Product Market Competition, Innovation, and Environmental Regulations

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Current Version: June 16, 2021

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ABSTRACT

This study examines whether and how competition affects corporate strategic responses to stringent environmental policies. Using the nonattainment status of U.S. counties as a source of exogenous variation in environmental regulation, we find that competition fosters green innovation as firms respond to stricter regulatory policy. Additional analyses using a subsample of firms in counties whose pollutant concentrations are marginally above or below EPA standards for regional air quality and exploiting exogenous variations in product market competition further reinforce our baseline evidence. The results suggest that the cost of relocation is a critical mechanism that compels firms to innovate when responding to tightened environmental policies and heightened competitive pressure. Regulation-induced green innovation helps competitive firms better achieve product differentiation and attract more corporate customers than their less competitive peers. Finally, competitive firms' strategic responses to stringent environmental regulations result in improved market share growth, markup, profit margin, and abnormal returns.

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

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

"Today, 63% of U.S. adults say stricter environmental regulations are "worth the cost," while 30% say such regulations "cost too many jobs and hurt the economy.""

The February 2019 Survey by Pew Research Center[1]

1. Introduction

Do environmental regulations do more harm or good? The above quote from the 2019 survey conducted by Pew Research Center shows that a majority of Americans say stricter environmental laws and regulations are "worth the cost." While the survey suggests that most Americans consider environmental regulations to do more good than harm, the question remains one of the most controversial political issues that society faces today as combating climate change becomes a growing global concern. U.S. leaders and policy makers have different views on the economic impact of environmental regulations. Some fear that environmental policies would threaten the competitiveness of business sectors and hamper economic growth.[2] They argue that regulations place firms at a competitive disadvantage as pollution reduction and cleanup costs lead to higher prices and reduced market share (e.g., McGuire 1982). Others, however, argue that regulatory pressures could enhance firm performance by encouraging innovation, thereby increasing economic prosperity (e.g., Porter 1991; Porter and van der Linde 1995). Yet there is limited research that looks at the underlying forces driving firms' varying responses to environmental regulations. Thus, the goal of this paper is to examine whether and how competition plays a crucial role in shaping corporate environmental policies when firms face stringent regulations and whether such policies bear significant economic consequences.

The conventional wisdom is that environmental regulations pose adverse consequences to many U.S. companies. The severity of such effects may vary with firms' product market competition. Firms that enjoy market power should experience a minimal negative economic impact on their product markets' competitive position as increased regulatory costs are passed through to product prices with little concerns for losing market share. Also, the opportunity cost for productive investments crowd

[1]https://www.pewresearch.org/fact-tank/2019/02/07/more-republicans-say-stricter-environmental-regulations-are-worth-the-cost/

[2]Following Bristow (2005), competitiveness is loosely defined as the ability of a firm to survive, compete, and grow in its market.

out by abatement should be small as firms facing less competition have fewer incentives to invest in innovation due to the "replacement effect" (Tirole 1988).[3] However, the negative consequences can be exceptionally costly for firms in fiercely competitive product markets. Economic theory posits that these firms are incentivized to develop innovation as a differentiation strategy to gain competitive advantages over their rivals (e.g., Aghion et al. 2005). Such benefits arising from innovative activity would result in better product-market performance and, in turn, a lower regulatory burden. Hence, product market competition ought to strengthen environmental regulations in promoting new pollution-reducing technologies (hereafter "green innovation").

We exploit the "nonattainment" status of U.S. counties as an exogenous source of variation in environmental regulation to examine whether competition affects firms' strategic responses to increased regulatory pressures. The Environmental Protection Agency (EPA) establishes National Ambient Air Quality Standards (NAAQS) for six widespread pollutants to act as a benchmark in assessing regional air quality. Counties whose pollutant concentrations are above (below) the specified threshold are designated as nonattainment (attainment) areas. Nonattainment counties are subject to much stricter regulatory monitoring and enforcement than attainment counties. Furthermore, we leverage the granularity of the recently available plant location data from Dun & Bradstreet and innovation output data from PATSTAT to construct a sample of innovative firms residing in 2,951 different counties during the 1996-2017 period.

Using county-level nonattainment designations as a quasi-natural experiment in a triple-difference setting, we study whether competition drives firms' green innovations when facing tight environmental regulation. Green innovations are identified as environmentally-sound technologies (ESTs) by the United Nations Framework Convention on Climate Change (UNFCCC).[4] Based on 523,791 firm-county-year observations and two different widely-employed firm-specific competition measures,[5] we find that competitive firms generate significantly more green innovation in response to an exogenous increase in environmental regulatory stringency than less competitive firms. For example, firms in the top competition-ranked decile experience an approximately 8% increase in green innovation out-

[3]A monopolist gains less from innovating than a competitive firm as the former is *replacing* itself as a monopolist.

[4]The list of ESTs is obtained from WIPO's website, https://www.wipo.int/classifications/ipc/en/green_inventory/.

[5]The competition measures are developed by Hoberg and Phillips (2010; 2016) and Hoberg, Phillips, and Prabhala (2014), namely, product market fluidity measure (*Fluidity*), and total product similarity score (*Similiarity*).

put relative to firms in the bottom decile following a nonattainment shock to one of their production locations. This evidence is robust to both two- and three-year-ahead innovative activity, more rigorous controls for county characteristics through county×year fixed effects, alternative classifications of pollution emitters, and the removal of firm-specific control variables.

One possible concern would be the endogeneity of nonattainment designations and regulatory stringency. Plausibly, a nonattainment status is not randomly assigned but hinges on county-specific characteristics such as the intensity of local business activity. Similarly, regulatory stringency could be endogenously driven by unobserved county-wide determinants, including the lobbying power of residing firms and strategic considerations of local governments, among others. However, the rigorous county×year fixed effects should largely alleviate such issues by controlling for all systematic differences across counties that may confound the causality of a nonattainment-induced regulatory shock. Nevertheless, to address any remaining concerns, we repeat the baseline analysis while restricting the sample to include only county-years whose pollutant concentrations are marginally above or below the NAAQS standards. In doing so, we reasonably ensure that any status change in a county arises from small variations in local emissions rather than heterogeneity in regional attributes. Alternatively, our results could also be spurious if the competition is endogenous. To mitigate such concern, we exploit large import tariff reductions to provide exogenous variations in a competitive environment. Import tariffs act as a barrier to entry for foreign rivals, so large cuts could lead to sharp shifts in competitive pressure that U.S. firms face from abroad. The findings from both quasi-natural experiments suggest that our baseline results are robust to potential endogeneity issues and that they capture a causal effect of competition on firms' strategic responses to regulatory changes.

Our analysis further shows that the relocation cost is a crucial mechanism that compels firms to innovate when responding to tightened environmental policies and heightened competitive pressure. In particular, we contend that competitive firms facing higher relocation costs would be more determined to foster green innovation in reacting to regulations than those facing lower costs. The reasons are twofold. First, firms facing high costs cannot readily shift their local production and must remain in areas undergoing nonattainment classifications and face the associated adverse consequences. These firms tend to bear a higher regulatory burden than companies with more mobility but choose to stay following policy shocks. In combating such negative regulatory impacts, locally entrenched competitive firms would have stronger incentives to innovate relative to those that can easily relocate. Second, the relocation cost would induce innovation as an alternative means to minimize compliance costs. Hence, regulations are more effective in triggering innovative activity among less mobile firms. Using plant fixed costs and the extent of agglomeration economies to measure relocation costs, we find evidence supporting the mechanism. Specifically, the baseline relationship is significantly more pronounced for industries that are less geographically mobile.

Next, we explore the possible sources of gain in competitive strengths arising from green innovation. In particular, competitive firms' innovative response to environmental regulations may lead to increased product differentiation and better customer attraction than other firms in less competitive markets. Consistent with this idea, we show that firms at the top competition-ranked decile achieve a 6% reduction in product similarity and a 5% increase in the number of corporate customers relative to firms in the bottom competition-ranked decile after a regulatory shock. Further analyses show that business expansion is concentrated in corporate customers that are unable to generate green innovation themselves, suggesting that newly developed emissions-cutting technologies can help competitive firms in accessing markets with strong demand for green inventions and products.

Finally, we evaluate the economic consequences of the heterogeneous firm responses to environmental regulations. Our results suggest that competitive firms achieve better post-regulatory-shock operating performance than their less competitive counterparts. Specifically, a higher level of competition is associated with significant increases in the treatment effects of a nonattainment shock on market share growth, pricing power, and profitability. We interpret the better product-market performance as an outcome of competitive firms' stronger incentives to innovate and differentiate, thereby reducing and, at times, even outweighing the compliance cost. Their performance in the financial market further substantiates this interpretation. We find that the market reacts more favorably to firms facing intense competition as measured by their buy-and-hold abnormal returns for the one year following a nonattainment shock. Also, in line with better performance, competitive firms are less likely to cut jobs in the regulated regions, challenging the conventional view that environmental regulations decrease labor demand.

This study makes an important contribution to the real impact of environmental regulations on firm competitiveness. One strand of the literature studies the effects of environmental regulations on green innovation. For example, Lanjouw and Mody (1996), Jaffe and Palmer (1997), and Brunnermeier and Cohen (2003) find that stricter regulations lead to higher R&D expenditures and more environmental patents. Gray and Shadbegian (1998), Popp and Newell (2012), and Aghion et al.(2016) show that increased green inventions crowd out other productivity-improving innovation and hence can be detrimental to firm competitiveness. In contrast, Calel and Dechezleprêtre (2016) find no evidence of firms diverting investments from productivity to abatement. Lanoie et al. (2011) also suggest a positive link between environmental innovation and business performance. Our paper advances this research by showing that competition plays a vital role in the interplay between regulatory stringency and innovative activity. Our study is the first to look at competition as a critical underlying mechanism that shapes corporate environmental policies in firms' response to stringent environmental regulations. Furthermore, our comprehensive approach to examining the innovation policies and a series of economic consequences allows us to better draw conclusions on the overall impact of environmental regulations and firm responses on competitiveness.

Our work also helps to address the criticism that value-enhancing innovation triggered by environmental regulations would be inconsistent with firm value-maximization (e.g., Palmer, Oates, and Portney 1995). Thus far, prior research takes a theoretical approach to show that this is not the case. For example, Ambec and Barla (2007) and Ambec et al. (2013) argue that asymmetric information about environmental quality creates a "market for lemons" where only dirty products would be supplied, and green investments would be curbed. Environmental regulations can reduce such information asymmetry and encourage green innovation by revealing information that benefits those who supply clean products. Other theoretical work such as Simpson and Bradford (1996) and Mohr (2002) similarly provide certain conditions under which post-regulatory value-enhancing innovation is consistent with value-maximizing goals. However, little is known whether these theoretical predictions hold in the data. Our study provides new empirical evidence that, under a competitive environment, regulations foster value-enhancing innovation for profit-maximizing firms. A recent study by Bartram, Hou, and Kim (2019) is related to our work. The authors empirically show that financial constraints play an important role in plant closure decisions when firms face environmental regulations. However, their study focuses on abatement performance rather than the competitiveness of affected firms.

Our paper also contributes to the corporate social responsibility (CSR) literature. Prior studies suggest that firms can "do well by doing good" as they benefit from high product quality signaling (e.g., Fisman, Heal, and Nair 2006; Siegel and Vitaliano 2007), increased customer willingness to pay (e.g., Bagnoli and Watts, 2003; Baron 2008, 2009), improved employee morale and retention (e.g., Turban and Greening 1997), and positive CSR spillovers to suppliers (e.g., Dai, Liang, and Ng 2020) among others. Fernandez-Kranz and Santalo (2010) and Flammer (2015) also document that firms under intense competition tend to strategically engage in CSR practices searching for competitive advantages. Our study expands this line of research by showing that competitive firms foster green innovation to better differentiate themselves from their rivals.

Finally, our results have important policy implications. They suggest that policy efforts to protect environments could benefit firms in competitive markets. Stringent environmental policy improves the environment and competitiveness by pushing competitive firms into developing cost-reducing clean technologies and more efficient ways to produce green products. Therefore, environmental regulations promote growth through green innovation that is more environmentally friendly.

The remainder of the paper is organized as follows. Section 2 details the nonattainment designation. Section 3 describes the data and construction of the primary sample. Section 4 formulates the empirical methodology used to conduct the main analyses and reports the results. Section 5 investigates a potential mechanism behind the relationship. Section 6 explores possible gains in firms' strategic positions, and Section 7 analyzes the resulting corporate environmental policies' economic consequences. The final section concludes.

2. Identification Strategy - Nonattainment Designations

Following the 1977 amendments to the Clean Air Act (CAA), EPA mandates every county in the United States to be classified as either an attainment or a nonattainment zone using the NAAQS standards as a benchmark. The NAAQS is established by EPA for six widespread pollutants (carbon monoxide, sulfur dioxide, lead, nitrogen dioxide, total suspended particulates, and ozone), specifying the maximum level of concentrations allowed without harming public health and the environment. EPA reviews, and if necessary, revises the NAAQS every five years to ensure adequate protection of air quality. Once a new set of standards is enforced, it triggers a classification process in which counties whose pollutant concentrations above (below) the most recent thresholds are designated as nonattainment (attainment) areas. The nonattainment areas are required to provide State Implementation Plans (SIPs) detailing the implementation, maintenance, and enforcement of local air quality management programs to better comply with the standards. When these counties attain the regulatory standards, they get reclassified as attainment zones. They remain at this status until the next NAAQS revision and classification process. While SIPs vary state-by-state, they generally follow EPA's guidelines in curbing emissions. Beyond the necessary emissions control, inspections and regulatory oversight are also more frequent in nonattainment areas. Thus, the existing polluting plants in nonattainment counties face significantly more stringent environmental regulations than similar polluters in attainment counties.

Such regulatory variations across attainment and nonattainment counties provide an appropriate setting for our study's identification strategy. First, it is reasonable to assume that regulations in nonattainment counties are significantly more stringent than those in attainment counties and effectively enforced on polluting plants. All SIPs must be approved by EPA to ensure a sufficient level of regulatory stringency for nonattainment areas. Failure to provide a satisfactory plan would result in the enforcement of the Federal Implementation Plan (FIP) developed by EPA. Upon approval, those control measures would be enforceable in state and federal courts, giving both the states and EPA legal standings to monitor progress and fine non-compliers. Furthermore, EPA can penalize states that do not sufficiently enforce the regulations, such as withholding federal grants and suspending new facility constructions (e.g., Dancy 1994; Becker and Henderson 2000; Greenstone 2002). These abatement programs in nonattainment areas are effective, as evident in the decline of emissions and the increase in plant operating costs relative to attainment areas (Becker and Henderson 2001; Chay and Greenstone 2005).

Second, nonattainment designations are as good as randomly assigned across counties. All counties are evaluated on the same NAAQS standards, so a nonattainment status should be exogenous to all county-specific characteristics other than local air quality conditions. While one might argue that economic activities affect air quality, such concern is less critical given a low correlation between the nonattainment status and the number of local production facilities. Existing studies also alleviate such concern by showing that nonattainment is often related to wind patterns, causing air pollutants to travel and accumulate in certain regions (Cleveland et al. 1976; Cleveland and Graedel 1979). Furthermore, only exogenous revisions of NAAQS rather than any substantial changes in county-level conditions can trigger a change from attainment to nonattainment designation. This regulatory design is consistently depicted in Figure 1.[6] Each panel of the figure illustrates the number of counties experiencing status change for one pollutant. A positive (negative) value indicates a net switch from attainment (nonattainment) to nonattainment (attainment) status. According to Figure 1, a net switch always reaches a local peak in few years following a standard revision but tends to stay non-positive for the remaining period, suggesting that only NAAQS revisions would drive nonattainment classifications. Nevertheless, we address any remaining concerns by restricting the sample to county-years, where the regional pollutant concentration is marginally above or below the standards. Our approach reasonably ensures that a status change is as good as randomly assigned while holding other county-specific conditions constant.

Lastly, the induced regulations are free from county-wide influences. EPA's approval of SIPs limits the variance in regulatory stringency across counties, and its enforcement power curbs the states' ability to overlook non-compliers. Thus, county-wide influences, such as local firms' collective lobbying power, the county's political environment, and other local government considerations, would have little effects on regional regulations. We also eliminate any remaining endogeneity concern by including county$\times$year fixed effects, which remove all unobserved time-varying county characteristics.

[6] Historical NAAQS are obtained from the EPA website: https://www.epa.gov/criteria-air-pollutants/naaqs-table.

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 World Patent Statistical Database (PASTAT) maintained by European Patent Office (EPO); (iii) product market competition measures developed in Hoberg et al. (2014) and Hoberg and Phillips (2010; 2016), which are made available via Hoberg and Phillips data library; (iv) historical CAA nonattainment designations information from EPA Green Book; (v) criteria pollutant emissions data from EPA's Enforcement and Compliance History Online (ECHO); (vi) supplier-customer relationship data from Factset Revere and Compustat's customer segment files; (vii) stock returns from CRSP; and (viii) firm financial information from Compustat.

We match the information on plants with a minimum of ten employees with publicly traded parent companies in Compustat using a linking table between plant DUNS numbers and CUSIP identifiers provided by Mergent. The matched data is used to form an initial sample of firm-county-level observations describing the number of plants a public firm has in a county each year. We restrict the sample to innovative firms with at least one patent filed (and granted) two years ahead to construct green innovation. Since nonattainment-induced regulatory shocks are only effective towards local "polluters", our sample further excludes non-emitting plants. Data limitations in ECHO render classifications of "polluters" and "nonpolluters" at the firm-level improbable. Plant-level emissions information on the six criteria pollutants is only available for years 2005, 2008, 2011, and 2014, and less than 10% of such data can be matched to a plant DUNS number.[7] To circumvent such data challenge, we define "polluters" at the industry-level, specifically, as those 3-digit SIC industries with positive total emissions over the four years during which ECHO data is available. Finally, we remove any observations with missing values for control variables and exclude financial and regulated utility firms (SIC codes 4900-4999 and 6000-6900). The selection process yields a sample of 523,791 firm-county-year observations, consisting of 1,932 unique innovative firms residing in 2,951 counties over the 1996-2017 period. Our sample period is bounded by the availability of Hoberg and Phillips'

[7] Using a linking table between ECHO's unique identifier FRS and DUNS number made available on EPA's website https://echo.epa.gov/tools/data-downloads, about 25,000 of over 260,000 plant-county-year observations are matched to Dun & Bradstreet.

competition data. The actual number of observations varies across analyses, given different data availability for the main variables of interest. The definitions for all the key variables are depicted in Appendix A.

3.1. Measures of green innovation

We construct measures of green innovation using data drawn from PATSTAT. The database contains more than 100 million patent records from over 40 patent authorities worldwide filed as far back as 1844. It provides detailed information on each of the patent applications, including the date of the application, the applicant's (owner's) name, citations made (backward) and received (forward) by each patent, the patent's technology field identified using International Patent Classification (IPC), and the grant status. We manually match the applicant information with firms in Compustat to obtain patents owned by U.S. corporations. Since most of a patent's value is achieved when the patent is granted and the owner can enforce its exclusive right, we focus on patent applications that are eventually granted.

From our sample of patent applications, we extract those relating to clean technologies. Our selection relies heavily on the work by the World Intellectual Property Organization (WIPO). The WIPO constructs a comprehensive list of IPCs considered environmentally-sound technologies (ESTs) from the information on essential green technologies provided by the United Nations Framework Convention on Climate Change. The list, also known as the IPC Green Inventory, contains 200 topics on alternative energy production, energy conservation, transportation, waste management, agriculture and forestry, and nuclear power generation.

Focusing on these ESTs, we construct four measures to capture green innovation output. The first measure is the total number of EST patent applications a firm files in a given year (*Green Patents*), following earlier studies (e.g., Brunnermeier and Cohen 2003; Aghion et al. 2016). It suffers from a truncation problem due to the lag between a patent's application year and its grant year. Many patent applications filed in the last few years of the sample period were still under review and hence are not included in our sample. In fact, we observe a gradual decline in the number of patents since 2015, which coincides with about two years of application-grant lag on average. Following

Hall et al. (2001; 2005), we correct for this truncation bias using weight factors estimated from the application-grant lag distribution of the patents filed and granted between 2010 and 2015.

The second measure is the total number of forward citations a firm's EST patents receive in subsequent years (*Green Cites*). *Green Cites* is a better metric to assess the quality of green patents by distinguishing breakthrough green innovation from incremental discoveries.[8] This citation measure also suffers from a truncation problem, whereby patents continue to be cited after the end of our sample period, but we only observe citations received up to 2017. To address this issue, we scale the citation measure by the technology-field-average citation counts (measured at the 3-digit IPC level) each year, following Hall et al. (2001; 2005).

Besides the firm-specific measures of green innovation, we take similar approaches to construct two more firm-county-specific proxies. Specifically, a slight variation of *Green Patents* is the number of a firm's EST patent applications cited by its local corporate customers with at least one plant residing in the same county ($Green\ Patents^{Local}$). Such a localized measure serves two purposes: (1) to gauge the impact of a regulatory shock on local innovative activity; and (2) to capture a firm's innovative efforts in maintaining or accessing the local product market. Similarly, $Green\ Cites^{Local}$ is defined as the number of citations on a firm's green patents received from local customers. All measures are adjusted for truncation biases.

We use the natural logarithm of the above four measures in our analysis. To avoid losing observations with zero green patents and citations, we add one to the actual values when calculating the log form.

3.2. Measures of product market competition

This study employs two firm-specific measures of product market competition.[9] First, we use the product market fluidity measure (*Fluidity*) introduced in Hoberg et al. (2014). The authors analyze

[8] In a previous version of the working paper, we construct another green innovation measure that considers all patents filed by a firm and count the number of forward citations they receive from other firms' green patents (*Cites By Green*). Such a measure accounts for inventions that may not necessarily classify as ESTs but are crucial components on which other green technologies are built. Analyses using *Cites By Green* yield similar findings as other proxies. Results can be provided upon request.

[9] We additionally employ Herfindahl-Hirschman Index as another measure of competition in a previous version of the paper. The analysis results are qualitatively similar as those from using the firm-level competition measures.

product descriptions in 10-K filings and construct *Fluidity* to capture the extent to which rivals with similar product vocabulary as a firm are changing their product keywords in the next year. It captures competitive threats from two dimensions: (1) the overlap of keywords between the firm and its rivals; and (2) the dynamic changes of rivals' products. Thus, fluidity reflects both the degree of product similarity with competitors and the product market's instabilities arising from competitor actions. A higher value is associated with a more significant competitive threat for a firm.

The second measure is the total product similarity score (*Similarity*) constructed by Hoberg and Phillips (2010, 2016). It also relies on the information drawn from 10-K filings. Using product keywords, the authors compute firm-by-firm pairwise cosine similarities to group firms into industries, known as text-based network industries (TNIC). The similarity score is then obtained by taking the sum of cosine similarities across all firm rivals in the same TNIC industry. It increases with both the number of competitors and product relatedness of each competitor, thereby reflecting the level of competitive pressure that a firm faces.

3.3. Summary statistics

Table 1 reports county-level characteristics by state. Columns (1) and (2) document the average number of firms and plants per county in each state. Massachusetts has the highest number of innovative firms and plants per county on average (46 and 109, respectively), whereas South Dakota has the lowest (2 and 3, respectively). This observation comes as no surprise given that Massachusetts is ranked as one of the most innovative states and South Dakota the least.[10] Column (3) shows the number of counties in each state that was nonattained at least once during the sample period. Column (5) reports the number in Column (3) as a percentage of the total number of counties in the sample. Hawaii, North Dakota, Oklahoma, South Dakota, and Vermont have the lowest percentage of nonattainment counties (0%) in the sample, an indication of their healthy air quality conditions according to the NAAQS. On the other hand, all the counties in Connecticut, Delaware, New Jersey, Massachusetts, and Rhode Island were once nonattained. Prior research attributes the low air quality in Connecticut, Delaware, and New Jersey to the pollution transported from upwind states (e.g.,

[10] An example of such ranking would be Bloomberg's annual State Innovation Index.

Cleveland et al. 1976, 1979).[11] The last column documents the average period of nonattainment status in each state. Mississippi, Iowa, Florida, and Minnesota have the shortest average duration of 4 years, while Connecticut, Delaware, New Jersey, Massachusetts, and Rhode Island have the longest of 20 years).

Table 2 presents summary statistics of the key variables used in this study. About 46% of the firm-county-years in the sample are in nonattainment counties. Conditioning on having plants in a county, an average firm owns about two plants in an area and employs over 50 workers (ln(1+50)=3.932). On average, a firm has 2.3 (ln(1+2.293)=1.192) granted EST patents per year, which is comparable to previous studies (e.g., Brunnermeier and Cohen 2003), and these patents receive about one technology-field-adjusted citation (ln(1+0.924)=0.654). The *Fluidity* measure has an average of 0.058 and a median of 0.052, which is consistent with the statistics reported in Hoberg et al. (2014).[12] *Similarity* takes on an average value of 0.024 and a median value of 0.013.

Drawn from the innovation literature, we control for a set of firm characteristics that may affect innovation output. They include the natural logarithm of total assets (*Size*), growth opportunities as measured by Tobin's Q (*TobinQ*), leverage ratio (*Leverage*), asset tangibility (*Tangibility*), R&D expenditures (*R&D*), capital expenditures (*CapEx*), profitability (*ROA*); and the natural logarithm of the number of a firm's local employees (*Employees*). An average firm has a book value of $5.412 billion, a Tobin's Q of 1.995, a leverage ratio of 23.8%, and a ROA of 0.140. In addition, R&D expenditures, capital expenditures, and tangible assets account for 3.4%, 4.6%, and 25.3% of an average firm's total assets, respectively.

4. Environmental Regulation, Competition, and Green Innovation

In this section, we examine whether competition influences corporate environmental policies when firms face stricter pollution regulations. Specifically, we investigate the effect of competition on a firm's green innovative output in its response to an exogenous increase in environmental regulatory stringency. We also conduct several tests to ensure robustness of our baseline evidence.

[11] https://www.law.nyu.edu/centers/state-impact/issues/clean-air/clean-air-act-and-upwind-pollution.

[12] *Fluidity* and *Similarity* are scaled by 100 in this study.

4.1. Baseline evidence

To examine the role of competition in shaping a firm's innovative response to environmental regulation, we estimate the following triple-difference model using pooled ordinary least squares (OLS) regressions:

$$\begin{aligned} Green\ Innovation_{y,t+z} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c \\ & + \alpha_3 Treat_c \times Comp_{i,t-1} + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} \\ & + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned} \tag{1}$$

where *Green Innovation*$_{y,t+z}$ denotes firm i's or firm-county i, c's green innovation outcomes at years $t+2$ and $t+3$, including *Green Patents*, *Green Cites*, *Green Patents*^{Local}, and *Green Cites*^{Local}. To reflect the long-term nature of investment in innovation, we consider the innovation output generated two and three years ahead. *Comp*$_{i,t-1}$ denotes one of firm i's competition measures, namely, *Fluidity* and *Similarity* at year $t-1$. Lagged competition measures are used to alleviate reverse causality concerns or omitted variables simultaneously affecting a firm's competitive environment and the regional regulatory stringency. *Treat*$_c$ is a binary indicator that equals 1 if the county c has ever been classified as a nonattainment county during the sample period and 0 otherwise. *Post*$_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise. $X_{i,c,t}$ is a vector of control variables defined earlier, measured for firm i in county c at the end of year t. A detailed definition of all variables is provided in Appendix A. We control for firm, county, and year fixed effects, which subsume the time-invariant $Treat$. Since $Treat$ would always equal to 1 when *Post* is 1, *Post* is perfectly correlated to $Post \times Treat$ and $Post \times Comp$ is perfectly correlated to $Post \times Treat \times Comp$. Thus, *Post* and $Post \times Comp$ are omitted in regressions. Standard errors are clustered at the firm-year level.

Table 3 contains the results of our main tests. Panels A and B of the table show the regression results where the dependent variables are firm-level and firm-county level green innovation at year $t+2$, respectively. The primary coefficient of interest is α_1, the triple interaction term $Post \times Treat \times Comp$, which captures the difference in treatment effects of a nonattainment shock across firms with varying degrees of competition. The α_1 estimates are all positive across different green innovation output measures. These estimates are mostly statistically significant at the 1% level, suggesting that competitive firms generate more green innovation in response to a regulatory change than firms with less competitive concerns. For example, Columns (1)-(2) of Panel A indicate that firms in the top competition-ranked decile produce about 2% (e.g., 0.343/1.192$\times$(0.103-0.024)=0.023, where 0.024 and 0.103 are the 10th and 90th percentile values of *Fluidity*, respectively) more EST patents than firms in the bottom decile following a nonattainment shock to one of their production locations. Such an effect has a significant bearing on a firm's overall green innovative investments since a median firm operates in eight nonattainment counties simultaneously, resulting in an aggregate impact of about 16%. The differential treatment effects on patent quality are also large. Columns (3)-(4) show that top competition-ranked decile firms receive about 4%-5% (e.g., 0.411/0.654$\times$(0.103-0.024)=0.050) more post-shock citations for their EST patents relative to bottom decile firms.

Panel B reveals strong influences of regional environmental regulations on local innovative activity. The triple interaction coefficients for $Green\ Patents^{Local}$ are positive and statistically significant at the 1% level, suggesting that competitive firms are more likely to adopt green innovation locally under stringent regulations than firms facing less competitive pressure. In terms of economic magnitude, the relative difference in the treatment effects between the top and bottom competition-ranked decile firms ranges from 23% to 42%. The findings on $Green\ Cites^{Local}$ further substantiate the importance of competition in encouraging post-shock local green innovation. The α_1 estimates are positive and significant in all specifications. Specifically, the point estimates are 0.025 ($t-$stat$=2.81$) in Column (3) and 0.027 ($t-$stat$=3.41$) in Column (4).

The difference-in-difference coefficient of $Post \times Treat$, α_2, on the other hand, indicates a negative treatment effect on less competitive firms. As shown in Panels A and B, the α_2 estimates are negative and statistically significant across all specifications. Such results, at the minimum, suggest that, without competitive pressure, environmental regulations alone are ineffective in encouraging green innovation, consistent with our *prior.* Interestingly, rules can go as far as to inhibit innovative activity for these firms. One potential explanation for such a negative impact on innovation would be the crowding-out effects of compliance costs. As previously hypothesized, less competitive firms have fewer incentives to innovate and can easily forego innovative investments for abatement expenditure.

We repeat our above tests using firm- and firm-county level green innovation at year $t+3$ and report these results in Panels C and D. While the findings are broadly consistent with those shown in Panels A and B, the α_1 estimates are slightly weaker, indicating that competitive firms' green innovative output occurs within the first two years following the shock. Taken together, our results provide strong and consistent evidence that product market competition strengthens environmental regulation in promoting green innovation. However, to conserve space, we shall report only results using two-year-ahead innovation in subsequent sections.

Our above findings advance the existing literature on the relationship between environmental policies and green innovation. While existing studies (e.g., Lanjouw and Mody 1996; Jaffe and Palmer 1997; Brunnermeier and Cohen 2003) point to an overall increase in green innovation activity for firms affected by environmental regulations, our results attribute such a boost to mainly competitive firms. Our findings suggest that regulations do more good for competitive firms than for other affected companies to the extent that green innovation may lead to enhanced firm performance and more robust growth.[13]

4.2. Robustness tests

We undertake a rich set of robustness tests for our baseline results. First, to control for any omitted county-specific characteristics, we repeat the baseline analysis using firm and county×year fixed effects. Such specification accounts for all systematic differences across counties, including factors that may potentially confound the causal relationship between regulations and firm behaviors. This approach helps to alleviate potential endogeneity concerns one may have over nonattainment designations and local regulatory stringency. Panel A of Table 4 presents the estimated results for firm-level green innovation measures. The multiplicative fixed effects subsume all the time-variant county-level variables, including the interaction term $Post \times Treat$, but the coefficient of $Post \times Treat \times Comp$ remains strongly positive. The coefficient estimates are statistically significant across all four sets of regressions, confirming our baseline findings on the asymmetric regulatory effects across firms in different competitive environments. Unreported analyses of firm-county-level green innovation

[13]We show in later sections that green innovation indeed contributes to the improvement of firm competitiveness.

measures yield a similar conclusion. That is, they generate significant results in all specifications.

Second, we test our findings against alternative classifications of polluting industries. One may argue that the current definition is incapable of eliminating all the non-polluters from the sample, and hence the baseline results could be driven by those non-polluters. While plausible, it should underestimate our coefficients since non-polluters are not subject to stricter regulations induced by nonattainment shocks. Nonetheless, to alleviate this concern, we apply more rigid definitions of polluting industries: (1) industries with average emissions of at least 100 tons per firm; (2) industries with above-median industry-total emissions. As shown in Panels B and C of Table 4, the results suggest that while the two alternative classifications, respectively, eliminate about 9% and 19% of the main sample, the α_1 estimates remain materially unaffected.

Finally, we address the potential issues arising from bad controls. To the extent that regional environmental regulations have other influences on a firm than its corporate environmental policies, firm-specific controls may themselves be outcomes of nonattainment treatment effects. For example, a firm's growth opportunities, as measured by Tobin's Q, may hinge on regulations and their impacts on corporate investment decisions. Having those endogenous variables as controls would produce biased estimates. To rule out such concerns, we remove the vector of time-variant control variables $X_{i,c,t}$ from the regression models and repeat our baseline analysis. The results, reported in Panel D of Table 4, show more robust estimates of the triple interaction variable in terms of both the magnitude and statistical significance than their baseline regression counterparts.

Overall, our key evidence is robust to a battery of tests and consistently suggests that competitive firms generate significantly more green innovation output following nonattainment shocks than their less competitive peers.

4.3. Additional endogeneity tests

As discussed in earlier sections, there should remain little concerns over the endogeneity of nonattainment designations and regulatory stringency. Nevertheless, we conduct an additional robustness check to support the causal interpretation of our baseline findings. Specifically, we re-estimate the baseline regressions using only the subsample of county-years whose pollutant concentrations are marginally above or below the NAAQS. Such an approach reasonably captures county status changes arising from small variations in local emissions rather than the heterogeneity in regional attribute, thereby, in effect, randomly assigns regulatory shocks across counties.

We employ county-level emissions data available in EPA's Air Quality System (AQS) database. For each of the six pollutants, we define a bandwidth around the NAAQS threshold as 10% above and below the threshold values and restrict the sample to county-years falling within the bandwidth.[14] Since NAAQS are revised every few years, so are the bandwidths. For example, between 1997 and 2007, the EPA requires the annual 4th highest daily maximum (4th maximum) 8-hour ozone concentration of fewer than 0.08 parts per million (ppm). The bandwidth of ozone concentration is, therefore, set to 0.072 and 0.088 ppm during the ten years. When the standard drops to 0.075 ppm in 2008, the revised bandwidth becomes 0.068-0.083 ppm. The restricted sample consists of about 150,603 firm-county-year observations. Table 5 presents the regression results. The estimates of α_1 are qualitatively similar to what we have found in the baseline analysis, with statistical significance in three of the four regressions on firm-level outcomes. Untabulated firm-county-level regression results reach a similar conclusion. These findings underscore the causal relationship between environmental regulations and green innovativeness.

Another potential endogeneity concern arises from product market competition. Our results could be spurious if the competition is endogenously determined by regulatory pressure or other unobservable shocks. To allay this concern, we exploit large import tariff reductions in the U.S. to provide exogenous variations in a competitive environment. Prior literature suggests that significant reductions in tariff rates will expose domestic firms to foreign rivals, leading to sharp increases in competition faced by U.S. corporations (e.g., Frésard 2010; Valta 2012). Using import data from Schott (2008), we compute the tariff rate for each industry-year as the collected duties divided by the custom value of imports.[15] Following Huang et al. (2017) and Chen et al. (2020), we identify large tariff reduction events as industry-years that experience tariff rate decreases relative to the previous year by more than four times the median tariff rate reduction during our sample period. To ensure

[14] Applying a narrower bandwidth at 5% around the threshold eliminates about 90% of the main sample and yields similar, albeit weaker, results as those from using 10%.

[15] The U.S. import data for the period 1996-2017 is obtained from Peter K. Scott's website: https://faculty.som.yale.edu/peterschott/international-trade-data/.

that these tariff rate reductions reflect only non-transitory changes in the competitive environment, we exclude declines preceded or followed by a tariff increase greater than 80 percent of the reduction. Our robust test uses a dummy indicator, $Tariff_{i,t-1}$, which equals to 1 for the two years after the industry has experienced a large tariff cut and 0 otherwise, in place of $Comp_{i,t-1}$ in Eq. (1).

As reported in Table 6, the estimates on $Post \times Treat \times Comp$ are positive and mostly statistically significant at the 5% level. The results confirm our prediction that competitive firms generate more green innovation in response to increased regulatory pressure than their less competitive counterparts. For instance, as shown in Column (1), an analysis of *Green Patents* yields an α_1 estimate of 0.035, indicating that firms in industries with tariff reductions develop about 3% (0.035/1.192=0.029) more EST patents following a nonattainment shock relative to other firms in industries without tariff reductions. In contrast, the coefficient on $Post \times Treat$ is negative and statistically significant, suggesting a reduction in green innovation for those firms not experiencing tariff reductions. Such a finding is also consistent with our *prior* that environmental regulations are ineffective in stimulating green innovation without competitive pressure.

Overall, the various endogeneity tests reported in this section support the causal interpretation of the combined effects of environmental regulation and competitive pressure on corporate environmental policies.

5. A Key Mechanism

In this section, we explore whether the cost of relocation is a critical underlying mechanism that compels firms to innovate when responding to tightened environmental policies and heightened competitive pressure. We posit that such a cost would intensify the real impacts of regulatory and competitive pressures for two reasons. First, firms facing higher relocation costs are geographically less mobile. These firms would be forced to remain in the local region following policy shocks and face the associated adverse consequences. In contrast, relocation would be easier for firms with more mobility to avoid significant compliance costs. Consequently, among the companies that remain following regulatory changes, those with less mobility tend to bear the disproportionate regulatory burden than their counterparts with greater mobility and, in turn, react more strongly to policy shocks. Second, higher relocation costs would induce alternative means of minimizing compliance costs, including integrating green innovation into their business strategies. Hence, the more geographically entrenched the firms are, the more likely they will respond through innovative activity.

If the cost of relocation is a crucial mechanism, our baseline relationship ought to be more pronounced for firms with less mobility. In particular, immobility should provide stronger incentives for competitive firms to innovate when facing severe negative consequences of regulations. Conversely, it would have little stimulating effects on less competitive firms given limited regulatory impacts on their competitiveness and a lack of desire for these firms to invest in innovation due to the "replacement effect". If anything, the higher regulatory costs induced by immobility may further divert resources from innovation to abatement through stronger crowding out effects.

To empirically test this mechanism, we conduct subsample analyses based on two alternative definitions of industry mobility. Our first measure of immobility is the industry-total plant fixed costs. Industries that sink a large amount of investments into local plants are less likely to close and relocate their local production, and hence, face a higher relocation cost. Following Ederington, Levinson, and Minier (2005), we use data from the NBER-CES Manufacturing Industry Database developed by Bartelsman, Becker, and Gray (2013) and define industry mobility as real structures capital stock scaled by the total value of shipments.[16] To overcome the coverage limitation of the data, we compute the industry means over the data period in constructing a time-invariant measure of plant fixed costs.

Another measure of immobility is the extent of agglomeration economies of an industry. Existing literature (e.g., Marshall 1920; Ellison and Glaeser 1999; Ellison, Glaeser, and Kerr 2010) demonstrate that firms concentrated in the same geographic area may benefit from economies of agglomeration in the form of reduced costs of transporting goods, people, and ideas. Such gains represent opportunity costs for those firms moving their plants away from the region. Thus, industries that enjoy agglomeration economies also face a high cost of relocation. Taking a similar approach as

[16] The plant fixed cost data is available at the 3-digit SIC industry level for the period 1996-2011 on the NBER website: https://www.nber.org/research/data/nber-ces-manufacturing-industry-database.

Ellison et al. (2010), we estimate each industry's geographic concentration. The measure is defined in Eq. (2) as shown below.

$$Agglomeration_{l,t} = \frac{\sum_{c}^{C}(s_{l,c,t} - x_{c,t})^2}{1 - \sum_{c}^{C} x_{c,t}^2}, \tag{2}$$

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. The construct measures deviations from randomly distributed employment patterns. It equals to zero when industry employment is randomly distributed across all C counties but increases with geographic clustering of employees in industry l. To identify industries with higher cost of relocation, we divide the sample into terciles every year based on each of the immobility measures. Industries in the top tercile of the distribution is grouped into the most mobile subsample, while those in the bottom tercile is grouped into the least mobile subsample. We re-estimate the main regressions separately for each subsample and present the results in Table 7.

Analyses based on plant fixed costs and agglomeration economies are reported in Panels A and B, respectively. Consistent with our prediction, the significant impact of environmental policies and competition is primarily concentrated in immobile industries. The estimates on the triple-interaction term are positive and mostly significant at the 5% level within the least mobile subsample, as shown in Columns (1)-(2) and (5)-(6) of both panels. An inter-decile increase in competition is associated with about a 2%-5% (e.g., 0.694/1.192×(0.103-0.024)=0.050) increase in post-regulatory green patents and 4-6% (e.g., 0.496/0.654×(0.103-0.024)=0.060) increase in forward citations. These results are in clear contrast to the insignificant α_1 estimates within the most mobile subsample, as shown in Columns (3)-(4) and (7)-(8). The mobile estimates are also generally smaller in magnitude relative to those in the immobile group.

As predicted, the coefficient on $Post \times Treat$ tends to be negative and are marginally significant within the least mobile industry subsample, suggesting a slightly negative regulatory impact on the innovative responses of less competitive and immobile firms (Columns (1)-(2) and (5)-(6)). The regulatory impact on more mobile industries is similarly negative but largely insignificant (Columns (3)-(4) and (7)-(8)). Such findings support the notion that environmental regulations have limited stimulating effects on green innovation for firms with little competitive concerns. It is also consistent with our conjecture that immobility may further reduce post-regulatory innovation output for these firms through crowding-out effects.

Taken together, the results in subsample analyses indicate that environmental regulations can trigger stronger reactions from firms with less mobility. These findings provide strong support to the cost of relocation mechanism.

6. Possible Gains in Competitive Firms' Strategic Positions

Thus far, the results demonstrate that competition plays a vital role in firms' strategic responses to environmental regulations. In this section, we explore the possible sources of gains in competitive strengths arising from these responses. More specifically, we examine whether regulation-induced green innovation would help competitive firms better achieve product differentiation and attract more corporate customers than less competitive firms.

6.1. Product differentiation

We contend that firms fostering green innovation after regulatory shocks would benefit from better product differentiation. To test this prediction, we construct two alternative proxies of product differentiation. Our first measure is the patent originality score proposed by Trajtenberg, Jaffe, and Henderson (1997). This score gauges the novelty of an invention by examining the breadth of technology domain on which the invention relies, as defined in Eq. (3) shown below.

$$Patent\ Originality_{j,t} = 1 - \sum_{k}^{n} p_{j,k,t}^2, \tag{3}$$

where $p_{j,k,t}$ is the percentage of backward citations made by patent j to patent class k (at the 3-digit IPC level) out of n patent classes. $Patent\ Originality_{j,t}$ takes on a higher value when patent j is built on a large number of diverse technology fields, and vice versa. As suggested by Trajtenberg et al. (1997), innovation advanced from a broad diversity of knowledge sources, as opposed to the same technology domain, should lead to more original output. Hence, a higher originality score indicates a greater degree of product novelty. We average the originality measure across all patents filed by firm i at year $t+2$ to proxy for product differentiation arising from green innovation.

Another measure of novelty is the product similarity score. To the extent that green innovation is an effective differentiating strategy, the product similarity score (Hoberg and Phillips 2010; 2016) between a competitive firm and its rivals should be reduced following a nonattainment shock. To facilitate comparison, we take the negative average value of the scores between firm i and its peers in the same industry at year $t+2$ (*Product Dissimilarity*). Similar to the *Patent Originality* score, a greater *Product Dissimilarity* value signifies more product novelty.

We next evaluate the differential treatment effects of nonattainment shocks across firms with varying degrees of competition by re-estimating Eq. (1) with a product differentiation measure in place of *Green Innovation*, as follows.

$$\begin{aligned} Product\ Diff_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c \\ & + \alpha_3 Treat_c \times Comp_{i,t-1} + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} \\ & + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned} \tag{4}$$

where $Product\ Diff_{i,t+2}$ denotes firm i's product differentiation measure at year $t+2$.

Table 8 presents the results. The estimates of the $Post \times Treat \times Comp$ coefficient are consistently positive in Columns (1)-(2) when *Patent Originality* is the dependent variable and in Columns (3)-(4) when *Product Dissimilarity* is the outcome variable. These α_1 estimates are mostly statistically significant at the 5% level, indicating that competitive firms achieve more originality or dissimilarity following a nonattainment shock than their less competitive peers. In terms of the economic magnitude, there is a 1.3% relative difference in the treatment effects between the top and bottom *Similarity*-ranked decile firms,[17] which translates to an aggregate impact of about 10% (e.g., 0.013×8 nonattainment counties ≈ 0.10; or 0.017×8 ≈ 0.14). Furthermore, in Column (3), an estimate of 0.029 ($t-$stat=3.64) on the triple-interaction term indicates that firms at the top *Fluidity*-ranked decile achieve a 7% (0.029/0.032×(0.103-0.024)=0.071), where 0.032 is the mean value of *Product Dissimilarity*) reduction in product similarity relative to firms in the bottom *Fluidity*-ranked

[17] In Column (2), a relative difference of 1.3% is obtained from 0.102/0.310×(0.048-0.010)=0.013, where 0.310 is the mean value of *Patent Originality*, and 0.010 and 0.048 are the 10th and 90th percentile values of *Similarity*, respectively.

decile after a regulatory shock. Regressions using *Similarity* further suggest an approximately 2% (0.013/0.032×(0.048-0.010)=0.015) reduction. In contrast, the coefficient on $Post \times Treat$ is, in general, not significantly different from zero, indicating minimal post-regulatory product differentiation achieved for less competitive firms. This finding is not surprising given a lack of innovative response from these firms.

The combined results support our prediction that regulation-induced green innovation allows competitive firms to better differentiate their products than others.

6.2. Corporate customer attraction

To the extent that green innovation can generate more business through product differentiation and quality signaling, we expect competitive firms to gain more customers following a nonattainment shock than less competitive firms. We employ two measures to capture such an effect. The first measure is the natural logarithm of each firm's total number of corporate customers at year $t + 2$. This metric evaluates the regulatory and competitive impacts on the overall firm-level customer attraction. The other measure is the natural logarithm of the number of corporate customers owning at least one plant in county c during year $t + 2$. It is used to gauge the local impact on affected counties.

We re-estimate Eq. (4) using either customer count measure as the dependent variable and report the results in Panel A of Table 9. The panel provides supportive evidence that firms facing intense competition are better able to attract customers following regulatory shocks compared to less competitive firms. As seen in Columns (1)-(2), the estimated coefficients for the triple-interaction term are positive but statistically significant when *Fluidity* is employed as a proxy for competition. These findings indicate that firms at the top competition-ranked decile achieve a 1.7% increase in the overall firm-level number of customers relative to firms in the bottom competition-ranked decile following a nonattainment shock, or an aggregate increase of about 14% given a median of eight nonattainment counties per firm-year. Such results are consistent with the notion that new clean technologies can help attract customers interested in green innovation and products. Columns (3)-(4) report the local attraction of customers drawn in by the green innovativeness of firms' local facilities. They show positive and statistically significant coefficients on $Post \times Treat \times Comp$ in the two specifications, indicating a 4%-6% increase in the treatment effects on the number of local customers from bottom to top competition-ranked decile firms. These results are consistent with our previous findings that competitive firms produce more green innovation adopted by local corporate customers following a regulatory shock.

The $Post \times Treat$ coefficient estimates are negative across all four sets of regressions but are only statistically significant in Columns (3)-(4). While less competitive firms tend to experience a loss in local customers who may switch to greener and more innovative products, such a loss has a limited impact on the total customer count at the firm-level. These findings are line with the notion that environmental regulations have little negative influences on the competitive position of those firms facing less intense competition.

We further investigate which corporate customers are more attracted to post-shock competitive firms. In particular, we compare the effects on customers who are unable to generate green innovation themselves (hereafter "non-green customers") with those who are able to (hereafter "green customers"). Non-green customers are defined as those who do not have any EST patent applications in a given year, whereas green customers are those with at least one EST patent application. We then replicate our triple-difference OLS regressions in Panel A using the ratio of non-green customers to green customers as the dependent variable and present the results in Panel B. The dependent variable for Columns (1)-(2) is the ratio of a firm's total number of non-green customers to its total number of green customers at year $t + 2$, whereas the dependent variable for Columns (3)-(4) is the ratio of a firm's number of local non-green customers in county c to its number of local green customers.

Panel B shows positive and significant triple interaction coefficients, suggesting that a competitive firm's business increases through its corporate customers that do not generate green technologies themselves. The α_1 estimates range between 0.924 in Column (1) and 1.072 in Column (3) and are significant at the 10% level, indicating that competitive firms can better access these markets that are likely more reliant on external sources of green inventions. In particular, a significant increase in the number of local non-green customers would come as no surprise since they are also subject to the same regulatory shock as their local suppliers. These non-green customers would, in turn, have a strong demand for green innovation and green products to comply with the regulation. The results complement our previous findings and support our prediction that green innovation can help more competitive firms generate more business.

In sum, contrary to conventional wisdom, environmental regulations can do good to firms, particularly to those in highly competitive product markets. Tighter pollution policies incentivize these firms to exploit green innovation as a competitive strategy to boost their business.

7. Economic Consequences of Corporate Environmental Policies

In the preceding sections, we have established that firms facing intense competition invest in green innovation in response to stricter environmental regulations and, simultaneously, achieve competitive strengths in their respective product markets. We now turn to investigate the economic consequences of such a strategic decision. This issue is of paramount importance to economists and policy makers interested in the overall impact of environmental regulations on the competitiveness of business sectors and economic growth. To provide insights into this issue, we examine the operating and market performances of affected firms and their employment conditions following regulatory changes.

7.1. Product market performance

We posit that gaining competitive advantages through green innovation would allow firms in competitive markets to experience better post-regulatory-shock product market performance than less competitive firms. To test this conjecture, we again conduct analyses using triple-difference regression models, where the dependent variable, $Firm\ Performance_{i,t+2}$, represents a firm's product market performance at year $t+2$, as follows.

$$\begin{aligned} Firm\ Performance_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c \\ & + \alpha_3 Treat_c \times Comp_{i,t-1} + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} \\ & + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}. \end{aligned} \tag{5}$$

Our study employs three firm-level product market performance measures: market share growth, price markup, and profit margin. *Market Share Growth* is computed as the difference in sales-based market share between the current and the previous year, expressed in percentage. It captures the product market expansion associated with a firm's ability to attract customers following a regulatory shock. *Markup* is the ratio of sales to the differences in sales and EBITDA, and *Profit Margin* is defined as the net income divided by total sales. They measure the extent to which gains in businesses translate to pricing power and profitability. Table 10 reports estimates of model (5).

A few notable results emerge from the table. Our findings suggest that a higher level of competition is associated with significant increases in the treatment effect of a nonattainment shock on firm performance. Columns (1)-(2) document the impact of a county-level shock on a firm's overall market share growth. The $Post \times Treat \times Comp$ coefficient estimates are positive and statistically significant in all specifications. In Column (1), an increase in competition measured by *Fluidity* from the bottom to the top decile of its distribution would lead to a 23% increase in the treatment effects of a regulatory shock.[18] In Column (2), an inter-decile increase in *Similarity* is associated with a 14% relative difference in treatment effects. The coefficient on $Post \times Treat$ reveals, at most, a weak negative impact on less competitive firms at year $t + 2$. The estimates are marginally significant in Column (1) and statistically insignificant in Column (2). Collectively, the results point to an overall increased market share growth for competitive firms due to stricter environmental regulations.

Results on *Markup* and *Profit Margin* presented in Columns (3)-(4) and (5)-(6), respectively, suggest that a favorable impact on market expansion can also translate to higher pricing power and profitability. The triple interaction coefficients are positive and statistically significant for both outcome variables and across all specifications, indicating that firms facing tougher competition enjoy a higher post-regulatory-shock markup and profit margin than their less competitive counterparts. In particular, the α_1 estimates for *Markup* range from 0.068 ($t-$stat$=$ 2.31) in Column (3) to 0.078 ($t-$stat$=$ 1.74) in Column (4), and the estimates for $Profit\ Margin$ range from 0.100 ($t-$stat$=$ 1.71) in Column (5) to 0.206 ($t-$stat$=$ 1.87) in Column (6). Similar to the results on *Market Share Growth*, less competitive firms also do not appear to suffer significant negative regulatory impacts on their price markup and profitability. The $Post \times Treat$ coefficient estimates are negative but largely insignificant, except for the regression on *Markup* shown in Column (3). This specification

[18] This percentage is computed as follows: 0.190/0.066×(0.103-0.024)=0.227, where 0.066 is the average market share growth value for firms in our sample.

yields a statistically significant α_2 estimate of -0.003, albeit small. Taken together, the α_1 and α_2 estimates suggest an overall improvement in product market performance for competitive firms following regulatory shocks.

These results complement our earlier findings on the innovative activity induced by environmental regulations and directly associate enhanced firm performance with clean technology development. Such an observation makes a critical addition to the literature as very few existing studies are able to show that green innovation leads to better firm performance. Most of these studies are limited to analyzing green technology patenting without drawing any inferences on the profitability and growth of regulated firms (e.g., Brunnermeier and Cohen 2003; Calel and Dechezleprêtre 2016). Some even suggest the possibility that despite new green inventions, there are high opportunity costs to diverting resources away from other productive investments, potentially hampering firm performance (Gray and Shadbegian 1998; Popp and Newell 2012; Aghion et al. 2016). Our analyses on a series of economic consequences allow us to better draw a conclusion on the overall impact of environmental regulation on firm competitiveness.

A prior study by Lanoie et al. (2011) is related to our work, except it employs postal survey data. The authors show that regulation-induced green innovation has positive effects on business performance but find no evidence that the cost-saving innovation can more than compensate for compliance costs. Our findings, instead, yield a stronger conclusion: the resulting positive operating outcomes suggest that the benefits arising from innovative responses to environmental regulations can outweigh the associated regulatory burden. These results are broadly consistent with prior studies that have found positive regulatory effects on firm productivity in the long-run (e.g., Berman and Bui 2001; Lanoie et al. 2008), supporting the notion that environmental policies can do more good than harm to firms. However, in contrast to prior research, our study finds that such positive effects from regulations are concentrated among competitive firms.

7.2. Market performance

In the preceding subsection, our analyses have shown that competitive firms enjoy better product market performance arising from their green innovative activity than firms in less competitive environments. We now test whether the financial market would react more favorably to these competitive firms and their associated benefits that reduce the regulatory burden.

One challenge we face in analyzing firms' market performance is identifying the actual announcement dates of nonattainment shocks. To circumvent this issue, we rely on long-run abnormal returns to observe market reactions to regulatory shocks instead of attempting short-term stock performance measures in narrow event windows around county status changes. Following He and Huang (2016), we calculate the one-year-ahead buy-and-hold abnormal returns (BHAR) using both the Fama-French three-factor and Fama-French-Carhart four-factor models over the one year following a nonattainment shock.[19] To assess the heterogeneous market reactions to county-level shocks, we estimate the following triple-interaction model using pooled OLS regressions:

$$\begin{aligned} BHAR_{i,t+1} &= \alpha_0 + \alpha_1 Event_{c,t} \times Comp_{i,t-1} + \alpha_2 Event_{c,t} + \alpha_3 Comp_{i,t-1} \\ &\quad + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned} \tag{6}$$

where $BHAR_{i,t+1}$ denotes the BHARs measured over the one-year period between t and $t+1$; and $Event_{c,t}$ is a dummy indicator that equals 1 for county c during the year in which c switches from an attainment to a nonattainment status.

Table 11 reports the regression results. We find evidence that competition has important influences over the market reactions to regulatory shocks. Columns (1)-(2) and Columns (3)-(4) document the effects on *Fama-French 3-factor BHAR* and *Fama-French 4-factor BHAR*, respectively. Consistent with our expectation, the coefficient on $Event \times Comp$ is positive and statistically significant for both BHAR measures and in all specifications, suggesting that investors react more positively to competitive firms undergoing nonattainment shocks than to firms with less competitive pressure. For example, Column (1) reports an estimate of 1.234 ($t-$stat= 2.67), implying that an inter-decile increase in $Fluidity$ would result in about 10 percentage points higher in the *Fama-French 3-factor BHAR* (1.234×(0.103-0.024)=0.097) following a nonattainment event. Similarly, Column (3) shows that the *Fama-French 4-factor BHAR* during the one-year following a nonattainment shock is approximately 13 percentage points (1.690×(0.103-0.024)=0.133) higher for firms in the top $Fluidity$-ranked

[19]Untabulated results show that using one-year-ahead cumulative abnormal returns as dependent variables would lead to qualitatively similar findings.

decile than firms in the bottom decile.

In contrast, the negative *Event* coefficients suggest an adverse market reaction to nonattainment shocks for firms in less competitive environments. The negative α_2 estimates in Model (6) range from -0.043 in Column (2) to -0.112 in Column (3) and are all statistically significant at the 1% level, implying a negative market reaction to a nonattainment event by 4-11 percentage points for less competitive firms.

The combined results indicate that while less competitive firms experience a negative BHAR following a nonattainment shock, the BHAR increases significantly with the competition. Such a pattern substantiates our hypothesis that investors expect competitive firms to extract more benefits from their strategic responses to environmental regulations than their less competitive peers, and the market incorporates such heterogeneity into stock prices.

7.3. Social welfare implications

Operating and market performance reveal the effects of environmental policies on firms' competitiveness. We now investigate how these effects influence the firms' abilities to create jobs and maintain labor demand. Policy makers and economists often view environmental regulations as detrimental to regional employment and their social welfare implications. We challenge this conventional view and argue, instead, that gaining competitive advantages and boosting businesses through green innovation would allow firms in competitive markets to better maintain their local employment than their less competitive counterparts.

To assess how regulations affect firms' local labor demand, we re-estimate Eq.(5) using the number of employees a firm has in a county during year $t{+}2$ as the dependent variable and report the results in Table 12. As demonstrated by the positive and significant coefficient on $Post{\times}Treat{\times}Comp$, a higher level of competition is associated with significant increases in the treatment effect of a nonattainment shock on local employment. Column (1) reports a coefficient estimate of 0.914 ($t-$stat= 2.88), indicating that firms in the top $Fluidity$-ranked decile have about 2% (0.914/3.932×(0.103-0.024)=0.018) more local employees than firms in the bottom decile following a regulatory shock. Column (2) implies a 1% relative difference in the treatment effects for an inter-decile change in $Similarity$. The coefficient estimates of $Post \times Treat$ are negative for regressions against both competition measures but are only marginally significant at the 10% level in Column (1). They indicate that environmental regulations have, at most, a weak negative impact on the local employment of firms with less competitive concerns.

Collectively, the results point to a net increase in regional employment for competitive firms following regulatory changes, possibly to satisfy the growing business gained through innovative responses. Our findings contradict prior claims that environmental regulations reduce labor demand (e.g., Kahn 1997; Greenstone 2002) and suggest that environmental policies may benefit regional social welfare given the appropriate corporate targets.

8. Conclusion

The conventional wisdom contends that environmental regulations impose onerous compliance costs on businesses and impede productivity and economic growth, thereby adversely affecting firm competitiveness. However, the existing literature has not fully explored the outcomes and implications of these regulatory and enforcement changes across different counties in the United States. The variation in the nonattainment status across counties provides a unique opportunity to test the impact of environmental rules in diverse economic and environmental settings. Our study, therefore, exploits these county-level nonattainment designation variations as a quasi-natural experiment to examine whether and how the intensity of product market competition influences firms' strategic responses to strict environmental policies. Using detailed plant-level information with publicly traded parent companies in the United States, we find that heightened competitive pressure induces firms to develop significantly more green innovation output when facing increased environmental regulatory stringency. We also explore whether there are sources of gains in competitive strengths arising from this green innovation strategy. Our findings indicate that regulation-induced green innovation helps competitive firms to improve competitiveness and differentiate themselves from competing rivals through product differentiation. These firms are also able to attract more corporate customers following a nonattainment shock than their less competitive counterparts.

A 2012 survey by the National Association of Manufacturers (NAM) reveals that U.S. manufacturers, especially small manufacturers with fewer than 50 employees, bear a disproportionate share of the regulatory burden and that such regulatory compliance costs are often not affected by economies of scale.[20] Resources complying with burdensome environmental regulations hinder manufacturers' ability to innovate and make better products. Yet there is virtually no prior research that looks at the economic consequences of these increasingly stricter environmental laws. Motivated by the survey, we examine the economic consequences of competitive firms' green innovation strategy. The findings suggest that competitive firms can increase their market share growth, markup, and profit margin and enjoy favorable market reactions, as measured by the firms' one-year buy-and-hold abnormal returns. We attribute our results to these firms' ability to leverage their strategic environmental policies to reduce the regulatory burden. It is important to stress that our evidence does not necessarily contradict the NAM's 2012 survey findings. The survey indicates that some of the costs associated with regulatory compliance are fixed costs, hence a firm with fewer employees bears roughly the same cost as a firm with many employees. Thus, on average, such costs put undue stress on smaller manufacturing firms that have to reallocate their resources toward abatement.

While our study provides new evidence that tighter pollution policies stimulate green innovation among firms in highly competitive product markets and, in turn, increase firm performance, it offers only one benefit of government intervention to promote a greener environment. Several schools of economics push for a limited governmental role in economic markets, unless in extreme cases of market failure (see, e.g., Stigler, 1971; Posner, 1974; Peltzman, 1976). They argue that corporations are incentivized to behave in an environmentally responsible manner by their commitment to stakeholders, their desire to preserve reputation, and their objective to improve long-term growth (e.g., Hart and Zingales 2017). Hence, we are inclined to argue that environmental regulation acts only as a catalyst to encourage corporations to become greener. With growing stakeholder engagement on corporate policy directions,[21] firms could have a greater desire to meet their environmentally-

[20] "The cost of federal regulation to the U.S. economy, manufacturing and small business" by W. Mark Crain and Nicole V. Crain of the National Association of Manufacturers; https://www.nam.org/wp-content/uploads/2019/05/Federal-Regulation-Full-Study.pdf

[21] In August 2019 Business Roundtable, 181 CEOs publicly committed to lead their corporations for the benefits of all stakeholders – customers, employees, suppliers, communities, and shareholders.

conscious stakeholders' demand and protect the environment, even without regulatory enforcement. Nonetheless, there are various economic costs and other environmental benefits that are beyond the current scope of our study. We will leave these issues for future research.

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Figure 1: NAAQS Revisions and Net Changes in Nonattainment Counties

The figure shows the net changes in the number of nonattainment counties by criteria pollutant during the sample period 1996-2017. The net changes, 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.

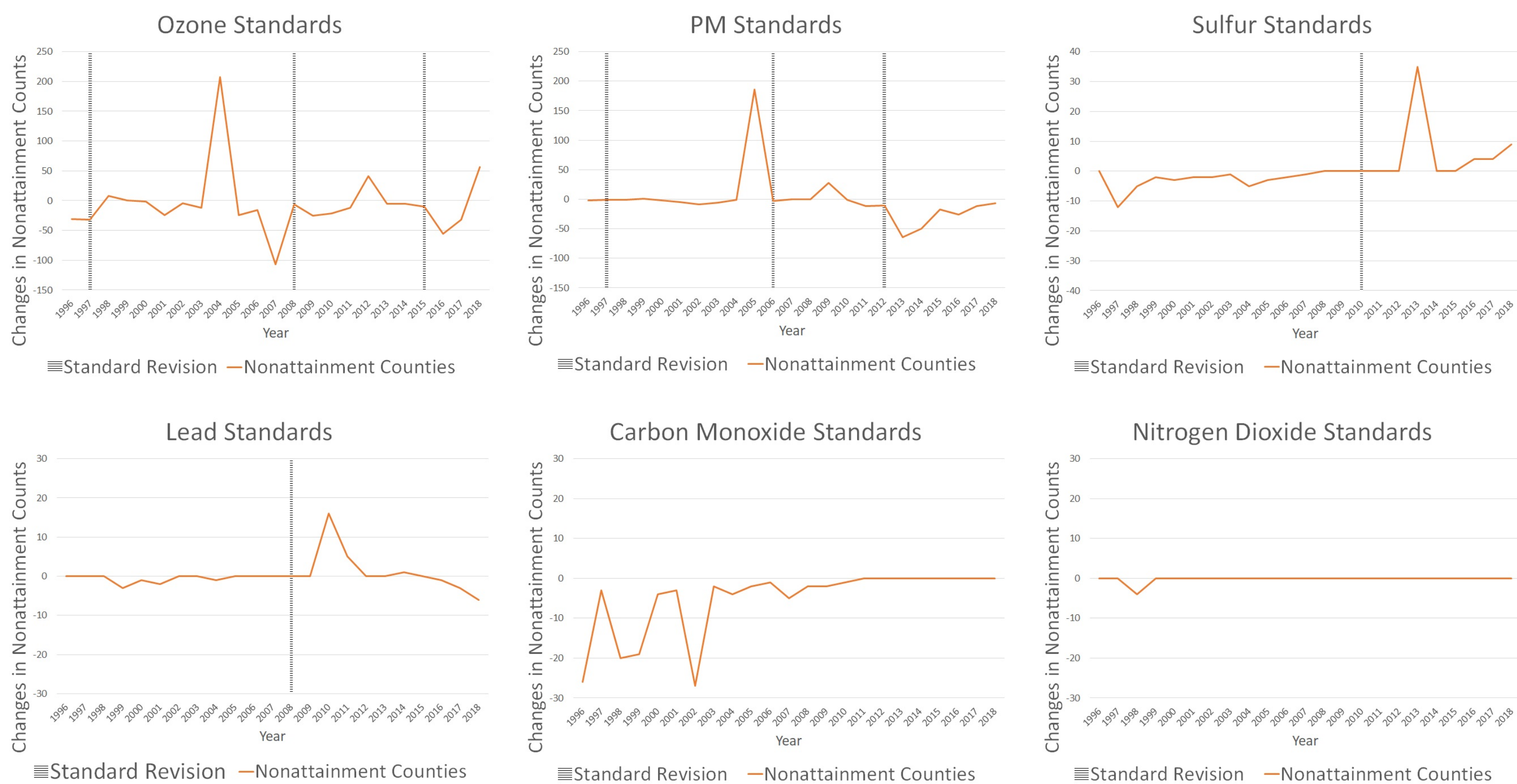

Table 1

Distribution of County Characteristics by State

This table reports the average number of firms per county, the average number of plants per county, the number of counties ever obtained a nonattainment status, the number of counties, the percentage of counties ever obtained a nonattainment status, and the average nonattainment period in years for the sample period from 1996 to 2017.

State	No. of Firms per County	No. of Plants per County	No. of Counties Nonattained	No. of Counties	% of Counties Nonattained	Nonattained Period (years)
Alabama	7.31	11.59	4	62	6.45	11.75
Arizona	22.73	74.60	9	15	60.00	16.33
Arkansas	4.49	6.30	1	74	1.35	9.00
California	38.45	133.39	44	58	75.86	16.20
Colorado	9.63	17.94	16	59	27.12	9.63
Connecticut	42.74	109.79	8	8	100.00	20.00
Delaware	31.64	57.62	3	3	100.00	19.67
Florida	19.41	42.62	2	66	3.03	4.00
Georgia	6.47	11.34	28	150	18.67	14.36
Hawaii	25.15	55.64	0	4	0.00	0.00
Idaho	4.32	6.09	6	41	14.63	12.50
Illinois	9.58	26.80	14	97	14.43	15.21
Indiana	7.93	13.17	31	90	34.44	7.42
Iowa	3.91	5.36	2	99	2.02	4.00
Kansas	3.67	5.58	1	98	1.02	5.00
Kentucky	4.26	6.55	10	115	8.70	11.40
Louisiana	7.74	12.69	8	62	12.90	12.50
Maine	9.29	12.95	10	16	62.50	8.30
Maryland	22.27	48.47	14	23	60.87	17.79
Massachusetts	45.78	109.07	14	14	100.00	19.86
Michigan	11.40	25.86	29	83	34.94	5.72
Minnesota	7.62	14.80	9	86	10.47	4.22
Mississippi	4.28	5.29	1	80	1.25	4.00
Missouri	5.49	9.60	7	111	6.31	13.29
Montana	2.80	3.31	10	49	20.41	15.80
Nebraska	3.65	5.62	1	74	1.35	5.00
Nevada	10.24	24.12	5	17	29.41	12.00
New Hampshire	12.21	17.52	4	9	44.44	16.50
New Jersey	40.17	84.37	21	21	100.00	19.90
New Mexico	6.62	11.31	2	30	6.67	12.50
New York	21.62	52.44	30	62	48.39	17.63
North Carolina	9.37	16.08	22	100	22.00	6.23
North Dakota	2.51	3.02	0	45	0.00	0.00
Ohio	13.85	29.04	40	88	45.45	10.50
Oklahoma	5.17	8.87	0	75	0.00	0.00
Oregon	10.55	19.40	11	35	31.43	8.36
Pennsylvania	17.09	32.82	49	67	73.13	13.65
Rhode Island	20.84	36.46	5	5	100.00	20.00
South Carolina	9.53	15.44	1	46	2.17	12.00
South Dakota	2.50	3.04	0	59	0.00	0.00
Tennessee	7.00	12.22	15	94	15.96	7.73
Texas	7.80	18.49	22	238	9.24	16.18
Utah	8.97	16.59	7	27	25.93	14.43
Vermont	6.46	8.16	0	14	0.00	0.00
Virginia	7.91	14.98	19	97	19.59	7.58
Washington	13.94	34.40	7	38	18.42	6.86
West Virginia	3.75	4.64	12	54	22.22	10.25
Wisconsin	9.56	15.97	12	71	16.90	13.50
Wyoming	4.43	5.32	4	22	18.18	6.75

Table 2

Summary Statistics

This table shows summary statistics for the main variables employed in this study over the 1996-2017 period. 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 include the number of green patents (*Green Patents*), number of citations on a firm's green patents (*Green Cites*), number of green patents cited by local customers (*Green Patents*^{Local}), and number of citations on a firm's green patents received from local customers (*Green Cites*^{Local}). Competition measures include product market fluidity (*Fluidity*) and total product similarity score (*Similarity*). Firm-specific variables include nonattainment county dummy (*NAttain*), an indicator variable that equals 1 if the firm is in an nonattainment county during the year and 0 otherwise, the number of plants a firm owns in a county (*Plants*), log of total assets (*Size*), Tobin's Q (*TobinQ*), leverage ratio (*Leverage*), asset tangibility (*Tangibility*), cumulative R&D stock (*R&D*), capital expenditure (*CapEx*), operating return to assets (*ROA*), and log number of employees a firm has in a county (*Employees*). Construction of the variables is presented in Appendix A. All variables are winsorized at 1% and 99%.

Variable	NObs	Mean	Std Dev	1st	25th	50th	75th	99th
Innovation Variables								
Green Patents	523,791	1.192	1.325	0.000	0.000	0.693	2.197	4.710
Green Cites	520,541	0.654	0.997	0.000	0.000	0.000	1.103	3.980
Green Patents^{Local}	477,686	0.018	0.111	0.000	0.000	0.000	0.000	0.693
Green Cites^{Local}	477,686	0.004	0.026	0.000	0.000	0.000	0.000	0.201
Competition Variables								
Fluidity	462,547	0.058	0.031	0.011	0.034	0.052	0.074	0.156
Similarity	490,050	0.024	0.028	0.010	0.011	0.013	0.022	0.180
Firm-specific Characteristics								
NAttain	523,791	0.456	0.498	0.000	0.000	0.000	1.000	1.000
Plants	523,791	2.139	4.022	1.000	1.000	1.000	2.000	15.000
Size	523,791	8.597	1.845	3.427	7.491	8.831	9.975	12.248
TobinQ	523,791	1.995	1.105	0.800	1.275	1.657	2.320	6.716
Leverage	523,791	0.238	0.156	0.000	0.132	0.223	0.323	0.713
Tangibility	523,791	0.253	0.170	0.024	0.125	0.210	0.334	0.695
R&D	523,791	0.034	0.053	0.000	0.001	0.017	0.042	0.287
CapEx	523,791	0.046	0.034	0.005	0.023	0.036	0.060	0.174
ROA	523,791	0.140	0.096	-0.274	0.100	0.142	0.191	0.332
Employees	523,791	3.932	1.255	2.398	2.890	3.714	4.718	7.419

Table 3

The Effect of Competitive Firms' Environmental Regulatory Response on Green Innovation

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on green innovation as follows:

$$\begin{aligned} Green\ Innovation_{y,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ & + FE + \epsilon_{i,c,t}, \end{aligned}$$

where $Green\ Innovation_{y,t+2}$ denotes firm i's or firm-county's green innovation and is measured by *Green Patents*, *Green Cites*, *Green Patents*^{Local} and *Green Cites*^{Local}; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* or *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Panel A: Firm-level Green Innovation in Year $t+2$			
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.343*	0.579***	0.411**	0.642***
	(2.01)	(3.72)	(2.39)	(4.61)
Post×Treat	-0.021*	-0.011*	-0.023**	-0.013**
	(-1.99)	(-1.88)	(-2.42)	(-2.86)
Treat×Comp	-0.408***	-0.387**	-0.508***	-0.513***
	(-3.10)	(-2.67)	(-3.63)	(-3.73)
Comp	-1.305	-2.437*	-0.248	-1.062
	(-0.75)	(-1.76)	(-0.15)	(-0.93)
Size	0.293***	0.299***	0.215**	0.209***
	(4.56)	(4.48)	(2.80)	(3.10)
TobinQ	0.052*	0.061**	0.053*	0.055*
	(1.83)	(2.14)	(2.05)	(2.08)
Leverage	0.015	0.084	0.045	0.086
	(0.05)	(0.29)	(0.22)	(0.41)
Tangibility	0.318	0.387	0.588	0.709
	(0.60)	(0.74)	(0.98)	(1.18)
R&D	2.044**	2.055**	1.496*	1.433*
	(2.67)	(2.58)	(1.97)	(1.84)
CapEx	1.165	1.521*	-0.309	-0.005
	(1.74)	(2.06)	(-0.32)	(-0.01)
ROA	0.158	0.273	-0.180	-0.068
	(0.50)	(0.87)	(-0.62)	(-0.22)
Employees	0.000	-0.001	0.001	0.000
	(0.18)	(-0.51)	(0.62)	(0.17)
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	459,335	486,671
Adj R^2	0.816	0.808	0.724	0.721

Table 3– Continued

The Effect of Competitive Firms' Environmental Regulatory Response on Green Innovation

	Panel B: Firm-County Level Green Innovation in Year $t+2$			
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.097**	0.111***	0.025**	0.027***
	(2.31)	(3.56)	(2.81)	(3.41)
Post×Treat	-0.005*	-0.002**	-0.001***	-0.001***
	(-2.14)	(-2.36)	(-3.03)	(-3.32)
Treat×Comp	-0.013	0.036	-0.003	0.012
	(-0.27)	(0.79)	(-0.22)	(0.99)
Comp	-0.017	0.111	-0.013	0.023
	(-0.11)	(0.75)	(-0.38)	(0.70)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	459,335	486,671
Adj R^2	0.816	0.808	0.724	0.721

	Panel C: Firm-Level Green Innovation in Year $t+3$			
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.355*	0.553***	0.513**	0.717***
	(2.01)	(3.73)	(2.70)	(4.57)
Post×Treat	-0.022*	-0.012**	-0.036***	-0.022***
	(-1.99)	(-2.12)	(-3.04)	(-4.07)
Treat×Comp	-0.416**	-0.336*	-0.553***	-0.506***
	(-2.26)	(-2.04)	(-4.51)	(-3.37)
Comp	-2.159	-1.358	-0.112	-1.177
	(-1.16)	(-0.89)	(-0.05)	(-1.06)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	376,504	397,775	373,906	395,019
Adj R^2	0.822	0.814	0.724	0.717

	Panel D: Firm-County Level Green Innovation in Year $t+3$			
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.135*	0.203***	0.050**	0.086***
	(2.05)	(3.02)	(2.15)	(3.08)
Post×Treat	-0.008*	-0.005**	-0.003*	-0.002**
	(-1.81)	(-2.42)	(-2.00)	(-2.60)
Treat×Comp	-0.015	0.099	0.000	0.000
	(-0.16)	(1.17)	(0.00)	(0.00)
Comp	-0.112	0.087	-0.065	-0.018
	(-0.44)	(0.18)	(-0.75)	(-0.13)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	338,654	358,846	338,654	358,846
Adj R^2	0.277	0.276	0.267	0.267

Table 4

Robustness Tests

This table reports robustness test results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on green innovation as follows:

$$\begin{aligned} Green\ Innovation_{i,t+2} &= \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} \\ & +\alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ & +FE + \epsilon_{i,c,t}, \end{aligned}$$

where $Green\ Innovation_{i,t+2}$ denotes firm i's green innovation and is measured by *Green Patents* and *Green Cites*; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* and *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. In Panel A, the regression model contains firm and county*times*year fixed effects (*FE*). In Panels B and C, the models are estimated on subsamples of firms from industries with average per-firm emissions greater than 100 tonnes and industries with above-median total emissions, respectively. In Panel D, the triple-difference model is estimated with no firm-specific control variables. *FE* denotes firm, county, and year fixed effects in the last three panels. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

Panel A: Control for Firm and County×Year Fixed Effects				
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.970*	1.871***	0.937**	1.502***
	(1.82)	(4.10)	(2.24)	(3.63)
Treat×Comp	-1.236**	-1.180**	-1.233**	-1.538***
	(-2.41)	(-2.46)	(-2.84)	(-3.91)
Comp	-3.338	-4.714***	-0.816	-1.848
	(-1.32)	(-2.89)	(-0.49)	(-1.60)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	453,028	479,984	450,622	477,401
Adj R^2	0.278	0.283	0.253	0.261

Table 4 – Continued

Robustness Tests

Panel B: Industries with Average Per-Firm Emissions > 100 Tonnes

	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.320*	0.596***	0.474**	0.654***
	(1.70)	(3.79)	(2.55)	(5.19)
Post×Treat	-0.021*	-0.013**	-0.028**	-0.014***
	(-1.78)	(-2.25)	(-2.63)	(-2.93)
Treat×Comp	-0.413***	-0.370***	-0.543***	-0.502***
	(-2.69)	(-2.76)	(-3.73)	(-3.80)
Comp	-0.782	-2.350*	-0.154	-1.128
	(-0.47)	(-1.78)	(-0.08)	(-0.98)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	421,278	448,057	418,240	444,849
Adj R^2	0.793	0.786	0.724	0.720

Panel C: Industries with Above-Median Total Emissions

	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.571**	0.627***	0.609***	0.653***
	(2.60)	(3.84)	(3.12)	(4.94)
Post×Treat	-0.038**	-0.015**	-0.038***	-0.015**
	(-2.63)	(-2.12)	(-3.12)	(-2.67)
Treat×Comp	-0.597***	-0.400**	-0.667***	-0.526***
	(-2.94)	(-2.73)	(-4.12)	(-3.86)
Comp	-1.636	-2.539*	-0.398	-1.160
	(-0.82)	(-1.85)	(-0.20)	(-0.96)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	373,058	396,120	370,176	393,068
Adj R^2	0.817	0.808	0.735	0.730

Panel D: Without Firm-Specific Characteristics

	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.379**	0.578***	0.444**	0.659***
	(2.06)	(3.53)	(2.46)	(4.65)
Post×Treat	-0.024*	-0.012*	-0.026**	-0.014**
	(-2.09)	(-1.80)	(-2.49)	(-2.84)
Treat×Comp	-0.464***	-0.404**	-0.554***	-0.535***
	(-3.47)	(-2.63)	(-3.77)	(-3.75)
Comp	-0.945	-2.612	0.175	-1.216
	(-0.55)	(-1.73)	(0.11)	(-1.12)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	459,335	486,671
Adj R^2	0.812	0.803	0.721	0.717

Table 5

Subsample Analysis of County-Level Emissions Marginally Above or Below NAAQS Thresholds

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on on green innovation using a subsample in which the county-level pollutant concentrations are 10% above or below the NAAQS threshold, as follows.

$$\begin{aligned} Green\ Innovation_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE \\ & + \epsilon_{i,c,t}, \end{aligned}$$

where *Green Innovation*$_{i,t+2}$ denotes firm i's green innovation and is measured by *Green Patents* and *Green Cites*; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* and *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees.* Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.698*	0.724**	0.496	0.803**
	(1.87)	(2.46)	(1.43)	(2.76)
Post×Treat	-0.045*	-0.019*	-0.032	-0.020*
	(-2.09)	(-2.00)	(-1.51)	(-1.85)
Treat×Comp	-0.677***	-0.288	-0.525**	-0.391*
	(-2.96)	(-1.56)	(-2.36)	(-1.74)
Comp	-0.837	-1.930	0.554	-1.008
	(-0.50)	(-1.36)	(0.34)	(-0.83)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	139,883	145,275	138,696	144,012
Adj R^2	0.816	0.808	0.713	0.709

Table 6

Effects of Environmental Regulations and Import Penetration on Green Innovation

This table reports regression results from triple-difference models that examine the joint effects of environmental regulations and import tariff reduction (*Tariff*) on green innovation, as follows.

$$\begin{aligned} Green\ Innovation_{i,t+2} &= \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Tariff_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Tariff_{i,t-1} \\ & +\alpha_4 Post_{c,t} \times Tariff_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Tariff_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ & +FE + \epsilon_{i,c,t}, \end{aligned}$$

where *Green Innovation*$_{i,t+2}$ denotes firm i's green innovation and is measured by *Green Patents*, *Green Cites*, *Green Patents*^{Local}, and *Green Cites*^{Local}; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; and Tariff is a binary indicator that equals to 1 if there is a significant import tariff rate reduction in the industry in previous year and 0 otherwise. $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Tariff	0.035**	0.017*	0.007**	0.001**
	(2.35)	(1.88)	(2.81)	(2.52)
Post×Treat	-0.035**	-0.019**	-0.007***	-0.002***
	(-2.28)	(-2.16)	(-3.25)	(-3.63)
Treat×Tariff	-0.009	-0.019**	0.000	0.000
	(-0.68)	(-2.69)	(0.04)	(1.45)
Tariff	0.392**	0.217***	0.023*	0.003
	(2.75)	(3.77)	(1.80)	(1.22)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	406,878	404,026	372,938	372,938
Adj R^2	0.804	0.7287	0.229	0.241

Table 7

The Effect of Competitive Firms' Environmental Regulatory Response on Green Innovation by Industry Type

This table reports subsample regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on green innovation , as follows.

$$Green\ Innovation_{i,t+2} = \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t},$$

where *Green Innovation*$_{i,t+2}$ defines firm i's green innovation and is measured by *Green Patents* or *Green Cites*; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise. $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. We divide firms into three terciles based on the degree of industry mobility they belong to. Industry mobility is measured by its plant fixed cost or agglomeration of economies. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

Panel A: Firms Grouped by Plant Fixed Costs

	Green Patents (t+2)				*Green Cites (t+2)*			
	Least Mobile Industry		Most Mobile Industry		Least Mobile Industry		Most Mobile Industry	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post×Treat×Comp	0.694**	0.732***	0.300	1.264	0.496*	0.661***	-0.229	0.157
	(2.31)	(3.05)	(0.78)	(1.55)	(1.78)	(3.09)	(-0.66)	(0.30)
Post×Treat	-0.054**	-0.029**	-0.002	-0.013	-0.025	-0.013	0.021	0.003
	(-2.47)	(-2.35)	(-0.06)	(-0.55)	(-1.29)	(-1.16)	(0.78)	(0.18)
Treat×Comp	-0.279	-0.403*	-0.644**	-1.078*	-0.499**	-0.587***	-0.133	-0.133
	(-0.86)	(-1.72)	(-2.20)	(-2.08)	(-2.05)	(-2.87)	(-0.43)	(-0.24)
Comp	0.054	0.812	0.147	-1.668	3.666**	1.170	-2.695	-2.847
	(0.02)	(0.46)	(0.05)	(-0.25)	(2.20)	(0.61)	(-0.90)	(-0.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	71,923	76,459	72,539	76,450	71,636	76,173	71,892	75,803
Adj R^2	0.876	0.860	0.852	0.852	0.822	0.816	0.762	0.766

Panel B: Firms Grouped by an Industry's Agglomeration of Economies

	Green Patents (t+2)				*Green Cites (t+2)*			
	Least Mobile Industry		Most Mobile Industry		Least Mobile Industry		Most Mobile Industry	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post×Treat×Comp	0.551*	0.956**	0.330	0.372	0.734***	0.986***	0.214	0.539
	(1.77)	(2.59)	(1.29)	(1.43)	(3.08)	(4.16)	(0.89)	(1.68)
Post×Treat	-0.029	-0.018	-0.022	-0.013	-0.041**	-0.020**	-0.014	-0.016
	(-1.24)	(-1.52)	(-1.27)	(-1.33)	(-2.52)	(-2.20)	(-0.85)	(-1.60)
Treat×Comp	-0.422*	-0.667***	-0.557*	-0.387	-0.554***	-0.791***	-0.423	-0.337
	(-2.10)	(-3.46)	(-1.99)	(-1.23)	(-3.42)	(-4.80)	(-1.44)	(-1.26)
Comp	-5.618	-0.544	-0.572	-0.819	-4.114	-2.084	-1.842	-1.741
	(-1.66)	(-0.16)	(-0.20)	(-0.42)	(-1.22)	(-0.82)	(-0.78)	(-0.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	125,340	134,585	118,399	123,509	125,057	134,302	117,589	122,696
Adj R^2	0.861	0.846	0.834	0.829	0.802	0.798	0.745	0.744

Table 8

The Effect of Competitive Firms' Environmental Regulatory Response on Product Differentiation

This table reports regression results from triple-difference models that examine competitive firms' environmental regulatory response on product differentiation as follows:

$$\begin{aligned} Product\ Diff_{i,t+2} &= \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} \\ &\quad + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned}$$

where $Product\ Diff_{i,t+2}$ is measured by firm i's patent originality score and average similarity score at $t+2$; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* or *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Patent Originality(t+2)		*Average Similarity (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.001	0.102**	0.029***	0.013**
	(0.03)	(2.32)	(3.64)	(1.99)
Post×Treat	0.000	-0.002	-0.001*	-0.000
	(0.22)	(-1.69)	(-1.93)	(-0.01)
Treat×Comp	-0.025	-0.079*	0.005	-0.021***
	(-0.75)	(-1.94)	(0.62)	(-2.93)
Comp	0.470*	0.344	-0.149***	0.025***
	(1.92)	(1.11)	(-15.59)	(3.61)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	362,970	384,332	211,536	222,444
Adj R^2	0.557	0.555	0.514	0.501

Table 9

The Effect of Competitive Firms' Environmental Regulatory Response on Corporate Customer Relationships

This table reports regression results from triple-difference models that examine competitive firms' environmental regulatory response on attracting corporate customers as follows:

$$
\begin{aligned}
Customers_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} \\
& + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\
& + FE + \epsilon_{i,c,t},
\end{aligned}
$$

where $Customers_{i,t+2}$ is defined by firm i's total number of corporate customers, number of local corporate customers, ratio of non-green customers to green customers, ratio of local non-green customers to local green customers; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* or *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Panel A: Number of Corporate Customers			
	Total No. of Customers (t+2)		*No. of Local Customers (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.300**	0.311	0.271*	0.825***
	(2.00)	(1.10)	(1.67)	(2.63)
Post×Treat	-0.014	0.011*	-0.018*	-0.023***
	(-1.48)	(-0.70)	(-1.81)	(-3.31)
Treat×Comp	-0.121	-0.003	0.585**	0.692
	(-1.05)	(-0.01)	(2.10)	(1.14)
Comp	1.629	3.657	0.575	0.116
	(1.39)	(1.40)	(0.91)	(0.09)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	462,413	489,919
Adj R^2	0.838	0.834	0.662	0.657
	Panel B: Ratio of Non-Green to Green Corporate Customers			
	Non-Green/Green Customers (t+2)		*Non-Green/Green Local Customers (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Post×Treat×Comp	0.924*	0.929*	1.072*	0.925*
	(1.69)	(1.94)	(1.81)	(2.09)
Post×Treat	-0.039	-0.003	-0.093*	-0.052*
	(-0.89)	(-0.09)	(-1.94)	(-2.04)
Treat×Comp	-1.517***	-0.734	0.580	0.107
	(-2.67)	(-1.42)	(0.85)	(0.14)
Comp	5.538***	-2.548***	-1.861	-0.383
	(10.49)	(-4.15)	(-0.86)	(-0.23)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	210,027	215,167	107,731	109,839
Adj R^2	0.687	0.688	0.553	0.555

Table 10

The Effect of Competitive Firms' Environmental Regulatory Response on Operating Performance

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on operating performance as follows:

$$\begin{aligned} OpPerformance_{i,t+2} &= \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} \\ &\quad + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned}$$

where $OpPerformance_{i,t+2}$ is measured by firm i's market share growth, markup, and profit margin; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* or *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Market Share Growth		*Markup*		*Profit Margin*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Post×Treat×Comp	0.190*	0.234**	0.068**	0.078*	0.100*	0.206*
	(2.08)	(2.51)	(2.31)	(1.74)	(1.71)	(1.87)
Post×Treat	-0.011*	-0.004	-0.003**	-0.001	-0.004	-0.003
	(-1.88)	(-1.64)	(-2.18)	(-1.40)	(-1.50)	(-1.44)
Treat×Comp	-0.157*	-0.191**	-0.040	-0.039	-0.133***	-0.250***
	(-1.78)	(-2.83)	(-1.60)	(-1.13)	(-2.62)	(-2.60)
Comp	-0.423	0.329	-0.008	-0.257	-0.015	-0.567
	(-0.73)	(1.20)	(-0.06)	(-1.42)	(-0.08)	(-1.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
NObs	461,927	489,414	462,292	489,798	462,100	489,603
Adj R^2	0.234	0.218	0.855	0.852	0.767	0.765

Table 11

The Effect of Competitive Firms' Environmental Regulatory Response on Market Performance

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on market performance as follows:

$$BHAR_{i,t+1} = \alpha_0 + \alpha_1 Event_{c,t} \times Comp_{i,t-1} + \alpha_2 Event_{c,t} + \alpha_3 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t},$$

where $BHAR_{i,t+1}$ is measured by a one-year buy and hold abnormal return using either the Fama-French three-factor or four-factor model; $Event_{c,t}$ equals 1 for county c during the year in which c switches from an attainment to a nonattainment status; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* or *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Fama-French 3-factor BHAR (t+1)		*Fama- French 4-factor BHAR (t+1)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Event×Comp	1.234***	1.205**	1.690***	1.807***
	(2.67)	(2.38)	(3.20)	(3.38)
Event	-0.086***	-0.043***	-0.112***	-0.058***
	(-3.14)	(-3.49)	(-3.59)	(-4.46)
Comp	-0.085	-0.716	-0.626	-0.856
	(-0.09)	(-0.60)	(-0.62)	(-0.63)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	454,487	481,742	454,487	481,742
Adj R^2	0.229	0.223	0.232	0.228

Table 12
The Effect of Competitive Firms' Environmental Regulatory Response on Firm-County-Level Employment

This table reports regression results from triple-difference models that examine competitive firms' environmental regulatory response on firm-county-level employment:

$$
\begin{aligned}
Labor_{i,c,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times Comp_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times Comp_{i,t-1} \\
& + \alpha_4 Post_{c,t} \times Comp_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t},
\end{aligned}
$$

where $Labor_{i,c,t+2}$ is defined by the log of one plus firm i's two-year ahead number of firm-county-level employees; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $Comp_{i,t-1}$ denotes competition and is measured by *Fluidity* or *Similarity*; $X_{i,t}$ is a vector of controls including *Size*, *TobinQ*, *Leverage*, *Tangibility*, *R&D*, *CapEx*, *ROA*, and *Employees*. Construction of the variables is presented in Appendix A. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ 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.

	Fluidity	*Similarity*
Variable	(1)	(2)
Post×Treat×Comp	0.914**	0.696*
	(2.88)	(1.98)
Post×Treat	-0.039*	-0.005
	(-2.08)	(-0.46)
Treat×Comp	0.928**	0.947**
	(2.65)	(2.61)
Comp	-0.757*	-1.068***
	(-2.01)	(-3.26)
Controls	Yes	Yes
Fixed Effects	Yes	Yes
NObs	462,413	489,919
Adj R^2	0.145	0.143

Appendix A

Variable	Definition	Data source
Measures of green innovation (firm-specific)		
Green Patents	The natural logarithm of one plus firm i's total number of green patents filed (and eventually granted) during the year, where green patents are those classified as environmentally sound technologies (ESTs) by WIPO based on their IPC patent classes	WIPO IPC Green Inventory; PATSTAT
Green Cites	The natural logarithm of one plus the total number of citations received by firm i's green patents filed (and eventually granted) during the year	WIPO IPC Green Inventory; PATSTAT
Measures of green innovation (firm-county-specific)		
Green Patents^{Local}	The natural logarithm of one plus the number of firm i's green patents filed during the year that have received citations from its local customers, where local customers are those with at least one plant in county c when citing firm i's patents	WIPO IPC Green Inventory; PATSTAT; Dun & Bradstreet
Green Cites^{Local}	The natural logarithm of one plus the number of citations received by firm i's green patents filed during the year from its local customers	WIPO IPC Green Inventory; PATSTAT; Dun & Bradstreet
Measures of competition		
Fluidity	Constructed by Hoberg, Phillips, and Prabhala (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 and Phillips (2016), 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
TariffReduction	A dummy variable equals to 1 for the two years after a major tariff reduction in firm i's industry and is equal to 0 for other years and for firms in industries without tariff changes; tariff rates are defined as the collected duties divided by the custom value of imports for each industry; a major tariff reduction event is defined as a decline in the tariff rate by more than 4 times larger than the average tariff reduction of the industry during the sample period, and it is not preceded or followed by a major tariff increase greater than 80% of the reduction	WITS World Bank
Identification strategy variables		
Treat	A binary variable that equals 1 if a county has ever been classified as a nonattainment area and 0 if otherwise	EPA Green Book
Post	A binary variable that equals 1 for a county during years in which the county has a nonattainment status and 0 if otherwise	EPA Green Book
Event	A binary variable that equals 1 for a county during the year in which the county switches from an attainment status to a nonattainment status	EPA Green Book

Appendix A – Continued

Variable	Definition	Data source
Measures of product differentiation, customer attraction, and other firm performance		
Patent Originality	One minus the sum of squared percentage of backward citations made by a patent to each patent class (at the three-digit IPC level), averaged across all patents filed by firm i during a year	PATSTAT
Average Similarity	The average of Hoberg and Phillip's (2016) product similarity score between firm i and its competitors in the same TNIC industry	Hoberg-Phillips Data Library
Total No. of Customers	The natural logarithm of one plus the total number of corporate customers firm i has in a year	Revere
No. of Local Customers	The natural logarithm of one plus the total number of local corporate customers firm i has in a year	Revere
Non-Green/Green Customers	The ratio of the number of corporate customers with no green patents to the number of corporate customers with at least one green patent	Revere; PATSTAT
Non-Green/Green Local Customers	The ratio of the number of local customers with no green patents to the number of local customers with at least one green patent	Revere; PATSTAT
Market Share Growth	Market share growth as the difference in firm i's market share between the current year and the previous year, scaled by the previous year's market share	Compustat
Markup	Ratio of sales to the difference of sales and earnings before interest, taxes, depreciation, and amortization	Compustat
Profit Margin	Income before extraordinary items divided by sales	Compustat
3-Factor BHAR	One-year buy-and-hold abnormal return obtained using the Fama-French three-factor model	CRSP
4-Factor BHAR	One-year buy-and-hold abnormal return obtained using the Fama-French Carhart four-factor model	CRSP
Control Variables		
Size	The natural logarithm of total assets	Compustat
TobinQ	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
ROA	operating income before depreciation divided by total assets	Compustat
KZIndex	KZ index defined as $-1.002\times$ cash flow $+0.283\times$ Tobin's Q$+3.139\times$ Leverage $-39.368\times$ dividends $-1.315\times$ cash holdings	Compustat
Employees	The natural logarithm of one plus the number of employees each firm has in a county during a year	Dun & Bradstreet