants

Variable / statistic	(1) Invention	(2) Utility model	(3) Any application	(4) Positive applicants
PosGHGGap	−0.0641	−0.0317	−0.0086	−0.0625
	(0.0215)	(0.0187)	(0.0073)	(0.0241)
NegGHGGap	−0.0023	−0.0054	−0.0002	−0.0062
	(0.0165)	(0.0131)	(0.0048)	(0.0176)
Bootstrap SE	0.0227	0.0193	0.0077	0.0243
Bootstrap p-value	0.0048	0.0998	0.2609	0.0102
Bootstrap 95% percentile CI	[−0.1021, −0.0126]	[−0.0652, 0.0095]	[−0.0232, 0.0067]	[−0.1035, −0.0065]
Observations	2,559	2,559	2,559	1,808
Firms	1,379	1,379	1,379	1,015
R^2	0.5743	0.5511	0.3378	0.5704

Note: Variable definitions appear in Table 1. All models include the baseline controls and industry and year effects. SE denotes standard error, and CI denotes the confidence interval. Parentheses contain firm-clustered SEs. Columns (1), (2), and (4) use winsorised ln(1 + applications). Column (3) is a linear probability model for any application. For PosGHGGap, normal-reference p-values and percentile intervals use 1,999 successful firm-cluster bootstrap replications with fixed winsorisation cutoffs. Each replication resamples the full panel and re-estimates the benchmark before selecting positive applicants for column (4).

Supplementary Pathway Analyses

Commercial Resource Commitment

The first pathway analysis examines whether weaker patenting is accompanied by lower spending on the commercial activities that help firms bring innovations to market. Table 8 shows that larger above-benchmark emissions gaps are associated with lower commercial resource commitment, which is positively related to green innovation. The estimated indirect association is negative, with a bootstrap confidence interval excluding zero. A significant negative direct association also remains after including the resource measure. These associations remain after controlling for R&D intensity.

Analyst Attention and Financing-Related Conditions

The second pathway analysis examines the information and financing conditions accompanying green innovation. Fiorillo, Meles, Salerno, and Verdoliva (2024) link a loss of analyst coverage to higher default risk and more conservative financing and investment policies. Other studies relate analyst coverage to green innovation (Fiorillo et al., 2022; Wang & Cao, 2024). Given the financing needs of green invention (Yu et al., 2021), these relationships motivate an examination of external information coverage alongside internal

commercial expenditure. All three equations in this supplementary analysis omit the baseline Size and Age controls because FC_SA is constructed from the related size and age measures defined in Table 1.

Table 9 shows that above-benchmark emissions are associated with lower analyst and report attention. Greater attention is associated with a lower value of the size–age score, which is negatively related to green innovation. The product of the serial coefficients is small and negative, with a bootstrap confidence interval that excludes zero. The direct association is statistically insignificant in this specification. This pattern connects the emissions position with both external information coverage and financing-related firm characteristics.

Table 8: Commercial resource commitment pathway analysis

Path/association	Estimate	SE	p-value	Bootstrap 95% CI
PosGHGGap → MRC	−0.1164***	0.0268	<0.001	—
MRC → GI	0.0907***	0.0280	0.0012	—
Indirect association	−0.0106	0.0044	—	[−0.0201, −0.0031]
Residual direct association	−0.0511**	0.0226	0.0238	—
Observations/firms	2,474 / 1,333	—	—	—

Note: Variable definitions appear in Table 1. MRC denotes commercial resource commitment. SE denotes standard error, and CI denotes the confidence interval. Two ordinary least-squares equations model MRC and GI conditional on MRC, retaining both gaps, baseline controls, and industry and year effects. Path and direct-association SEs are firm-clustered. Indirect-association inference uses 2,000 firm-cluster bootstrap replications that re-estimate the benchmark and pathway equations (Hayes & Rockwood, 2017). Both pathway analyses start from the same baseline sample of 2,559 firm-year observations from 1,379 firms. This analysis excludes 85 observations with missing annual selling expenses, which are required to construct MRC. Table 9 retains the full baseline sample. ***, ** denote significance at 1%, 5%, respectively.

Table 9: Analyst attention and financing-related pathway analysis

Path/association	Estimate	SE	p-value	Bootstrap 95% CI
PosGHGGap → ReportAttention	−0.0781***	0.0282	0.0056	—
ReportAttention → FC_SA	−0.0326***	0.0064	<0.001	—
FC_SA → GI	−0.4896***	0.1077	<0.001	—
Specific serial indirect association	−0.0012	0.0006	—	[−0.0027, −0.0002]
Residual direct association	−0.0317	0.0229	0.1678	—
Observations/firms	2,559 / 1,379	—	—	—

Note: Variable definitions appear in Table 1. ReportAttention measures analyst and report attention. FC_SA is an absolute size–age score based on the functional form of Hadlock and Pierce (2010). SE denotes standard error and CI denotes the confidence interval. Three ordinary least-squares equations model ReportAttention, FC_SA conditional on ReportAttention, and GI conditional on both. Each retains both gaps, industry and year effects, and the baseline financial and organisational controls, excluding Size and Age because FC_SA is constructed from the related SizeSA and FirmAge measures. Path and direct-association SEs are firm-clustered. Serial-product inference uses 2,000 firm-cluster bootstrap replications that re-estimate the benchmark and all pathway equations. *** denote significance at 1%, respectively.

Exploratory Heterogeneity

Resource-based reasoning also raises the question of where the association is strongest. Table 10 examines firm age and prior green innovation efficiency as indicators of organisational experience and earlier inventive performance. Firms are also grouped by the level of government subsidies, in order to explore differences in external support. These exploratory tests use formal between-group comparisons and adjust for multiple testing.

The above-benchmark coefficient is more negative among younger firms than among older firms. This difference is consistent with the idea that younger firms have accumulated fewer organisational resources to support operational adjustment and invention simultaneously.

Higher prior green innovation efficiency also corresponds to a more negative above-benchmark coefficient. The grouping uses the lagged ratio of the log of green applications to the log of R&D spending, as defined in Table 10.

The association is more negative in the higher-subsidy group, although the between-group difference receives statistical support only at the 10% level after adjustment. Larger subsidies may reflect policy eligibility, existing adjustment needs, or the scale of planned projects.

Table 10: Heterogeneity analyses

Variable / Statistic	Firm age		Prior green innovation efficiency		Government subsidies	
	(1) Low	(2) High	(3) Low	(4) High	(5) Low	(6) High
PosGHGGap	−0.1404***	0.0038	0.0147	−0.0786***	−0.0264	−0.1053***
	(0.0306)	(0.0270)	(0.0216)	(0.0281)	(0.0266)	(0.0335)
NegGHGGap	−0.0335	0.0316	0.0095	0.0025	0.0083	−0.0297
	(0.0210)	(0.0222)	(0.0123)	(0.0179)	(0.0218)	(0.0240)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,451	1,108	1,233	1,232	1,280	1,279
Firm clusters	814	661	751	699	843	651
R-squared	0.6376	0.6264	0.3295	0.5999	0.4865	0.6498
PosGHGGap difference (High – low)	0.1442***		−0.0933**		−0.0790*	
Group-difference p-value	0.0004		0.0100		0.0587	
Holm-adjusted p-value	0.0011		0.0200		0.0587	

Note: Variable definitions appear in Table 1. Age and subsidy groups use pooled medians. Prior efficiency uses annual medians of lagged ln(1 + green applications)/ln(1 + research and development expenditure), requiring positive expenditure. Parentheses contain firm-clustered standard errors. Group differences are high minus low from fully interacted models. Holm adjustment covers the three comparisons (Holm, 1979). ***, ** and * denote significance at 1%, 5% and 10%, respectively.

CONCLUSION

This study links the direction of firms' emissions deviations from an operating benchmark to their green inventive activity. In the Chinese disclosure sample, larger above-benchmark gaps are associated with fewer green patent applications, while the relationship below the benchmark is statistically insignificant and differs from the above-benchmark association. The negative association is retained under alternative emissions benchmarks and with fixed effects for each industry and year combination. It also appears for invention applications and application volume among current applicants. Lower commercial resource commitment accompanies both above-benchmark emissions and weaker patenting, even after accounting for R&D intensity. These findings extend the use of benchmarked carbon-accounting information by connecting emissions positions with inventive activity and its commercial support. They suggest that assessments of corporate transition plans should consider the resources available for invention and commercialisation alongside research spending and emissions positions. The relationship between operational adjustment and these complementary resources warrants examination in other economies where carbon-intensive production and clean-technology development coexist.

Limitations and Future Research

The sample is restricted to firms with usable positive GHG disclosures. This relatively limited coverage restricts the generalisation of the results to the broader population of Chinese listed firms. Inverse-probability

weighting improves balance on observed characteristics, but selection on unobserved reporting incentives can remain. The emissions benchmark also depends on available operating characteristics and consistent accounting boundaries (He et al., 2022; Klaaßen & Stoll, 2021). The resulting deviations provide conditional comparisons only and may reflect omitted fundamentals or variation in reporting as well as genuine differences in production.

The short, unbalanced panel covering 2020–2024 limits the assessment of longer adjustment processes. An auxiliary model with firm and year fixed effects does not yield a statistically significant within-firm estimate. The robustness and endogeneity analyses address several sources of bias, but unobserved firm differences and feedback between emissions and innovation cannot be fully excluded (Bellemare, Masaki, & Pepinsky, 2017). Truong (2025) reports an association between green patenting and higher subsequent MSCI emissions ratings, highlighting the possibility that innovation also shapes emissions performance. The estimates should therefore be read as conditional associations. Longer panels, together with credible disclosure or regulatory shocks, would help to distinguish persistent firm differences from changes in inventive activity and would strengthen causal identification.

The interpretation of the mechanisms is constrained by the available proxies and by the contemporaneous nature of the observations. Selling expenses measure broad commercial commitment rather than green-project budgets, while coverage counts measure the volume of analyst attention rather than its content. Asset-adjustment costs and managerial perceptions are not directly observed. Taking absolute values reverses the ordering of negative values of the underlying score. A higher value of FC_SA therefore cannot be interpreted simply as tighter financing constraints. Its construction also requires a different control set in the serial pathway. Consequently, the indirect associations cannot establish a causal sequence or full mediation. Measures of project-level resources, financing, and information content observed over time would allow a more direct examination of these relationships.

Patent applications capture inventive activity but do not measure realised emissions reductions or commercial value. The participation analysis also does not identify entry into or exit from patenting activity over time. Future work could connect patenting with technology adoption and verified environmental outcomes. The exploratory subgroup comparisons do not isolate the effects of firm age, prior inventive performance, or subsidies. They therefore warrant independent replication before they inform targeted policy. Cross-country research using comparable patent and emissions definitions could examine how financing institutions and production technologies shape the relationships documented here.

Theoretical Implications

The findings indicate that any interpretation of a firm's emissions position should consider innovation incentives and the resources that support inventive effort together. Studies of aspiration shortfalls and emissions levels identify settings in which environmental pressure accompanies greater innovation (Ma, 2024; Sun et al., 2024). The operating comparison used here points to weaker green patenting above the fitted emissions level, together with lower commercial resource commitment. These results suggest that an emissions position alone provides an incomplete account of firms' inventive responses. The resource pattern is consistent with the allocation pressures examined by Cui et al. (2023).

Retaining the direction of the benchmark deviation also extends the economic use of carbon-accounting information. Gipper et al. (2026) use absolute deviations to assess reporting quality. An absolute deviation places firms with equally large positive and negative gaps together. Their different associations with inventive activity show why retaining direction can add information to this comparison. This application complements policy-shock and emissions-level research by identifying where the negative association lies relative to an operating reference point (Cui et al., 2023; Liu & Li, 2022).

The results on resource commitment link the emissions position to the support available for environmental strategy. The natural-resource-based view emphasises capabilities for environmental improvement (Hart, 1995) while subsequent empirical work highlights financial conditions (Cecere et al., 2020; Chang & Wang, 2024). Because the models account for R&D intensity, the results on commercial expenditure draw attention to the activities that connect invention with customers and markets. Assessments of firms'

preparedness for cleaner innovation should therefore consider complementary commercial resources alongside research funding.

The patent analyses provide further insight into what the emissions comparison reveals about environmental response. The supported estimates relate to invention applications and to application volume among current applicants, while the evidence on participation remains inconclusive. Assessing firms only by whether they apply for any green patents can therefore obscure variation in the scale of current inventive activity. Firms may also acquire cleaner technologies without patenting them (Cui et al., 2023).

The Chinese evidence also raises a question that can be examined in other institutional settings. British evidence separates low-carbon inventive responses from immediate reductions in carbon intensity (Calel, 2020), while research on European SMEs highlights complementarities between public and other funding for eco-innovation (Cecere et al., 2020). Alongside the present findings, these studies motivate further tests. One question is whether the emissions–innovation association becomes more negative where asset adjustment is costly and complementary resources are difficult to mobilise. Such comparisons would show how firm-level resource conditions shape inventive activity, including in economies that already have substantial clean-technology industries.

Practical Implications and Recommendations

For boards and managers, an above-benchmark position can prompt a joint review of operating assets and green-project resources. The result for current applicants suggests that assessments should consider application volume alongside whether a firm files any green patent applications. Reviews can relate equipment replacement needs to project budgets, research milestones and customer-development resources. Consistent reporting boundaries and attention to production mix can help to focus these reviews on the firm's own operating needs.

For analysts and lenders comparing transition plans across markets, the results highlight the value of examining the firm-specific commitments that lie behind national targets and corporate claims. Assessments can connect disclosed emissions and benchmark inputs with project budgets, cash-flow coverage and commercialisation arrangements. Differences in reporting boundaries complicate comparisons of corporate emissions (Klaaßen & Stoll, 2021). Financing assessments should therefore use benchmarks calibrated to comparable operations and disclosure scopes.

For policymakers, the findings motivate transition programmes that consider implementation capacity alongside emissions requirements. This resource-allocation issue is also relevant to economies that are pursuing industrial upgrading as well as decarbonisation. In those settings, access to markets, skills and infrastructure also shapes investment in clean technology (International Energy Agency, 2024). Where project assessment identifies gaps, programmes can pair access to finance, technical expertise and commercial support with requirements to develop cleaner technologies. Programme evaluation should distinguish additional innovation, adoption of existing technology and verified emissions reductions.

FUNDING: This study received no specific financial support.
INSTITUTIONAL REVIEW BOARD STATEMENT: Not applicable.
TRANSPARENCY: The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
COMPETING INTERESTS: The author declares that there are no conflicts of interests regarding the publication of this paper.
DISCLOSURE OF AI USE: The author used OpenAI's GPT-6 for language polishing and grammar checking. All outputs were reviewed and verified by the author, who takes full responsibility for the manuscript.

REFERENCES

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, *124*(1), 1-51. https://doi.org/10.1086/684581

Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effect. *The Journal of Politics*, *79*(3), 949-963. https://doi.org/10.1086/690946

Bendig, D., Schäper, T., Strehlow, M., & Foege, J. N. (2026). Leveraging digital alliances for green innovations: A pathway to becoming green. *European Journal of Information Systems*, *35*(1), 1-25. https://doi.org/10.1080/0960085X.2025.2522799

Bui, B., Houqe, M. N., & Zaman, M. (2020). Climate governance effects on carbon disclosure and performance. *The British Accounting Review*, *52*(2), 100880. https://doi.org/10.1016/j.bar.2019.100880

Calel, R. (2020). Adopt or innovate: Understanding technological responses to cap-and-trade. *American Economic Journal: Economic Policy*, *12*(3), 170-201. https://doi.org/10.1257/pol.20180135

Cecere, G., Corrocher, N., & Mancusi, M. L. (2020). Financial constraints and public funding of eco-innovation: Empirical evidence from European SMEs. *Small Business Economics*, *54*(1), 285-302. https://doi.org/10.1007/s11187-018-0090-9

Chang, Y., & Wang, S. (2024). A study on the impact of ESG rating on green technology innovation in enterprises: An empirical study based on informal environmental governance. *Journal of Environmental Management*, *358*, 120878. https://doi.org/10.1016/j.jenvman.2024.120878

Chen, J., & Roth, J. (2024). Logs with zeros? Some problems and solutions. *The Quarterly Journal of Economics*, *139*(2), 891-936. https://doi.org/10.1093/qje/qjad054

Choi, B., & Luo, L. (2021). Does the market value greenhouse gas emissions? Evidence from multi-country firm data. *The British Accounting Review*, *53*(1), 100909. https://doi.org/10.1016/j.bar.2020.100909

Colmer, J., Martin, R., Muûls, M., & Wagner, U. J. (2025). Does pricing carbon mitigate climate change? Firm-level evidence from the European Union emissions trading system. *The Review of Economic Studies*, *92*(3), 1625-1660. https://doi.org/10.1093/restud/rdae055

Cui, D., Ding, M., Han, Y., & Suardi, S. (2023). Regulation-induced financial constraints, carbon emission and corporate innovation: Evidence from China. *Energy Economics*, *127*, 107081. https://doi.org/10.1016/j.eneco.2023.107081

Cui, J., Dai, J., Wang, Z., & Zhao, X. (2022). Does environmental regulation induce green innovation? A panel study of Chinese listed firms. *Technological Forecasting and Social Change*, *176*, 121492. https://doi.org/10.1016/j.techfore.2022.121492

D'Haultfœuille, X., & Tuvaandorj, P. (2024). A robust permutation test for subvector inference in linear regressions. *Quantitative Economics*, *15*(1), 27-87. https://doi.org/10.3982/QE2269

Dagenais, M. G., & Dagenais, D. L. (1997). Higher moment estimators for linear regression models with errors in the variables. *Journal of Econometrics*, *76*(1-2), 193-221. https://doi.org/10.1016/0304-4076(95)01789-5

De Haas, R., Martin, R., Muûls, M., & Schweiger, H. (2025). Managerial and financial barriers to the green transition. *Management Science*, *71*(4), 2890-2921. https://doi.org/10.1287/mnsc.2023.00772

Dechezleprêtre, A., & Sato, M. (2017). The impacts of environmental regulations on competitiveness. *Review of Environmental Economics and Policy*, *11*(2), 183–206. https://doi.org/10.1093/reep/rex013

DiCiccio, C. J., & Romano, J. P. (2017). Robust permutation tests for correlation and regression coefficients. *Journal of the American Statistical Association*, *112*(519), 1211–1220. https://doi.org/10.1080/01621459.2016.1202117

Fiorillo, P., Meles, A., Mustilli, M., & Salerno, D. (2022). How does the financial market influence firms' green innovation? The role of equity analysts. *Journal of International Financial Management & Accounting*, *33*(3), 428-458. https://doi.org/10.1111/jifm.12152

Fiorillo, P., Meles, A., Salerno, D., & Verdoliva, V. (2024). Analyst coverage and default risk. *International Review of Economics & Finance*, *94*, 103412. https://doi.org/10.1016/j.iref.2024.103412

Gipper, B., Sequeira, F., & Shi, S. X. (2026). Carbon accounting quality: Measurement and the role of assurance. *Journal of Accounting and Economics*, *81*(2), 101849. https://doi.org/10.1016/j.jacceco.2025.101849

Goldstein, J. E., Neimark, B., Garvey, B., & Phelps, J. (2023). Unlocking "lock-in" and path dependency: A review across disciplines and socio-environmental contexts. *World Development*, *161*, 106116. https://doi.org/10.1016/j.worlddev.2022.106116

Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, *23*(5), 1909-1940. https://doi.org/10.1093/rfs/hhq009

Hart, S. L. (1995). A natural-resource-based view of the firm. *The Academy of Management Review*, *20*(4), 986-1014. https://doi.org/10.5465/amr.1995.9512280033

Hayes, A. F., & Rockwood, N. J. (2017). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy*, *98*, 39-57. https://doi.org/10.1016/j.brat.2016.11.001

He, L., & Wang, M. (2023). Environmental regulation and green innovation of polluting firms in China. *PLoS ONE*, *18*(3), e0281303. https://doi.org/10.1371/journal.pone.0281303

He, R., Luo, L., Shamsuddin, A., & Tang, Q. (2022). Corporate carbon accounting: A literature review of carbon accounting research from the Kyoto Protocol to the Paris Agreement. *Accounting & Finance*, *62*(1), 261-298. https://doi.org/10.1111/acfi.12789

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, *6*(2), 65-70.

Hong, M., Drakeford, B., & Zhang, K. (2020). The impact of mandatory CSR disclosure on green innovation: Evidence from China. *Green Finance*, *2*(3), 302-322. https://doi.org/10.3934/GF.2020017

Howell, S. T. (2017). Financing innovation: Evidence from R&D grants. *American Economic Review*, *107*(4), 1136-1164. https://doi.org/10.1257/aer.20150808
Huang, M., Chen, S., & Cheng, P. (2025). Green path without waste: Zero-waste city pilot construction and corporate green innovation. *Humanities and Social Sciences Communications*, *12*(1), 1771. https://doi.org/10.1057/s41599-025-06034-w
Huang, Z., Cao, J., & Pan, L. (2024). Greening your way to profits: Green strategies and green revenues. *Finance Research Letters*, *61*, 105029. https://doi.org/10.1016/j.frl.2024.105029
International Energy Agency. (2024). *Energy technology perspectives 2024*. Retrieved from https://www.iea.org/reports/energy-technology-perspectives-2024
Jiang, F. (2025). Digital transformation and green innovation: The mediating role of green management disclosure and the moderating role of institutional pressure. *Journal of General Management*. https://doi.org/10.1177/03063070241308100
Keane, M. P., & Neal, T. (2024). A practical guide to weak instruments. *Annual Review of Economics*, *16*(1), 185-212. https://doi.org/10.1146/annurev-economics-092123-111021
Klaaßen, L., & Stoll, C. (2021). Harmonizing corporate carbon footprints. *Nature Communications*, *12*(1), 6149. https://doi.org/10.1038/s41467-021-26349-x
Liu, M., & Li, Y. (2022). Environmental regulation and green innovation: Evidence from China's carbon emissions trading policy. *Finance Research Letters*, *48*, 103051. https://doi.org/10.1016/j.frl.2022.103051
Ma, J. (2024). Carbon emissions and low-carbon innovation in firms. *PLoS ONE*, *19*(10), e0312759. https://doi.org/10.1371/journal.pone.0312759
MacKinnon, J. G., Nielsen, M. Ø., & Webb, M. D. (2023). Cluster-robust inference: A guide to empirical practice. *Journal of Econometrics*, *232*(2), 272-299. https://doi.org/10.1016/j.jeconom.2022.04.001
Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37*(2), 187-204. https://doi.org/10.1080/07350015.2016.1227711
Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, *9*(4), 97-118. https://doi.org/10.1257/jep.9.4.97
Qin, X., Muskat, B., Ambrosini, V., Mair, J., & Chih, Y.-Y. (2026). Green innovation implementation: A systematic review and research directions. *Journal of Management*, *52*(1), 255-282. https://doi.org/10.1177/01492063241312656
Richey, R. G., Jr., Musgrove, C. F., Gillison, S. T., & Gabler, C. B. (2014). The effects of environmental focus and program timing on green marketing performance and the moderating role of resource commitment. *Industrial Marketing Management*, *43*(7), 1246-1257. https://doi.org/10.1016/j.indmarman.2014.06.014
Seaman, S. R., & Vansteelandt, S. (2018). Introduction to double robust methods for incomplete data. *Statistical Science*, *33*(2), 184-197. https://doi.org/10.1214/18-STS647
Sun, Z., Sun, X., & Dong, Y. (2024). Does negative environmental performance feedback induce substantive green innovation? The moderating roles of external regulations and internal incentive. *Corporate Social Responsibility and Environmental Management*, *31*(4), 2953-2976. https://doi.org/10.1002/csr.2722
Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research Policy*, *47*(8), 1367-1387. https://doi.org/10.1016/j.respol.2017.01.015
Truong, Y. (2025). Green innovations and toxic emissions of manufacturing firms: Do green innovative firms pollute less? *Corporate Social Responsibility and Environmental Management*, *32*(5), 6831-6842. https://doi.org/10.1002/csr.70065
United Nations Environment Programme. (2025). *Emissions gap report 2025: Off target – Continued collective inaction puts global temperature goal at risk*. Nairobi, Kenya: United Nations Environment Programme.
Wang, L., & Cao, L. (2024). Analyst attention and corporate green innovation. *Finance Research Letters*, *60*, 104924. https://doi.org/10.1016/j.frl.2023.104924
World Bank Group. (2022). *China country climate and development report*. Retrieved from https://www.worldbank.org/en/country/china/publication/china-country-climate-and-development-report
Yin, J., & Gao, X. (2026). Do the environmental underperformance intensity and duration affect corporate green innovation? Evidence from the Chinese manufacturing industry. *Journal of Business Research*, *209*, 116093. https://doi.org/10.1016/j.jbusres.2026.116093
Yu, C.-H., Wu, X., Zhang, D., Chen, S., & Zhao, J. (2021). Demand for green finance: Resolving financing constraints on green innovation in China. *Energy Policy*, *153*, 112255. https://doi.org/10.1016/j.enpol.2021.112255
Zhang, J., Liang, G., Feng, T., Yuan, C., & Jiang, W. (2020). Green innovation to respond to environmental regulation: How external knowledge adoption and green absorptive capacity matter? *Business Strategy and the Environment*, *29*(1), 39-53. https://doi.org/10.1002/bse.2349

Asian Online Journal Publishing Group *is not responsible or answerable for any loss, damage or liability, etc. caused in relation to/arising out of the use of the content. Any queries should be directed to the corresponding author of the article.*