Innovating Green: Competition Meets Regulation

Finance Working Paper N° 725/2021

June 2025

Rui Dai
The Chinese University of Hong Kong, Shenzhen

Rui Duan
McMaster University

Lilian Ng
York University and ECGI

ECGI Working Paper Series in Finance

Innovating Green: Competition Meets Regulation

Working Paper N° 725/2021
June 2025

Rui Dai
Rui Duan
Lilian Ng

We thank Ian Appel (Discussant), Kentaro Asai, Ines Chaieb, Mark Kamstra, Ambrus Kecskes, Yrjo Koskinen (Discussant), Yelena Larkin, Harald Hau, Yongtae Kim (Discussant), Haekwon Lee, Hao Liang, Claire Liu, Angie Low, Abdullah Mamun, Alexander Murmann, Peter Pham, Buhui Qiu, Ben Sands, Matthew Ser ing (Discussant), Fabio Trojani, Christian Wagner, Ying Xia (Discussant), Victor Song (Discussant), Joakim Westerholm, Craig Wilson, and Jing Yu for their valuable comments and suggestions. We also thank the participants from the Canadian Sustainable Finance Network, ITAM Finance Conference, Nanyang Technological University, University of Geneva, University of Sydney, WRDS, WU Vienna University of Economics and Business, York University, Alliance for Research in Corporate Sustainability Conference, China International Conference in Finance, Northern Finance Association, International Workshop on Financial System Architecture & Stability, the International Conference on Corporate Finance organized by the Darla Moore School of Business and Hitotsubashi University, and the Financial Management Association Conference for their insightful feedback.

Abstract

This study shows that competition drives corporate innovation under intense environmental regulatory pressure. Using the nonattainment status of U.S. counties as an exogenous variation in regulation, we find that competition spurs green innovation as firms respond to stricter policies. Firms are particularly motivated to innovate in clean technology when operating in pollution-intensive industries, facing high relocation costs, and possessing a strong history of innovation. Regulation-driven green innovation allows firms to differentiate their products, enhance their ESG reputation, and attract more corporate customers, leading to higher sales growth, increased market share, and improved profitability, although not necessarily higher valuation. Stricter regulations in competitive environments not only curb pollution but also serve as a catalyst for sustainable, long-term innovation. These findings emphasize the vital role of environmental regulations in promoting sustainable practices and operational benefits, underscoring the importance of well-designed policies to drive long-term economic and environmental progress.

Keywords: Corporate Environmental Policy, Green Innovation, Economic Consequences, Competition

JEL Classifications: G38, M14, Q52, Q53, Q55

Rui Dai*
Fractional Research Assistant Professor
The Chinese University of Hong Kong, Shenzhen
NO.1006 Shennan Road
Futian District, Shenzhen City, Guangdong Province, China
e-mail: dairui@cuhk.edu.cn

Rui Duan
Assistant Professor
McMaster University
1280 Main Street West
Hamilton, Ontario, Canada
e-mail: duanr10@mcmaster.ca

Lilian Ng
Professor of Finance
York University, Schulich School of Business
4700 Keele Street
North York, Ontario M3J 1P3, Canada
phone: +1 416 736 2100 77944
e-mail: lng@schulich.yorku.ca

*Corresponding Author

Innovating Green: Competition Meets Regulation

Rui Dai, Rui Duan, and Lilian Ng[1]

Current Version: February 23, 2025

[1]Dai is from WRDS, The Wharton School, University of Pennsylvania, USA and School of Management and Economics - Chinese University of Hong Kong (Shenzhen) and Shenzhen Finance Institute, China; Duan is from the DeGroote School of Business, McMaster University, Canada; and Ng is from the Schulich School of Business, York University, Canada. Authors' email information: Dai: rui.dai.wrds@outlook.com; Duan: duanr10@mcmaster.ca; Ng: lng@schulich.york.ca. We thank Ian Appel (Discussant), Kentaro Asai, Ines Chaieb, Mark Kamstra, Ambrus Kecskes, Yrjö Koskinen (Discussant), Yelena Larkin, Harald Hau, Yongtae Kim (Discussant), Haekwon Lee, Hao Liang, Claire Liu, Angie Low, Abdullah Mamun, Alexander Mürmann, Peter Pham, Buhui Qiu, Ben Sands, Matthew Serfling (Discussant), Fabio Trojani, Christian Wagner, Ying Xia (Discussant), Victor Song (Discussant), Joakim Westerholm, Craig Wilson, and Jing Yu for their valuable comments and suggestions. We also thank the participants from the Canadian Sustainable Finance Network, ITAM Finance Conference, Nanyang Technological University, University of Geneva, University of Sydney, WRDS, WU Vienna University of Economics and Business, York University, Alliance for Research in Corporate Sustainability Conference, China International Conference in Finance, Northern Finance Association, International Workshop on Financial System Architecture & Stability, the International Conference on Corporate Finance organized by the Darla Moore School of Business and Hitotsubashi University, and the Financial Management Association Conference for their insightful feedback.

Innovating Green: Competition Meets Regulation

ABSTRACT

This study shows that competition drives corporate innovation under intense environmental regulatory pressure. Using the nonattainment status of U.S. counties as an exogenous variation in regulation, we find that competition spurs green innovation as firms respond to stricter policies. Firms are particularly motivated to innovate in clean technology when operating in pollution-intensive industries, facing high relocation costs, and possessing a strong history of innovation. Regulation-driven green innovation allows firms to differentiate their products, enhance their ESG reputation, and attract more corporate customers, leading to higher sales growth, increased market share, and improved profitability, although not necessarily higher valuation. Stricter regulations in competitive environments not only curb pollution but also serve as a catalyst for sustainable, long-term innovation. These findings emphasize the vital role of environmental regulations in promoting sustainable practices and operational benefits, underscoring the importance of well-designed policies to drive long-term economic and environmental progress.

Keywords: Corporate Environmental Policy, Product Market Competition, Green Innovation, Economic Consequences

JEL classification: G38, M14, Q52, Q53, Q55

1. Introduction

In recent decades, increasingly stricter environmental policies have responded aggressively to global environmental crises, demanding stringent action against environmental degradation.[1] This intensifying regulatory landscape raises critical questions about its economic impact on affected firms and sectors. Porter (1991) and Porter and Van der Linde (1995) argue that well-designed environmental policies can enhance financial performance by driving innovation and boosting economic prosperity. While theoretical models (e.g., Acemoglu et al., 2012, 2016) highlight the importance of such policies, empirical studies show significant variability in their effects on productivity, with mixed outcomes for innovation and economic performance across firms and countries, as well as notable differences in firms' responses to regulatory stringency (Cohen and Tubb, 2018).[2] The disconnect between theoretical predictions and empirical evidence may arise from a limited focus on market competition's role in shaping firms' innovation strategies. Our study addresses this gap by identifying product market competition as a key factor influencing firm responses to regulatory stringency. Leveraging exogenous differences in regulatory stringency between attainment and nonattainment counties in the U.S., we use a quasi-natural experimental design to analyze firm responses to a uniform environmental policy within a single country. This approach controls for cross-regulation differences, isolating the effects of stringency on firm behavior and providing insights into balancing compliance costs with technological progress.

Economic theory suggests that competition significantly shapes innovation incentives. Aghion et al. (2005) model an inverted-U relationship, demonstrating that moderate competition spurs innovation as firms strive to strengthen their market position, while intense competition erodes profit margins, discouraging R&D investment. Lambertini et al. (2017) develop a similar result in an oligopolistic market context, revealing the nuanced and context-dependent nature of this dynamic through numerical analysis. Recognizing the vital role of competition in driving innovation, we argue that understanding the intricate dynamics of product market competition is key to explaining the diverse and, at times, unexpected innovation efforts triggered by regulatory pressures. Our study examines the directional effects of these market forces and uncovers the underlying mechanisms, emphasizing the direct impact of corporate strategic responses. Importantly, our analyses offer unique insights that challenge established models of the competition-innovation relationship under regulatory constraints.

We leverage a critical regulatory feature of the Clean Air Act (CAA), which classifies U.S. counties as either attainment or nonattainment areas based on the U.S. National Ambient Air Quality Standards (NAAQS) set by the Environmental Protection Agency (EPA) for six major pollutants. Counties exceeding these thresholds are designated as nonattainment areas and face stricter regulatory consequences, while attainment areas are subject to more lenient regulations. Firms operating polluting facilities in nonattainment counties must comply with stringent pollution control measures, unlike their counterparts in attainment areas. Using county-level nonattainment designations as an exogenous source of variation in regulatory stringency enables us to analyze how competitive pressures influence firms' incentives to innovate in environmental technologies under heightened regulatory demands.

Merging detailed plant location data from Dun & Bradstreet with innovation output data from PATSTAT and Hoberg-Phillips firm-specific competition measures,[3] we create a robust sample of 51,810 firm-county-year observations. This sample spans 1,903 innovative firms across 438 counties (including 118 event counties) from 2000 to 2021. Using a stacked difference-in-differences (DiD) approach, our analysis shows that product market competition amplifies regulatory incentives for green innovation. Specifically, firms under intense competitive pressure significantly boost green innovation following a nonattainment shock at one of their facilities—an effect not observed in firms without similar regulatory changes. In less competitive sectors, firms do not display a comparable technological shift. A one-standard-deviation increase in the intensity of competition leads to a 5.57%–7.19% rise in green patent counts and an 8.10%–11.64% increase in green citations, highlighting that regulation combined with competitive dynamics is a key driver of green innovation.

Our baseline results remain robust across a comprehensive set of tests that reinforce our causal interpretation, including: (1) regression discontinuity design (RDD) analyses on pollution concentrations around the NAAQS threshold, further randomizing nonattainment assignments across counties; (2) controlling for country-level characteristics using explicit controls, firm-cohort$\times$year-cohort fixed effects, and alternative treatment-control matching based on county-specific attributes in propensity score estimation; and (3) leveraging import tariff reductions as an exogenous variation in competitive intensity for U.S. firms. This robustness extends to alternative empirical designs, including firm-level analysis of the cumulative impact of multiple nonattainment locations and a focused examination of nonattainment shocks on a representative county per firm to capture regulatory effects on key operational sites. Furthermore, placebo analyses—employing non-green innovation outputs and substituting nonattainment shocks with status reversals—show no significant effects, underscoring the specificity and reliability of our results.

Our findings depart from the static conventional inverted U-shaped relationship, revealing that competition level dynamically influences green technological responses to regulatory changes. This effect seems to arise from the combined pressures of environmental regulations and market competition, which together amplify the costs of staying "brown" and strengthen the incentives for pursuing green innovation. Stricter regulations may restrict a firm's expansion ability without adopting cleaner processes. In competitive markets, the cost of stagnation can be high, as rivals or new entrants can capture market share. Thus, green innovation becomes a strategic choice to avoid such setbacks and maintain competitive position. Moreover, green innovations allow firms to differentiate, enhance their reputation, and attract consumers, while patenting these technologies provides proprietary benefits and deters competitors. The dual benefits of regulatory compliance and competitive positioning reinforce incentives for green innovation, especially in highly competitive industries. Our subsequent analysis provides empirical support for this argument.

We empirically investigate why firms under intense competition are more responsive to regulatory pressure through green innovation, structuring our analysis in three parts. First, we conduct cross-sectional analyses to examine two key factors shaping firms' responses: (1) regulatory burden and (2) the capability to adopt advanced green technologies. As discussed, green innovation could serve as a defensive strategy, allowing firms operating in highly competitive markets to mitigate the high costs of non-compliance. In line with this perspective, we find that the combined impact of competition and regulatory pressure is particularly pronounced for firms in highly polluting sectors or those with significant geographic constraints, as these firms face greater compliance costs. Additionally, prior research indicates that a firm's strategic response is closely tied to its history of innovation (e.g., Aghion et al., 2016). Firms at the leading edge of technological advancements are better positioned to invest in R&D, lowering their costs of adopting new innovations. Consistent with this, our analysis shows that competitive firms with a strong track record in green innovation respond more effectively to regulatory demands than those with limited experience.

Second, we examine whether green innovation driven by regulatory pressures creates strategic opportunities for firms to maintain or strengthen their competitive position. By adopting green technologies, these firms can enhance their reputation, attracting stakeholders who prioritize sustainability and boosting their value among investors, consumers, and policymakers. Our analysis reveals that firms can achieve product differentiation and signal enhanced quality through regulation-driven green innovation. Green inventions resulting from regulatory changes are often more significant than non-green inventions or green inventions unrelated to regulation. Moreover, firms with substantial green innovation portfolios experience shifts in market dynamics, reflected by fewer new entrants, suggesting that these firms use regulation-driven green patents as barriers to entry. Their ESG ratings also improve, underscoring that green innovators can enhance both reputation and perceived product quality in response to regulatory shocks.

Third, we explore the post-regulatory impacts of green innovation, examining whether these benefits extend to stronger product market performance, especially in attracting corporate customers relative to non-green firms. Our analysis reveals that firms with robust green patent portfolios tend to draw more corporate customers in local markets and strengthen collaborative alliances following regulatory changes. This expansion is particularly pronounced among customers with limited green innovation capabilities, opening new markets where demand for green solutions is rising. Moreover, competitive firms engaged in green innovation experience increased market share, return on assets (ROA), and sales following regulatory enforcement—contrasting sharply with non-green innovators, who generally see declines in these areas. However, while green innovation enhances post-regulatory performance, it does not significantly boost overall firm value, suggesting that financial gains may not fully offset regulatory costs. Collectively, these findings reveal key mechanisms driving green innovation under the combined influence of competitive and regulatory pressures, where the benefits of green innovation help offset regulatory costs for firms in highly competitive sectors. They also shed light on why firms may hesitate to adopt green strategies voluntarily in the absence of strict environmental mandates.

Finally, we also examine the policy implications of green innovation, particularly its impact on local pollution reduction and potential policy reversals. Our findings indicate that stricter regulations in competitive markets not only stimulate green innovation but also accelerate pollution control, enabling high-pollution areas to meet regulatory standards more quickly and reverse their nonattainment status. These results underscore the societal benefits of green innovation beyond individual firm gains, emphasizing its pivotal role in advancing broader environmental and public health objectives.

Our research delivers key contributions to the literature on environmental policy and innovation, as well as competition and innovation. Previous studies, such as Rubashkina et al. (2015) and Peng et al. (2021), explore the impact of environmental policy on innovation and competitiveness. Rubashkina et al. find that regulations promote innovation across European sectors without enhancing productivity-based competitiveness. In contrast, Peng et al., using Chinese firm-level data, show that environmental regulations can drive both productivity and competitiveness. These differences may reflect country and sectoral variations, along with distinct measures of regulatory stringency. Yet, as Peng et al. and others (e.g., Cohen and Tubb, 2018) observe, a central question persists: why do corporate responses to policy interventions vary so widely? Our work addresses this question by identifying a critical condition that shapes corporate responses, offering practical insights into regulatory design to minimize economic harm. Leveraging exogenous differences in regulatory stringency across attainment and nonattainment counties, we use a quasi-natural experimental setting to deepen our understanding of these dynamics.

Our work also contributes to the competition and innovation literature, as illustrated by Aghion et al. (2005) and Lambertini et al. (2017). A synthesis of competition-innovation research with environmental policy-innovation literature suggests that stringent regulations generally stimulate green innovation (e.g., Rubashkina et al., 2015; Peng et al., 2021). However, this effect may weaken under intense competition, aligning with an inverted U-relationship between competition and innovation (e.g., Lambertini et al., 2017). In contrast, our findings reveal a distinct pattern: stringent environmental policies encourage firms facing high competition to innovate even more, offering nuanced insights beyond existing syntheses.

Lastly, our study target pressing gaps in the literature. While Nesta et al. (2014) explore a similar research focus, critical distinctions in regulatory implications emerge. Their study examines the energy sector, centered on market liberalization and renewable energy subsidies, yet applying these findings across sectors proves challenging. In many industries, green practices are neither essential to survival nor closely tied to long-term success, fueling debate over the alignment of sustainability with shareholder value. Our analysis extends across various sectors, uncovering conditions where green innovations contribute to firm value. Moreover, our study uniquely assesses firm-level green inventions and their association with competitive dynamics. In contrast, Nesta et al. analyze renewable energy patents at the country level, capturing broader influences, such as shifts in production costs, that impact non-energy sectors beyond specific competitive contexts.

2. Nonattainment Designations

Under the U.S. Clean Air Act (CAA), the EPA establishes the NAAQS for six key pollutants: carbon monoxide, sulfur dioxide, lead, nitrogen dioxide, particulate matter, and ozone. These standards are designed to protect public health and the environment by setting safe concentration limits for each pollutant. Since the 1977 amendments to the CAA, U.S. counties have been classified as either "attainment" or "nonattainment" zones based on these criteria. The EPA must review and, if necessary, update the NAAQS every five years to ensure their continued relevance and effectiveness. When standards are updated, a reevaluation occurs: counties exceeding the pollutant thresholds are designated as nonattainment, while those meeting or falling below the thresholds are classified as attainment. State Implementation Plans (SIPs) are then required to bring nonattainment areas back into compliance, detailing local strategies and enforcement mechanisms for air quality management. Counties that achieve the necessary standards are re-designated as attainment areas until the next evaluation cycle.

The different regulatory frameworks between attainment and nonattainment counties present a robust empirical context for a quasi-natural experiment. First, polluting facilities in nonattainment areas are subject to significantly stricter regulations than those in attainment zones. While SIPs vary across states, they generally adhere to EPA guidelines and impose more stringent controls in nonattainment areas. If a SIP does not meet EPA standards, the EPA can enforce a Federal Implementation Plan (FIP). Once enacted, these regulatory frameworks have legal authority at both state and federal levels, empowering states and the EPA to enforce compliance and impose penalties on violators. The EPA significantly influences non-compliant states and can impose sanctions such as withholding federal grants or freezing infrastructure projects (e.g., Dancy, 1993; Greenstone, 2002). The impact of these measures is clear, with nonattainment zones typically experiencing significant reductions in emissions compared to their attainment counterparts (e.g., Chay and Greenstone, 2005).

In addition to stricter emissions controls, nonattainment zones undergo more frequent inspections and face heightened regulatory scrutiny. Table **1** shows marked disparities in policy enforcement based on county designation. Regulatory enforcement is measured by several factors: (i) the total number of air pollution compliance evaluations conducted by the EPA at the county level (*Number of Inspections*); (ii) the number of onsite evaluations (*Number of Onsite Inspections*); and (iii) the fines and penalties imposed for non-compliance with environmental laws (*Penalty Amount*). The table presents annual averages of these metrics for counties during their nonattainment and attainment periods.[4] Columns (1) and (2) show an increase in inspection frequency during nonattainment years, while Column (3) reveals substantially higher penalties for violations in these periods, highlighting the stricter enforcement in nonattainment zones.

Second, the assignment of nonattainment status across counties is effectively random. Each region is evaluated against a uniform set of standards, and a county's nonattainment status is primarily determined by local air quality rather than other specific county factors. While one could theorize that economic activities influence air quality, this notion becomes less pressing considering the low correlation between nonattainment status and the number of local production facilities. Supporting this, prior research indicates that nonattainment often arises from wind patterns that transport and concentrate pollutants in certain areas (Cleveland and Graedel, 1979; Cleveland et al., 1976). Moreover, changes from attainment to nonattainment status are triggered only by exogenous updates to the NAAQS rather than by changes in local conditions. This pattern is depicted in Figure 1,[5] which shows the number of counties changing status for each pollutant. Positive (negative) values indicate a net increase (decrease) in the number of counties moving from attainment (nonattainment) to nonattainment (attainment). There is typically a notable increase in counties moving to nonattainment following a standard revision, which then stabilizes or reverses until the next cycle of revisions. This pattern indicates that updates to the NAAQS are the primary drivers of changes in nonattainment designations.

Our empirical design addresses any remaining concerns about endogeneity. We match attainment and nonattainment counties based on their average EPA inspection frequency prior to designation, approximating the random assignment of nonattainment status. Additionally, robustness tests focusing on counties with pollution levels near the NAAQS threshold, as well as alternative matching procedures incorporating additional county-level characteristics, further validate that nonattainment designations are independent of other county-specific factors. This approach strengthens the credibility of our findings by ensuring comparability between the two groups.

Lastly, policy changes resulting from nonattainment status are unaffected by county-specific dynamics. The EPA's approval of SIPs ensures uniform application across all nonattainment counties, and its oversight guarantees that states enforce these regulations rigorously, minimizing the risk of lax enforcement. This consistency helps insulate regional regulations from local influences, such as business lobbying, political climates, or other local government actions. To further mitigate potential endogeneity issues, we include county$\times$year fixed effects in our analysis, effectively controlling for and removing any unobserved, time-varying attributes unique to each county.

3. Data and Sample Construction

This study employs data from several different sources: (i) plant and location data from Dun & Bradstreet made available via Mergent; (ii) innovation output data from the World Patent Statistical Database (PATSTAT); (iii) product market competition measures developed in Hoberg et al. (2014), and Hoberg and Phillips (2010, 2016), available in the Hoberg and Phillips data library; (iv) historical CAA nonattainment designations information from the EPA Green Book; (v) information on regional enforcement and limited criteria pollutant emissions data from the EPA's Enforcement and Compliance History Online (ECHO); (vi) county-level emissions information collected over monitoring stations, available in the EPA's Air Quality System (AQS) database; (vii) U.S. import data from Peter K. Scott's website; (viii) firm ESG scores from Refinitiv; (ix) supplier-customer relationship data from Factset Revere and Compustat's customer segment files; (x) firm financial information from Compustat; and (xi) county characteristics from United States Census Bureau (Census) and Bureau of Economic Analysis (BEA).

We merge production plants with their publicly traded parent companies in Compustat using a linking table from Mergent that matches plant DUNS numbers with CUSIP identifiers. This process results in an initial dataset of firm-county-level observations, capturing the annual number of plants each public firm operates in a given county. Our sample is restricted to innovative firms that have filed at least one patent, subsequently granted. Given that nonattainment status regulatory shocks mainly affect local "polluters," we exclude non-emitting plants from the analysis. However, data limitations in ECHO complicate firm-level classifications of "polluters" and "non-polluters." Detailed plant-level emissions data for criteria pollutants, except ozone, are only available for 2005, 2008, 2011, and 2014, and fewer than 10% of these records can be linked to a plant DUNS number. To address these limitations, we classify "polluters" at the industry level, defining industries with positive total emissions across the four available years as "polluters." We further refine the dataset by excluding observations with missing values for competition measures and control variables, as well as financial and regulated utility firms (SIC codes 4900-4999 and 6000-6900).

Using the resulting observations from 1996 to 2021,[6] we construct a matched sample encompassing four years before and four years after nonattainment shocks. Treatment counties are those transitioning from attainment to nonattainment status in year t. Each treatment county is matched with up to four control counties that maintained their attainment status throughout the nine-year window. Control counties are selected from the same state and year as the treatment counties, based on the average annual county-wide EPA inspection frequency during the pre-shock period (-4 to -1 years in the event window). We apply a caliper of 0.01 for the closest propensity score matches (PSM). This method ensures that the control group experiences similar regulatory scrutiny and enforcement as the treatment group before policy changes while remaining independent of key location characteristics—such as local air quality and political factors—that could influence pollution control efforts.

The selection process yields a sample comprising 51,810 firm-county-year observations, representing 1,903 innovative firms with plants located across 438 counties, including 118 event counties, from 2000 to 2021.[7] It is important to note that the exact number of observations may vary depending on the specific analysis conducted. Detailed definitions of all key variables can be found in Appendix A.

3.1. Measuring green innovation

Our green innovation metrics are sourced from the PATSTAT database, an extensive repository containing over 100 million patent records from more than 40 global patent authorities, with data dating back to 1844. This database provides detailed information on each patent application, including the application date, applicant and owner details, backward and forward citations, associated technology fields classified by the International Patent Classification (IPC), and final grant status. We manually match applicant information with firms in Compustat to identify patents owned by U.S. corporations. Since the primary value and enforceability of a patent are realized upon its granting, we focus exclusively on patent applications that are eventually granted.

From our sample of patent applications, we identify "green" technologies using the classification scheme developed by the World Intellectual Property Organization (WIPO). Specifically, we focus on "environmentally sound technologies" as defined by the Secretariat of the United Nations Framework Convention on Climate Change (UNFCCC) in their guidelines for essential green technologies. These technologies, cataloged in WIPO's IPC Green Inventory, encompass a wide range of IPC codes related to green patents across various fields, including alternative energy production (e.g., biofuels and other renewable sources), energy conservation (e.g., low-energy lighting), waste management (e.g., waste treatment and pollution control), transportation (e.g., electric vehicles), and agriculture and forestry (e.g., soil conservation management).[8]

We use clean IPC codes to construct two measures of green innovation output. The first measure, *Green Patents*, is the total number of green patent applications a firm files in a given year, as used in previous studies (e.g., Brunnermeier and Cohen, 2003; Aghion et al., 2016). This measure faces a truncation issue due to the lag between a patent's application and its grant year, resulting in recent applications potentially still being under review and excluded from our sample. To correct this truncation bias, we apply weight factors derived from the application-grant lag distribution of patents filed and granted between 2017 and 2021, following Hall et al. (2001, 2005). The second measure, *Green Cites*, counts the total forward citations a firm's green patents receive in subsequent years. This metric captures breakthrough innovations with greater knowledge spillovers, distinguishing them from incremental inventions (e.g., Aghion et al., 2023). Similar to *Green Patents*, *Green Cites* also suffers from truncation, as patents continue to receive citations beyond our sample period, which is 2021. To address this, we scale the citation measure using the average annual citation counts for each IPC category (Hall et al., 2001, 2005).

3.2. Measuring product market competition

Our study employs three firm-specific measures of product market competition developed by Hoberg et al. (2014), and Hoberg and Phillips (2010, 2016).[9] The first metric, product market fluidity (*Fluidity*), gauges how much competitors—who share similar product descriptions in their 10-K filings—alter their product keywords the following year. This metric captures competitive threats by assessing (i) the overlap in product vocabulary between the firm and its competitors and (ii) dynamic shifts in competitors' products. Thus, *Fluidity* reflects both the degree of product alignment with competitors and market volatility driven by rivals' actions. Higher *Fluidity* indicates increased competitive pressure on the firm. The second metric is the total product similarity score (*Similarity*), derived from 10-K filings and based on product keywords. Hoberg and Phillips calculate pairwise cosine similarities between firms to group them into text-based network industries (TNIC). The similarity score is obtained by aggregating these cosine similarities across all rivals within a given TNIC industry. This score increases with both the number of competitors and the product relatedness of each competitor, indicating the level of competitive pressure a firm faces. The third metric is a firm-specific Herfindahl-Hirschman Index (HHI) based on TNIC classifications, measuring market concentration using sales data from Compustat. To facilitate interpretation, we construct a variation called *NegHHI* (one minus the HHI). A higher *NegHHI* value represents greater competition.

3.3. Summary statistics

Table **2** summarizes county-level characteristics across states. Columns (1) and (2) report the average number of firms and plants per county in each state, highlighting significant variation in industrial density. For example, the sample shows an average of three innovative firms (and three plants) per county in Missouri, compared to a much higher concentration of 114 firms (and 334 plants) per county in Florida. Column (3) lists the number of treatment counties—those transitioning to nonattainment status—in each state, while Column (5) expresses this count as a percentage of the total number of counties, shown in Column (4). Notably, in many states, the percentage of nonattainment counties reaches or exceeds 20%, aligning with our empirical strategy that incorporates a one-to-four match ratio between treatment and control counties in each state.

Table **3** presents the descriptive statistics for the key variables in this study. On average, firms operating in a county own approximately two plants in the county and employ around 47 individuals. ($\ln(1+47) \approx 3.779$). Furthermore, firms file an average of 7.50 green patents annually and receive around 2.80 IPC-adjusted citations for those patents. The *Fluidity* measure registers an average value of 5.79 and a median of 5.23, consistent with the statistics reported in Hoberg et al. (2014). The *Similarity* metric averages 2.33, with a median of 1.36. The *NegHHI* index has an average value of 0.68 and a median of 0.76. We control for various firm attributes drawn from the innovation literature that could influence innovation output. These include the natural logarithm of total assets (*Size*), growth opportunities measured by Tobin's Q (*Tobin's Q*), the leverage ratio (*Leverage*), asset tangibility (*Tangibility*), R&D expenditures (*R&D*), capital expenditures (*CapEx*), operating cash flow (*OCF*), and the natural logarithm of the number of a firm's local employees (*Employees*). On average, firms have a book value of $6.38 billion in total assets, a Tobin's Q of 1.91, and a leverage ratio of 23.6%. Additionally, R&D spending, capital expenditures, operating cash flow, and tangible assets represent 3.3%, 4.3%, 13.6%, and 24.7% of total assets, respectively.

As robustness checks, we control for and conduct PSM analysis using various county-specific characteristics. Following Greenstone (2002), we include county population (*Population*), total sales across all plants in the county (*Regional Sales*), per capita personal income (*Income*), and the educational attainment of the population aged 25 and older: the percentage with only a high school diploma (*Highschool%)*), some college education (*College%*), and a bachelor's degree (*Bachelor%*). Table **3** reveals that, on average, a county has a population of 176,740, generates approximately $752 million in sales, and a per capita income of $33,364. About 31.0% of the adult population hold only a high school diploma, 25.8% have up to three years of college experience, and 24.2% possess a bachelor's degree.

4. Corporate Responses to Environmental Regulatory Shocks

In this section, we evaluate how product market competition affects firms' responses to environmental regulations. To reinforce our causal interpretation, we conduct three sets of additional tests to address endogeneity concerns related to nonattainment designations and competition. We also perform a battery of other robustness to validate our findings on green innovation incentives.

4.1. Baseline evidence

To test the joint impact of competition and environmental regulation on green innovation, we use the following stacked difference-in-differences model:

$$\begin{aligned} Green\ Innovation_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_t \times Treat_{i,c} \times Comp_i + \alpha_2 Post_t \times Treat_{i,c} \\ & + \alpha_3 Treat_{i,c} \times Comp_i + \alpha_4 Post_t \times Comp_i + \alpha_5 Comp_i \\ & + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned} \tag{1}$$

where $Green\ Innovation_{i,t+2}$ represents firm i's green innovation outcomes in year $t+2$, measured by *Green Patents (t+2)* or *Green Cites (t+2)*. We use two-year-ahead innovation output measures to account for the lag between innovation investments and their observable outcomes.[10] To capture dynamic effects, we also conduct robustness analyses using one- and three-year outcomes. Treatment counties are those that transitioned from attainment to nonattainment status during the sample period. Each treatment county is matched with up to four control counties that maintained an attainment status throughout the nine-year window (-4, +4) surrounding the status change. $Post_t$ is a binary variable set to 1 during the (0, +4) year window following nonattainment events. $Treat_{i,c}$ is an indicator equal to 1 if county c, where at least one of firm i's plants is located, has nonattainment status, and 0 otherwise. Detailed sample construction and matching procedure is discussed in Section 3. $Comp_i$ is firm i's average competition level during the four-year pre-shock period (-4,-1), using measures such as *Fluidity*, *Similarity*, and *NegHHI*.[11] This pre-shock period mitigates potential reverse causality and omitted variable bias. $X_{i,c,t}$ is a vector of firm-specific control variables detailed in Appendix A. Eq. (1) also includes firm-, county-, and year-cohort fixed effects (**FE**). Firm- and county-cohort fixed effects capture time-invariant characteristics within the treatment-control groups, while year-cohort fixed effects account for time-varying shocks common across all firms in the same cohort. We estimate this model using the Poisson Pseudo-Maximum Likelihood (PPML) method, suited for non-negative count data like patent counts. Standard errors are clustered at the firm and year levels to ensure robust inference.

Panel A of Table **4** presents PPML estimates from Eq. (1).[12] The $Post \times Treat \times Comp$ interaction coefficients emphasize the triple effect, highlighting how regulatory shocks, combined with competitive pressure, drive green innovation. These coefficients are consistently positive and largely significant at the 1% level across all columns, indicating that firms in competitive markets are markedly more likely to strengthen their green innovation efforts in response to regulatory shocks, compared to those facing less intense competition. Specifically, a one-standard-deviation increase in competition results in a 5.57% to 7.19% rise in green patent counts (Columns (1)-(3))[13] and an 8.10% to 11.64% increase in green citations (Columns (4)-(6)). These findings stand in clear contrast to the $Post \times Treat$ coefficients, which capture the regulatory effects on monopolistic firms. The α_2 coefficients are mostly negative and statistically insignificant across all columns, indicating that environmental regulations alone do not motivate monopolistic firms to pursue green innovation. These results highlight that the combined influence of regulation and competitive intensity is a key driver in promoting green innovation. The observed triple interaction effect provides a clearer explanation for the previously mixed regulatory impacts across various firms, sectors, and regions, underscoring competition as the pivotal factor. The coefficients for *Comp* lack consistent signs or statistical significance, aligning with existing literature that indicates the relationship between competition and innovation is complex and non-linear (e.g. Aghion et al., 2005).

Our findings rule out the possibility that competition alone drives these results. Instead, we contend that competition under regulatory constraints uniquely impacts firms due to the heightened costs of non-compliance and increased returns on green innovation in competitive markets. Stricter regulations restrict a firm's ability to expand production without penalties unless it adopts cleaner processes. In highly competitive markets, the cost of not expanding can be substantial, as rivals or new entrants may seize market share. Consequently, competition compels firms to pursue more green innovation. This strategic response also provides competitive advantages by enhancing firms' positions in the market—a particularly valuable benefit in competitive sectors. Green innovation enables firms to differentiate, enhance their reputation, and attract eco-conscious consumers. Additionally, patenting green technologies can create barriers to entry, deterring competitors. While these benefits always exist for competitive firms, they may not be sufficient to drive green innovation without regulatory pressure. Regulatory constraints introduce additional incentives, as green innovation helps firms offset compliance costs, ultimately strengthening their commitment to sustainable innovation. In contrast, firms with less competitive pressure may lack similar motivation to invest in green initiatives, as they may perceive the costs of green technologies to outweigh potential savings from reduced compliance costs and other benefits (Bloom et al., 2013). The negative sign in the $Post \times Treat$ term supports this perspective, suggesting that these firms may deprioritize green innovation, opting instead for cost-effective compliance measures to protect profit margins, effectively crowding out innovative activities.

We draw similar conclusions using one- and three-year-ahead green innovation as outcomes, as shown in Panels B and C of Table **4**. The significant and positive coefficients on the triple interaction term in both panels indicate that competitive firms tend to increase their green activities immediately after a nonattainment shock and sustain these efforts over multiple years. The $Post \times Treat$ coefficients remain negative and are statistically significant in two specifications (Columns (3) and (6) of

Panel B), reinforcing our argument that environmental policies may discourage monopolistic firms from investing in clean technology. These results confirm our findings and demonstrate that the effects of regulatory shocks are non-transitory.

Figure 2 further supports our results by illustrating the annual treatment effects of nonattainment status over a nine-year event window, segmented by competition levels. Firms are categorized into highly competitive and less competitive groups, based on the top and bottom terciles of *Fluidity* values. The absence of significant differences in innovative activities between treatment and control firms before the nonattainment shocks affirms the parallel-trend assumption. After the shock, the highly competitive group shows pronounced and sustained positive effects, indicating a stronger and more persistent response to regulatory changes. This underscores the crucial role of competition in driving innovation following regulatory shocks. In contrast, the less competitive group exhibits minimal change, maintaining a pattern similar to pre-shock levels.

In essence, our results provide strong evidence that regulatory incentives for green innovation are most effective among competitive firms, highlighting the importance of product market structure in evaluating environmental policies. Competition amplifies the innovative response to regulatory pressures, advancing policy goals. Our study illustrates how policy design can harness competitive dynamics to promote sustainable practices and technological progress across industries.

4.2. Additional endogeneity tests

While the preceding section offers compelling evidence of the causal effects of regulatory shocks on corporate behavior, concerns about the potential endogeneity of nonattainment designations and the competitive environment may persist. To address these concerns, we conduct additional rigorous tests.

First, we redefine our sample using PSM to create treatment-control cohorts representing county-years with pollutant levels just above or below NAAQS thresholds.[14] This approach helps randomize nonattainment assignments across counties. We use county-specific emissions data from the EPA's AQS database and establish a 5% bandwidth above and below the NAAQS threshold for each of the six pollutants for a given year. Counties meeting attainment and nonattainment criteria within this range are identified, while ensuring they stay below the standard for all other pollutants. These treated counties are matched to control counties where the focal pollutant is near the threshold, while other pollutants meet standards. However, this matching approach has drawbacks, such as a smaller sample size and the removal of initial restrictions ensuring exogeneity. To address these concerns, we employ a refined discontinuity design using the entire matched sample, rather than only the within-bandwidth sample, while incorporating polynomial functions to capture emissions-outcome relationships. Following prior studies (e.g., Chen et al., 2020b; Cuñat et al., 2012; Flammer, 2015), we use separate polynomials for emissions on each side of the NAAQS standard to account for the discontinuous change in nonattainment status and regional variations affecting status shocks. Quadratic functions are used in Eq. (1), with consistent results when using linear or cubic polynomials. Table **5** presents results from both approaches in Panels A and B. Panel A shows that the α_1 coefficients for the triple-interaction term are positive and statistically significant in all but one column. The $Post \times Treat$ coefficients remain negative and mostly insignificant. Panel B reveals a similar pattern for both key terms. These findings complement our baseline results and reinforce the causal link between environmental regulation and green innovation.

Second, we conduct additional tests to address potential concerns over omitted county attributes. The first test includes county-specific characteristics as additional control variables in Eq. (1), including income per capita, population, regional sales, and education statistics. The second test uses county×year fixed effects to better capture unobserved, time-varying county-level factors. We further enhance the analysis by refining the randomization of nonattainment assignments and policy enforcement through a repeated PSM process. This involves conducting Probit regressions on pre-shock averages of county-level variables, including population, regional sales, per capita income, education statistics, and EPA inspection frequency. Each county-year receives a propensity score, and a new matched control group is selected within the same state, using a caliper of 0.01 to ensure precise matching.[15] The results of these additional tests,[16] presented in Table **6**, reinforce our causal interpretation and align with our earlier findings.

Finally, while pre-treatment competition measures have reduced endogeneity concerns, we address any remaining issues by using significant import tariff reductions as an exogenous source of increased competition. Existing literature shows that lower tariffs intensify competition for domestic firms facing international rivals (e.g., Fresard, 2010; Valta, 2012). Following Huang et al. (2017) and Chen et al. (2020a), we define tariff reduction events as industry-years where the tariff rate decreases by more than three times the average drop observed during the sample period. We calculate the industry-year tariff rate by dividing collected duties by the customs value of imports.[17] To capture non-transitory changes in competition, we exclude events followed or preceded by a tariff hike exceeding 80% of the reduction. Our analysis replaces *Comp* with *Tariff Reduction*, set to 1 when a firm experienced a significant tariff reduction by year $t-1$ and 0 otherwise. Table **7** shows a positive and significant coefficient for *Post* $\times$ *Treat* $\times$ *Tariff Reduction*, reinforcing the causal link between environmental regulations and competitive pressures on a firm's environmental strategies.

4.3. Other robustness tests

We conduct several robustness tests to confirm the reliability of our findings. First, we assess whether environmental regulatory pressure affects non-green innovation to rule out the possibility that our results are due to a general increase in overall innovation rather than targeted green innovation. The test examines patent counts and citations for non-green technologies to see if similar patterns appear under regulatory shocks. Next, we explore whether firms continue to pursue green innovation after policy reversal shocks, such as when their county transitions from nonattainment to attainment status. In particular, the counties are matched to nonattainment control counties without reversals based on pre-reversal EPA inspection levels within the same state and year. This analysis clarifies whether the incentives for green innovation persist or diminish when regulatory pressure is removed. Panels A and B of Table **8** summarize the results. The findings show no evidence that regulatory pressure affects non-green innovation, nor do they suggest that relaxed environmental policies reverse the influence on firms' green strategies. Our results on policy reversals indicate that the CAA NAAQS regime has sustained effects on green innovation that persist even after the regulation is lifted. This lasting impact may be attributed to the requirements counties must meet before reclassifying from nonattainment to attainment status, such as implementing a 10-year maintenance plan to ensure continued compliance with NAAQS standards.

Furthermore, we address potential issues with firm-county level analysis, as firms often operate in multiple regions, making it difficult to pinpoint which county-level changes drive firm-level green innovation. To tackle this, we use two approaches. First, we aggregate nonattainment counties for each firm and examine whether broader exposure to stricter environmental policies, represented by the percentage of a firm's plants in nonattainment zones (*%Nonattained*), intensifies its response. Second, we conduct county-level analysis by focusing on each firm's largest plant by employee size, refining treatment-control cohorts through the PSM procedure to determine whether nonattainment shocks significantly impact key operational locations.[18] A caveat is that, while these two tests help address potential concerns, the former remains susceptible to endogeneity issues, and the latter is restricted by sample size constraints. Due these limitations, we present the results in Internet Appendix Table IA 2 for further insight. Panel A shows that as more of a firm's operations are subject to environmental regulations, firms in competitive markets are more likely to increase their green innovation efforts. Panel B highlights that nonattainment shocks in key locations have a stronger influence on firms' innovative activities, showing a greater impact than the baseline analysis, which includes all plants and locations. Thus, stricter regulations in key counties play a significant role in driving the baseline findings.

Across these different specifications, our findings remain consistent, confirming that regulatory impacts on firms vary based on their competitive market environment. For brevity, we use *Fluidity* as the representative competition measure for subsequent tests. In the following sections, we conduct extensive tests to empirically examine the mechanisms that drive firms in competitive markets to respond more actively to regulatory pressure through green innovation.

5. Cross-sectional analysis

In exploring the underlying mechanisms, we begin with cross-sectional tests to identify key factors influencing a firm's green innovation efforts: (i) the regulatory burden it faces and (ii) its capacity to adopt green technologies. By segmenting the data according to various proxies for these factors, we can more precisely assess how each influences green innovation in response to regulatory pressure. Specifically, we apply PPML analysis to these subsamples and presented the detailed results in

Table **9**.

5.1. Regulatory burden

As previously discussed, we argue that firms in competitive markets pursue green innovation as a strategy to offset the costs imposed by environmental regulations. If this is indeed the case, the degree of regulatory burden should significantly shape these firms' strategic responses, particularly in their efforts to adopt green innovation as a means to maintain their competitive edge. Our tests specifically examine whether this response is more pronounced among firms operating in sectors with high pollution levels and those with limited geographic mobility, as these characteristics correlate with a higher regulatory burden.

Firms in highly polluting sectors face stringent environmental controls and increased regulatory scrutiny, leading to higher compliance costs and greater incentives to align operations with environmental standards. For these firms, adopting green technologies is essential to avoid penalties and maintain market position.[19] To test the relationship between regulatory burden and green innovation, we categorize firms into terciles based on industry-average emissions. These emissions are measured by total emissions of the six criteria pollutants at the 3-digit SIC level using ECHO data.[20] We then re-estimate Eq. (1) for firms in the top and bottom terciles. Panel A of Table **9** shows that significant regulatory impacts are concentrated among firms in highly polluting industries. The coefficients for the triple-interaction term are positive and statistically significant in the top tercile but negative and insignificant in the bottom tercile. Moreover, the coefficient magnitudes in the top tercile are statistically greater than those in the bottom tercile, with p-values around 0.05. These findings align with Cohen et al. (2020) and help explain why oil, gas, and energy-producing firms often lead in U.S. green patent innovations.

Firms with restricted mobility—those tied to their regions due to substantial investments in infrastructure or workforce—are more vulnerable to regulatory changes. Unlike mobile firms that can relocate to areas with less stringent regulations, immobile firms must adapt by investing in green innovations to comply with new policies and sustain operations. We assess a firm's mobility using three proxies: plant fixed costs, local plant size, and agglomeration economies. Plant fixed costs are measured as the 3-digit SIC industry-level real structures capital stock scaled by the total value of shipments (Ederington et al., 2005).[21] Due to significant investments in infrastructure and workforce, larger plants are less mobile, so we proxy local plant size by the proportion of local employees relative to the firm's total workforce. Lastly, agglomeration economies influence mobility, as firms in regional clusters benefit from reduced transport and communication costs, making relocation less appealing (e.g., Ellison and Glaeser, 1997; Ellison et al., 2010). We capture this by analyzing the geographic distribution of industry employment shares across counties (Ellison et al., 2010). We repeat the subsample analysis using tercile divisions based on three immobility proxies, with results shown in Panels B, C, and D. The coefficients for *Post* × *Treat* × *Fluidity* are positive and significant in the top terciles for all proxies, while remaining insignificant in the lower terciles. Chow tests confirm that the triple-interaction coefficients in the top terciles consistently exceed those in the bottom. These findings emphasize the substantial impact on less mobile firms that cannot relocate to avoid regulatory costs.

5.2. Technological adaptability

A firm's capacity for developing green technologies is crucial in shaping its response to regulatory changes. Mohr (2002) emphasizes that adopting radical green technologies demands substantial effort and investment, creating a barrier for firms that lack experience or preparation in this field. This perspective helps explain why some firms are less inclined to pursue green innovation unless its benefits clearly outweigh the associated costs, particularly in the face of competitive and regulatory pressures. Building on this view, we expect that incentives for green innovation are greater when adoption costs are lower. Innovation often follows a path-dependent trajectory (Acemoglu et al., 2016; Aghion et al., 2016), such that firms with a history of investment in "brown" technologies tend to remain on that path due to accumulated expertise, established processes, and economies of scale—making a shift to green innovation more costly. In contrast, firms with a track record in green innovation can overcome these barriers more easily, as they already possess the necessary expertise, technological know-how, and resources to adapt operations and integrate sustainable practices seamlessly. Thus, we test whether firms with prior experience in green innovation have stronger incentives to expand their green technological efforts in response to new regulatory pressures.

We estimate a firm's historical green patenting activity by calculating the average number of green patents filed annually during the pre-shock period. Dividing the sample into terciles based on this metric, Panel E reveals a clear pattern in the differential impacts of regulatory pressure: the triple-interaction coefficients are consistently positive and statistically significant for firms in the top tercile, while coefficients for firms in the bottom tercile remain insignificant. This pattern indicates that regulatory impacts on green innovation are more pronounced in firms with lower innovation costs.

6. Real Effects of Regulation-Induced Green Innovation

To better understand why firms facing intense competition respond more proactively to regulatory pressures through green innovation, we explore the strategic advantages these firms may gain from adopting green technologies. We propose that regulatory-driven green innovation not only ensures compliance but also creates opportunities for firms in competitive markets to differentiate themselves, capture greater market share, and improve profitability, thereby offsetting the costs of compliance.

Beyond these strategic benefits, green innovation holds significant policy implications, particularly in reducing local pollution and mitigating the likelihood of policy reversals. By examining how firms' adoption of green technologies contributes to environmental improvements, we shed light on the broader impact of green innovation on environmental outcomes. This analysis provides valuable insights into how green technologies enhance local environmental quality while reinforcing the long-term stability of regulatory frameworks.

6.1. Leveraging differentiation and product quality signaling

We investigate whether firms can achieve differentiation and signal product quality through green innovation in response to regulatory changes. The first proxy for differentiation is technological proximity (*Tech Proximity*), which measures the technological similarity between a firm and its competitors within the same product market. Following Jaffe (1986), *Tech Proximity* is calculated as the correlation between the technology field vectors of firm i's patents and those of rival firm j's, averaged across all competitors for each firm i. A lower *Tech Proximity* value suggests that firm i's inventions are more radical and distinctive within the technological innovation landscape, indicating a greater potential for product differentiation. Another measure is the patent originality score, introduced by Trajtenberg et al. (1997), which evaluates the novelty of an invention by analyzing the range of technological domains it draws upon. This score reflects how innovative an invention is based on the diversity of fields it incorporates, as defined in Eq. (2) below.

$$Originality_{k,t} = 1 - \sum_{l}^{n} p_{k,l,t}^{2}, \tag{2}$$

where $p_{k,l,t}$ represents the percentage of backward citations made by patent k to patent class l (at the 3-digit IPC level) among n patent classes. The originality score $Originality_{k,t}$ is higher when patent k draws on a diverse range of technology fields, signifying a broader and more innovative technological base. A higher score signals a more radical invention, integrating concepts from multiple domains rather than incrementally advancing within a single field (Trajtenberg et al., 1997). To capture differentiation from green innovation, we average the originality scores across all patents filed by firm i.

To evaluate the impact of green activities following policy shocks, we use the model specified below:[22]

$$\begin{aligned} Diff_{i,t} \quad = \quad & \alpha_0 + \alpha_1 Post_t \times Treat_{i,c} \times Green\ Patents_{i,t} + \alpha_2 Post_t \times Treat_{i,c} \\ & + \alpha_3 Treat_{i,c} \times Green\ Patents_{i,t} + \alpha_4 Post_t \times Green\ Patents_{i,t} \\ & + \alpha_5 Green\ Patents_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $\mathit{Diff}_{i,t}$ is *Tech Proximity* or *Originality* for firm i, measured in year t to assess the technological novelty on newly filed patents. We apply a logarithmic transformation to $Green\ Patents_{i,t}$ plus one to address skewness. One potential concern is that *Green Patents* may be endogenous to factors beyond regulatory changes. To mitigate this, we include firm characteristic controls to account for potential endogeneity. Additionally, we control for both total and green patent stock, estimated using the perpetual inventory method. This method accumulates yearly historical patents with a

20% depreciation rate (Aghion et al., 2016), beginning in 1980 and extending to the year before the nonattainment shock, to capture factors contributing to a firm's overall innovation capacity and green initiatives prior to environmental regulations. Both variables are expressed in logarithmic form. Detailed definitions of all variables can be found in Appendix A.

Panel A of Table **10** presents the estimates of Eq. 3, highlighting one key observation. The coefficient on $Post \times Treat \times Green\ Patents$ is significantly negative for $Tech\ Proximity$ and positive for $Originality$. This indicates that green inventions following environmental regulations tend to be more radical breakthroughs compared to both non-green inventions, as suggested by the $Post \times Treat$ term, and green inventions unrelated to regulatory changes, as shown by the $Green\ Patents$ term.[23] In contrast to the triple-interaction estimate, the coefficients for these two terms are largely insignificant and often in the opposite direction, implying that they typically represent incremental advancements rather than transformative innovations. These results are consistent with prior literature (e.g. Acemoglu et al., 2016), which suggests that major technological shifts often require external drivers, such as policy-induced shocks. This emphasizes the critical role of regulations in fostering transformative innovation.

We further investigate differentiation within the product market space. Applying the approach of Hoberg and Phillips (2010, 2016), which identifies rivals based on shared product keywords, differentiation is anticipated to manifest in changes to these keywords. As firms differentiate, they reduce overlap in product descriptions with competitors, leading to fewer new entrants to shared keyword pools and/or more exits by existing competitors. To test this, we count the number of new firms entering the product space defined by Hoberg and Phillips (*Entries*), competitors exiting (*Exits*), and the net change ratio of these variables to measure changes in firm i's product market space (Δ *Product Market Space*). This approach quantifies how differentiation influences competitive dynamics in the product market.

We employ ESG ratings from Refinitiv to capture a firm's observable environment-related performance, reflecting its "green" reputation and ability to signal quality. This aligns with prior research suggesting that firms with strong ESG performance can effectively convey high product quality to consumers (e.g., Feddersen and Gilligan, 2001; McWilliams and Siegel, 2001; Siegel and Vitaliano, 2007). We also employ Refinitiv's innovation rating, which indicates a company's capacity to reduce its environmental impact and customer burdens through new processes or products. The firm's environmental innovation should contribute to its overall ESG score, contributing to its reputation and market positioning.

Eq. (3) is re-estimated using additional proxies for differentiation and ESG reputation, evaluated in year $t+2$ to capture the time lag before green innovation influences a firm's product descriptions and ESG ratings. In this model specification, *Green Patents* is replaced by green patent stock (*Green Stock*), which accumulates historical green patents up to year t. This approach better reflects endogenous green innovation activities, recognizing that some inventions may not have been directly regulation-driven but could still shape a firm's strategy post-regulation. By considering the full breadth of a firm's green patent portfolio, this method offers a comprehensive perspective on how firms strategically leverage their innovation efforts—regardless of initial motivations—to maintain or enhance their competitive position following regulatory changes. Panel B provides evidence that government interventions push green innovators to differentiate more effectively within their product markets and boost their green reputation in subsequent years. Columns (1)-(3) show that firms with substantial green innovation portfolios experience shifts in market dynamics, marked by fewer new entrants, suggesting that these firms leverage regulation-driven green patents as a strategy to block entry. The triple-interaction coefficients for ESG reputation measures in Columns (4) and (5) are positive and statistically significant, highlighting that green innovators can enhance their reputation and product quality following regulatory shocks.

6.2. Product market performance

We next explore whether the benefits of green innovation lead to improved post-regulatory product market performance, specifically in attracting more corporate customers compared to non-green firms. This impact is measured using three indicators: (i) the number of corporate customers with local access to firm i in county c based on their facilities in the area; (ii) the number of unique collaborative relationships firm i has with local corporate customers;[24] and (iii) the ratio of corporate customers not producing green patents (non-green customers) to those filing at least one green patent (green customers).

Table **11** report the results of re-estimated Eq. (3), where *Diff* is replaced by the three customer attraction metrics captured in year $t+2$ and *Green Patents* is again substituted with *Green Stock* in year t. Columns (1) and (2) show that firms with substantial green patent portfolios attract more corporate customers in local markets and form stronger collaborative alliances with them following regulatory shifts.[25] This business growth is more pronounced among non-green customers than green ones, as shown in Column (3), allowing firms to tap into markets with high demand for green solutions. Notably, green patent stock itself has significantly positive coefficients across all columns, underscoring its independent contribution to these outcomes. However, regulatory changes have incremental effects, possibly stemming from both an increase in radically new green patents and the push for firms to more aggressively leverage their existing green technologies.

Product market performance is also captured by sales growth and market share growth, defined as the annual percentage change in sales and sales-based market share. Columns (4) and (5) align with the above findings on increased customer attraction: enhanced market access results in a surge in post-regulatory market share, as green innovators experience a rise in sales. However, in general, affected firms show declines in both sales and market share growth following regulatory shocks, as indicated by the negative $Post \times Treat$ coefficients. These results suggest that non-green innovators may lose market share to more innovative competitors who expand their green activities in response to stricter regulations.

When examining two other commonly used performance metrics, return on assets (ROA) and *Tobin's Q* in Columns (6) and (7), clear patterns emerge. The triple-interaction coefficient is positive and statistically significant for two-year ahead ROA but insignificant for Tobin's Q, suggesting that firm profitability, but not valuation, is influenced by firms' responses to regulatory shocks. Overall, while green innovation enhances post-regulatory performance, there is no evidence that its subsequent benefits can fully offset the regulatory costs based on market evaluation. This may explain why firms are hesitant to voluntarily pursue green strategies without the presence of stringent environmental regulations.

Taken together, our findings highlight the key drivers that incentivize green innovation under the combined influence of competition and regulation. In highly competitive markets, the strategic benefits of green innovation—such as enhanced differentiation, increased market share, and improved profitability—help offset regulatory burdens. While these benefits always exist, firms often forgo green innovation in the absence of regulatory pressure, as the costs outweigh the gains. However, regulation introduces additional incentives, making green innovation a more viable and attractive strategy. This synergy between competition and regulation not only drives firms to adopt greener technologies but also positions green innovation as a valuable tool for maintaining a competitive edge while ensuring compliance.

6.3. Regional air quality and policy implications

We have previously examined the real effects of regulation-induced green innovation on firm product market performance and valuation. In this section, we shift our focus to its broader social impact, specifically how green innovation enhances the effectiveness of the NAAQS regime in reducing local pollution and influencing policy reversals. To explore these questions, we conduct a county-level analysis centered on counties during their nonattainment years. We measure local pollution levels using the Air Quality Index (AQI), developed by the EPA to monitor criteria pollutants, with data sourced from the AQS database covering the period from 1980 to 2024. The AQI provides a standardized way to assess pollution severity, with higher values indicating greater pollution and associated health risks. The reversal of NAAQS status is captured by a binary variable set to one if a county transitions to attainment status in the following year, and zero otherwise. This allows us to study how green innovation influences not only pollution levels but also the likelihood of regulatory status changes. We employ the following panel regression model to link green innovation activities to changes in pollution metrics and policy shifts:

$$\begin{aligned} County\ Outcome_{c,t+y} &= \alpha_0 + \alpha_1 County\ Green\ Stock_{c,t} + \alpha_2 County\ Total\ Stock_{c,t} \\ &\quad + \sum_{k=1}^{K} \beta_k X_{c,t} + FE + \epsilon_{c,t}, \end{aligned} \tag{4}$$

where $County\ Outcome_{c,t+y}$ represents either the AQI or the status reversal indicator. These outcomes are assessed for year t, $t+1$, and $t+2$ to account for potential delayed effects of green innovation, as new green technologies may take time to effectively reduce air pollution and enable the region to achieve attainment status. $County\ Green\ Stock_{c,t}$ denotes the accumulated green patent stock in year t, across all firms with plants in county c, capturing the total historical green innovation activity within the county. $County\ Total\ Stock_{c,t}$ is the total patent stock aggregated within county c in year t and serves as a control to isolate the effects of green innovation from general local innovation activity. $X_{c,t}$ includes county-level controls such as EPA inspection frequency, population, regional sales, personal income, and educational attainment. We also incorporate county and year fixed effects (**FE**) to account for unobserved heterogeneity.

Table **12** presents the results, indicating that nonattainment counties with larger accumulated green innovation portfolios experience a significant reduction in AQI over time. This is supported by the negative and statistically significant coefficients for *County Green Stock* over the three years in Columns (1)-(3). In contrast, the accumulation of other technologies, represented by $County\ Total\ Stock_{c,t}$, shows no impact on AQI reduction. The decline in AQI corresponds to an increased likelihood of nonattainment status reversal in years $t+1$ and $t+2$, as shown in Columns (5) and (6), enabling polluting zones to meet regulatory standards more rapidly. These findings highlight the broader societal benefits of green innovation beyond firm-level gains, reinforcing its critical role in advancing environmental and public health policy objectives.

In sum, our findings carry important policy implications. Stricter regulations imposed on firms in competitive environments do more than just curb pollution; they act as a catalyst for green innovation, promoting sustainable, long-term solutions to environmental challenges. This underscores the dual benefit of well-designed regulatory frameworks: they not only achieve immediate environmental goals but also encourage firms to innovate and develop technologies that contribute to sustained ecological improvements. Overall, these findings advocate for the strategic use of regulations as a tool to drive both environmental progress and economic development through sustained innovation.

7. Concluding Remarks

This study investigates the factors driving varied responses of firms to environmental regulatory stringency and the subsequent economic impacts in a post-regulatory landscape. Using county-level nonattainment designations as a quasi-natural experiment, we find that firms under competitive pressure significantly increase their green innovation in response to stricter environmental regulations. These firms adopt such innovation as a strategic tool to differentiate their products, strengthen their market position, and enhance profitability. However, while green innovation bolsters firm performance, it does not translate into higher firm valuations, suggesting that the benefits primarily manifest through operational gains rather than market perceptions. In contrast, firms in less competitive markets, which are less inclined toward innovation, experience minimal impact from regulatory changes, underscoring the role of competition in driving the effectiveness of environmental policies.

Our findings carry significant policy implications, demonstrating that well-designed environmental regulations catalyze green innovation and support long-term economic and environmental goals. Beyond firm-level outcomes, county-level analysis reveals that nonattainment areas with greater green innovation portfolios see significant reductions in local pollution. This, in turn, increases the likelihood of these counties transitioning to attainment status, highlighting the broader societal benefits of regulation-induced green innovation. While some economic theories advocate for minimal government intervention, our study suggests that strategic regulations can stimulate sustainable practices in competitive firms, fostering innovation and aligning corporate strategies with ecological objectives. As stakeholder expectations for sustainability rise, firms may become more inclined to adopt greener practices, even without strict regulations. This possibility suggests that regulatory frameworks could play a crucial role in supporting both economic and environmental resilience.

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, 2012, The environment and directed technical change, *American Economic Review* 102, 131–66.

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley, and William Kerr, 2016, Transition to clean technology, *Journal of Political Economy* 124, 52–104.

Aghion, Philippe, Antonin Bergeaud, , and John Van Reenen, 2023, The impact of regulation on innovation, *American Economic Review* 113, 2894–2936.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005, Competition and innovation: An inverted-U relationship, *Quarterly Journal of Economics* 120, 701–728.

Aghion, Philippe, Antoine Dechezleprêtre, David Hemous, Ralf Martin, and John Van Reenen, 2016, Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry, *Journal of Political Economy* 124, 1–51.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2013, Identifying technology spillovers and product market rivalry, *Econometrica* 81, 1347–1393.

Brunnermeier, Smita B, and Mark A Cohen, 2003, Determinants of environmental innovation in US manufacturing industries, *Journal of Environmental Economics and Management* 45, 278–293.

Chay, Kenneth Y, and Michael Greenstone, 2005, Does air quality matter? Evidence from the housing market, *Journal of Political Economy* 113, 376–424.

Chen, Chen, Sudipto Dasgupta, Thanh Huynh, and Ying Xia, 2020a, Product market competition and the relocation of economic activity: Evidence from the supply chain, *CEPR Discussion Paper No. DP15056* .

Chen, Tao, Hui Dong, and Chen Lin, 2020b, Institutional shareholders and corporate social responsibility, *Journal of Financial Economics* 135, 483–504.

Cleveland, William S, and TE Graedel, 1979, Photochemical air pollution in the northeast United States, *Science* 204, 1273–1278.

Cleveland, William S, Beat Kleiner, Jean E Mcrae, and Jack L Warner, 1976, Photochemical air pollution: Transport from the New York City area into Connecticut and Massachusetts, *Science* 191, 179–181.

Cohen, Lauren, Umit G Gurun, and Quoc H Nguyen, 2020, The ESG-innovation disconnect: Evidence from green patenting, Technical report, National Bureau of Economic Research.

Cohen, Mark A, and Adeline Tubb, 2018, The impact of environmental regulation on firm and country competitiveness: A meta-analysis of the Porter hypothesis, *Journal of the Association of Environmental and Resource Economists* 5, 371–399.

Cohn, Jonathan B, Zack Liu, and Malcolm I Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

Cuñat, Vicente, Mireia Gine, and Maria Guadalupe, 2012, The vote is cast: The effect of corporate governance on shareholder value, *The Journal of Finance* 67, 1943–1977.

Dancy, Joseph R, 1993, The impact of the Clean Air Act's ozone non-attainment areas on Texas: Major problems and suggested solutions, *SMU Law Review* 47, 451.

Ederington, Josh, Arik Levinson, and Jenny Minier, 2005, Footloose and pollution-free, *Review of Economics and Statistics* 87, 92–99.

Ellison, Glenn, and Edward L Glaeser, 1997, Geographic concentration in US manufacturing industries: A dartboard approach, *Journal of Political Economy* 105, 889–927.

Ellison, Glenn, Edward L Glaeser, and William R Kerr, 2010, What causes industry agglomeration? Evidence from coagglomeration patterns, *American Economic Review* 100, 1195–1213.

Feddersen, Timothy J, and Thomas W Gilligan, 2001, Saints and markets: Activists and the supply of credence goods, *Journal of Economics & Management Strategy* 10, 149–171.

Flammer, Caroline, 2015, Does product market competition foster corporate social responsibility? Evidence from trade liberalization, *Strategic Management Journal* 36, 1469–1485.

Fresard, Laurent, 2010, Financial strength and product market behavior: The real effects of corporate cash holdings, *The Journal of Finance* 65, 1097–1122.

Greenstone, Michael, 2002, The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures, *Journal of Political Economy* 110, 1175–1219.

Hall, Bronwyn H, Adam Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *RAND Journal of Economics* 16–38.

Hall, Bronwyn H, Adam B Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, *NBER Working Paper* .

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423–1465.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product market threats, payouts, and financial flexibility, *The Journal of Finance* 69, 293–324.

Huang, Ying, Ross Jennings, and Yong Yu, 2017, Product market competition and managerial disclosure of earnings forecasts: Evidence from import tariff rate reductions, *The Accounting Review* 92, 185–207.

Jaffe, Adam B, 1986, Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value, *NBER Working Paper* .

Lambertini, Luca, Joanna Poyago-Theotoky, and Alessandro Tampieri, 2017, Cournot competition and "green" innovation: An inverted-u relationship, *Energy Economics* 68, 116–123.

McWilliams, Abagail, and Donald Siegel, 2001, Corporate social responsibility: A theory of the firm perspective, *Academy of Management Review* 26, 117–127.

Mohr, Robert D, 2002, Technical change, external economies, and the Porter hypothesis, *Journal of Environmental Economics and Management* 43, 158–168.

Nesta, Lionel, Francesco Vona, and Francesco Nicolli, 2014, Environmental policies, competition and innovation in renewable energy, *Journal of Environmental Economics and Management* 67, 396–411.

Peng, Jiaying, Rui Xie, Chunbo Ma, and Yang Fu, 2021, Market-based environmental regulation and total factor productivity: Evidence from chinese enterprises, *Economic Modelling* 95, 394–407.

Porter, M, 1991, America's green strategy, *Scientific American* 168.

Porter, Michael E, and Claas Van der Linde, 1995, Toward a new conception of the environment-competitiveness relationship, *Journal of Economic Perspectives* 9, 97–118.

Rubashkina, Yana, Marzio Galeotti, and Elena Verdolini, 2015, Environmental regulation and competitiveness: Empirical evidence on the porter hypothesis from european manufacturing sectors, *Energy Policy* 83, 288–300.

Siegel, Donald S, and Donald F Vitaliano, 2007, An empirical analysis of the strategic use of corporate social responsibility, *Journal of Economics & Management Strategy* 16, 773–792.

Trajtenberg, Manuel, Rebecca Henderson, and Adam Jaffe, 1997, University versus corporate patents: A window on the basicness of invention, *Economics of Innovation and New Technology* 5, 19–50.

Valta, Philip, 2012, Competition and the cost of debt, *Journal of Financial Economics* 105, 661–682.

Notes

[1]See "*Climate Plans Remain Insufficient: More Ambitious Action Needed Now*" in UN Climate Change (October 2022). The Executive Secretary of UN Climate Change urges national governments to strengthen their climate action plans through legislation, policies, and programs to better mitigate climate change.

[2]Subsequent studies similarly report mixed evidence, likely influenced by cross-country, sectoral, and firm-level variations, along with differences in how regulatory stringency is measured (e.g., Rubashkina et al., 2015; Peng et al., 2021).

[3]The firm-specific competition measures are product market fluidity (*Fluidity*) and total product similarity score (*Similiarity*) from *Hoberg-Phillips Data Library*, as well as the Herfindahl–Hirschman index (*HHI*). The construction of green inventions and competition proxies is detailed in Section 3.

[4]While the differential regulatory enforcement is more pronounced when examining all counties, the table focuses on those that have experienced both attainment and nonattainment status over time. This approach helps tease out systematic heterogeneities across counties that may influence designation status.

[5]Historical NAAQS are obtained from the *EPA's website*.

[6]This period is defined by the availability of competition and plant location data.

[7]The sample period is further constrained by the nonattainment event windows.

[8]Since nonattainment-induced policy shocks are expected to primarily affect green technologies related to air pollution, this quasi-natural experiment likely captures the lower bound of the broader impact of environmental regulations on green innovation.

[9]The measures can be obtained from the authors' website: https://hobergphillips.tuck.dartmouth.edu/

[10]We incorporate a two-year gap between a firm's status in year t and the observed innovation outcome. For example, during the nonattainment shock year (t=0), we assess its impact on patenting activity in year +2.

[11]We test alternative pre-shock competition measures, including data from year -5, and untabulated results confirm the robustness of our findings to these specifications.

[12]The fixed effects Poisson regressions exclude any firm-county group with zero green innovation counts across all observations (Cohn et al., 2022), leading to a smaller sample size compared to the summary statistics. This exclusion does not bias the regression estimates, as these observations do not contribute information relevant to the coefficients.

[13]Column (3) captures the lower bound in economic impact at exp(0.222×0.244)-1≈5.57%, while Column (2) captures the upper bound, exp(0.029×0.2394)-1≈7.19.

[14]To maximize sample size under this stringent matching approach, we relax prior restrictions on average EPA inspection frequency and state boundaries.

[15]Internet Appendix Table IA 1 indicates a largely indistinguishable variation in county characteristics between the treatment and the newly matched control groups prior to the regulatory shifts.

[16]In Panel B, all county-level variables including $Post \times Treat$ are subsumed by the county×year fixed effects.

[17]The U.S. import data is obtained from *Peter K. Scott's website*.

[18]While retaining the EPA inspection criterion, we forgo state boundary restrictions to preserve the sample size.

[19]Unreported univariate analysis supports this, showing that industries with higher pollution levels undergo more frequent EPA inspections and penalties, prompting greater compliance efforts compared to less-polluted sectors.

[20]The data is averaged over the four years during which emissions data is available on ECHO, creating a time-invariant proxy.

[21]Plant fixed cost data is only available for the period 1996-2011 from *Manufacturing Industry Databases* of National Bureau of Economic Research (NBER). We overcome the data coverage limitation by taking the average measure over the entire data period in constructing a time-invariant proxy for plant fixed costs.

[22]For all subsequent analyses, count outcomes are estimated using fixed-effects Poisson regression, while continuous outcomes are estimated using panel OLS regression.

[23]Forward citations, often used as a proxy for breakthrough technologies (e.g., Aghion et al., 2023), further support

this, as higher citation counts found in the baseline analysis suggest that green inventions are typically more innovative.

[24]Collaboration incorporates the following forms of partnership identified in FactSet Revere: research collaboration, integrated product offering, joint venture, and products, patents, and intellectual property licensing.

[25]The PPML analysis with fixed effects resulting in a smaller sample size for Column (2) compared to other tests, as many firm-county groups have zero collaboration counts throughout the period.

Figure 1
NAAQS Revisions and Net Changes in Nonattainment Counties

The figure shows the net change in the number of nonattainment counties by criteria pollutant during the period 1996-2021. The net change, defined as the difference in the number of nonattainment counties between the current year and the previous year, are plotted as solid orange lines. The years of NAAQS revisions are illustrated by vertical dashed lines.

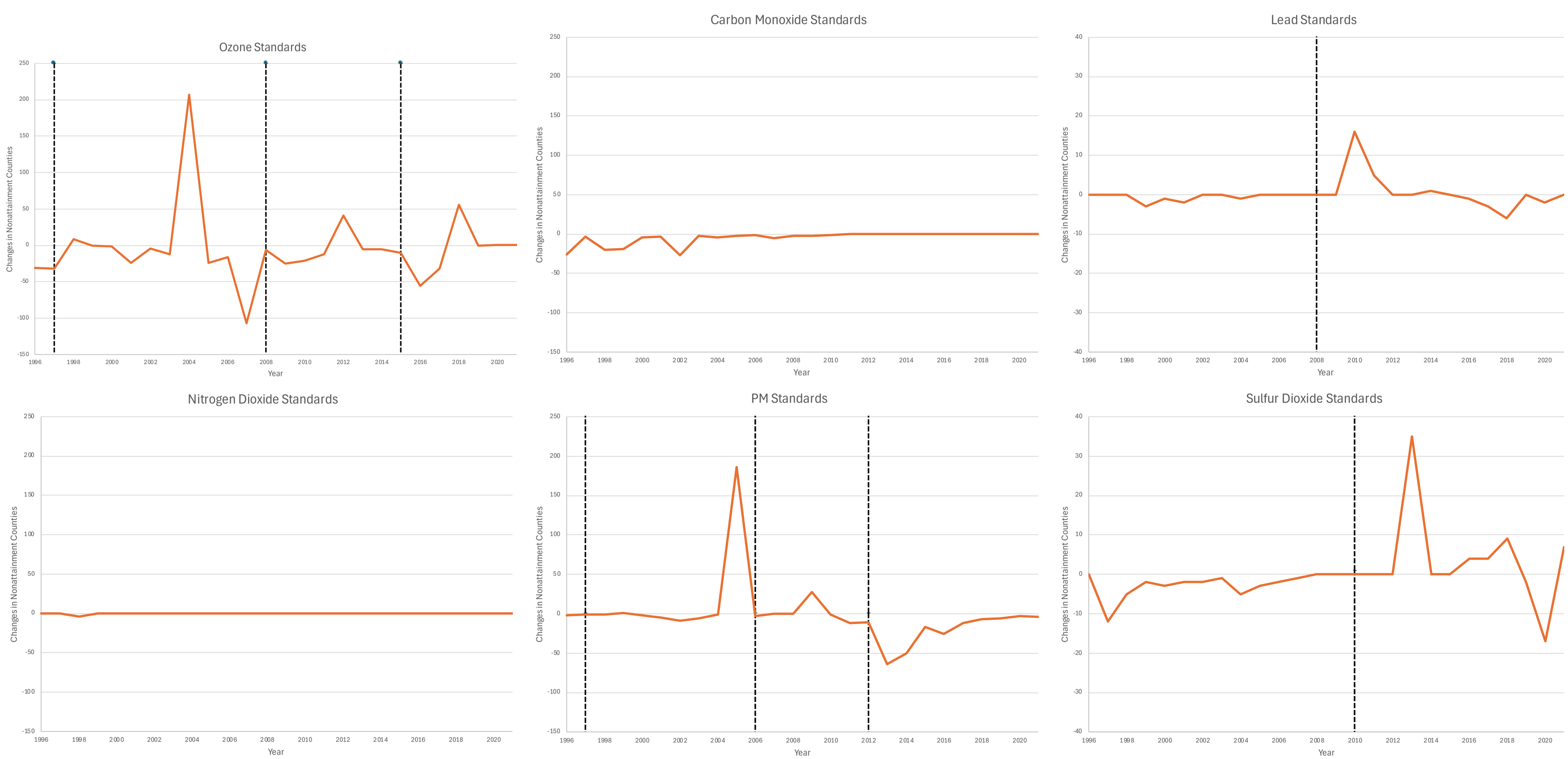

Figure 2
Corporate Innovation Responses to Regulatory Shocks by Competition

This figure depicts the dynamic treatment effects of nonattainment designation on green innovation by competitive intensity. The sample is split into terciles based on *Fluidity*, with treatment effects displayed separately for the top and bottom terciles. Each graph presents the point estimates and 95% confidence intervals for the differential effects between treatment and control groups over a time window of -4 to +4 years around the nonattainment shocks. Green innovation outcome is alternately proxied by *Green Patents (t+2)* and *Green Cites (t+2)*.

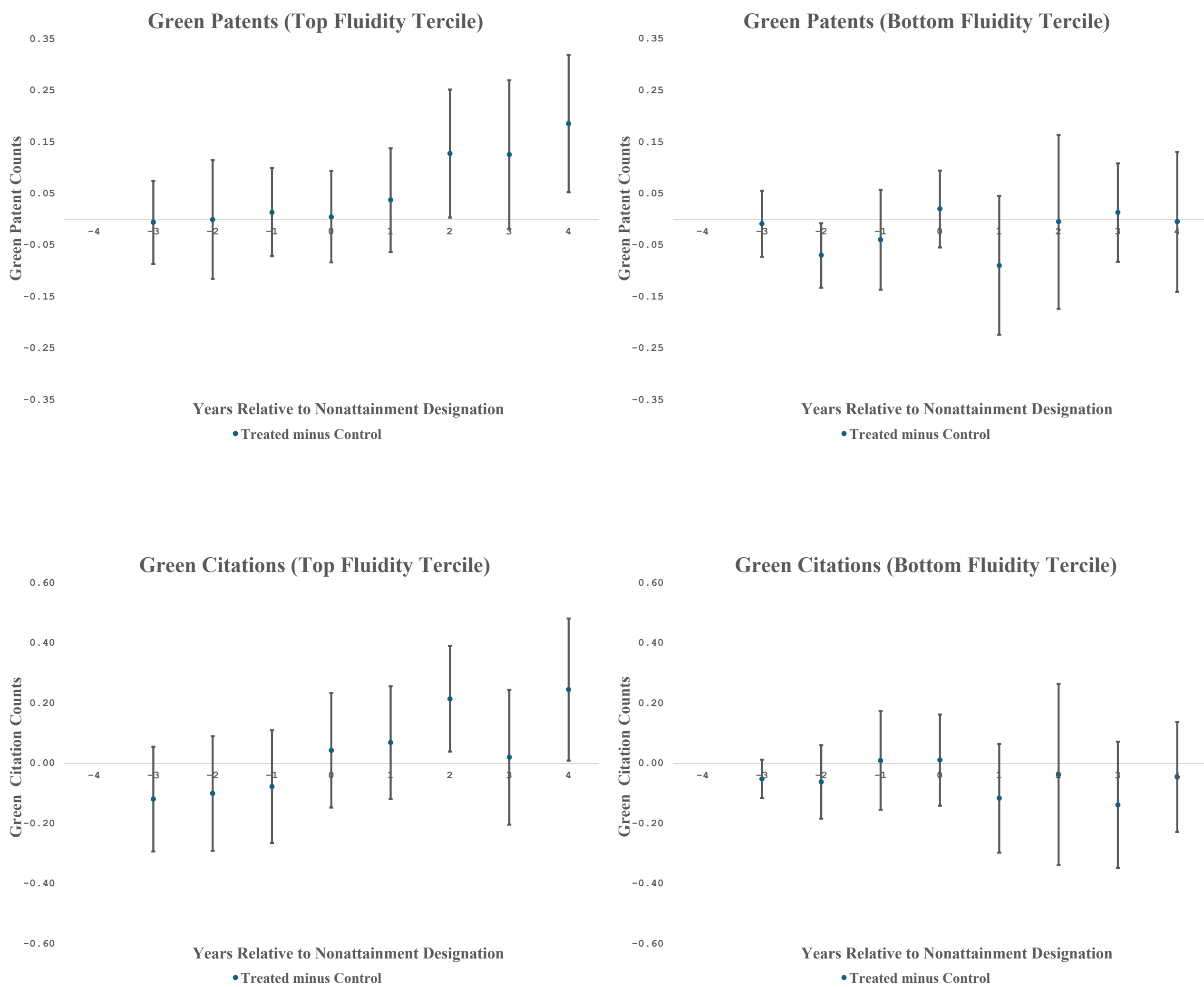

Table 1
Tests of Difference in Means by Attainment/Nonattainment Status

This table reports the differences in mean values of regulatory scrutiny and enforcement measures for counties previously held nonattainment status. It presents the mean number of inspections, defined as the county-level aggregate number of both onsite and offsite pollution compliance evaluations conducted by EPA averaged across county-years, during each of the attainment and nonattainment periods; the mean number of onsite inspections, defined as the county-level aggregate number of onsite air pollution compliance evaluations conducted by EPA averaged across county-years, during each of the attainment and nonattainment periods; the mean penalty amount, defined as the total amount of fines and penalties that violators in each county pay in connection with noncompliance to air-related environmental laws averaged across county-years, during each of the attainment and nonattainment periods; and the difference in the means across the two periods. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Attainment Period	Nonattainment Period	Difference in Means
	(1)	(2)	(3)
Number of Inspections	34.578	61.870	27.292***
Number of Onsite Inspections	20.359	38.103	17.744***
Penalty Amount	$79,367	$193,685	$114,318***

Table 2
Distribution of County Characteristics by State

This table reports the average number of firms and plants per county included in the sample, the number of treatment counties that experienced a change in nonattainment status, the total number of counties in the sample, and the percentage of treatment counties within the event windows during the sample period from 2000 to 2021.

	No. of Firms per County	No. of Plants per County	No. of Counties Nonattained	No. of Counties	% of Counties Nonattained
State	(1)	(2)	(3)	(4)	(5)
Alabama	8.39	9.51	2	10	20%
Arkansas	5.62	6.38	1	5	20%
California	7.06	9.04	6	18	33%
Colorado	28.39	50.80	4	14	29%
Florida	113.49	333.84	1	5	20%
Georgia	7.87	9.15	11	43	26%
Idaho	2.89	2.89	1	5	20%
Illinois	7.97	13.41	4	17	24%
Indiana	8.19	10.52	11	39	28%
Iowa	14.73	18.87	1	5	20%
Kansas	8.17	10.28	1	5	20%
Louisiana	10.92	14.55	1	5	20%
Michigan	12.49	18.15	5	19	26%
Minnesota	66.42	166.22	1	5	20%
Missouri	2.66	2.88	2	9	22%
New York	15.03	22.79	7	25	28%
North Carolina	14.10	22.70	5	18	28%
Ohio	13.49	21.46	20	52	38%
Oregon	10.49	12.38	1	5	20%
Pennsylvania	12.06	16.25	4	12	33%
South Carolina	20.64	28.84	1	5	20%
Tennessee	11.53	15.77	9	38	24%
Texas	10.94	16.58	7	34	21%
Utah	4.72	5.99	2	10	20%
Washington	67.58	232.78	1	5	20%
West Virginia	6.29	7.36	4	13	31%
Wisconsin	7.71	9.85	2	10	20%
Wyoming	10.41	14.38	2	7	29%

Table 3
Summary Statistics

This table shows summary statistics for the main variables employed in this study during the event windows for the sample period from 2000 to 2021. It provides the number of observations (NObs), mean, standard deviation (Std Dev), and various levels of percentiles from the 1st to the 99th percentile. Measures of green innovation are the number of green patents (*Green Patents*) and number of citations on a firm's green patents (*Green Cites*). Competition measures include product market fluidity (*Fluidity*), total product similarity score (*Similarity*), and one minus HHI (*NegHHI*). Firm-specific variables include the number of plants a firm owns in a county (*Plants*), log of total assets (*Size*), Tobin's Q (*Tobin's Q*), leverage ratio (*Leverage*), asset tangibility (*Tangibility*), cumulative R&D stock (*R&D*), capital expenditure (*CapEx*), operating cash flow (*OCF*), and log number of employees a firm has in a county (*Employees*). County-level variables include regional population (*Population*) and sales (*Regional Sales*), per capita personal income *Income*, and educational attainment information including the percentage of adults with a high school diploma only (*Highschool%*), with some college education (*College%*), and with a Bachelor's degree or higher (*Bachelor%*). Construction of the variables is presented in Appendix A. All variables are winsorized at 1% and 99%.

	NObs	Mean	Std Dev	1st	25th	50th	75th	99th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation Variables								
Green Patents	51,810	7.494	16.274	0.000	0.000	1.000	7.692	102.000
Green Cites	51,589	2.792	6.875	0.000	0.000	0.000	2.010	42.299
Competition Variables								
Fluidity	51,479	5.785	3.074	1.230	3.403	5.225	7.379	15.142
Similarity	51,810	2.327	2.394	1.000	1.081	1.362	2.411	15.480
NegHHI	51,810	0.681	0.244	0.000	0.572	0.756	0.861	0.953
Firm-Specific Characteristics								
Plants	51,810	1.774	3.113	1	1	1	2	11
Size	51,810	8.761	1.766	3.657	7.716	8.988	10.072	12.248
TobinQ	51,810	1.911	0.993	0.766	1.238	1.617	2.246	5.685
Leverage	51,810	0.236	0.153	0.000	0.132	0.224	0.318	0.721
Tangibility	51,810	0.247	0.170	0.024	0.120	0.196	0.324	0.695
R&D	51,810	0.033	0.049	0.000	0.001	0.016	0.040	0.270
CapEx	51,810	0.043	0.033	0.005	0.022	0.033	0.054	0.167
OCF	51,810	0.136	0.093	-0.262	0.093	0.136	0.186	0.328
Employees	51,810	3.779	1.185	2.398	2.773	3.466	4.511	7.216
County-Specific Characteristics								
Population	51,810	12.082	1.279	9.470	11.118	11.844	13.033	14.466
Regional Sales	51,810	20.439	1.604	16.936	19.349	20.187	21.690	23.405
Income	51,810	10.415	0.267	9.953	10.206	10.382	10.580	11.081
Highschool%	51,810	31.045	7.918	15.935	26.036	30.200	36.356	49.500
College%	51,810	28.501	4.795	17.800	25.900	28.400	31.100	40.400
Bachelor%	51,810	24.175	10.675	9.000	15.900	21.893	30.300	51.199

Table 4

Competition and Corporate Innovation Responses to Regulatory Shocks

This table presents the PPML estimation results from the triple-interaction analysis, highlighting the differential effects of nonattainment shocks on green innovation across varying levels of competition. *Treat* is a binary variable set to 1 for treatment counties that switch from attainment to nonattainment status and 0 for matched control counties that maintain attainment status during the -4 to +4 window surrounding nonattainment events, forming treatment-control cohorts. *Post* is a binary variable equal to 1 for the five years following nonattainment events and 0 otherwise. Competitive intensity is measured using *Fluidity*, *Similarity*, and *NegHHI*. Innovation efforts are captured by the two-year-ahead green patent output, *Green Patents (t+2)* and *Green Cites (t+2)* in Panel A, one-year-ahead green patent output in Panel B, and three-year-ahead output in Panel C. Control variables include firm characteristics such as *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, along with firm-, county-, and year-cohort fixed effects. Detailed construction of the variables is provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs represents the number of firm-county-year observations, and R^2 is the pseudo R-squared value from the PPML estimations. All z-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Green Patents $(t+2)$			Green Cites $(t+2)$		
	Fluidity	Similarity	NegHHI	Fluidity	Similarity	NegHHI
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Green Patenting Output in $t+2$					
Post×Treat×Comp	0.021***	0.029***	0.222**	0.027***	0.046***	0.319***
	(2.79)	(3.28)	(2.53)	(2.58)	(3.45)	(2.80)
Post×Treat	-0.047	0.001	-0.086	-0.083	-0.027	-0.136
	(-0.92)	(0.03)	(-1.38)	(-1.14)	(-0.66)	(-1.62)
Treat×Comp	-0.001	-0.003	-0.044	-0.003	-0.010	-0.021
	(-0.14)	(-0.63)	(-1.14)	(-0.40)	(-1.24)	(-0.49)
Post×Comp	-0.016	-0.008	-0.054	0.009	-0.020	-0.154
	(-1.27)	(-0.72)	(-0.39)	(0.39)	(-1.06)	(-0.76)
Comp	0.010	-0.018	-0.287	0.022	0.052	0.052
	(0.58)	(-0.66)	(-1.61)	(1.07)	(1.30)	(0.27)
Size	0.398***	0.398***	0.401***	0.323**	0.330**	0.333**
	(4.75)	(4.71)	(4.68)	(2.32)	(2.47)	(2.47)
Tobin's Q	0.134***	0.137***	0.137***	0.108*	0.105*	0.105*
	(3.80)	(4.23)	(4.25)	(1.83)	(1.68)	(1.66)
Leverage	-0.150	-0.157	-0.153	-0.499	-0.458	-0.455
	(-0.40)	(-0.42)	(-0.41)	(-0.97)	(-0.93)	(-0.91)
Tangibility	0.683	0.586	0.620	1.114	1.233	1.277
	(0.69)	(0.60)	(0.64)	(1.05)	(1.13)	(1.17)
R&D	3.782***	3.785***	3.809***	4.317***	4.270***	4.289***
	(2.90)	(2.88)	(2.93)	(2.77)	(2.75)	(2.75)
CapEx	0.950	1.067	1.025	1.775	1.678	1.648
	(0.61)	(0.68)	(0.65)	(1.03)	(0.96)	(0.93)
OCF	0.583	0.521	0.519	0.757	0.885	0.887
	(1.23)	(1.15)	(1.15)	(1.11)	(1.33)	(1.31)
Employees	-0.003	-0.004	-0.004	-0.000	0.000	-0.001
	(-0.70)	(-0.75)	(-0.92)	(-0.02)	(0.02)	(-0.07)
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	41,123	41,407	41,407	37,014	37,289	37,289
R^2	0.788	0.787	0.787	0.691	0.692	0.692

Table 4 Continued

	Green Patents $(t+y)$			Green Cites $(t+y)$		
	Fluidity	Similarity	NegHHI	Fluidity	Similarity	NegHHI
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel B: Green Patenting Output in $t+1$					
Post×Treat×Comp	0.021**	0.028***	0.316***	0.021**	0.038***	0.363***
	(2.14)	(2.68)	(3.64)	(2.05)	(2.73)	(2.61)
Post×Treat	-0.059	-0.012	-0.162***	-0.058	-0.030	-0.181*
	(-0.89)	(-0.31)	(-2.76)	(-0.78)	(-0.67)	(-1.78)
Treat×Comp	-0.006	-0.005	-0.125***	-0.005	-0.011	-0.106*
	(-1.29)	(-1.10)	(-2.93)	(-0.84)	(-1.57)	(-1.90)
Post×Comp	-0.027*	-0.013	-0.241	-0.024	-0.024	-0.579**
	(-1.95)	(-1.01)	(-1.50)	(-1.01)	(-1.22)	(-2.17)
Comp	0.020*	0.001	0.038	0.009	0.051*	0.355
	(1.72)	(0.06)	(0.23)	(0.31)	(1.81)	(1.18)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	43,535	43,858	43,858	38,259	38,549	38,549
R^2	0.794	0.793	0.793	0.702	0.702	0.703
	Panel C: Green Patenting Output in $t+3$					
Post×Treat×Comp	0.020***	0.035***	0.163**	0.007	0.036**	0.179*
	(3.18)	(4.24)	(2.52)	(0.66)	(2.44)	(1.78)
Post×Treat	-0.034	-0.002	-0.037	0.017	-0.016	-0.057
	(-0.73)	(-0.07)	(-0.81)	(0.21)	(-0.34)	(-0.70)
Treat×Comp	0.001	-0.006	-0.031	0.008	-0.002	-0.026
	(0.29)	(-1.24)	(-0.99)	(1.19)	(-0.28)	(-0.38)
Post×Comp	0.001	-0.000	0.118	0.015	-0.025	-0.127
	(0.09)	(-0.01)	(0.91)	(0.61)	(-1.43)	(-0.78)
Comp	-0.023	-0.039	-0.257*	0.003	-0.003	-0.167
	(-1.16)	(-1.22)	(-1.83)	(0.13)	(-0.11)	(-0.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	38,726	38,988	38,988	34,100	34,363	34,363
R^2	0.784	0.783	0.783	0.621	0.622	0.622

Table 5

Competition and Corporate Innovation Responses to Regulatory Shocks: Marginally Defined Nonattainment Status

This table presents the PPML estimation results from the triple-interaction analysis examining the differential effects of nonattainment shocks on green innovation across varying levels of competition, using a regression discontinuity design. Panel A restricts the analysis to treatment-control cohorts comprising county-years with pollutant concentrations within a 5% margin above or below the NAAQS threshold. Panel B includes the full sample and incorporates quadratic functions of county-level emissions on both sides of the NAAQS threshold. *Treat* is a binary indicator set to 1 for treated counties transitioning from attainment to nonattainment status, and 0 for matched control counties maintaining attainment status within a window of -4 to +4 years around nonattainment events, forming treatment-control cohorts. *Post* is a binary variable set to 1 for the five years following nonattainment events, and 0 otherwise. Competitive intensity is measured using *Fluidity*, *Similarity*, and *NegHHI*. Innovation efforts are captured through two-year-ahead green patenting outputs, represented by *Green Patents (t+2)* and *Green Cites (t+2)*. Control variables include firm characteristics, such as *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, along with fixed effects for firms, counties, and year cohorts. Detailed definitions of these variables are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of firm-county-year observations, and R^2 is the pseudo R-squared value from PPML estimations. All z-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Green Patents (t+2)			*Green Cites (t+2)*		
	Fluidity	Similarity	NegHHI	Fluidity	Similarity	NegHHI
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bandwith ± 5%						
Post×Treat×Comp	0.048**	0.050*	0.549**	0.029**	0.026	0.411*
	(2.52)	(1.77)	(2.13)	(2.02)	(0.83)	(1.82)
Post×Treat	-0.229*	-0.052	-0.260	-0.198	-0.100	-0.258
	(-1.83)	(-0.70)	(-1.55)	(-1.54)	(-1.33)	(-1.32)
Treat×Comp	-0.036***	-0.068***	-0.313**	-0.017	-0.021	-0.218
	(-3.42)	(-3.27)	(-2.08)	(-1.13)	(-0.52)	(-1.21)
Post×Comp	-0.000	0.013	0.002	0.030*	0.048	0.318
	(-0.01)	(0.48)	(0.02)	(1.92)	(1.29)	(1.63)
Comp	0.030	-0.120*	0.008	0.051	-0.005	0.052
	(0.81)	(-1.79)	(0.03)	(0.72)	(-0.07)	(0.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	3,193	3,220	3,220	2,947	2,974	2,974
R^2	0.797	0.796	0.796	0.735	0.735	0.734
Panel B: Full Model with Controls						
Post×Treat×Comp	0.028***	0.038***	0.236**	0.033*	0.064***	0.410**
	(2.82)	(3.25)	(2.03)	(1.84)	(2.99)	(2.07)
Post×Treat	-0.074	-0.001	-0.081	-0.071	-0.027	-0.165
	(-1.06)	(-0.04)	(-0.95)	(-0.50)	(-0.42)	(-1.05)
Treat×Comp	-0.005	-0.007	-0.088	-0.001	-0.014	-0.037
	(-0.72)	(-1.11)	(-1.18)	(-0.07)	(-1.47)	(-0.37)
Post×Comp	-0.021**	-0.015	-0.067	0.009	-0.036*	-0.231
	(-2.02)	(-1.36)	(-0.48)	(0.30)	(-1.86)	(-1.06)
Comp	-0.002	-0.021	-0.231	0.031	0.055	0.059
	(-0.15)	(-0.71)	(-1.01)	(1.24)	(1.13)	(0.20)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	28,829	29,052	29,052	25,645	25,864	25,864
R^2	0.796	0.795	0.795	0.688	0.688	0.688

Table 6

Competition and Corporate Innovation Responses to Regulatory Shocks: County-Specific Characteristics

This table presents the PPML estimation results from the triple-interaction analysis examining the differential effects of nonattainment shocks on green innovation across varying levels of competition, while accounting for county-level characteristics. Panel A includes controls for county-specific variables such as population (*Population*), regional sales (*Regional Sales*), per capita income (*Income*), and educational attainment levels (*Highschool%*, *College%*, *Bachelor%*). Panel B re-estimates the analysis with firm-cohort and county-cohort×year-cohort fixed effects. Panel C displays results using an alternative treatment-control matching procedure that incorporates these county-specific characteristics in the propensity score estimation. *Treat* is a binary indicator set to 1 for treatment counties transitioning from attainment to nonattainment status and 0 for matched control counties maintaining attainment status within a window of -4 to +4 years around nonattainment events, forming treatment-control cohorts. *Post* is a binary variable set to 1 for the five years following nonattainment events and 0 otherwise. Competitive intensity is measured using proxies such as *Fluidity*, *Similarity*, and *NegHHI*. Innovation outcomes are represented by two-year-ahead green patenting activity, specifically *Green Patents (t+2)* and *Green Cites (t+2)*. Firm-specific controls include *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, along with fixed effects for firms, counties, and year cohorts. Detailed variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of firm-county-year observations, and R^2 is the pseudo R-squared value from PPML estimations. All z-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Green Patents $(t+2)$			Green Cites $(t+2)$		
	Fluidity	Similarity	NegHHI	Fluidity	Similarity	NegHHI
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Additional County-Level Controls					
Post×Treat×Comp	0.021***	0.031***	0.228**	0.027**	0.047***	0.320***
	(2.80)	(3.46)	(2.54)	(2.55)	(3.52)	(2.73)
Post×Treat	-0.052	-0.004	-0.092	-0.094	-0.039	-0.147
	(-0.95)	(-0.12)	(-1.44)	(-1.19)	(-0.83)	(-1.63)
Treat×Comp	-0.001	-0.004	-0.047	-0.003	-0.010	-0.023
	(-0.26)	(-0.77)	(-1.15)	(-0.44)	(-1.21)	(-0.46)
Post×Comp	-0.016	-0.009	-0.055	0.009	-0.020	-0.157
	(-1.30)	(-0.76)	(-0.41)	(0.37)	(-1.10)	(-0.78)
Comp	0.009	-0.019	-0.298	0.021	0.049	0.035
	(0.52)	(-0.72)	(-1.63)	(0.96)	(1.21)	(0.17)
Population	0.244	0.226	0.220	0.501	0.562	0.535
	(1.02)	(0.96)	(0.91)	(1.43)	(1.61)	(1.50)
Regional Sales	0.015	0.016	0.017	-0.044	-0.048	-0.047
	(0.56)	(0.61)	(0.67)	(-1.09)	(-1.14)	(-1.11)
Income	-0.448***	-0.475***	-0.459***	-0.055	-0.110	-0.075
	(-2.70)	(-2.94)	(-2.85)	(-0.21)	(-0.43)	(-0.30)
Highschool%	-0.009	-0.008	-0.009	0.002	-0.002	-0.002
	(-1.08)	(-1.01)	(-1.07)	(0.18)	(-0.18)	(-0.22)
College%	-0.001	-0.001	-0.001	-0.013	-0.015	-0.015
	(-0.09)	(-0.12)	(-0.16)	(-1.26)	(-1.57)	(-1.59)
Bachelor%	0.006	0.005	0.004	0.009	0.005	0.005
	(0.76)	(0.62)	(0.55)	(0.41)	(0.26)	(0.26)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	41,123	41,407	41,407	37,014	37,289	37,289
R^2	0.788	0.787	0.787	0.691	0.692	0.692

Table 6 Continued

	Green Patents($t+2$)			Green Cites($t+2$)		
	Fluidity	Similarity	NegHHI	Fluidity	Similarity	NegHHI
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel B: Firm-Cohort×Year-Cohort Fixed Effects					
Post×Treat×Comp	0.026***	0.037***	0.264**	0.030**	0.049***	0.343**
	(2.96)	(3.45)	(2.46)	(2.35)	(3.22)	(2.55)
Treat×Comp	-0.004	-0.008	-0.076	-0.005	-0.010	-0.056
	(-0.66)	(-1.28)	(-1.48)	(-0.78)	(-1.39)	(-1.39)
Post×Comp	-0.020*	-0.013	-0.079	0.006	-0.022	-0.178
	(-1.76)	(-1.23)	(-0.60)	(0.24)	(-1.22)	(-0.84)
Comp	0.006	-0.017	-0.273	0.025	0.057	0.090
	(0.37)	(-0.62)	(-1.46)	(0.87)	(1.34)	(0.32)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort×Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	40,570	40,857	40,857	36,142	36,419	36,419
R^2	0.795	0.795	0.795	0.702	0.703	0.703
	Panel C: Additional County Characteristics in Sample Matching					
Post×Treat×Comp	0.013**	0.013*	0.135*	0.014**	0.023**	0.110
	(2.05)	(1.88)	(1.89)	(1.99)	(2.11)	(1.00)
Post×Treat	-0.042	0.001	-0.063	-0.060	-0.031	-0.053
	(-1.11)	(0.03)	(-1.37)	(-1.08)	(-0.84)	(-0.64)
Treat×Comp	-0.002	0.008	-0.048	0.001	-0.004	0.014
	(-0.62)	(1.43)	(-1.05)	(0.20)	(-0.65)	(0.23)
Post×Comp	-0.013	-0.005	-0.031	0.001	-0.014	-0.102
	(-1.00)	(-0.40)	(-0.24)	(0.03)	(-0.79)	(-0.52)
Comp	0.013	-0.056	-0.400**	0.048**	-0.002	0.017
	(0.76)	(-1.17)	(-2.16)	(2.51)	(-0.04)	(0.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	32,385	32,604	32,604	29,130	29,351	29,351
R^2	0.782	0.781	0.781	0.612	0.612	0.612

Table 7

Import Penetration and Corporate Innovation Responses to Nonattainment Shocks

This table presents the PPML estimation results from the triple-interaction analysis examining the combined effects of environmental regulation and import tariff reductions on green innovation. *Treat* is a binary indicator set to 1 for treatment counties transitioning from attainment to nonattainment status, and 0 for matched control counties maintaining attainment status within a window of -4 to +4 years around nonattainment events, forming treatment-control cohorts. *Post* is a binary variable set to 1 for the five years following nonattainment events and 0 otherwise. *Tariff Reduction* is an indicator set to 1 if firm i experiences a significant tariff reduction by year $t-1$, and 0 otherwise. Innovation efforts are measured using two-year-ahead green patenting outputs, represented by *Green Patents (t+2)* and *Green Cites (t+2)*. Firm-specific control variables include *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, alongside firm-, county-, and year-cohort fixed effects. Detailed definitions of all variables are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of firm-county-year observations, and R^2 is the pseudo R-squared value from PPML estimations. All z-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Green Patents $(t+2)$	Green Cites $(t+2)$
	(1)	(2)
Post×Treat×Tariff Reduction	0.069*	0.284**
	(1.73)	(2.41)
Post×Treat	-0.004	-0.193
	(-0.11)	(-1.53)
Treat×Tariff Reduction	0.072	-0.010
	(1.48)	(-0.13)
Post×Tariff Reduction	-0.194*	-0.454***
	(-1.93)	(-3.31)
Tariff Reduction	0.392**	0.383
	(2.03)	(1.56)
Controls	Yes	Yes
Firm-Cohort FE	Yes	Yes
County-Cohort FE	Yes	Yes
Year-Cohort FE	Yes	Yes
NObs	34,846	30,456
R^2	0.795	0.694

Table 8
Placebo Tests

This table presents the results from a series of placebo tests examining the differential effects of environmental regulatory shocks across varying levels of competition. Panel A replicates the triple-interaction analysis using non-green innovation outputs as outcome variables. Panel B re-estimates the analysis, substituting nonattainment shocks with nonattainment status reversals. Green innovation is measured by *Green Patents (t+2)* and *Green Cites (t+2)*, while non-green innovation is captured by *Non-Green Patents (t+2)* and *Non-Green Cites (t+2)*. Competition is assessed using proxies such as *Fluidity*, *Similarity*, and *NegHHI*. *Treat* is a binary indicator set to 1 for treatment counties that transition from attainment to nonattainment status, and 0 for matched control counties maintaining attainment status within a -4 to +4 year window around nonattainment events, forming treatment-control cohorts. The variable *Reversal* is set to 1 for counties transitioning from nonattainment to attainment status, and 0 for matched control counties with consistent nonattainment status in the same time window, creating an alternative set of treatment-control cohorts. *Post* is a binary variable set to 1 for the five years following these events, and 0 otherwise. Control variables include firm characteristics such as *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, along with firm-, county-, and year-cohort fixed effects. Detailed definitions of these variables are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of firm-county-year observations, and R^2 is the pseudo R-squared value from PPML estimations. All z-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Non-Green Patents $(t+2)$			Non-Green Cites $(t+2)$		
	Fluidity	Similarity	NegHHI	Fluidity	Similarity	NegHHI
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Non-Green innovation					
Post×Treat×Comp	0.005	0.018	0.044	0.004	0.021	0.046
	(0.73)	(1.38)	(0.80)	(0.60)	(1.19)	(0.38)
Post×Treat	-0.010	-0.019	-0.008	-0.019	-0.033	-0.023
	(-0.27)	(-0.78)	(-0.25)	(-0.39)	(-0.75)	(-0.29)
Treat×Comp	0.002	-0.002	-0.003	-0.004	-0.006	-0.029
	(0.40)	(-0.62)	(-0.10)	(-1.33)	(-0.69)	(-0.49)
Post×Comp	-0.001	-0.008	0.152*	0.006	-0.002	0.235*
	(-0.12)	(-0.74)	(1.94)	(0.58)	(-0.09)	(1.66)
Comp	-0.007	-0.005	-0.130*	-0.024	-0.051***	-0.023
	(-0.81)	(-0.24)	(-1.79)	(-1.28)	(-4.52)	(-0.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	48,462	48,754	48,754	41,578	41,854	41,854
R^2	0.924	0.924	0.924	0.853	0.853	0.853
	Green Patents $(t+2)$			Green Cites $(t+2)$		
	Panel B: Nonattainment Status Reversal					
Post×Reversal×Comp	-0.003	-0.001	0.010	0.000	0.008	-0.134
	(-0.25)	(-0.09)	(0.07)	(0.03)	(0.63)	(-0.81)
Post×Reversal	0.025	0.023	0.010	-0.038	-0.045	0.066
	(0.39)	(0.52)	(0.11)	(-0.59)	(-0.80)	(0.59)
Reversal×Comp	0.002	0.007	-0.041	-0.006	-0.006	-0.076
	(0.35)	(0.96)	(-0.63)	(-0.84)	(-0.87)	(-0.90)
Post×Comp	-0.006	0.015	0.199	0.007	-0.002	0.101
	(-0.41)	(1.39)	(1.26)	(0.38)	(-0.13)	(0.52)
Comp	0.009	-0.006	-0.747***	-0.031*	-0.015	-0.820***
	(0.56)	(-0.34)	(-4.06)	(-1.69)	(-0.55)	(-2.94)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	32,598	32,916	32,916	28,952	29,206	29,206
R^2	0.788	0.788	0.788	0.677	0.679	0.679

Table 9
Cross-Sectional Analysis

This table presents subsample regression results from the triple-interaction analysis examining cross-sectional variations in the combined effects of environmental regulation and competition on green innovation. Firms are grouped into terciles based on the following criteria: (A) industry-level pollution, measured by total emissions of the six criteria pollutants; (B) plant fixed costs, defined as real structures capital stock scaled by total shipment value; (C) local plant size, represented by the proportion of local employees relative to the firm's total workforce averaged over the pre-event window; (D) agglomeration economies, assessed by the geographic concentration of industry employment shares across counties; and (E) historical green patenting activity, measured by average annual green patent counts during the pre-event window. Separate estimations are conducted for firms in the top and bottom terciles of each criterion, with the results reported in Panels A–E. *Treat* is a binary variable set to 1 for treatment counties transitioning from attainment to nonattainment status and 0 for matched control counties maintaining attainment status within a -4 to +4 year window around nonattainment events, forming treatment-control cohorts. *Post* is a binary variable set to 1 for the five years following nonattainment events and 0 otherwise. Competitive intensity is measured using proxies such as *Fluidity*, *Similarity*, and *NegHHI*. Innovation efforts are quantified using a firm's two-year-ahead green patenting output, represented by *Green Patents (t+2)* and *Green Cites (t+2)*. Control variables include firm characteristics such as *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, along with firm-, county-, and year-cohort fixed effects. Detailed variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of firm-county-year observations, and R^2 is the pseudo R-squared value from PPML estimations. All z-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Green Patents $(t+2)$		Green Cites $(t+2)$	
	Bottom	Top	Bottom	Top
	(1)	(2)	(3)	(4)
	Panel A: Terciles by Industry Pollution			
Post × Treat × Fluidity	-0.049	0.024**	-0.076	0.022**
	(-1.58)	(2.55)	(-1.36)	(2.03)
Top>Bottom (p-value)	(0.052)		(0.051)	
Post × Treat	0.138	-0.047	0.192	-0.050
	(1.13)	(-0.69)	(0.71)	(-0.64)
Treat × Fluidity	0.011	0.003	0.000	0.006
	(0.58)	(0.55)	(0.01)	(0.70)
Post × Fluidity	0.004	-0.007	-0.107	0.019
	(0.07)	(-0.51)	(-1.23)	(0.76)
Fluidity	0.169***	-0.010	0.180***	0.020
	(5.32)	(-0.41)	(2.63)	(0.75)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
NObs	4,763	22,465	3,992	20,121
Adjusted R^2	0.661	0.800	0.593	0.716
	Panel B: Terciles by Plant Fixed Costs			
Post × Treat × Fluidity	0.001	0.034**	0.010	0.050***
	(0.18)	(2.37)	(0.38)	(2.82)
Top>Bottom (p-value)	(0.023)		(0.087)	
Post × Treat	0.038	-0.140	0.079	-0.397***
	(0.55)	(-1.33)	(0.51)	(-2.74)
Treat × Fluidity	0.005	-0.004	0.006	-0.013
	(0.95)	(-0.51)	(0.50)	(-1.52)
Post × Fluidity	-0.024	-0.008	0.054	-0.012
	(-1.06)	(-0.42)	(1.27)	(-0.49)
Fluidity	0.051	-0.017	0.053	0.019
	(1.32)	(-0.93)	(0.77)	(1.01)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
NObs	10,525	7,766	8,630	6,606
Adjusted R^2	0.731	0.852	0.674	0.752

Table 9 Continued

	Green Patents ($t+2$)		Green Cites ($t+2$)	
	Bottom	Top	Bottom	Top
	(1)	(2)	(3)	(4)
Panel C: Terciles by Plant Size				
Post × Treat × Fluidity	0.005	0.043*	-0.000	0.050*
	(0.34)	(1.94)	(-0.02)	(1.85)
Top>Bottom (p-value)	(0.072)		(0.070)	
Post × Treat	0.062	-0.284**	0.026	-0.225
	(0.81)	(-2.22)	(0.22)	(-1.31)
Treat × Fluidity	-0.002	-0.001	0.007	0.003
	(-0.23)	(-0.07)	(0.60)	(0.17)
Post × Fluidity	-0.028	-0.024*	0.023	-0.007
	(-1.55)	(-1.92)	(0.66)	(-0.39)
Fluidity	0.028	-0.073*	-0.028	-0.059
	(0.74)	(-1.84)	(-0.54)	(-0.88)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
NObs	15,089	11,773	14,094	9,991
Adjusted R^2	0.797	0.792	0.729	0.713
Panel D: Terciles by Agglomeration Economies				
Post × Treat × Fluidity	-0.005	0.036***	-0.035	0.036*
	(-0.34)	(2.97)	(-1.34)	(1.72)
Top>Bottom (p-value)	(0.020)		(0.018)	
Post × Treat	0.072	-0.108	0.184	-0.069
	(0.85)	(-1.13)	(1.16)	(-0.40)
Treat × Fluidity	0.009*	-0.011**	0.020*	-0.013*
	(1.76)	(-2.15)	(1.95)	(-1.78)
Post × Fluidity	-0.047	-0.030	-0.026	-0.099**
	(-1.43)	(-0.86)	(-0.68)	(-2.19)
Fluidity	0.041	0.006	-0.060	0.109**
	(1.21)	(0.16)	(-1.41)	(2.44)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
NObs	8,345	8,178	7,573	7,100
Adjusted R^2	0.761	0.821	0.795	0.786
Panel E: Terciles by Historical Green Patenting Activities				
Post × Treat × Fluidity	-0.043	0.021***	-0.048	0.023**
	(-1.10)	(2.66)	(-0.78)	(2.00)
Top>Bottom (p-value)	(0.052)		(0.128)	
Post × Treat	0.129	-0.053	0.259	-0.060
	(0.65)	(-0.90)	(0.53)	(-0.72)
Treat × Fluidity	0.039*	-0.001	0.031	-0.003
	(1.84)	(-0.23)	(0.96)	(-0.42)
Post × Fluidity	-0.042	-0.011	0.083	0.015
	(-0.79)	(-0.84)	(0.70)	(0.58)
Fluidity	0.278**	0.007	-0.263*	0.021
	(2.06)	(0.38)	(-1.75)	(1.19)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
NObs	9,090	19,846	5,622	19,762
Adjusted R^2	0.357	0.727	0.479	0.647

Table 10

Differentiation and Signaling Strategies, Innovation, and Regulatory Shocks

This table presents regression results from the triple-interaction analysis examining the impact of green innovation on corporate differentiation strategies and ESG reputation following environmental regulation. Panel A estimates the immediate effects of regulation-induced green innovation on technological differentiation, using *Tech Proximity* and *Originality* as proxies. *Green Patents* is defined as the natural logarithm of one plus the number of green patents filed by a firm during the year. Panel B explores the delayed effects of existing green patent portfolios on product market differentiation and ESG reputation after nonattainment shocks. Product market differentiation is represented by *Entries*, *Exits*, and $\Delta Product;Market;Space$, while ESG reputation is assessed using the overall ESG score and the innovation score from Refinitiv. *Green Stock* is the natural logarithm of one plus the cumulative green patent stock, decayed annually by 20% until year t. Both panels include controls for historical patent stock prior to the nonattainment event year (*Pre-Shock Green Stock* and *Pre-Shock Total Stock*). *Treat* is a binary indicator set to 1 for treatment counties transitioning from attainment to nonattainment status and 0 for matched control counties that maintain attainment status within a -4 to +4 year window, forming treatment-control cohorts. *Post* is a binary variable set to 1 for the five years following nonattainment events and 0 otherwise. Additional controls include firm characteristics such as *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, along with firm-, county-, and year-cohort fixed effects. Detailed variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of firm-county-year observations. Columns (1)-(3) of Panel B reports the results of PPML estimations along with the pseudo R-squared value in R^2 and the z-statistics reported in parentheses. For all remaining columns and panel, R^2 is the adjusted R-squared value, and all t-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Tech Proximity (t)	*Originality (t)*
	(1)	(2)
	Panel A: Innovation Novelty	
Post × Treat × Green Patents	-0.005**	0.004**
	(-2.19)	(2.16)
Post × Treat	0.012*	-0.004
	(1.84)	(-1.02)
Treat × Green Patents	0.003	-0.003**
	(1.58)	(-2.18)
Post × Green Patents	0.003	0.002
	(0.67)	(0.82)
Green Patents	0.015*	0.009
	(1.73)	(1.69)
Pre-Shock Green Stock	0.016	-0.007
	(0.59)	(-0.68)
Pre-Shock Total Stock	-0.003	-0.007
	(-0.18)	(-0.69)
Controls	Yes	Yes
Firm-Cohort FE	Yes	Yes
County-Cohort FE	Yes	Yes
Year-Cohort FE	Yes	Yes
NObs	42,393	42,393
R^2	0.657	0.467

Table 10 Continued

	Product Differentiation ($t+2$)			ESG Rating ($t+2$)	
	Entries	Exits	Δ Product Market Space	ESG Score	Innovation Score
	(1)	(2)	(3)	(4)	(5)
	Panel B: Product Differentiation and ESG Reputation				
Post×Treat×Green Stock	-0.022*	0.002	0.029*	0.004**	0.011**
	(-1.70)	(0.20)	(1.73)	(2.19)	(2.39)
Post×Treat	0.020	-0.025	-0.049	-0.008*	-0.033**
	(0.56)	(-0.90)	(-1.13)	(-1.78)	(-2.53)
Treat×Green Stock	0.002	-0.005	-0.013	-0.002*	-0.008**
	(0.33)	(-0.75)	(-1.18)	(-2.09)	(-2.24)
Post×Green Stock	0.008	0.002	0.004	-0.001	-0.003
	(0.45)	(0.13)	(0.13)	(-0.14)	(-0.56)
Green Stock	-0.029	0.008	0.175*	-0.001	0.013
	(-0.48)	(0.14)	(1.65)	(-0.04)	(0.39)
Pre-Shock Green Stock	-0.028	0.062	0.199	0.005	-0.017
	(-0.17)	(0.99)	(1.22)	(0.37)	(-0.43)
Pre-Shock Total Stock	0.059	-0.009	-0.191	0.009	0.003
	(0.49)	(-0.15)	(-1.39)	(1.02)	(0.16)
Controls	Yes	Yes	Yes	Yes	Yes
Firm Cohort FE	Yes	Yes	Yes	Yes	Yes
County Cohort FE	Yes	Yes	Yes	Yes	Yes
Year Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	48,254	48,735	43,972	33,504	33,504
Adjusted R-squared	0.746	0.753	0.197	0.868	0.749

Table 11
Product Market Performance, Innovation, and Regulatory Shocks

This table presents regression results from the triple-interaction analysis examining the effects of green innovation on corporate customer relationships and firm performance following environmental regulation. The outcome variables include the number of corporate customers with a local county presence (*# Local Customers*), the number of a firm's unique collaborative relationships with these customers (*# Customer Alliances*), the ratio of non-green to green customers (*Non-Green/Green Customers*), as well as *Sales Growth*, *Market Share Growth*, *ROA*, and *Tobin's Q*. *Green Stock* is defined as the natural logarithm of one plus the accumulated green patent stock, with a 20% annual decay rate, up to year t. All estimations control for historical patent stock prior to the nonattainment event (*Pre-Shock Green Stock* and *Pre-Shock Total Stock*). *Treat* is a binary variable set to 1 for treatment counties transitioning from attainment to nonattainment status and 0 for matched control counties maintaining attainment status within a -4 to +4 year window, forming treatment-control cohorts. *Post* is a binary variable set to 1 for the five years following nonattainment events, and 0 otherwise. Additional controls include firm characteristics such as *Size*, *Tobin's Q*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *OCF*, and *Employees*, along with firm-, county-, and year-cohort fixed effects. Detailed variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of firm-county-year observations. Columns (1)-(3) reports the results of PPML estimations along with the pseudo R-squared value in R^2 and the z-statistics reported in parentheses. For all remaining columns, R^2 is the adjusted R-squared value, and all t-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Value Chain ($t+2$)			Performance Metric ($t+2$)			
	# Local Customers	# Customer Alliances	Non-Green/Green Customers	Sales Growth	Market Share Growth	ROA	Tobin's Q
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post×Treat×Green Stock	0.044***	0.101**	0.029*	0.005**	0.003**	0.002**	0.001
	(2.73)	(2.14)	(1.86)	(2.56)	(2.23)	(2.20)	(0.07)
Post×Treat	-0.047	-0.126	-0.024	-0.013**	-0.011*	-0.004*	-0.007
	(-0.86)	(-0.78)	(-0.48)	(-2.42)	(-1.98)	(-1.79)	(-0.39)
Treat×Green Stock	-0.022	-0.007	-0.016	-0.001	-0.000	-0.001**	-0.006*
	(-1.50)	(-0.17)	(-1.27)	(-1.29)	(-0.25)	(-2.19)	(-1.77)
Post×Green Stock	-0.026	0.005	-0.003	-0.006*	-0.003	0.000	-0.005
	(-1.54)	(0.11)	(-0.22)	(-2.00)	(-1.35)	(0.01)	(-0.41)
Green Stock	0.099*	-0.035	0.069	0.023*	0.026***	-0.001	-0.048
	(1.72)	(-0.17)	(1.12)	(1.80)	(2.89)	(-0.20)	(-1.00)
Pre-Shock Green Stock	0.645***	1.796***	0.540*	-0.015	-0.007	-0.008*	0.011
	(2.59)	(3.32)	(1.90)	(-0.85)	(-0.47)	(-1.97)	(0.21)
Pre-Shock Total Stock	0.048	0.034	0.056	0.030**	0.015	0.017**	0.035
	(0.21)	(0.10)	(0.24)	(2.32)	(0.83)	(2.32)	(0.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,938	9,666	31,441	59,298	59,298	59,350	57,731
Adjusted R-squared	0.409	0.270	0.352	0.368	0.207	0.809	0.836

Table 12
Regional Air Quality, Policy Reversal, and Innovation

This table presents the results of the county-level analysis examining the impact of green innovation on regional air quality and nonattainment status reversal for nonattainment counties. The AQI Index, established by the EPA, measures county-level pollution based on criteria pollutants, with higher values indicating greater pollution levels. Status Reversal is a binary variable set to 1 if a nonattainment county transitions to attainment status in the following year, and 0 otherwise. *County Green Stock* is defined as the natural logarithm of one plus the cumulative green patent stock up to year t for all firms with local plants in the county. *County Total Stock* represents the natural logarithm of one plus the total patent stock, regardless of classification, up to year t for all firms with local plants. County-level controls include *Population*, *Regional Sales*, *Income*, and educational attainment metrics (*Highschool%*, *College%*, and *Bachelor%*). The analysis incorporates county and year fixed effects. Detailed variable construction is provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. NObs is the number of county-year observations, and R^2 is the adjusted R-squared value. All t-statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	AQI Index			Status Reversal		
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
County Green Stock	-0.020**	-0.020**	-0.017*	-0.003	0.021**	0.017**
	(-2.47)	(-1.98)	(-1.91)	(-0.29)	(2.30)	(2.37)
County Total Stock	0.021**	0.026**	0.021**	0.014	-0.007	-0.005
	(2.21)	(2.44)	(2.50)	(1.33)	(-0.71)	(-0.55)
EPA Inspections	-0.001	-0.001	-0.002	-0.002	-0.005	-0.007
	(-0.14)	(-0.16)	(-0.34)	(-0.45)	(-1.00)	(-1.70)
Population	0.013	-0.030	-0.080	-0.028	-0.018	-0.003
	(0.24)	(-0.56)	(-1.31)	(-0.36)	(-0.21)	(-0.04)
Regional Sales	-0.002	-0.003	-0.006**	-0.003	-0.002	-0.005
	(-0.98)	(-1.35)	(-2.21)	(-1.25)	(-0.99)	(-1.11)
Income	0.180**	0.192***	0.176**	0.050	0.025	0.021
	(2.46)	(2.59)	(2.12)	(0.95)	(0.41)	(0.36)
Highschool%	-0.009**	-0.009**	-0.010**	0.000	0.000	0.002
	(-2.36)	(-2.18)	(-2.36)	(0.01)	(0.10)	(0.53)
College%	-0.003	-0.004	-0.003	0.007**	0.009***	0.010***
	(-1.28)	(-1.45)	(-1.20)	(2.70)	(2.85)	(2.82)
Bachelor%	-0.006*	-0.006*	-0.005	-0.000	-0.001	-0.001
	(-1.89)	(-1.79)	(-1.49)	(-0.11)	(-0.33)	(-0.52)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NObs	6,633	6,093	5,595	7,885	7,207	6,592
R^2	0.295	0.299	0.302	0.108	0.129	0.088

Appendix A

Variable	Definition	Data source
Measures of innovation		
Green Patents	Firm i's total number of green patents filed (and eventually granted) during the year, where green patents are those identified as "environmentally-sound technologies" classified by the UNFCCC and WIPO based on IPC patent classes	PATSTAT; WIPO IPC Green Inventory
Green Cites	The total number of citations received by firm i's green patents filed (and eventually granted) during the year	PATSTAT; WIPO IPC Green Inventory
Non-Green Patents	Firm i's total number of patents minus the number of green patent count filed (and eventually granted) during the year	PATSTAT; Computation
Non-Green Cites	The number of citations received by firm i's non-green patents filed (and eventually granted) during the year	PATSTAT; Computation
Green Stock	Green patent stock estimated using perpetual inventory method, where historical green patents are accumulated up to year t, starting from 1980, with an annual depreciation rate of 20% (Aghion et al., 2016); the variable is transformed by taking the logarithm of its value plus one	Computation
Pre-Shock Green Stock	The natural logarithm of one plus the accumulated green patent stock up to the year prior to the nonattainment shock event with an annual depreciation rate of 20%	Computation
Pre-Shock Total Stock	The natural logarithm of one plus the accumulated patent (of any classification) stock up to the year prior to the nonattainment shock event with an annual depreciation rate of 20%	Computation
County Green Stock	The natural logarithm of one plus the sum of green patent stock up to year t across all firms with local plants in the county	Computation
County Total Stock	The natural logarithm of one plus the sum of patent stock (of any classification) up to year t across all firms with local plants in the county	Computation
Measures of competition		
Fluidity	Constructed by Hoberg et al. (2014), which is a "cosine" similarity score between firm i's own word usage in its 10-K product descriptions and the aggregate changes in the product key words used by its competitors within the same TNIC industry	Hoberg-Phillips Data Library
Similarity	Constructed by Hoberg et al. (2014), which measures the total "cosine" similarity score between firm i's products and those of its peers within the same TNIC industry	Hoberg-Phillips Data Library
NegHHI	One minus the firm-specific HHI computed as the sum of squared market share of all firms in the same TNIC industry where market share is a firm's sales divided by the industry's total sales	Hoberg-Phillips Data Library
Tariff Reduction	A dummy variable equals to 1 for the years after a major tariff reduction in firm i's industry and is equal to 0 otherwise; tariff rates are defined as the collected duties divided by the custom value of imports for each 3-digit SIC industry; a major tariff reduction event is defined as a decline in the tariff rate by more than three times larger than the average tariff reduction of the industry during the sample period, and it is not preceded or followed by a tariff increase greater than 80% of the reduction	Peter K. Scott's website
Nonattainment status variables		
Treat	A binary variable that equals 1 if a county in which firm's plants reside undergoes a status switch from attainment to nonattainment during the nine-year event window, and 0 otherwise	EPA Green Book
Post	A binary variable that equals 1 for the five years following nonattainment events, and 0 otherwise	EPA Green Book
Reversal	A binary variable that equals 1 if a county in which firm's plants reside undergoes a status switch from nonattainment to attainment during the nine-year event window, and 0 otherwise	EPA Green Book

Appendix A – Continued

Variable	Definition	Data source
Variables in cross-sectional analysis		
Industry Pollution	3-digit SIC industry-total emissions of the six NAAQS criteria pollutants, averaged over the four years during which the emissions data is available	ECHO
Plant Fixed Costs	Industry-level real structures capital stock scaled by the total value of shipments, averaged over the period of data availability	NBER-CES
Plant Size	The proportion of a firm's local employees relative to its total workforce, averaged over the years before nonattainment events.	D&B
Agglomeration	Extent of an industry's geographic concentration of employment shares across counties, and is measured by $Agglomeration_{l,t} = \frac{\sum_c^C (s_{l,c,t} - x_{c,t})^2}{1-\sum_c^C x_{c,t}^2}$, where $s_{l,c,t}$ is the share of industry l's employment contained in county c during year t; and $x_{c,t}$ is the mean employment share in county c across all industries. It measures deviations from randomly distributed employment patterns and equals to zero when industry employment is randomly distributed across all C counties but increases with geographic clustering of employees in industry l	D&B
Measures of real consequences analysis		
Tech Proximity	Technological proximity of firm i with all its competitors, estimated as the pairwise correlation between firm i and firm j's patent class vectors (at the 3-digit IPC level), averaged across all firm js in the same TNIC industry	PATSTAT
Originality	One minus the sum of squared percentage of backward citations made by a patent to each patent class, average across all patents filed by firm i during a year	PATSTAT
Entries	The number of new peers entering into the product market space as firm i, where a product market space is defined based on TNIC industry classification	Hoberg-Phillips Data Library
Exits	The number of existing competitors leaving the product market space of firm i as identified by TNIC industry classification	Hoberg-Phillips Data Library
Δ Product Market Space	The ratio of the number of entries to the number of exits	Computation
ESG Score	An overall company score based on the self-reported information in the environmental, social, and corporate governance pillars	Refinitiv ESG
Innovation Score	A component of the environmental pillar in Refinitiv's ESG score, reflecting a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes, or eco-designed products	Refinitiv ESG
# Local Customers	The number of corporate customers with at least one plant residing in the county	Revere; D&B
# Customer Alliances	The number of unique collaborative relationships a firm has with its local corporate customers, forming any of following types of partnership: research collaboration; integrated product offering, joint venture; and products, patents, and intellectual property licensing	Revere
Non-Green/Green Customers	The ratio of the number of corporate customers not generating any green patent output during the year to those generating at least one green patent	Revere; PATSTAT

Appendix A – Continued

Variable	Definition	Data source
Measures of real consequences analysis – continued		
Sales Growth	The percentage change in firm i's sales from the previous year to the current year	Compustat
Market Share Growth	The percentage change in firm i's market share from the previous year to the current year, where market share is defined as the share of firm i's in its industry's sales	Compustat
ROA	Earnings before interest and taxes divided by total assets	Compustat
AQI Index	The Air Quality Index established by the EPA to measure the level of pollution in an area based on the criteria pollutants	AQS
Status Reversal	A dummy indicator set to one if a county switches from nonattainment to attainment status by the following year, and zero otherwise	Computation
Measures of firm-specific characteristics		
Size	The natural logarithm of total assets	Compustat
Tobin's Q	Total assets plus the market value of equity minus the book value of equity minus deferred taxes divided by total assets	Compustat
Leverage	Total debt divided by total asset	Compustat
Tangibility	Net property, plant, and equipment divided by total assets	Compustat
R&D	Research and development expenditures divided by total assets	Compustat
CapEx	capital expenditures divided by total assets	Compustat
OCF	Operating cash flow proxied by operating income before depreciation divided by total assets	Compustat
Employees	The natural logarithm of one plus the number of employees each firm has in a county during a year	D&B
Measures of county-specific characteristics		
Number of Inspections	The natural logarithm of one plus the number of onsite and offsite air pollution compliance evaluations conducted by the EPA in a county during a given year	ECHO
Number of Onsite Inspections	The natural logarithm of one plus the number of onsite air pollution compliance evaluations conducted by the EPA	ECHO
Penalty Amount	The total amount of fines and penalites that violators in each county pay in connection with noncompliance to air-related environmental laws	ECHO
Population	The natural logarithm of county-level population	Census
Regional Sales	The natural logarithm of total sales attributed to plants in the county	D&B
Income	The natural logarithm of per capita personal income	BEA
Highschool%	The percentage of adults age 25 and older in the county with a high school diploma only	Census
College%	The percentage of adults in the county with 1 to 3 years of college experience	Census
Bachelor%	The percentage of adults in the county with a Bachelor's degree or higher	Census

about ECGI

The European Corporate Governance Institute has been established to improve *corporate governance through fostering independent scientific research and related activities.*

The ECGI will produce and disseminate high quality research while remaining close to the concerns and interests of corporate, financial and public policy makers. It will draw on the expertise of scholars from numerous countries and bring together a critical mass of expertise and interest to bear on this important subject.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.

Electronic Access to the Working Paper Series

The full set of ECGI working papers can be accessed through the Institute's Web-site (www.ecgi.global/content/working-papers) or SSRN:

Finance Paper Series	http://www.ssrn.com/link/ECGI-Fin.html
Law Paper Series	http://www.ssrn.com/link/ECGI-Law.html