Grow in the Sun: Valuation and Development of Green Innovation under Mandatory Carbon Disclosure

By Jianqiang Chen, Pei-Fang Hsieh and Po-Hsuan Hsu*

This study examines how mandatory carbon disclosure shifts stock investors' reactions to and corporate investment in green innovation. Using a regression discontinuity design, we show that the proposal of the Greenhouse Gas Reporting Program (GHGRP) increases the value of low-carbon patents, identified either through patent office classifications or the large language model BERT. A difference-in-differences analysis suggests that firms with higher estimated CO_2 emissions in the past produce more low-carbon patents after the proposal. Also, the values of these firms' low-carbon patents increase, and their CO_2 emissions decrease. Instead of shifting existing inventors' research trajectory, these firms hire external inventors with low-carbon expertise and encourage them to collaborate with incumbents. The effect of mandatory disclosure is stronger among firms under higher competitive pressure and for stocks with greater price efficiency.

JEL: D22; O32; Q54; Q58
Keywords: greenhouse gas; innovation; environmental regulations; climate change

I. Introduction

Firms' investment decisions hinge on different production technologies' costs and productivity (Jaffe, Newell and Stavins, 2003; Syverson, 2011; Grullon and Ikenberry, 2025). Among all related costs, the externalities of carbon emissions present an especially pressing issue, given heightened concerns about climate change and its potential economic costs to society. The private sector lacks an incentive to disclose carbon emissions as such information asymmetry enables emitters to externalize carbon costs, shifting climate-related risks onto society (Hall and Helmers, 2010; Frankel, Kothari and Raghunandan, 2025).[1] Greenhouse gas (GHG) disclosure, a policy initiative since the Kyoto Protocol in 1997, requires firms to report carbon emissions transparently. Such mandatory disclosure increases the public's attention to firms' environmental impact and may incentivize managers to attend to pollution abatement and green innovation in order to preempt reputational damage, litigation, and regulatory penalties.

* Chen: School of Economics, Ocean University of China (chenjianqiang@ouc.edu.cn); Hsieh: College of Technology Management, National Tsing Hua University (pfhsieh@mx.nthu.edu.tw); Hsu: College of Technology Management, National Tsing Hua University (pohsuanhsu@mx.nthu.edu.tw). We thank Reinhilde Veugelers, Thomas Astebro, Hao Liang, Michelle Lowry, Stefano Lovo, Jan Starmans, Emilio Bisetti, Alminas Zaldokas, Elvira Sojli, Wing Wah Tham, Poorya Kabir, Laveen Daniel, Chuck Fang, Daniel Dorn, Tak Yuen Wong, Yanzhi Wang, YiHou Huang, Woan-Lih Liang, Hui-Ching Chuang, William Bazley, Ebenezer Effah, Dien Giau Bui, seminar participants at HEC-HKUST-NUS Sustainable Finance Webinar, Drexel University and National Tsing Hua University, and conference participants at the FMA Annual Meeting, the Australasian Finance and Banking Conference (AFBC), GRASFI Asia, the NTHU Symposium on Sustainable Finance and Economics, the Taiwan Symposium on Innovation Economics and Entrepreneurship, Taiwan Finance Association Annual Meeting (TFA), and International Conference for Financial Engineering Association of Taiwan (FeAT) for their valuable comments.

[1] In 2002, the Carbon Disclosure Project (CDP), which promotes corporate transparency on climate risks, had only 35 investors requesting climate disclosures, and CDP itself received responses from just 245 companies. In 2022, half of the world's publicly traded firms in terms of market capitalization still do not disclose emissions. See the CDP Media Factsheet. https://cdn.cdp.net/cdp-production/comfy/cms/files/files/000/003/419/original/CDP-Media-Factsheet.pdf

Prior literature on green innovation focuses on policies related to monetary interest like R&D grants, tax credits, subsidies, and cap-and-trade systems drive green technology development (Acemoglu et al., 2012, 2016; Calel, 2020), but less is known about the impact of mandatory disclosure before financial incentives or stricter regulations take effect. In this paper, we use the proposal of the U.S. Greenhouse Gas Reporting Program (GHGRP) as a natural experiment to examine whether the resultant transparency reshapes firms' green technology development and valuations.

On December 26, 2007, President George W. Bush signed the Consolidated Appropriations Act of 2008 (Public Law 110-161) into law. This omnibus appropriations bill, which bundled funding for most federal agencies, constituted must-pass legislation. Because it was passed under tight time limits to avoid a government shutdown, several provisions received limited scrutiny and were largely unanticipated. In his signing statement, President Bush criticized Congress for including nearly 9,800 earmarks totaling over $10 billion, describing them as non–merit-based and wasteful.[2] For the *first* time, the Act appropriated funds to the Environmental Protection Agency (EPA) to develop a mandatory GHG reporting rule.

This budget allocation and the initiation of the draft ("GHGRP proposal" hereafter) was largely unanticipated by firms for the following three reasons. First, the provision was a last-minute addition to a must-pass appropriations bill. Congress inserted funding for the mandatory GHG reporting rule in mid-December, leaving little opportunity for advance notice or debate. Second, the Act mandated a draft rule within nine months and a final rule to be effective within 18 months of its enactment. Although the EPA had requested funds since 2003 to implement a regulatory impact analysis (RIA) in order to draft rules, such funds were never approved until December 26, 2007, resulting in low expectations of imminent carbon disclosure. Third, the critical details and scope of the disclosure are highly uncertain when the Act was passed – firms and other interest groups expressed serious concerns over uncertainties with respect to reporting thresholds, formats, scope, and industry coverage in the meetings held by the EPA in the drafting stage.[3]

We propose that the GHGRP proposal encourages high-emission firms to pursue green innovation internally, which results in more low-carbon patents, due to the following incentives. First, customers' green preferences and intensified competition incentivize these firms to demonstrate their green transition efforts for corporate reputation and new product opportunities, as firms in competitive industries have stronger incentives to innovate and differentiate (Aghion et al.,

[2]See: https://georgewbush-whitehouse.archives.gov/news/releases/2007/12/20071226-1.html

[3]For example, after the EPA's initial proposal, thousands of public comments raised concerns, including ambiguous emissions definitions and the potential for arbitrary thresholds. Financial services firms like the RiskMetrics Group suggested including Scope 2 emissions, while others proposed limiting reporting to upstream emissions. Many commenters argued that the rule would increase regulatory burdens, particularly in certain industries. Further details are discussed in Section 2.1.

2001, 2005). Second, green patenting sends strong signals to financial markets because such intellectual property enhances firms' appropriability of environmental technologies by deterring imitation and strengthening litigation positions (Teece, 1986; Budish, Roin and Williams, 2016; Farre-Mensa, Hegde and Ljungqvist, 2020).

To capture firms' green innovation activities, we adopt two approaches to identify low-carbon patents. In our first approach, we classify a patent as low-carbon if it belongs to the Cooperative Patent Classification (CPC) Y02 class (Sautner et al., 2023*a*; Cohen, Gurun and Nguyen, 2024).[4] Second, to capture patents that may contribute to addressing climate change but are not labeled under Y02, we use the Bidirectional Encoder Representations from Transformers (BERT) for Patents model to label low-carbon patents based on the brief descriptions of remaining non-Y02 patents. Patents with a predicted probability of being low-carbon are included, thereby extending the universe of low-carbon patents beyond the Y02 class. We then follow the method of Kogan et al. (2017) based on the efficient market hypothesis and use stock price appreciation upon the announcement of a green patent grant to measure its value.

We first use a regression discontinuity design (RDD) to examine whether the value of green innovation increased right after the proposal date (i.e., the Act's enactment on December 26, 2007), which validates managers' incentives under stakeholders' pressure. We exploit the lag between patent filing and grant dates and compare the values of low-carbon patents filed *before* but granted shortly *after* the proposal to those being granted just before the proposal. Our results reveal a sharp 70% increase in the value of low-carbon patents after the proposal, even though the two groups' patent characteristics are similar and vary smoothly around the threshold. We also implement a placebo test on other green patents unrelated to climate change (e.g., water adaptation, biodiversity protection technologies), and find no significant increase for these patents' values. Our finding indicates that the stock market assigns higher values to low-carbon patents after the proposal, likely due to perceived regulatory risks and the potential of these patents to mitigate such risks. These findings highlight shareholders' motivation for supporting firms' green transition, which in turn influences firms' investment in low-carbon technologies.

We then design a difference-in-differences (DID) regression to examine how the GHGRP proposal changes firms' incentives to develop green innovation. We define the proposal's effective date to be 2008 and years after. Our treatment variable is based on firms' *estimated* CO_2 emissions before the proposal. At that time, firms were required to report process-level carbon monoxide (CO) emissions because of its toxicity. As CO emissions are highly correlated with CO_2 emissions (Gurney et al., 2009, 2010; Tomar, 2023), we use firms' CO emissions from the National Emissions Inventory (NEI) to estimate their pre-proposal greenhouse gas emissions

[4]For robustness checks, we further refine this definition by requiring Y02 patents to contain at least one green innovation keyword (e.g., carbon reduction, energy efficiency, or cleaner energy) in its brief description. We find consistent results.

using standard conversion factors in the literature. We categorize firms into within-industry quartiles based on their estimated pre-proposal CO_2 emissions, so we may examine variations in their low-carbon patent filings following the proposal.

We find that if a firm's estimated emission quartile rank increases by one, then it produces approximately 3.5% more low-carbon patents after the proposal. Additionally, the quality of these patents, as measured by forward citations, increases by about 4.3%, and their total value rises by about 6%. Additional tests confirm a causal interpretation of our difference-in-differences results: we first consider a synthetic DID approach (Arkhangelsky et al., 2021) that combines DID and synthetic control methods, reweighting and matching pre-exposure trends in order to force parallel trend assumptions to hold. Second, we apply the approach of Rambachan and Roth (2023) to assess sensitivity under possible deviations from the parallel trends assumption, and find that our results are robust to 20-30% deviations from that assumption.

We then conduct a placebo test by examining other green patents unrelated to climate change, and find no significant differences across firms in different estimated emission quartiles. These results suggest that firms' changes in low-carbon innovations are driven by the GHGRP proposal, rather than overall environmental regulation and policy. We also observe a significant decline in estimated CO_2 emissions among firms in higher emission quartiles. Moreover, we also find that high-emission firms further improve their environmental scores rated by the KLD.

We further account for potential confounding effects from contemporaneous policy uncertainty and the 2008 financial crisis by implementing placebo tests using firm-level exposures to climate policy uncertainty, economic policy uncertainty, oil prices, and aggregate market returns. Insignificant coefficients on all these interaction terms confirm that our results cannot be simply attributed to such concerns.

To understand how firms execute this technological transition, we investigate the underlying mechanisms. Firms may enhance low-carbon technologies by hiring external inventors with expertise in low-carbon technologies or by encouraging existing inventors to develop green innovations (Darendeli, Law and Shen, 2022; Sautner et al., 2023*a*).[5] Our analysis shows that firms enhance their low-carbon technologies primarily by acquiring external low-carbon experts and encouraging collaborations between these new hires and existing inventors. On the other hand, we find no evidence for existing inventors to increase their low-carbon patenting productivity. These results indicate that high-emission firms rely on external hires and intra-firm knowledge spillovers rather than expecting incumbents to independently shift their research focus.

Finally, we examine heterogeneous treatment effects to further justify high-emission firms' incentives related to competition and market valuation. First, these firms facing higher com-

[5] Darendeli, Law and Shen (2022) and Sautner et al. (2023*a*) find that green transitions drive firms to increase green human capital and produce more green patents.

petitive pressure or greater green preferences, proxied by product market similarity with peers and the coverage of climate risk-oriented analysts, respectively, file more low-carbon patents after the proposal. This finding confirms the competition incentive as low-carbon technologies help high-emission firms differentiate from rivals. Second, high-emission firms with greater market information efficiency, proxied by higher option trading volume and lower probability of informed trading (PIN), also increase low-carbon patenting following the proposal. This evidence confirms these firms' market valuation incentive because their efforts are more likely to be rewarded by stock markets with greater price efficiency.

This study adds to the literature in several ways. First, we contribute to the emerging literature on the valuation of green innovation and investment. Prior research has highlighted the importance of green innovation in mitigating climate risk and reducing regulatory uncertainty for firms (Brown, Martinsson and Thomann, 2022; Sautner et al., 2023*a*,*b*). Some parallel studies examine how stock investors react to firms' green investment choices (Duchin, Gao and Xu, 2024) and their announcements of green patents and innovations (Hege, Pouget and Zhang, 2023; Reza and Wu, 2024; Yu, 2024).[6] Our approach differs from those studies with respect to methodology: we use an RDD approach based on the GHGRP proposal to identify (and quantify) how the mandatory disclosure of GHG emissions increases the valuation of green patents. In addition, we incorporate textual information and apply a large language model, BERT for Patents, to extend our classification of low-carbon innovation beyond the Y02 class.

Second, our study aligns with recent research exploring the real effects of mandatory disclosure with respect to GHG emissions (Yang, Muller and Liang, 2021; Ilhan et al., 2023; Tomar, 2023). Although previous research has documented significant reductions in GHG emissions due to the GHGRP in the U.S. and the GHG emissions disclosure law in the U.K. (Jouvenot and Krueger, 2020; Downar et al., 2021; Tomar, 2023), there is little discussion on how such reductions are achieved other than from scaling down production. Our evidence of increased low-carbon patents highlights the critical role that technology plays in addressing climate change and risk. More broadly, our study adds to the expanding literature on the real effects of ESG disclosure mandates.[7] Specifically, we offer a new perspective to this literature by focusing on the valuation and development of firms' innovation activities.

Third, this paper extends the literature on the determinants of firms' investment in green

[6] Among those studies, Reza and Wu (2024) and Hege, Pouget and Zhang (2023) focus on identification tests to explain why patent valuation changes: the former uses a difference-in-differences approach based on the 1970 and 1990 Clean Air Act (CAA) Amendments, and the latter uses a quasi-random assignment of patent examiners.

[7] Prior research has examined the real effects of ESG disclosure mandates from different perspectives, such as that of shareholders (Gibbons, 2023), institutional investors (Ilhan et al., 2023), banks (Giannetti et al., 2023), stakeholders (Christensen, Hail and Leuz, 2021), and international markets (Krueger et al., 2024). In addition, the inclusion of safety records in financial reports was found to be associated with a decrease in mining-related citations and injuries (Christensen et al., 2017). Also, China's 2008 mandate, which required firms to disclose their ESG activities, led to a reduction in wastewater and SO_2 emission levels (Chen, Hung and Wang, 2018). Air quality disclosure reduces pollution-related harm by prompting public protective behaviors (Barwick et al., 2024). More accurate pollution data amplify these effects (Greenstone et al., 2022).

innovation (Bolton, Kacperczyk and Wiedemann, 2023; Cohen, Gurun and Nguyen, 2024), especially with respect to the internalization of negative externalities.[8] Our research complements prior work in this direction that focuses on environmental regulations[9] or touches upon additional factors (e.g., energy prices, corporate governance, financial frictions, policy uncertainty, climate risk exposure).[10] Our results, however, suggest that mandatory disclosure can be less costly to implement and may even benefit compliant firms (Boyer and Laffont, 1999).[11]

The remainder of this paper is structured as follows. Section 2 presents a detailed overview of the GHGRP proposal and describes our data and sample construction. In Section 3, we discuss the results of our patent-level RDD analysis. Section 4 shows the difference-in-differences results when we compare changes in low-carbon patents and GHG emissions of firms with different pre-event estimated emission levels following the proposal. Section 5 investigates the mechanisms through which firms develop their low-carbon innovation, and Section 6 examines corporate incentives driven by the GHGRP. Section 7 concludes.

II. Background, Data, and Sample Construction

A. *The Greenhouse Gas Reporting Program (GHGRP)*

The Consolidated Appropriations Act of 2008 (Public Law 110-161), signed by President George W. Bush on December 26, 2007, provided fiscal year 2008 funding for nearly all federal agencies and was widely recognized as must-pass legislation, as failing to enact it would have resulted in a government shutdown. While the bill was originally introduced in June 2007 to fund only State and Foreign Operations, it was substantially amended in mid-December to become a massive, full-year omnibus package. The House passed the final package on December 17, and the Senate considered and agreed to the House amendments on December 18 and 19, after

[8] Public disclosures facilitate the internalization of pollution externalities, creating financial incentives for resource reallocation: consumers prefer sustainable alternatives (Luo and Bhattacharya, 2006), investors price carbon risk into stock returns (Bolton and Kacperczyk, 2021), shifting customer and investor preferences increase green asset values (Pástor, Stambaugh and Taylor, 2021), and firms that disclose emissions enjoy higher valuations (Matsumura, Prakash and Vera-Muñoz, 2014).

[9] Stricter environmental regulations may result in significant economic costs for firms and plants (Greenstone, 2002; Keller and Levinson, 2002; Greenstone, List and Syverson, 2012; Huang and Kopytov, 2023), which reduce firms' incentives to adopt green technologies. However, such regulations may also spur green innovation (Lanjouw and Mody, 1996; Newell, Jaffe and Stavins, 1999; Berman and Bui, 2001; Brunnermeier and Cohen, 2003; Popp, 2003; Johnstone, Haščič and Popp, 2010; Lanoie et al., 2011; Berrone et al., 2013; Calel, 2020; Brown, Martinsson and Thomann, 2022). Some studies focus on the trade-offs of policies (Acemoglu et al., 2012, 2016; Aghion et al., 2016; Shapiro and Metcalf, 2023). As noted by Porter (1991), well-designed environmental regulations can have positive side effects that boost competitiveness by reducing costs associated with waste disposal and costly chemical use. The literature debates whether environmental regulations can enhance competitiveness through firm innovation (Palmer, Oates and Portney, 1995; Porter and Linde, 1995).

[10] Popp (2002) reports the positive impact of higher energy prices on green patent incentives. Better-governed firms are also more likely to generate green patents (Amore and Bennedsen, 2016). Lanteri and Rampini (2023) argue that financial constraints and policy uncertainty can reduce incentives for firms to pursue pollution abatement activities. Also, Sautner et al. (2023*a*) show how firms' exposure to climate risk explains their green patenting decisions.

[11] Policymakers often favor mandatory disclosure as a lower-cost, less intrusive alternative to direct regulation, making it a significant policy tool across many economic sectors, including health care, education, and finance (Hastings and Weinstein, 2008; Bollinger, Leslie and Sorensen, 2011; Seira, Elizondo and Laguna-Müggenburg, 2017). In theory, mandated disclosure reduces information asymmetry between economic agents, enabling more informed decisions (Myers, Puller and West, 2022). Empirical evidence shows that it narrows the gap between insiders and outsiders, strengthens external monitoring, and improves capital allocation (Healy and Palepu, 2001; Hermalin and Weisbach, 2012; Christensen, Hail and Leuz, 2013; Christensen et al., 2017).

which the enrolled bill was returned to the House and then sent to the President on December 24. This compressed legislative sequence left limited time for review or debate and allowed the inclusion of numerous provisions that received minimal scrutiny. In his signing statement, President Bush highlighted this rushed compilation, criticizing the inclusion of "nearly 9,800 earmarks that total more than $10 billion" without a merit-based process and describing them as a "vehicle for wasteful Government spending."[12]

In particular, for the first time, the Act allocated funds to the Environmental Protection Agency (EPA) to conduct a regulatory impact analysis (RIA) and to develop mandatory greenhouse gas emissions reporting requirements.[13] The Act stipulated that at least $3.5 million from the Environmental Programs and Management budget be used to publish a draft rule within nine months and publish a final rule within 18 months. In addition, the Act required the final rule to establish mandatory reporting standards for greenhouse gas emissions above specified thresholds across all U.S. economic sectors.

This GHGRP proposal (i.e., the budget allocation and the initiation of the draft) was largely unexpected to firms. First,

Such funding has never been approved previously, and it was added by Congress to a must-pass appropriations package in mid-December. During the proposal preparation, firms faced significant uncertainties regarding various program details, including reporting thresholds (i.e., minimum levels of GHG emissions to be reported), the reporting format (facility-level vs. firm-level aggregation), and the extent to which the reporting requirement (if required at all) varied across sectors. Furthermore, questions arose about coverage, such as whether direct or indirect emissions should be reported. For instance, after the EPA's initial GHGRP proposal, the agency received thousands of public comments. These collective responses all suggest that the majority of firms were unclear about specific emission requirements that would trigger reporting obligations in advance.[14] Representative examples of such comments are summarized in Internet Appendix Section A.

This funding marked a pivotal shift in federal climate policy: it emphasized the need to collect and manage GHG emissions data, and enabled the EPA to begin early planning for the GHGRP. It is also noteworthy that this budget allocation and accelerated timeline are somewhat unexpected because the EPA's budgetary request, first made in 2003, to implement an RIA and draft such rules was not approved until December 26, 2007.

While it is true that the GHGRP proposal occurred amid a broader global shift toward climate regulation following the Kyoto Protocol, the timing and specifics of the EPA's proposal

[12]See: https://georgewbush-whitehouse.archives.gov/news/releases/2007/12/20071226-1.html

[13]121 STAT. 2128 of H.R.2764 - Consolidated Appropriations Act, 2008. See https://www.congress.gov/bill/110th-congress/house-bill/2764/text

[14]Under uncertainty, standard real options theory predicts that firms delay irreversible investments, potentially reducing low-carbon innovation. However, the program's compressed timeline limits firms' ability to wait.

were largely unexpected. Notably, the U.S. chose not to ratify the Kyoto Protocol and formally withdrew from it in 2001. For years afterward, the federal government remained reluctant to implement binding climate policies. Multiple federal climate bills, including the Lieberman-McCain Climate Stewardship Acts of 2003 and 2005, failed to pass. This reinforced the perception among firms that nationwide GHG disclosure mandates were politically unlikely in the near term. Thus, the GHGRP proposal represented a discrete policy shock from the perspective of U.S. firms. In this paper, we use 2008 as the event year to capture the regulatory initiative that laid the foundation for the GHGRP's formal proposal and its lasting impact on federal climate policy.

On April 10, 2009, building on the groundwork established in 2008, the EPA formally presented the GHGRP as a mandatory reporting rule for GHG emissions.[15] This rule required large GHG emitters, suppliers of fuel and industrial gas, and CO_2 injection sites to annually report their emissions to the EPA. Facilities that emitted more than 25,000 metric tons of GHGs per year were now required to report their emissions under the GHGRP. After receiving thousands of comment letters from the public in response to the proposed GHGRP, the EPA released a final version of the rule on October 30, 2009.[16] The GHGRP went into effect on January 1, 2010, and monitoring began. Initial disclosure reports for 2010 were submitted to the EPA on September 30, 2011 and they were made available to the public on January 11, 2012. Figure 1 illustrates the timeline for these events.

[Figure 1 about here]

In accordance with regulatory requirements, annual reports submitted to the EPA must incorporate a GHG Monitoring Plan.[17] The EPA employs an advanced electronic reporting platform that provides real-time feedback to identify potential errors prior to submission, which ensures the accuracy, completeness, and truthfulness of reported data and information.[18] If irregularities are detected, the EPA may then request further information from a facility in question. The EPA also has the authority to conduct inspections, require emissions monitoring or testing, and request documents to identify any violations. Any instances of noncompliance (e.g., failure to report emissions, failure to retain records needed to verify emissions, falsification of

[15]The following greenhouse gases are regulated by GHGRP: carbon dioxide (CO_2), methane (CH4), nitrous oxide (N2O), and fluorinated gases (HFCs, PFCs, SF6, NF3, Other Fully Fluorinated GHGs, HFEs, Very Short Lived Compounds, Other). CO_2 is the most prevalent GHG, accounting for 91.9% of all GHGRP-based GHGs reported in 2023, while CH4 represented 7.1% and N2O represented 0.7%. See https://www.epa.gov/ghgreporting/ghgrp-emissions-ghg

[16]See https://www.regulations.gov/document/EPA-HQ-OAR-2008-0508-0139/comment

[17]The report is required to include three crucial elements: (a) the identification of personnel responsible for collecting emissions data along with their corresponding job titles, (b) an explanation of the procedures utilized for emissions data collection, and (c) a comprehensive account of methods and protocols employed for ensuring the quality, maintenance, and repair of continuous monitoring systems. See https://sgp.fas.org/crs/misc/IF11754.pdf

[18]After submission, a report is evaluated and undergoes an extensive verification process, including logical, statistical, and external data checks, to assess potential errors in reports submitted by facilities. Thousands of pre-submission and post-submission checks are employed to evaluate a given report. See https://www.epa.gov/ghgreporting/ghgrp-methodology-and-verification and Figure IA7 in the Internet Appendix. The latter illustrates the process for verifying GHGRP reports.

reports) with the GHGRP constitute violations of the Clean Air Act, making the offender liable to administrative penalties up to $37,500 per day of violation.[19]

The disclosed amount of GHG emissions is sizable: in 2023, more than 8,000 facilities and suppliers report to the EPA's Greenhouse Gas Reporting Program. Facilities in nine industrial sectors disclose 2.58 billion metric tons of CO_2e in direct emissions, which account for about half of total U.S. emissions. Nearly 1,000 fuel and gas suppliers also report, and their data capture the emissions that occur when fuels are eventually used. When facility and supplier data are combined, program coverage rises to about 90% of national emissions. The GHGRP therefore provides granular facility-level information on major emitters while also capturing most economy-wide emissions.[20]

B. Low-Carbon Patents

We collect patent data from the United States Patent and Trademark Office (USPTO) and link it to U.S. public firms' patent records of Kogan et al. (2017).[21] Our dataset includes information on patents assigned to public firms (identified by CRSP identifiers) and contains details such as patent grant date, filing date, forward citation counts, patent valuations, brief descriptions, the number of claims, and inventor names as well as identifiers. We also collect each patent's process and product claims are obtained from Ganglmair, Robinson and Seeligson (2022), and inventor ages from Kaltenberg, Jaffe and Lachman (2023).

To identify low-carbon patents, we use the Cooperative Patent Classification (CPC) system: patents falling into the Y02 class in the CPC "technologies or applications for mitigation or adaptation against climate change" are defined as low-carbon ones.[22] It is noteworthy that, for patents filed before 2013, the patent office also assigns them new CPC codes after the introduction of the CPC system (Veefkind et al., 2012; Calel, 2020). Therefore, for most of our sample period (2002-2014), firms did not know the CPC codes of their patents, which mitigates the concern that firms can manipulate such patents or even mislabel them as low-carbon patents.

Many patents from our sample firms are not classified in Y02, but some of them may still contribute to low-carbon innovation. To account for these, we consider an alternative approach using a patent-domain large language model, BERT for Patents, which is a transformer-based language model pre-trained by Google on over 100 million patents (not just U.S. patents). We fine-tune the model using patents from non-sample firms that have been labeled as low-

[19] See https://www.ecfr.gov/current/title-40/chapter-I/subchapter-C/part-98

[20] See https://www.epa.gov/ghgreporting/ghgrp-reported-data and https://www.epa.gov/ghgreporting/learn-about-greenhouse-gas-reporting-program-ghgrp

[21] See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data

[22] The Y02 class was unveiled in 2010 as a new patent class that resulted from the joint efforts of the U.S. Patent and Trademark Office (USPTO) and the European Patent Office (EPO). See https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html#Y02. In 2018, the EPO extended and developed a similar definition for a classification scheme of climate change mitigation technologies that includes both the Y02 and Y04S (smart grids) classes (Angelucci, Hurtado-Albir and Volpe, 2018). Our results hold when we include the Y04S class.

carbon, other green, or non-green based on CPC codes. The model is trained on the brief descriptions (titles and abstracts) of these patents to learn the relationship between language and the probability of contributing to low-carbon innovation.[23] Since the model accepts a maximum of 512 tokens per input, we retain only the first 512 tokens of each brief description. We then apply the fine-tuned model to classify approximately 3.8 million patents from our sample firms. To reduce false positives, we keep only predictions with a probability (sigmoid output) above 0.7, labeling those below this threshold as "unclear." Our results remain robust when using higher thresholds of 0.8 or 0.9. Finally, we define a BERT-based low-carbon patent as one that either (a) is assigned a Y02 classification code or (b) is classified as low-carbon by our BERT for Patents model.

We also adopt an alternative definition of low-carbon patents based on keyword search as a robustness check. We begin by obtaining patent descriptions from PatentsView, a dataset provided by the USPTO that includes technical fields, backgrounds, and summaries of inventions. We then propose a list of keywords from Internet Appendix Table IA1 (e.g., carbon reduction, energy efficiency, cleaner energy),[24] and we identify patents in category Y02 that also contain these keywords, classifying them as keyword-based low-carbon patents. This definition is narrower than our Y02-based low-carbon patents.

For placebo tests, we use the OECD's patent classification system to define firms' other green patents as those falling under the OECD's green patent classification system (Haščič and Migotto, 2015), but that are not included in the Y02 class (e.g., water adaptation technologies, biodiversity protection technologies). In our analyses, these patents should not be impacted by the proposal because they are not directly related to climate issues.

C. National Emissions Inventory Data and CO_2 Estimation

Prior to the passage of GHGRP, firms were not required to report their carbon dioxide (CO_2) emissions.[25] However, the National Emissions Inventory (NEI) database provides information about carbon monoxide (CO) emissions at the process level, which firms must report due to CO's toxicity. While CO is not a direct measure of GHG emissions, it is nonetheless strongly correlated with CO_2 emissions (Gurney et al., 2009, 2010; Tomar, 2023), and thus makes the NEI database a valuable proxy for studying emissions patterns prior to mandatory CO_2 reporting. Updated every three years (e.g., 2005, 2008, 2011), the database includes detailed information

[23] There are 41,007 low-carbon patents and 5,132 other green patents in our non-sample firms during the sample period. To balance the sample, we randomly select 41,007 "rest" patents to match the number of low-carbon patents. Twenty percent of the total training sample is held out as a validation set. We choose the second epoch based on overall performance. The final fine-tuned model achieves an accuracy of 86.00% and an F1 score of 0.8599.

[24] We input these keywords into ChatGPT and DeepSeek to assess whether they capture the features of low-carbon patents. Both generative AI models consider the keywords to be comprehensive in scope.

[25] CO_2 accounts for 91.9% of all GHGs reported to the GHGRP in 2023. See https://www.epa.gov/ghgreporting/ghgrp-emissions-ghg

on the sources of criteria air pollutants (CAPs) and 187 hazardous air pollutants (HAPs).[26] In Internet Appendix Section B1, we explain the steps we took to link the NEI database to public firms in the U.S.

To estimate CO_2 emissions of each process at each facility before the proposal, we utilize conversion factors from Gurney et al. (2010) that are known as Vulcan Science Methods Documentation.[27] Using these conversion factors, we calculate CO_2 emissions for each process and aggregate them to estimate total firm-level CO_2 emissions before the GHGRP proposal. The detailed methodology for these calculations is outlined in Internet Appendix Section B2. Figure 2 shows the relationship between the estimated CO_2 that we convert from CO by using NEI data and actual CO_2 emissions from the GHGRP in 2011. The estimates are positively correlated with actual firm-level emissions, supporting the validity of our estimation of CO_2 emissions.

[Figure 2 about here]

D. Summary Statistics

Table 1 presents summary statistics for our sample. Panel A reports summary statistics for the patent-level RDD sample, with Panel A1 for Y02 low-carbon patents and Panel A2 for BERT-based low-carbon patents. We define our sample as publicly listed firms with facilities in the NEI database that have CO emissions data before the GHGRP proposal. Specifically, firms must have CO emissions data for the years 2005 and 2008 (the NEI updates occur every three years). Additionally, these firms must be listed in the Compustat database for at least three years before and three years after the event to be included in our statistical analysis.

In our RDD estimation of changes in patent valuation (deflated to 1982 dollars) around the GHGRP proposal, we conduct patent-level regressions. We focus on patents granted to public firms in the Compustat/CRSP database in the 12-week window centered around the GHGRP proposal date. Patent valuation, which reflects a patent's private economic value, is estimated based on stock market reactions to patent grant announcements, adjusted for return volatility, day-of-week fixed effects, and firm-year fixed effects (Kogan et al., 2017). The market value of each patent is determined by the market capitalization change (benchmarked against the market return) over a 3-day window (from day t to day t+2) commencing on the announcement day when a patent is approved (day t). We also include several patent-level control variables, such as *brief word count, Backward Citations, Claims, Process Claim Ratio, Number of Inventors, and Inventor Average Age* (definitions are provided in Appendix A).

[26] CAPs refer to a group of pollutants that includes carbon monoxide (CO), ammonia (NH3), nitrogen oxides (NOX), particulate matter smaller than 10 microns (PM10), particulate matter smaller than 2.5 microns (PM2.5), sulfur dioxide (SO_2), volatile organic compounds (VOC), and lead (Pb). HAPs encompass the 187 pollutants specified in Section 112(b) of the 1990 Clean Air Act Amendments, such as mercury, hydrochloric acid, nickel, and benzene. See https://www3.epa.gov/ttn/atw/188polls.html

[27] Tomar (2023) also uses these factors to estimate CO_2 emissions before the passage of GHGRP as a robust test. See https://vulcan.rc.nau.edu/assets/files/Vulcan.documentation.v2.0.online.pdf

In Table 1 Panel A1, the average Y02 low-carbon patent value is $34 million (deflated to 1982 dollars). The brief description of each patent averages 1,250 words. Patents typically cite about 23 prior patents and have an average of 3 claims, of which about 40% are process claims and the rest are product claims. The average number of inventors is 3, and the average inventor age is 44. In Panel A2, which reports BERT-based low-carbon patents, the summary statistics are similar to those in Panel A1, but the sample size is nearly twice as large.

For our difference-in-differences estimation, the period spans 2002 to 2014. We define a variable, Emitter, that ranges from one to four, for which a value of one (four) indicates that a company's estimated CO_2 emissions in 2005 fall within the lowest (highest) quartile of its industry (based on the three-digit NAICS code). We also use Compustat data to construct a range of control variables, including *R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing* (definitions are provided in Appendix A).

Table 1, Panel B reports firm-level summary statistics for the difference-in-differences analysis. The average number of Y02 low-carbon patents is about 5, the average number of Y02 low-carbon patent citations is 5.67, and the average firm-level Y02 low-carbon patent valuation is $79 million (deflated to 1982 dollars). For BERT-based low-carbon patents, the average number is 10.07 per firm-year. This includes 5.00 patents classified under Y02 and an additional 5.07 patents identified by our fine-tuned BERT model.

[Table 1 about here]

Internet Appendix Table IA2 presents summary statistics of keyword-based low-carbon patents among firms. The average number of keyword-based low-carbon patents per firm-year in Panel A2 is 3.26, compared to 5.00 for Y02 low-carbon patents in Table 1.

III. Regression Discontinuity Design (RDD) for Valuation of Green Innovation

To empirically examine how the GHGRP proposal influences the value of green innovation, we use a RDD method for patents granted around the enactment of the Consolidated Appropriations Act of 2008 on December 26, 2007. A small difference in a grant date should not significantly affect a patent's value, as the timing of patent issuance is often random and determined by the efficiency of the USPTO (and presumably there is no major event related to patent value). To test the difference in valuation, we conduct a patent-level regression analysis, focusing on low-carbon patents filed between 2002 and 2006 and granted in the 12-week window centered around December 26, 2007. The RDD equation is specified as follows:

$$(1) \qquad Ln(Patent\ Valuation)_p = \alpha + \beta_1 GHGRP_w + \beta_2 T_w + \gamma' Control_p + \theta_i + \theta_c + \varepsilon_p,$$

in which p indexes patents, w represents the patent issue week, θ_i indicates fixed effects for the patent-holding firm, and θ_c denotes fixed effects for the patent's four-digit CPC code. $Ln(Patent\ Valuation)_p$ is Kogan et al. (2017) value of patent p in logarithm. We define the variable $GHGRP_w$ as an indicator that equals one for patents being issued at weeks after December 26, 2007. The variable T_w is a flexible function of the running variable, the issue week. The vector $Control_p$ includes patent-level controls, such as *Brief Word Count*, *Cite Backward*, *Claims*, *Process Claim Ratio*, *Inventor Number*, and *Inventor Average Age*. We double-cluster standard errors based on the issue week as well as the four-digit CPC patent technology code.

Table 2 reports results using both local linear regression with a rectangular kernel function and flexible polynomials, all with a consistent 12-week bandwidth around the GHGRP proposal date. Columns (1) and (4) report results for Y02 low-carbon patents. Columns (2) and (5) for BERT-based low-carbon patents, and Columns (3) and (6) for other green patents. Columns (1) and (2) show that the GHGRP increases low carbon patent value by about 70%, significant at the 1% level. Column (3) reports insignificant effects for other green patents, which are classified as green under the OECD system but outside the Y02 class, serving as a placebo test. Results remain robust when we use a quadratic polynomial with the same bandwidth, as shown in Columns (4) through (6). Panel A of Internet Appendix Table IA3 reports similar results for keyword-based low-carbon patents, providing a robust relation that is not sensitive to our definitions of low-carbon patents.[28]

[Table 2 about here]

Figure 3 presents our results graphically. The dots represent weekly averages of the residuals from a regression of Ln(*Patent Valuation*) on patent-holding firm fixed effects, the patent's four-digit CPC code fixed effects, and control variables. The red fitted curves depict separate linear or quadratic polynomials for the periods before and after the GHGRP proposal, illustrating a clear cutoff in patent valuation for low-carbon patents: the value of low-carbon patents increases immediately after the proposal. These graphical results align with our findings reported in Table 2.

[Figure 3 about here]

The validity of an RDD relies on two key assumptions: (a) patent issue dates cannot be precisely manipulated to fall immediately after the GHGRP, and (b) all other patent characteristics vary smoothly with the running variable at the threshold. We find evidence supporting both of these assumptions. A formal density test (Cattaneo, Jansson and Ma, 2018) does not reject

[28]Both retail and institutional investor attention is significantly lower in late December due to the holiday season and rebounds in January (Chava and Paradkar, 2024) . Our results may reflect this seasonal pattern. The results are robust to excluding December observations.

the null hypothesis of smooth density across the threshold (p-value=0.3914), and most patent characteristics, with the exception of *Brief Word Count*, do not show a discontinuous change at the threshold (see Internet Appendix Table IA4).[29] More importantly, we perform a joint test and find that the Multinomial ANOVA F-statistic in Internet Appendix Table IA4 does not reject the null hypothesis: all firm characteristics of patents granted before and after the GHGRP are statistically indifferent. Similar results can be found for BERT-based low-carbon patents.

One concern is that large firms often receive multiple patent grants on the same day, making it difficult to attribute stock market reactions to individual patents. This complicates the identification of value signals for specific innovations. Our results remain robust when we exclude large firms, defined as those with assets above the sample median (table unreported).[30]

Our RDD results indicate that the GHGRP proposal increases the value of low-carbon patents, suggesting that the financial market assess low-carbon patents differently after the proposal date, confirming the enhanced value-relevance of those patents due to the GHGRP.

IV. Difference-in-Differences Analysis for Green Innovation Development

A. Patenting Activities

To measure how firms react to the proposal, we calculate the number of low-carbon patents filed by each firm in a year. We also calculate firm-level forward citations measure the frequency with which a firm's patents (filed in a year) is cited by subsequent patents, indicating its scientific value. It requires adjustment due to vintage (i.e., older patents tend to receive more citations) and to heterogeneity across fields (i.e., forward citations are more likely to occur in some fields than in others). Thus, we scale each patent's number of forward citations received by the average number of forward citations of public firms' patents filed in the same year and technology class (CPC Subclass 4-digit). If a patent is assigned to multiple subclasses, we then use the mode to define the patent's technology subclass. We sum up the adjusted forward citations of all low-carbon patents for which a firm applies (and which are eventually granted by the USPTO) in a given year. For the valuation of a firm's patents, we sum the values of its patents (deflated to 1982 dollars).

To examine how firms' low-carbon patenting activities react to the GHGRP proposal, we estimate the following difference-in-differences regression:

[29]To measure document length (and possibly complexity), we use the Brief Word Count. One concern is that more complex patents might face longer approval delays. However, we find that patents granted before the proposal date actually have larger Brief Word Counts, as reported in Internet Appendix Table IA4. As a result, the before-versus-after differences in this variable are unlikely to invalidate our RDD setting because we find higher value of patents granted in the post-event period.

[30]Admittedly, Kogan et al. (2017) acknowledge that information leakage during the patent application process may lead to a gradual incorporation of patent value into stock prices. Consequently, the market reaction on the grant date likely understates the patent's total value, potentially biasing our estimates downward.

$$
\begin{aligned}
Ln(1 + Low - Carbon\ Tech_{it}) =& \beta(GHGRP_t \times Emitter_i) \\
&+ \gamma' Controls_{it} + \eta_t + \varphi_{jt} + \varepsilon_{it},
\end{aligned} \tag{2}
$$

in which i represents firms, t represents years 2002 to 2014, and j indicates a firm's industry (three-digit NAICS code). $Ln(1 + Low - Carbon\ Tech_{it})$ in Equation (2) denotes the natural logarithm of one plus the count, citations, or values of Y02 low-carbon patents or BERT-based low-carbon patents filed by firm i in year t.[31] We also consider Poisson regressions using $Low - Carbon\ Tech_{it}$ as the dependent variable in a robustness check. $GHGRP_t$ is a binary variable that is equal to one for years after 2007 and zero otherwise.

Our variable for treatment, $Emitter_i$, ranges from one to four: firms with an estimated 2005 CO_2 emission level in the lowest industry quartile (based on the three-digit NAICS code) are assigned a value of one, while those in the highest quartile are assigned a value of four. We measure firms' emissions relative to their industry peers to identify treated firms, following Berrone et al. (2013). Given that the format, coverage, scope, and threshold of the GHGRP are largely unclear to firms before the proposal, their pre-proposal estimated CO_2 emissions (based on CO emissions in 2005) and corresponding treatment assignment are unlikely affected by firms' expectation of mandatory disclosure or their manipulation or misreporting of CO emissions. Thus, our treatment assignment is not subject to reverse causality and selection concerns.

$Controls_{it}$ includes a range of control variables: *R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing* (we provide their definitions in Appendix A). The results are robust when the control variables are not included, as shown in Internet Appendix Table IA6. In our regression analysis, we control for firm and industry-year fixed effects (η_t and φ_{jt}) and use double-clustered standard errors by industry and year.

Our results in Table 3 indicate that high-emission firms file significantly more, and higher-quality, low-carbon patents following the GHGRP proposal. Specifically, the estimated coefficients for $GHGRP \times Emitter$ in Columns (1) and (3) are 0.0353 for low-carbon patent counts and 0.0428 for citations, both of which are statistically significant at the 5% level. For BERT-based patent counts and citations in our regressions (Columns (2) and (4)), the coefficients on $GHGRP \times Emitter$ remain similar to those for Y02 low-carbon patents.

Table 3 also shows an increase in high-emission firms' low-carbon patent values following the

[31] Since taking the natural logarithm of one plus patents may alter the original interpretation of the log transformation, we present our robust results in Internet Appendix Table IA5 using a Poisson model that directly uses patent counts and citations without log transformation.

GHGRP proposal. Columns (5) and (6) report firm-level results for Y02 and BERT-based low-carbon patent valuations. Low-carbon patent valuation of high-emission firms rises significantly, at least at the 10% level, after the proposal. Hence, the stock market perceives low-carbon patents as more valuable to those firms after the proposal.

[Table 3 about here]

In terms of economic significance, the coefficient of 0.0353 for low-carbon patent counts (Column (1)) implies that a one-quartile increase in a firm's industry emission rank (e.g., moving from the first to the second quartile) corresponds to a 3.5% rise in low-carbon patent filings following the GHGRP proposal. This translates to 0.21 additional patents annually per firm.[32] Similarly, the coefficient of 0.0428 for patent citations (in Column (3)) suggests a 4.3% increase in forward citations of low-carbon patents for firms in higher emission quartiles, equating to 0.29 additional adjusted citations per year, consistent with improved patent quality post-GHGRP. For patent value, the proposal leads to a 6% economic gain, or approximately $4.9 million in annual patent value per firm, for a one-quartile rise in emission rank.

These findings underscore the economic significance of the GHGRP proposal. High-emission firms face greater pressure to internalize the externalities they create, which increases their incentives to invest in more and better carbon-related technologies.[33]

We consider several robustness checks and find consistent results. First, we estimate Equation (2) using an alternative definition of low-carbon patents based on keyword-based classifications. Panel B of Internet Appendix Table IA3 shows that the counts, citations, and valuations of firms' keyword-based low-carbon patents remain robust, confirming that these patents are closely related to areas such as carbon emissions, energy efficiency, and cleaner energy. Second, we acknowledge possible offshored emissions and thus exclude firms with high foreign income (which reflects their overseas activities).[34] Internet Appendix Table IA7 presents consistent results. Third, we use a binary variable $Emitter_i$, such that firms with an estimated 2005 CO_2 emission level above the industry median are assigned a value of one, and zero otherwise. We report our results in Internet Appendix Figure IA8 and Table IA8. Fourth, we consider synthetic difference-in-differences (SDID) (Arkhangelsky et al., 2021) with a specification similar to Equation (2). This approach combines difference-in-differences and synthetic control methods, reweighting

[32] Differentiating both sides of the model: $\frac{\partial ln(1+Y)}{\partial(GHGRP \times Emitter)} = \frac{\partial ln(1+Y)}{\partial Y} \cdot \frac{\partial Y}{\partial(GHGRP \times Emitter)}$. Since $\frac{\partial ln(1+Y)}{\partial Y} = \frac{1}{1+Y}$, we obtain $\frac{\partial Y}{\partial(GHGRP \times Emitter)} = \beta \cdot (1+Y)$. The change in the number of patents is: $\Delta Y = \frac{\partial Y}{\partial(GHGRP \times Emitter)} \cdot \Delta(GHGRP \times Emitter) = \beta \cdot (1+Y) \cdot \Delta(GHGRP \times Emitter)$. Taking the sample average for Y, and noting that after the proposal, a one-level higher emitter implies $\Delta(GHGRP \times Emitter) = 1$, the change in the number of patents is: $\Delta Y = \beta \cdot (1+\bar{Y})$.

[33] The observed increase in patents may reflect firms' incentives to patent existing technologies as a signal of clean innovation, potentially placing competitors at a disadvantage (Liu et al., 2024).

[34] Although about 60% of sample firms reported foreign sales in 2008, these sales were economically small, averaging only about 2% of total assets or total sales.

and matching pre-exposure trends to force the parallel trend assumption to be valid. We report our results in Internet Appendix Figure IA9 and Table IA9.[35]

B. Parallel Trends Assumption

To analyze cross-year differences in low-carbon innovation, we estimated a modified version of Equation (2) by including interactions between $Emitters$ and year-specific dummy variables (I_t) as follows:

$$Ln\,(1 + Low - Carbon\,Tech_{it}) = \sum_{t=2002, t\neq 2008}^{2014} \beta_t (I_t \times Emitter_i) + \gamma' Controls_{it} + \eta_i + \varphi_{jt} + \varepsilon_{it}. \quad (3)$$

Figure 4 displays the sequence of β_t for YO2 and BERT-based low-carbon patent counts, citations, and valuations estimated using the standard DID approach from Equation (3). The figure presents 90% confidence intervals annually for those panels presenting results that incorporate control variables. Figure 4 supports the validity of our parallel trends assumption, showing that the trends in low-carbon patent counts, citations, and valuations among higher quartile carbon emitters remain similar to those of lower quartile emitters prior to the proposal.

[Figure 4 about here]

We also use the "honestDiD" method of Rambachan and Roth (2023) to assess the sensitivity of our causal conclusions under different assumptions about potential deviations from the parallel trends assumption. Internet Appendix Figure IA10 presents our dynamic analysis results, showing stable confidence intervals for the average treatment effect during the post-period. Our findings are robust under a linear trend assumption (Mbar = 0), holding true for patent counts, citations, and valuations. As we increase allowance for nonlinearity (Mbar > 0), we reach a significance threshold of Mbar = 0.3 to fail to reject the null hypothesis for patent counts. In practical terms, a 30% increase in patent counts is unlikely. For patent citations and patent valuation (Panels B and C, respectively), our results remain consistent until Mbar reaches approximately 0.2. Our analysis confirms that our findings are robust to moderate deviations from the parallel trends assumption.

[35] Although the p-value for Y02 low-carbon patent valuation in the SDID model is approximately 0.13, our parallel trend plot shows a notable increase in patent value following the proposal. For BERT-based low-carbon patents, the results are statistically significant.

C. *Real Effects: CO_2 Emissions, Air Pollution, and Environmental Scores*

In our previous sections, we observe that after the GHGRP proposal, high-emission firms tend to invest more in low-carbon technologies. Prior research also indicates that firms typically reduce their GHG emissions after mandatory disclosure (Tomar, 2023).[36] These findings motivate us to test if such technologies could result in a significant reduction in GHG emissions.

Moreover, when firms become more energy-efficient, low-carbon technologies could have spillover effects that could reduce other types of air pollutions. For example, the adoption of low-carbon technologies may lower the consumption of fossil fuels, resulting in reduced emissions of not only carbon dioxide but also other harmful pollutants such as sulfur dioxide (SO_2) and nitrogen oxides (NO_X). These pollutants are known contributors to smog formation and respiratory illnesses. Additionally, improvements in manufacturing processes that utilize low-carbon technologies can lead to less waste and lower emissions of volatile organic compounds (VOCs), which can also enhance air quality.

As a validation test, we use estimated CO_2 emissions as the dependent variable in Equation (2) for our sample because (a) we only have data for 2005, 2008, 2011, and 2014, as the NEI database updates every three years; and (b) real CO_2 data are unavailable before 2010. Nevertheless, we find consistent results when we use estimated CO_2 emissions for the pre-period of 2008 and use actual CO_2 emissions for the post-period from 2010 to 2014, as shown in Table IA10 in the Internet Appendix. To further examine the spillover effects of low-carbon technologies, we also analyze non-CO criteria air releases (NH_3, NO_x, PM_{10}, SO_2, and VOC).

Our results, presented in Table 4, indicate that estimated CO_2 emissions significantly decline after the GHGR proposal. Non-CO criteria air releases also show significant results; however, the effects are much smaller: the difference in DID coefficients for estimated CO_2 and Non-CO criteria air releases is significant as shown in the bottom of the table. Overall, while low-carbon technologies primarily target carbon emissions, they also reduce other pollutants.

[Table 4 about here]

We also conduct an additional test by measuring a firm's environmental performance using its E score, which is calculated as the number of KLD environmental strengths (scaled by total environmental strengths items) minus the number of KLD environmental concerns (scaled by total environmental concerns items). Using the structure of Equation (2) with firm-level E scores as the dependent variable, Table 5 shows that firms with higher carbon emissions after the event exhibit a greater increase in E scores. These results suggest that mandatory GHG disclosure also enhances firms' environmental performance perceived by the rating agency.

[36] Unlike Tomar (2023), who uses the period 2010-2011 as the pre-event date and uses 2012 as the event date, we extend our analysis to include the period before 2010, similar to Yang, Muller and Liang (2021).

[Table 5 about here]

D. Alternative Explanations

While our baseline results suggest that the GHGRP significantly stimulated low-carbon innovation among high-emission firms, it is important to consider potential alternative explanations. In particular, the observed increase in low-carbon patenting could reflect broader regulatory shifts or macroeconomic shocks that occurred around the same time as the GHGRP's introduction. For instance, the election of President Barack Obama in 2008 and the launch of the Green Technology Pilot Program in 2009 may have signalled a broader pro-environment policy stance, potentially encouraging green innovation. Similarly, the 2008 financial crisis brought substantial economic and energy market disruptions that may have differentially affected high-emission firms, particularly those in energy-intensive sectors, thereby inducing innovation patterns unrelated to the GHGRP itself.

To address these concerns, we conduct a series of placebo tests aimed at disentangling the effects of the GHGRP from other coinciding factors. First, we examine whether the observed effects extend to other types of green patents that are unrelated to greenhouse gas emissions. Second, we assess whether exposure to policy uncertainty, oil price volatility, or aggregate macroeconomic shocks, proxied by climate policy uncertainty (CPU) beta, economic policy uncertainty (EPU) beta, oil beta, and market beta, can account for the observed innovation responses. Finally, we consider whether firms may have responded to the GHGRP through symbolic "greenwashing" rather than substantive innovation. The results of these tests consistently indicate that alternative explanations are unlikely to fully explain the increase in low-carbon patenting, thereby reinforcing our interpretation that the GHGRP was a key driver of this response.

Confounding Policies

The election of Barack Obama in 2008 and the subsequent implementation of the Green Technology Pilot Program[37] in 2009 may have potentially bolstered regulatory oversight on chemical releases, subsequently fostering a surge in overall green innovation that included low-carbon innovation within firms. To address these alternative explanations, we conduct placebo tests using other green patents (we define in Section 2.2) as our dependent variable in Equation (2). As shown in Panel A of Table 6, there is no statistically significant difference in the filing of other green patents between firms in the higher and lower quartiles of carbon emissions following the GHGRP proposal. The coefficients in all columns are also relatively small compared to our

[37] See https://www.uspto.gov/patents/initiatives/green-technology-pilot-program-closed

baseline results. These findings imply that the increase in low-carbon patents observed in our baseline analysis is more likely influenced by the GHGRP rather than other policies.

[Table 6 about here]

Policy Uncertainty and Macroeconomic Shocks

One alternative explanation is that our results are driven by contemporaneous policy uncertainties. The timing of the GHGRP coincided with heightened climate-specific and aggregate economic policy uncertainty. It could be argued that the observed increase in green innovation was merely a response to climate policy uncertainty (Gavriilidis, Känzig and Stock, 2023), where firms facing high uncertainty arbitrarily alter their strategies without clear regulatory direction. Similarly, generalized economic policy uncertainty (Baker, Bloom and Davis, 2016) could have differentially affected firms based on their historical exposure. To test this, we replace the Emitter indicator with firm-level CPU beta and EPU beta, estimated using monthly return data from 2007, excluding December.[38] We classify firms into quartiles based on these betas and construct indicator variables for the top quartile.

As shown in Panels B and C of Table 6, firms with high CPU beta do not exhibit a statistically significant increase in low-carbon patenting, indicating that climate policy uncertainty alone is insufficient to drive our findings. Interestingly, the coefficient on the EPU beta is significantly negative for patent counts, suggesting that generalized economic uncertainty actually dampens green innovation. This aligns perfectly with recent evidence by Wang, Wurgler and Zhang (2026), who document that policy uncertainty reduces corporate green R&D. This significantly negative effect fundamentally contradicts the alternative explanation that uncertainty spurred the observed innovation surge.

Beyond policy uncertainty, one can also argue that the observed increase in low-carbon patenting following the GHGRP proposal may have been influenced by confounding macroeconomic events, most notably the onset of the 2008 financial crisis, which coincided almost exactly with the timing of the regulation's introduction. During this period, global oil prices collapsed, leading to significant revaluation of high-carbon industries, particularly the energy sector, which is also a major contributor to low-carbon technological innovation. In addition to oil price volatility, high-emission firms may have faced heightened pressure from investors to adopt more sustainable practices amid increasing risk aversion. Moreover, the clean energy stimulus provi-

[38] CPU beta ($\beta_{CPU,i}$) and EPU beta ($\beta_{EPU,i}$) are estimated from the time-series regression using monthly data:

$$Ret_{i,t} = \alpha_i + \beta_{CPU,i} \times CPU_Shock_t + \beta_{EPU,i} \times \Delta \ln(EPU_t) + \beta^M_{mkt,i} \times Ret^M_{mkt,t} + \varepsilon_{i,t}$$

where $Ret_{i,t}$ denotes the stock return of firm i in month t, CPU_Shock_t represents the climate policy uncertainty shock, $\Delta \ln(EPU_t)$ is the log-difference of the news-based US Monthly Economic Policy Uncertainty Index, and $Ret^M_{mkt,t}$ is the monthly value-weighted market return.

sions included in the 2009 American Recovery and Reinvestment Act could have independently motivated firms to shift toward green technologies, regardless of the GHGRP.

There is another possibility that high-emission firms responded to the crisis in ways distinct from their lower-emission peers within the same industry. For example, differences in access to capital during the credit freeze or variations in business diversification could have led to firm-level heterogeneity in innovation activity that is unrelated to the GHGRP itself. While our main specification includes industry-year fixed effects to control for common time-varying shocks within industries, these controls may not fully capture such within-industry differences.

To address these concerns, we further conduct placebo tests designed to isolate the impact of these contemporaneous shocks. Specifically, we replace the Emitter indicator with two firm-level exposure measures: oil beta and daily market beta, both calculated using daily firm-level return data from 2007, excluding dates after December 26, 2007, which is the date the U.S. Congress passed the Consolidated Appropriations Act of 2008.[39] The oil beta captures a firm's sensitivity to oil price movements, while the market beta reflects exposure to aggregate macroeconomic conditions. We classify firms into quartiles based on these betas within their three-digit NAICS industry and construct indicator variables equal to one for firms in the top quartile, representing high exposure.

These betas, as reported in Panels D and E of Table 6, show no robust, statistically significant positive effects on low-carbon patenting when using oil beta or market beta as treatment variables. These findings suggest that neither oil price shocks nor broader financial market turbulence can explain the post-2007 low-carbon innovation patterns observed among high-emission firms. Taken together, these placebo tests help rule out alternative explanations related to both policy uncertainty and the financial crisis.

Anticipated ESG Mandates and Reputational Motives

Another potential explanation is that firms may have anticipated the introduction of broader environmental disclosure mandates, extending beyond GHG emissions to include areas such as water usage, pollution intensity, or other ESG dimensions. In response, they may have proactively increased their environmental innovation efforts. However, if this were the primary driver, we would expect to observe a uniform rise in all categories of green patents. Our placebo tests in Section 4.4.1, however, reveal that the increase is concentrated in patents specifically related to greenhouse gas emissions, making it unlikely that generalized regulatory anticipation

[39] Oil beta $\beta_{oil,i}$ and daily market beta $\beta^{D}_{mkt,i}$ are estimated from the regression using daily data:

$$Ret_{i,t} = \alpha_i + \beta_{oil,i} \times Ret_{oil,t} + \beta^{D}_{mkt,i} \times Ret^{D}_{mkt,t} + \varepsilon_{i,t}$$

where $Ret_{i,t}$ denotes the stock return of firm i on day t, $Ret_{oil,t}$ is the return on Brent crude oil futures, and $Ret^{D}_{mkt,t}$ is the return on a daily value-weighted market index.

alone can explain the pattern.

Finally, one might argue that high-emission firms engage in low-carbon patenting primarily for reputational purposes, as a form of strategic signaling or so-called "greenwashing." While plausible, this explanation appears insufficient. As shown in Section 4.3, firms that increased low-carbon patenting also experienced subsequent reductions in CO_2 and other pollutant emissions. This alignment between innovation and actual environmental performance suggests that the observed patenting surge reflects substantive behavioral change rather than mere symbolic compliance or greenwashing.

V. Mechanisms

The proposal of the GHGRP placed substantial pressure on high-emission firms to internalize their environmental externalities through engaging in low-carbon technology. They might achieve this through several channels: hiring external inventors with targeted expertise in low-carbon technologies, encouraging existing internal inventors to develop green innovations independently, or fostering collaborations between newly hired experts and incumbent inventors to facilitate knowledge spillovers. To unpack these mechanisms, we sequentially investigate (a) firms' acquisition of external low-carbon inventors, (b) the standalone low-carbon patenting productivity of incumbent inventors, and (c) the collaborative innovation outcomes between newly hired experts and incumbents.

A. Acquiring Inventors with Low-Carbon Technology Experience

To capture firms' acquisition of external inventors, we first define a newly hired inventor's low-carbon technology experience as the number of years between the year s/he first patented a low-carbon technology and the year s/he joins the focal firm. We then sum these numbers for all experienced inventors that the focal firm hires in a given year, and estimate Equation (2) using this total acquired experience measure.

Our results in Table 7 show that, following the GHGRP proposal, high-emission firms are significantly more likely to acquire low-carbon expertise from the external human capital market. The coefficients across all columns are statistically significant at the 1% level. In terms of economic magnitude, based on Column (2), a one-rank increase in a firm's emission quartile (e.g., from the first to the second) is associated with an increase of about 0.84 years in newly hired inventors' aggregate years of experience with low-carbon technologies. These findings suggest that the GHGRP proposal effectively incentivized high-emission firms to recruit experienced inventors from the labor market to bridge their low-carbon technology gaps.

[Table 7 about here]

B. *Incumbent Inventors' Low-Carbon Patenting Activities*

Next, we evaluate whether the GHGRP proposal directly stimulated the low-carbon patenting activities of firms' existing (incumbent) inventors working independently. We define incumbent inventors as those with a firm tenure of more than four years. We re-estimate Equation (2) using the natural logarithm of one plus the number of Y02 or BERT-based low-carbon patents authored exclusively by these incumbents.

As reported in Table 8, the DID coefficients across all columns are small and statistically insignificant. This indicates that the GHGRP proposal did not successfully trigger a surge in the standalone productivity of incumbent inventors regarding low-carbon innovation. A plausible explanation is that existing inventors, particularly those historically focused on traditional or high-carbon processes, face steep learning curves and significant friction when abruptly shifting their technological focus without external guidance.

[Table 8 about here]

C. *Collaborations Between Incumbents and Newly Hired Experts*

While incumbents struggle to innovate in low-carbon technologies independently, the influx of external experts may generate intra-firm knowledge spillovers. To test this, we examine whether incumbent inventors learn and adapt by collaborating with newly hired experts. We define a new expert as an inventor with a tenure of two years or less who has prior low-carbon patenting experience. We then run our baseline specification on two novel collaboration metrics.

Table 9 examines the *propensity* of collaboration by using the natural logarithm of one plus the unique count of incumbent co-inventors in a given year who collaborated with new experts on low-carbon patents. The significantly positive coefficients suggest that high-emission firms increasingly integrated their seasoned internal staff into green R&D teams led by newly acquired talent.

[Table 9 about here]

Table 10 further evaluates the *outcomes* of these collaborations, where the dependent variable is the natural logarithm of one plus the number of joint patents co-authored by at least one new expert and at least one incumbent. The results show a robust and statistically significant increase in joint low-carbon patenting output.

[Table 10 about here]

Collectively, the mechanism tests in this section paint a comprehensive picture of how high-emission firms navigate sudden climate regulatory pressures. Rather than simply firing old staff

or expecting incumbents to overcome steep learning curves independently, firms act strategically: they rapidly acquire targeted low-carbon expertise from the external labor market and pair these new experts with incumbent inventors. This collaborative synergy facilitates internal knowledge spillovers, transforming external human capital acquisition into sustained, firm-wide green innovation capabilities.

VI. Incentive Tests

A. *Competition Pressure*

In this section, we examine whether the effect of the GHGRP varies with firms' exposure to competition pressure that may be driven by customers' environmental preferences. Intense competition motivates firms to develop distinctive innovations that reshape the market and create product differentiation (Aghion et al., 2001, 2005). Intense competition also reduces the incentive for firms to share or license valuable technologies to others, as licensors typically maintain a competitive advantage by limiting access to rivals (Rockett, 1990).

We classify firms into high- and low-competition groups using two measures: (a) product market similarity and (b) climate risk-concerned analyst coverage. Higher product similarity indicates greater competitive pressure, as customers perceive fewer differences across products. Firms with product market similarity (Hoberg and Phillips 2016) in 2006 above the sample median are classified as *High Product Similarity, and the remainder as Low Product Similarity.*

On the other hand, analysts systematically respond to changes in customer sentiment (Luo, Homburg and Wieseke, 2010). In the context of climate risk, greater coverage of climate risk-concerned analysts signals stronger customer concerns about climate-related issues, making it a useful measure of competition pressure tied to customers' environmental preferences. To measure climate risk-concerned analyst coverage, we first use I/B/E/S data to calculate each analyst's climate risk orientation using the following formula:

$$\text{Climate Risk Orientation}_a = \frac{1}{N}\left(\sum_{i=1}^{N}\frac{\text{Low-Carbon Pat Val}_{ai}}{\text{Total Pat Val}_{ai}}\right), \tag{4}$$

in which N represents the total number of firms i covered by analyst a in 2006. For each analyst, we compute the ratio of low-carbon patent valuation (Low-Carbon Pat Val_{ai}) to total patent valuation (Total Pat Val_{ai}) for each firm that they cover and then take the average of these ratios. If the resulting average exceeds the median ratio of all analysts in $I/B/E/S$ for 2006, we then classify the analyst as being more concerned about climate risk. We then calculate the number of climate risk-concerned analysts for each sample firm by summing the

total number of such analysts. Firms with a total number of such analysts that exceeds the sample median in 2006 are assigned to the group of high climate risk-concerned analyst coverage (*High Climate Risk Analyst*). All other firms are classified as having low climate risk-concerned analyst coverage.

We estimate Equation (2) separately for each group: Panel A is for product market similarity, and Panel B is for climate risk-concerned analyst coverage. Table 11 shows that high-emission firms facing greater competition pressure significantly increase their low-carbon patenting after the GHGRP proposal, whereas such firms with lower competition pressure show no significant change. We observe similar patterns for low-carbon patent citations (Columns (5) through (8) of Panels A and B) and for patent valuations in Internet Appendix Table IA11. Taken together, these results indicate that the GHGRP effect is stronger among firms under greater competitive pressure, consistent with the view that low-carbon innovation serves as a means of product differentiation.

[Table 11 about here]

B. Price Efficiency

Lower information asymmetry enables stock markets to better evaluate firms' technological capabilities, align stock prices with fundamentals, and reward firms' innovation efforts (Edmans and Manso, 2011). Since managers care about stock prices when making investment decisions (Chen, Goldstein and Jiang, 2007; Bakke and Whited, 2010; Lin, Liu and Sun, 2019), more efficient prices improve their efficiency in capital allocation. As stock markets react favorably to high-emission firms' low-carbon patents, we predict that such firms with higher price efficiency (lower information asymmetry) are more likely to be more active in low-carbon patenting following the GHGRP proposal.

We classify firms into high- and low-price-efficiency groups using two measures: (a) option trading volume and (b) the probability of informed trading (PIN). Options may impact firm value by helping to complete markets and stimulate informed trades (Roll, Schwartz and Subrahmanyam, 2009). Also, the enhanced informational efficiency driven by options leads to a more efficient allocation of corporate resources (Blanco and Wehrheim, 2017). PIN is derived from the Bayesian microstructure model of Easley, Hvidkjaer and O'Hara (2002) and estimates the probability that a given order originates from an informed trader. Thus, PIN measures the extent of informed trading in a stock; a lower PIN indicates lower information asymmetry.[40]

We measure options trading volume by multiplying the total trade volume of each option by the end-of-day quote midpoint for that option, and then aggregating this value annually across

[40]PIN data are obtained from https://terpconnect.umd.edu/ stephenb/EKOpins.html and are also used in Brown, Hillegeist and Lo (2004).

all trading days and options listed for a focal firm's stocks. Firms with total option trading volume in 2006 above the sample median are classified in the group of high option trading, while all other firms are categorized in the group of low option trading. Similarly, firms with PIN in 2006 above the sample median are classified as High PIN, and the remainder as Low PIN.

We estimate Equation (2) separately for the high and low price efficiency groups. Panel A of Table 12 is for option trading, and Panel B is for PIN. Table 12 shows that, following the GHGRP proposal, high-emission firms with higher price efficiency are more active in low-carbon patenting. The DID coefficients in the high price efficiency group are statistically significant, whereas no significant effects appear for the low price efficiency group. We find similar patterns for patent citations (reported in Columns (5) to (8) in Table 12) and for patent valuation (reported in Internet Appendix Table IA12). Overall, these results suggest that the GHGRP effect is stronger for firms with more efficient stock pricing. [41]

[Table 12 about here]

VII. Conclusion

While low-carbon technologies are important tools to achieve low/zero-emission economies, their development hinges on corporate resources and managerial incentives. In this paper, we focus on is how observed environmental externalities influence such technologies through mandatory disclosure. As the private sector often lacks the motivation to internalize externalities, policies that provide transparency and reduce uncertainty about future regulations can help redirect corporate choices in investment. We present compelling evidence that the GHGRP proposal incentivizes high-emission firms to invest in low-carbon technologies and reduce their GHG emissions. Moreover, the GHGRP not only helps reduce CO_2 emissions but also leads to broader environmental benefits (e.g., reduced non-GHG air pollutants) and hence positive spillover effects. Such a transition in production technologies is positively received by the stock market, indicating that heavy emitters' incentives to mitigate environmental externalities are valued by investors.

We offer new insights into how corporate innovation decisions can be shaped by public disclosure. In addition, our research underscores the potential and efficiency of emissions disclosure as a policy tool for mitigating negative externalities and social welfare loss. Unlike other regulatory measures, such as carbon taxes and investment subsidies, the GHGRP proposal offers a low-cost approach that encourages firms to develop low-carbon technologies without imposing significant economic burdens.

[41] To provide further evidence on the market's valuation of low-carbon innovation capacity, we examine the impact of the GHGRP proposal on overall firm market value. As shown in Table IA13, firms with high pre-event low-carbon patent valuations experienced a significantly higher increase in market value after the GHGRP announcement relative to their industry peers.

Appendix A Variables Definition

Variables	Definition	Source
Panel A. Patent-level RDD Sample		
Y02 Low-Carbon Valuation	The natural logarithm of the valuation of CPC Y02 low-carbon patents. Kogan et al. (2017) supplies patent value information, reflecting the private economic value of patents. The market value of each patent is determined by the market capitalization change (benchmarked against the market return) over a 3-day window (from day t to day t+2) commencing on the announcement day when a patent is approved (day t).	USPTO; Kogan et al. (2017)
BERT Low-Carbon Valuation	The natural logarithm of the valuations of BERT-based low-carbon patents. A patent is classified as BERT-based low-carbon if it either carries a Y02 code or is identified as low-carbon by our fine-tuned BERT model.	USPTO; Kogan et al. (2017)
Other Green Valuation	The natural logarithm of the valuations of other green patents. Other green patents are defined by the OECD as green patents excluding CPC Y02.	USPTO; Hašić and Migotto (2015); Kogan et al. (2017)
Brief Word Count	The word count (in thousands) of a patent's brief introduction document.	USPTO
Cite Backward	The number of backward citations included in a patent.	USPTO
Claims	The total number of claims within a patent.	USPTO
Process Claim Ratio	The ratio of process claims to the total claims of a patent.	USPTO; Ganglmair et al. (2022)
Inventor Number	The total number of inventors listed on a patent.	USPTO
Inventor Average Age	The average age of inventors listed on a patent, with missing values replaced by the sample median.	USPTO; Kaltenberg et al. (2023)
Panel B. Firm-level DID Sample		
Estimated CO_2	The CO_2 emissions estimate is obtained by utilizing process-level CO data and industry-process specific conversion factors (Gurney et al. 2009; Gurney et al. 2010) to convert CO to CO_2. These emissions are then accumulated at the company level.	NEI
Real CO_2	The actual CO_2 emissions data are obtained from the Greenhouse Gas Reporting Program (GHGRP). We aggregate facility-level data into firm-level data on an annual basis, spanning the years 2010 to 2014.	GHGRP
Emitter	The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level.	NEI
GHGRP	GHGRP equals one if a year is 2008 or later.	USPTO
Y02 Low-Carbon Count	The natural logarithm of one plus the number of newly applied (and eventually granted) CPC Y02 low-carbon patents for a firm in a given year.	USPTO
Y02 Low-Carbon Cite	The natural logarithm of one plus the number of adjusted citations received by a firm's newly applied (eventually granted) CPC Y02 low-carbon patents in a given year. Each patent's citations are adjusted by the average number of forward citations received by all public firms in the same year and technology class (CPC 4-digit subclass).	USPTO
Y02 Low-Carbon Valuation	The natural logarithm of one plus the total valuation of a firm's CPC Y02 low-carbon patents in a given year. Kogan et al. (2017) supplies patent value information, reflecting the private economic value of patents. The market value of each patent is determined by the market capitalization change (benchmarked against the market return) over a 3-day window (from day t to day t+2) commencing on the announcement day when a patent is approved (day t).	USPTO; Kogan et al. (2017)
BERT Low-Carbon Count	The natural logarithm of one plus the number of newly applied (and eventually granted) BERT-based low-carbon patents for a firm in a given year. A patent is classified as BERT-based low-carbon if it either carries a Y02 code or is identified as low-carbon by our fine-tuned BERT model.	USPTO

BERT Low-Carbon Cite	The natural logarithm of one plus the number of adjusted citations received by a firm's newly applied (eventually granted) BERT-based low-carbon patents in a given year. Each patent's citations are adjusted by the average number of forward citations received by all public firms in the same year and technology class (CPC 4-digit subclass). A patent is classified as BERT-based low-carbon if it either carries a Y02 code or is identified as low-carbon by our fine-tuned BERT model.	USPTO
BERT Low-Carbon Valuation	The natural logarithm of one plus the total valuation of a firm's BERT-based low-carbon patents in a given year. A patent is classified as BERT-based low-carbon if it either carries a Y02 code or is identified as low-carbon by our fine-tuned BERT model. Kogan et al. (2017) supplies patent value information, reflecting the private economic value of patents. The market value of each patent is determined by the market capitalization change (benchmarked against the market return) over a 3-day window (from day t to day t+2) commencing on the announcement day when a patent is approved (day t).	USPTO; Kogan et al. (2017)
Other Green Count	The natural logarithm of one plus the number of patents related to other forms of environmental technology (OECD green patents, excluding CPC Y02 patents).	USPTO; Hašić and Migotto (2015)
Other Green Cite	The natural logarithm of one plus the citations of patents related to other forms of environmental technology (OECD green patents, excluding CPC Y02 patents).	USPTO; Hašić and Migotto (2015)
Other Green Valuation	The natural logarithm of one plus the value of patents related to other forms of environmental technology (OECD green patents, excluding CPC Y02 patents). Kogan et al. (2017) supplies patent value information, reflecting the private economic value of patents. The market value of each patent is determined by the market capitalization change (benchmarked against the market return) over a 3-day window (from day t to day t+2) commencing on the announcement day when a patent is approved (day t).	USPTO; Hašić and Migotto (2015); Kogan et al. (2017)
Estimated CO_2	The natural logarithm of one plus estimated CO_2 emissions.	NEI
Non-CO Criteria Air	The natural logarithm of one plus the non-CO criteria air releases (NH_3, NO_x, PM_{10}, SO_2, and VOC) of a firm.	NEI
E Score	The natural logarithm of KLD environmental strengths (scaled by the total environmental strengths items) minus the number of KLD environmental concerns (scaled by the total environmental concerns items).	KLD
New Y02 Low-Carbon Experience	The total years of CPC Y02 low-carbon inventor experience acquired by a firm from the labor market. The total years of low-carbon inventor experience is the sum of the years between the hiring of experienced inventors and the years that they first patented low-carbon technology. An experienced inventor is defined as one with previous low-carbon patents who was not previously employed by a given firm.	USPTO
New BERT Low-Carbon Experience	Similar to New Low-Carbon Experience, based on BERT-classified low-carbon patents.	USPTO
Y02 Low-Carbon Incumbent-Only Patent Count	The natural logarithm of one plus the total number of CPC Y02 low-carbon patents authored exclusively by incumbent inventors in a given year. An incumbent inventor is defined as having a firm tenure of more than four years.	USPTO
BERT Low-Carbon Incumbent-Only Patent Count	The natural logarithm of one plus the total number of BERT-based low-carbon patents authored exclusively by incumbent inventors (tenure $>$ 4 years) in a given year.	USPTO
Y02 Low-Carbon Incumbent Co-Inventors	The natural logarithm of one plus the unique count of incumbent co-inventors (tenure $>$ 4 years) in a given year who collaborated with newly hired experts on CPC Y02 low-carbon patents. A new expert is defined as an inventor with a tenure of two years or less who has prior low-carbon patenting experience.	USPTO
BERT Low-Carbon Incumbent Co-Inventors	Similar to Y02 Low-Carbon Incumbent Co-Inventors, but based on BERT-classified low-carbon patents in a given year.	USPTO
Y02 Low-Carbon Joint Patent Count	The natural logarithm of one plus the number of CPC Y02 low-carbon joint patents in a given year. A joint patent is defined as a patent co-authored by at least one new expert (tenure $\leq$ 2 years with prior low-carbon experience) and at least one incumbent (tenure $>$ 4 years).	USPTO
BERT Low-Carbon Joint Patent Count	Similar to Y02 Low-Carbon Joint Patent Count, but based on BERT-classified low-carbon joint patents in a given year.	USPTO

High/Low Product Similarity	Firms with product market similarity (Hoberg and Phillips 2016) in 2006 above the sample median are classified as High Product Similarity, and the remainder as Low Product Similarity.	Hoberg and Phillips (2016)
High/Low Climate Risk Analyst	Firms with high climate risk analyst coverage (High Climate Risk Analyst) are those that had a greater number of climate risk-concerned analysts in 2006 than the sample median. All other firms are considered to have low climate risk analyst coverage (Low Climate Risk Analyst). For each analyst, we compute the ratio of low-carbon patent valuation to total patent valuation for each firm that they cover and then take the average of these ratios. If the resulting average exceeds the median ratio of all analysts in I/B/E/S for 2006, we then classify the analyst as having a greater focus on climate risk.	I/B/E/S
High/Low Option Trading	Firms with total option trading volume in 2006 above the sample median are classified as having High Option Trading volume, while all other firms are categorized as having Low Option Trading volume.	OptionMetrics
High/Low PIN	Firms with PIN in 2006 above the sample median are classified as High PIN, and the remainder as Low PIN.	Easley et al. (2002); Brown et al. (2004)
R&D Intensity	Research and development expenditures divided by total assets, which are set to zero if missing.	Compustat
XAD/AT	The ratio of advertising expenses to total assets, which are set to zero if data are not available.	Compustat
CAPX/AT	The proportion of capital expenditures to the book value of total assets, which is set to zero if data are not available.	Compustat
Ln(AT)	The natural logarithm of the book value of total assets (in millions), which is set to zero if data are not available.	Compustat
Tangibility	The ratio of property, plant, and equipment to total assets, which is set to zero if data are not available.	Compustat
Labor/Capital	The ratio of the number of employees to property, plant, and equipment, which is set to zero if data are not available.	Compustat
Tobin's Q	The ratio of total assets plus the market value of equity minus the book value of equity to the book value of total assets, which is set to zero if data are not available.	Compustat
Firm Age	The number of years a firm has been listed on Compustat.	Compustat
Leverage	The ratio of total debt to shareholder equity, which is set to zero if data are not available.	Compustat
ROA	The ratio of net income to the book value of assets, which is set to zero if data are not available.	Compustat
Cash/AT	Cash/AT is defined as the ratio of a firm's cash and short-term investments to its total assets.	Compustat
R&D Missing	R&D Missing is a dummy variable that equals one if a firm has missing R&D data for the year, and zero otherwise.	Compustat

Figure 1. : Timeline of GHGRP

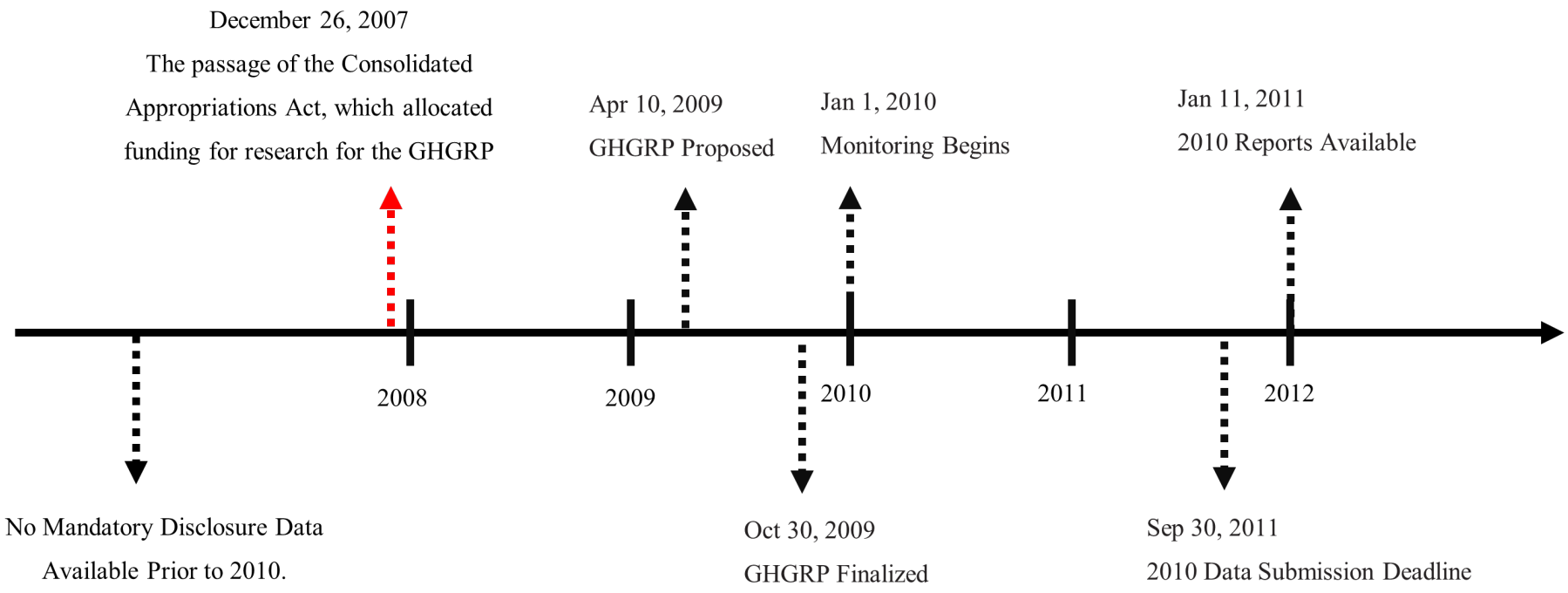
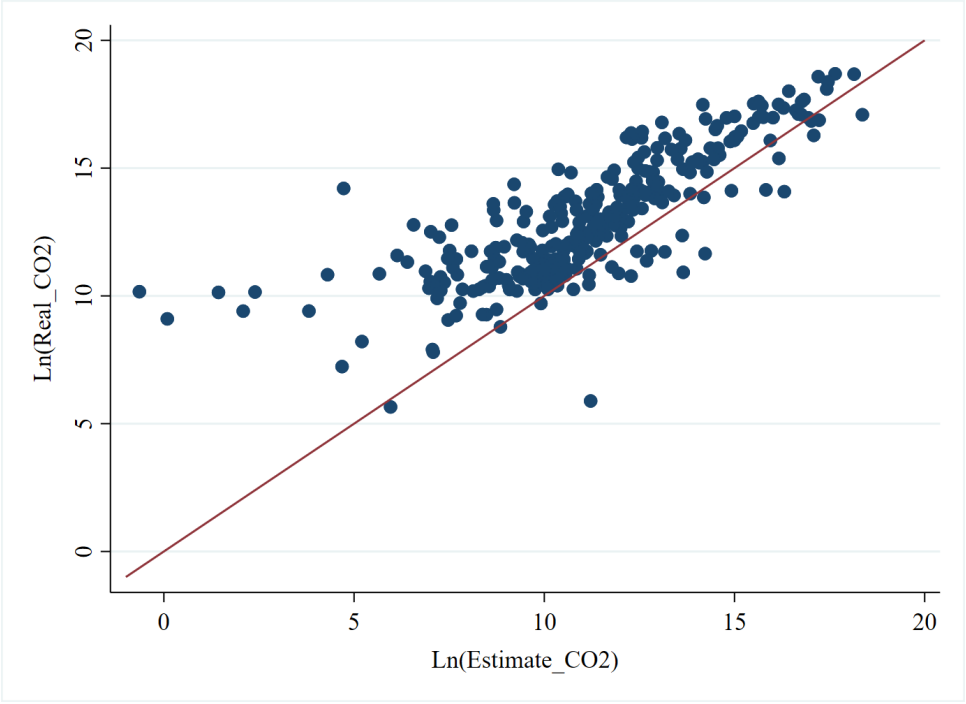
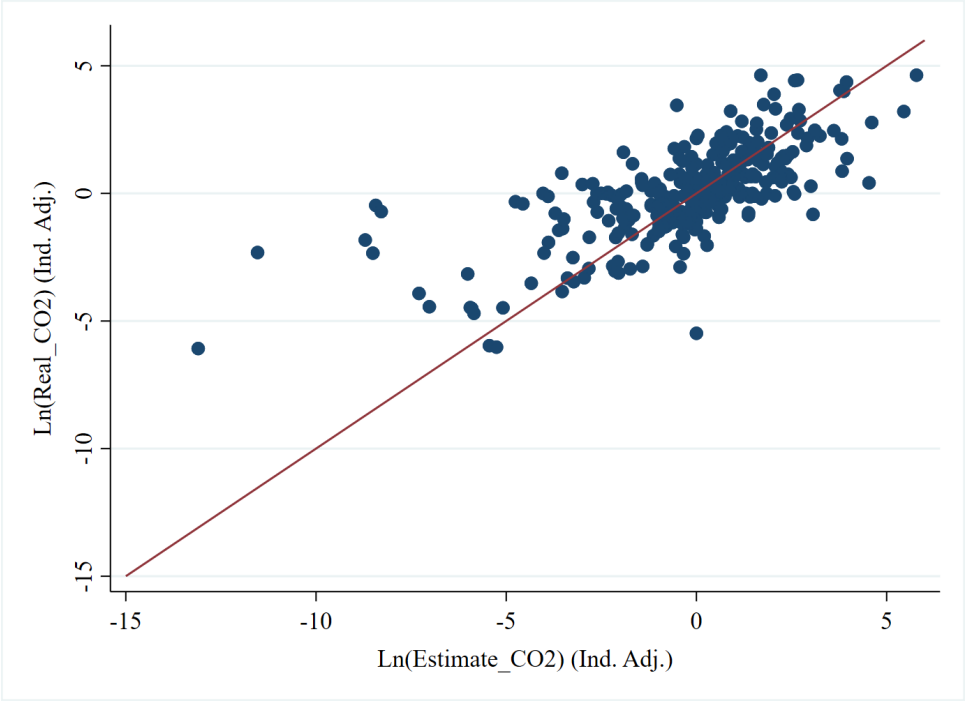


Figure 2. : Estimated CO_2 vs. Real CO_2 Reporting in 2011

This figure shows the relationship between estimated and actual carbon dioxide emissions in 2011. Panel A plots the unadjusted natural logarithm of CO_2 emissions. Estimated CO_2 emissions are calculated by applying conversion factors to transform process-level CO into CO_2 and aggregating the results at the firm level, using data from the 2011 NEI database. Real CO_2 emissions data are sourced from the Greenhouse Gas Reporting Program (GHGRP). Panel B plots the industry-adjusted emissions, calculated as the natural logarithm of a firm's emissions minus the natural logarithm of the median emissions of its corresponding three-digit NAICS industry. The solid maroon line in both panels represents the 45-degree line ($y = x$).



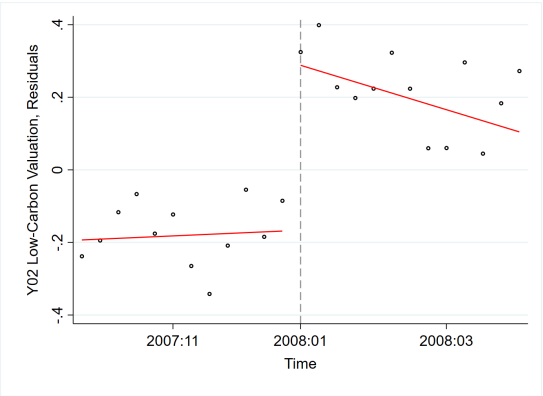
Panel A. Unadjusted Emissions



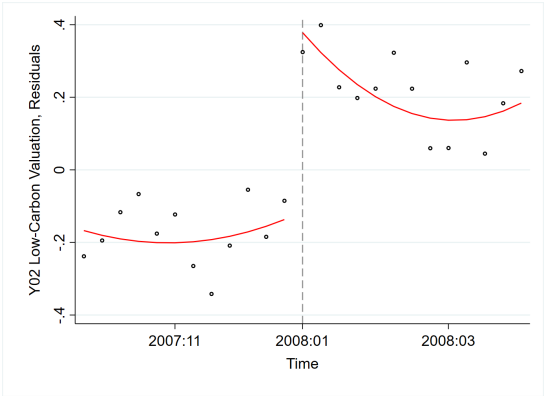
Panel B. Industry-Adjusted Emissions

Figure 3. : The Effect of the GHGRP on Patent Valuation

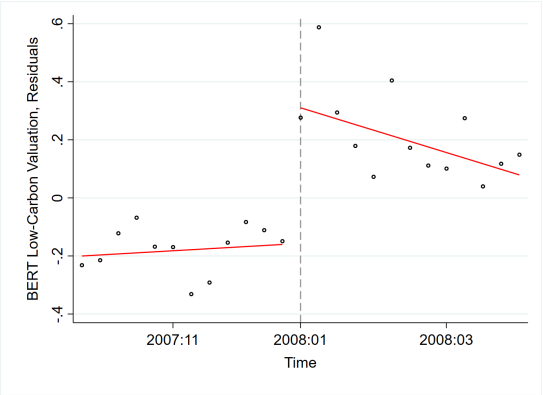
This figure shows the impact of the Greenhouse Gas Reporting Program (GHGRP) on the market valuation of low-carbon patents, measured by CPC Y02 or BERT-based classifications. The dots represent weekly averages of residuals obtained from a regression of the logarithm of patent valuation (Y02 or BERT-based) on four-digit CPC fixed effects, parent firm fixed effects, and patent-level controls. The red fitted curves depict separate linear or quadratic polynomials for the periods before and after December 26, 2007, corresponding to the timing of the funding grant for the GHGRP. Panels A1 and B1 present results from local linear regressions with a 12-week bandwidth, while Panels A2 and B2 employ a quadratic polynomial on either side of the GHGRP date, also with a 12-week bandwidth.



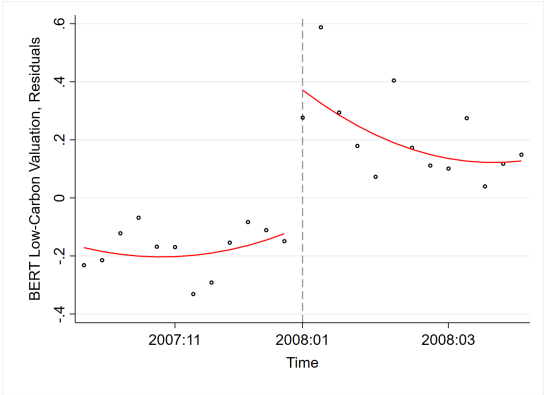
Panel A1. Y02 Patent Local Linear



Panel A2. Y02 Patent Quadratic Polynomial



Panel B1. BERT Patent Local Linear



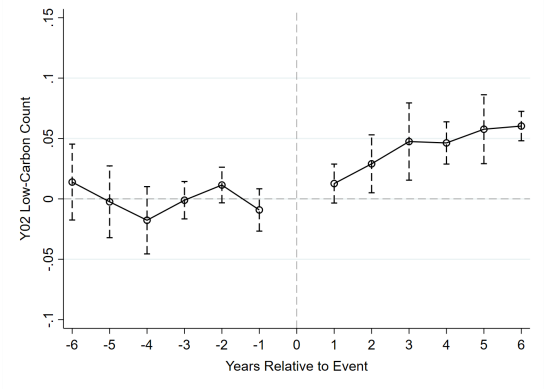
Panel B2. BERT Patent Quadratic Polynomial

Figure 4. : Parallel Trend Plots

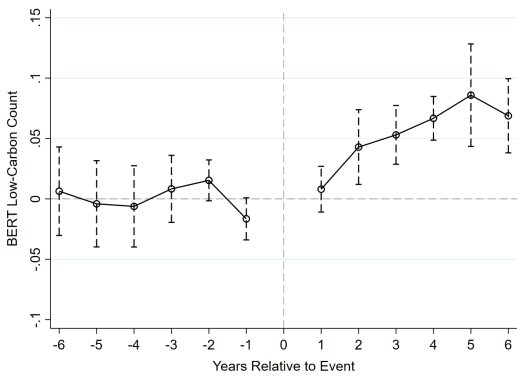
The following plots show how low-carbon innovation varies across different CO_2 emitter quartiles over time. We plot the estimated β_t's of the DID model from the following regression:

$$Ln(1 + Low\text{-}Carbon\ Tech_{it}) = \sum_{t=2002, t\neq 2008}^{2014} \beta_t (I_t \times Emitter_i) + \gamma' Controls_{it} + \eta_i + \varphi_{jt} + \varepsilon_{it}.$$

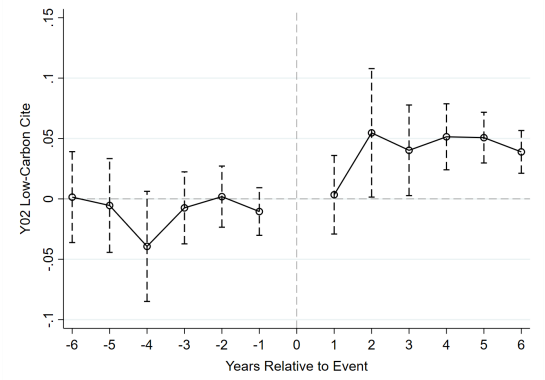
Panels A, B, and C report the counts, citations, and valuations of CPC Y02 or BERT-based low-carbon patents, respectively. Vertical lines in the plots represent 90% confidence intervals for the estimated β_t's. The year 2008 is denoted as 0 on the x-axis.



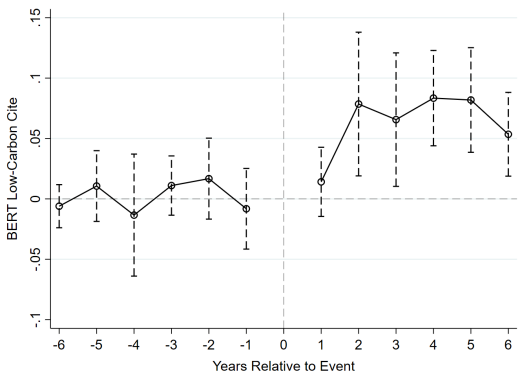
Panel A1. Y02 Patent Local Linear



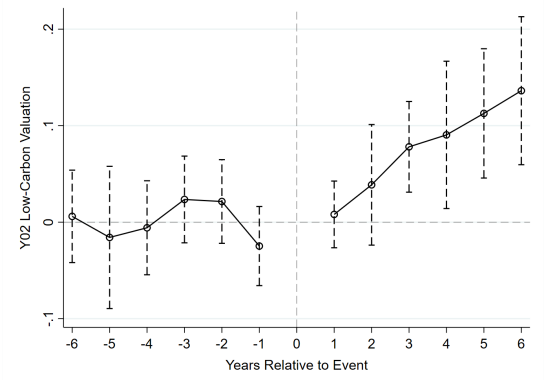
Panel A2.Y02 Patent Quadratic Polynomial



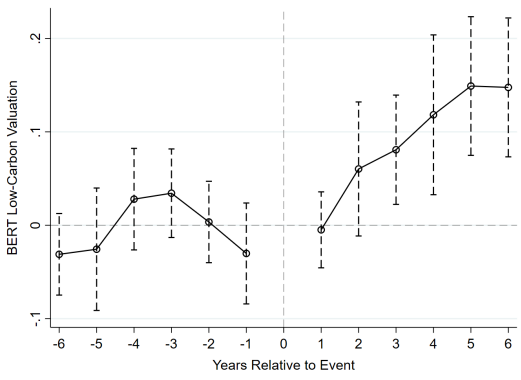
Panel B1. BERT Patent Local Linear



Panel B2. BERT Patent Quadratic Polynomial



Panel B1. BERT Patent Local Linear



Panel B2. BERT Patent Quadratic Polynomial

Table 1: Summary Statistics

This table presents summary statistics for the sample. Panel A reports patent-level variables for the RDD sample, with Panel A1 showing CPC Y02 low-carbon patents and Panel A2 showing BERT-based low-carbon patents. Panel B reports firm-level variables for the DID sample. For Count, Cite, or Valuation, this table reports the raw numbers without taking logarithms. Detailed variable definitions are provided in Appendix A.

Variables	Obs	Mean	SD	p10	p50	p90
Panel A1. Patent-level RDD Sample (Y02)						
Y02 Low-Carbon Valuation	524	34.24	59.22	3.01	13.35	76.85
Brief Word Count	524	1.25	1.33	0.31	0.88	2.30
Cite Backward	524	23.22	42.33	3.00	11.00	44.00
Claims	524	3.03	1.99	1.00	3.00	5.00
Process Claim Ratio	524	0.40	0.38	0.00	0.33	1.00
Inventor Number	524	3.09	2.26	1.00	3.00	6.00
Inventor Average Age	524	44.41	7.52	35.50	44.00	53.50
Panel A2. Patent-level RDD Sample (BERT)						
BERT Low-Carbon Valuation	996	33.99	73.26	4.46	13.12	72.17
Brief Word Count	996	1.23	1.25	0.30	0.88	2.32
Cite Backward	996	21.20	38.75	2.00	10.00	42.00
Claims	996	3.03	1.86	1.00	3.00	5.00
Process Claim Ratio	996	0.39	0.37	0.00	0.33	1.00
Inventor Number	996	2.99	2.07	1.00	3.00	6.00
Inventor Average Age	996	44.51	7.86	35.00	44.00	54.50
Panel B. Firm-level DID Sample						
Estimated CO_2 2005 (1000 tons)	444	1463.33	9168.91	0.08	6.05	1397.89
Emitter	5573	2.47	1.10	1.00	2.00	4.00
Y02 Low-Carbon Count	5573	5.00	27.02	0.00	0.00	6.00
Y02 Low-Carbon Cite	5573	5.67	30.35	0.00	0.00	6.92
Y02 Low-Carbon Valuation	5573	78.71	490.96	0.00	0.00	90.86
BERT Low-Carbon Count	5573	10.07	47.13	0.00	0.00	15.00
BERT Low-Carbon Cite	5573	10.48	47.82	0.00	0.00	15.45
BERT Low-Carbon Valuation	5573	160.23	852.36	0.00	0.00	238.79
Other Green Count	5573	1.10	6.78	0.00	0.00	1.00
Other Green Cite	5573	1.17	7.48	0.00	0.00	0.69
Other Green Valuation	5573	17.11	109.14	0.00	0.00	12.06
R&D Intensity	5573	0.02	0.05	0.00	0.00	0.06
XAD/AT	5573	0.01	0.02	0.00	0.00	0.02
CAPX/AT	5573	0.05	0.04	0.02	0.04	0.09
Ln(AT)	5573	8.30	1.87	5.91	8.29	10.64
Tangibility	5573	0.35	0.22	0.10	0.30	0.69
Labor/Capital	5573	0.02	0.02	0.00	0.01	0.04
Tobin's Q	5573	1.49	0.85	0.86	1.32	2.48
Firm Age	5573	31.99	16.49	9.00	35.00	52.00
Leverage	5573	1.34	23.11	0.04	0.63	2.30
ROA	5573	0.04	0.12	-0.02	0.05	0.12
Cash/AT	5573	0.10	0.13	0.01	0.06	0.24
R&D Missing	5573	0.42	0.49	0.00	0.00	1.00

Table 2: Patent Valuation

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on the market valuation of low-carbon patents using RDD models. The dependent variables are the natural logarithms of the valuations of (a) CPC Y02 low-carbon patents, (b) BERT model-based low-carbon patents, and (c) other green patents. Low-carbon patents are identified using either the CPC Y02 classification or a large language model (BERT for Patents). We also examine other green patents, defined by the OECD as green patents excluding CPC Y02. The sample includes low-carbon patents (in Columns (1), (2), and (5)) and other green patents (in Columns (3) and (6)) filed by our sample firms between 2002 and 2006 and issued by the USPTO within 12 weeks before or after the passage of the Consolidated Appropriations Act, which established funding for the GHGRP, on December 26, 2007. The regressions include fixed effects for patent parent firms and four-digit patent CPC codes. Columns (1) to (3) show results from local linear regressions with a 12-week bandwidth, while Columns (4) to (6) use a quadratic polynomial on either side of the GHGRP date, also with a 12-week bandwidth. All models control for patent-level variables, including Brief Word Count, Cite Backward, Claims, Process Claim Ratio, Inventor Number, and Inventor Average Age. Definitions for these variables are in Appendix A. Standard errors are double-clustered by patent industry (four-digit patent CPC) and issue week, and are shown in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Variables	(1) Y02 Low-Carbon Valuation	(2) BERT Low-Carbon Valuation	(3) Other Green Valuation	(4) Y02 Low-Carbon Valuation	(5) BERT Low-Carbon Valuation	(6) Other Green Valuation
GHGRP	0.6977***	0.6821***	0.2537	0.8384***	0.7232***	0.1747
	(0.1331)	(0.1213)	(0.2920)	(0.1351)	(0.1368)	(0.3893)
Brief Word Count	-0.0100	-0.0067	-0.1436*	-0.0078	-0.0050	-0.1476
	(0.0085)	(0.0090)	(0.0759)	(0.0089)	(0.0091)	(0.0837)
Cite Backward	-0.0009*	-0.0003	0.0013	-0.0009*	-0.0003	0.0011
	(0.0005)	(0.0004)	(0.0015)	(0.0005)	(0.0004)	(0.0013)
Claims	-0.0048	-0.0031	0.0389	-0.0050	-0.0033	0.0363
	(0.0090)	(0.0064)	(0.0263)	(0.0098)	(0.0067)	(0.0265)
Process Claim Ratio	-0.0066	-0.0050	0.0150	0.0010	-0.0010	0.0144
	(0.0387)	(0.0276)	(0.1824)	(0.0431)	(0.0278)	(0.2334)
Inventor Number	-0.0086	-0.0036	-0.0246	-0.0073	-0.0027	-0.0230
	(0.0116)	(0.0082)	(0.0273)	(0.0115)	(0.0082)	(0.0281)
Inventor Average Age	-0.0001	0.0027	0.0103	0.0001	0.0029	0.0077
	(0.0030)	(0.0031)	(0.0087)	(0.0030)	(0.0031)	(0.0078)
Constant	2.4994***	2.3804***	1.9377***	2.4852***	2.4228***	2.2264***
	(0.1197)	(0.1704)	(0.2524)	(0.1589)	(0.1685)	(0.1459)
Observations	524	996	120	524	996	120
R-squared	0.927	0.910	0.912	0.928	0.910	0.914
Specification	Local linear regression	Local linear regression	Local linear regression	Quadratic polynomial	Quadratic polynomial	Quadratic polynomial
Firm FE	YES	YES	YES	YES	YES	YES
CPC4 FE	YES	YES	YES	YES	YES	YES

Table 3: Firm Patenting Activities

This table reports the effect of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents. The firm-level dependent variables are the logarithm of one plus (a) the number of CPC Y02 or BERT-based low-carbon patents, (b) their citations, and (c) their valuation. Patents are classified using either the CPC Y02 code or a BERT-based model. The sample period is from 2002 to 2014. We define a patent as BERT-based low-carbon if it either carries a Y02 code or is classified as low-carbon by our fine-tuned BERT model. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Columns also include the following variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. The definitions for these variables can be found in Appendix A. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×Emitter	0.0353**	0.0435*	0.0428**	0.0501**	0.0611*	0.0767**
	(0.0161)	(0.0210)	(0.0160)	(0.0201)	(0.0307)	(0.0352)
R&D Intensity	0.3490*	0.2679	0.0091	0.1957	0.9652**	0.1812
	(0.1913)	(0.2150)	(0.3385)	(0.2475)	(0.4172)	(0.5632)
XAD/AT	-0.7415	-0.4246	0.6871	0.8139	-0.3961	0.2429
	(2.3996)	(2.9479)	(1.4703)	(1.7788)	(5.6617)	(5.7135)
CAPX/AT	-0.0178	-0.1467	-0.1732	-0.2711	-0.0135	-0.1101
	(0.2301)	(0.2484)	(0.2719)	(0.2475)	(0.4322)	(0.5234)
Ln(AT)	0.1203**	0.1522**	0.1355**	0.1555**	0.2631***	0.2983***
	(0.0502)	(0.0630)	(0.0490)	(0.0578)	(0.0712)	(0.0894)
Tangibility	0.0185	-0.0124	0.1668	0.0385	0.1837	-0.0392
	(0.1556)	(0.1784)	(0.1793)	(0.1830)	(0.3508)	(0.3440)
Labor/Capital	-0.3708	0.8068	-0.5552	-0.4202	-0.3535	1.4606
	(0.6174)	(0.9775)	(0.5828)	(0.8683)	(0.8382)	(1.3211)
Tobin's Q	0.0359*	0.0312	0.0452**	0.0574**	0.0634	0.0516
	(0.0170)	(0.0187)	(0.0205)	(0.0251)	(0.0361)	(0.0326)
Firm Age	-0.0031	-0.0076	0.0084	0.0051	0.0172	0.0010
	(0.0088)	(0.0080)	(0.0075)	(0.0078)	(0.0272)	(0.0091)
Leverage	-0.0002	-0.0001	-0.0001	0.0001	0.0000	0.0002
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
ROA	0.0458	0.0079	0.0736	-0.0219	0.0673	-0.1919
	(0.0760)	(0.0707)	(0.0725)	(0.0816)	(0.1722)	(0.1637)
Cash/AT	-0.1229*	-0.0850	-0.0667	-0.1742**	0.1256	0.2189
	(0.0602)	(0.0943)	(0.0806)	(0.0747)	(0.2038)	(0.2951)
R&D Missing	-0.0500	-0.0566	-0.0809	-0.0463	-0.1215	-0.1901
	(0.0832)	(0.0927)	(0.1109)	(0.1113)	(0.1496)	(0.1475)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.905	0.926	0.859	0.892	0.847	0.889
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Table 4: Emissions Reduction

This table reports how the Greenhouse Gas Reporting Program (GHGRP) affects firm estimated CO_2 emissions and other criteria air emissions. The sample period is four years (2005, 2008, 2011 and 2014) because the NEI data is updated every three years. The dependent variables are the natural logarithm of one plus (a) the estimated CO_2 emissions through CO and (b) non-CO criteria air releases (NH_3, NO_x, PM_{10}, SO_2, and VOC). Estimated CO_2 emissions are derived from process-level CO data, using the CO-to-CO_2 industry process conversion factors, and are then aggregated at the firm level. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The bottom of the table presents the p-values from the coefficient difference test for GHGRP×Emitter. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Estimated CO_2	(2) Non-CO Criteria Air	(3) Estimated CO_2	(4) Non-CO Criteria Air
GHGRP×Emitter	-0.3190**	-0.1495*	-0.3305***	-0.1456*
	(0.0566)	(0.0514)	(0.0565)	(0.0526)
R&D Intensity			-1.8259	-0.6779
			(1.2934)	(0.3136)
XAD/AT			-4.1750	0.6443
			(6.0214)	(2.8889)
CAPX/AT			1.6081	1.3251
			(1.7093)	(0.9156)
Ln(AT)			0.0364	-0.0310
			(0.1310)	(0.0704)
Tangibility			1.1240	0.3010
			(0.6017)	(0.5196)
Labor/Capital			-2.3251	-6.2954
			(3.1854)	(3.2041)
Tobin's Q			0.0837	0.0124
			(0.0622)	(0.0260)
Firm Age			0.0517	0.0575
			(0.0713)	(0.0364)
Leverage			-0.0041	0.0077*
			(0.0060)	(0.0032)
ROA			-0.3959	-0.3135
			(0.4490)	(0.2710)
Cash/AT			0.6691	-0.2460
			(0.3010)	(0.3361)
R&D Missing			-0.1183	0.0487
			(0.3783)	(0.1708)
Observations	1,654	1,654	1,654	1,654
R-squared	0.945	0.961	0.945	0.962
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES
Diff Test (P-value)	0.0104**		0.0046***	

Table 5: Environmental Score

This table examines the impact of the Greenhouse Gas Reporting Program (GHGRP) on Environmental scores over the sample period from 2002 to 2014. The dependent variable is the firm's total E score, calculated as the number of KLD environmental strengths (scaled by the total environmental strengths items) minus the number of KLD environmental concerns (scaled by the total environmental concerns items). The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Column (2) also include the following variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. The definitions for these variables can be found in Appendix A. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) E Score	(2) E Score
GHGRP×Emitter	0.0264**	0.0268**
	(0.0106)	(0.0102)
R&D Intensity		-0.7693**
		(0.3213)
XAD/AT		0.1324
		(0.8716)
CAPX/AT		0.1261
		(0.1740)
Ln(AT)		-0.0571***
		(0.0094)
Tangibility		0.1025
		(0.1709)
Labor/Capital		0.6651
		(0.5859)
Tobin's Q		-0.0073
		(0.0115)
Firm Age		-0.0041
		(0.0083)
Leverage		-0.0001
		(0.0001)
ROA		0.1439*
		(0.0711)
Cash/AT		-0.0382
		(0.1048)
R&D Missing		-0.0120
		(0.0404)
Observations	4,090	4,090
R-squared	0.662	0.667
Firm FE	YES	YES
Industry-Year FE	YES	YES

Table 6: Placebo Tests

This table reports placebo tests for the Greenhouse Gas Reporting Program (GHGRP), using data from 2002 to 2014. Panel A uses other green patents, defined as OECD green patents excluding CPC Y02 patents, as the dependent variable. Panels B, C, D, and E use CPC Y02 or BERT-based low-carbon patents as the dependent variable, replacing the original Emitter variable with the firm's CPU beta in Panel B, EPU beta in Panel C, oil beta in Panel D, and daily market beta in Panel E, respectively. In all panels, the dependent variables are measured as the natural logarithm of one plus: (a) the number of relevant patents, (b) their citation counts, and (c) their valuations. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. CPU beta, EPU beta, oil beta, and daily market beta are also categorized into quartiles by industry. A value of one represents firms in the first quartile of the respective beta within their three-digit NAICS industry. CPU beta ($\beta_{CPU,i}$) and EPU beta ($\beta_{EPU,i}$) are estimated using monthly firm return data from January to November 2007 based on the time-series regression: $Ret_{i,t} = \alpha_i + \beta_{CPU,i} \times CPU_Shock_t + \beta_{EPU,i} \times \Delta \ln(EPU_t) + \beta^M_{mkt,i} \times Ret^M_{mkt,t} + \varepsilon_{i,t}$. CPU_Shock_t represents the climate policy uncertainty shock from Gavriilidis, Känzig and Stock (2023). $\Delta \ln(EPU_t)$ is the log-difference of the news-based US Monthly Economic Policy Uncertainty Index developed by Baker, Bloom and Davis (2016), and $Ret^M_{mkt,t}$ is the monthly value-weighted market return. Both oil and daily market betas are calculated using daily firm return data from 2007, excluding dates after December 26, 2007, which is the date the U.S. Congress passed the Consolidated Appropriations Act of 2008. Oil beta $\beta_{oil,i}$ and daily market beta $\beta^D_{mkt,i}$ are estimated from the regression: $Ret_{i,t} = \alpha_i + \beta_{oil,i} \times Ret_{oil,t} + \beta^D_{mkt,i} \times Ret^D_{mkt,t} + \varepsilon_{i,t}$. $Ret_{oil,t}$ is based on Brent crude oil futures prices, and $Ret^D_{mkt,t}$ is the daily value-weighted market index. Regressions presented in this table include firm and industry-year fixed effects. Control variables are R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Panel A. Other Green Patents

Variables	(1) Other Green Count	(2) Other Green Count	(3) Other Green Cite	(4) Other Green Cite	(5) Other Green Valuation	(6) Other Green Valuation
GHGRP×Emitter	0.0162	0.0157	0.0144	0.0146	0.0178	0.0172
	(0.0098)	(0.0090)	(0.0100)	(0.0095)	(0.0189)	(0.0180)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.844	0.844	0.806	0.806	0.791	0.791
Controls	NO	YES	NO	YES	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Panel B. Treatment Based on Firm CPU Beta

Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×CPU Beta	0.0087	0.0061	-0.0070	-0.0040	-0.0009	0.0041
	(0.0141)	(0.0156)	(0.0206)	(0.0227)	(0.0198)	(0.0288)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.905	0.926	0.859	0.892	0.847	0.889
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Panel C. Treatment Based on Firm EPU Beta

Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×EPU Beta	-0.0464**	-0.0485**	-0.0236	-0.0258	-0.0486	-0.0296
	(0.0177)	(0.0173)	(0.0244)	(0.0236)	(0.0388)	(0.0447)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.905	0.926	0.859	0.892	0.847	0.889
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Table 6: Placebo Tests (Continued)

Panel D. Treatment Based on Firm Oil Beta						
Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×Oil Beta	-0.0210	-0.0293	-0.0302	-0.0312	-0.0111	-0.0292
	(0.0247)	(0.0306)	(0.0241)	(0.0262)	(0.0361)	(0.0491)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.905	0.926	0.859	0.892	0.847	0.889
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Panel E. Treatment Based on Firm Market Beta						
Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×Market Beta	0.0124	0.0079	0.0258	0.0317	0.0416	0.0219
	(0.0160)	(0.0205)	(0.0203)	(0.0213)	(0.0334)	(0.0483)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.905	0.926	0.859	0.892	0.847	0.889
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Table 7: New Low-Carbon Experience Acquiring

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on firms acquiring inventors based on their years of experience in low-carbon patenting. The sample covers the period from 2002 to 2014. The dependent variable is the total years of CPC Y02 or BERT-based low-carbon inventor experience that a firm acquires from the labor market in a given year. The total years of low-carbon inventor experience is the sum of the years between the hiring of experienced inventors and the years they first patented low-carbon technology. An experienced inventor is defined as one with previous low-carbon patents who was not previously employed by the firm. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Columns (2) and (4) also include the following variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. The definitions for these variables can be found in Appendix A. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) New Y02 Low-Carbon Experience	(2) New Y02 Low-Carbon Experience	(3) New BERT Low-Carbon Experience	(4) New BERT Low-Carbon Experience
GHGRP×Emitter	0.8042***	0.8434***	1.0337***	1.0786***
	(0.2292)	(0.2563)	(0.3235)	(0.3430)
R&D Intensity		8.7477		7.9021
		(10.1965)		(10.8834)
XAD/AT		-93.2127		-111.7575
		(75.6000)		(87.0064)
CAPX/AT		-2.0779		-1.9974
		(14.3468)		(15.4806)
Ln(AT)		2.6851		2.8679
		(2.0850)		(2.3468)
Tangibility		-1.2956		-1.5931
		(4.5996)		(5.1486)
Labor/Capital		-10.0152		-8.0420
		(20.7186)		(21.3990)
Tobin's Q		0.1915		0.1872
		(0.5592)		(0.6460)
Firm Age		-0.1050		-0.1290
		(0.1435)		(0.1906)
Leverage		-0.0022		-0.0014
		(0.0071)		(0.0074)
ROA		2.8491		3.1424
		(2.0168)		(2.1010)
Cash/AT		-17.5495		-19.8603
		(10.4386)		(12.0972)
R&D Missing		0.2883		0.3178
		(1.6640)		(1.7820)
Observations	5,573	5,573	5,573	5,573
R-squared	0.757	0.759	0.760	0.762
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Table 8: Existing Inventors' Low-Carbon Patenting Activities

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on the low-carbon patenting activities of incumbent inventors. The sample covers the period from 2002 to 2014. The dependent variable is the natural logarithm of one plus the number of Y02 or BERT-based low-carbon patents authored by incumbent inventors. An incumbent inventor is defined as an inventor with a firm tenure of more than four years. GHGRP is a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Columns (2) and (4) also include the following control variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Incumbent-Only Patent Count	(2) Y02 Low-Carbon Incumbent-Only Patent Count	(3) BERT Low-Carbon Incumbent-Only Patent Count	(4) BERT Low-Carbon Incumbent-Only Patent Count
GHGRP×Emitter	0.0302	0.0303	0.0292	0.0293
	(0.0196)	(0.0192)	(0.0246)	(0.0237)
R&D Intensity		-0.0434		0.0620
		(0.1621)		(0.2449)
XAD/AT		-1.0876		0.0527
		(2.0057)		(2.3909)
CAPX/AT		-0.0542		-0.1859
		(0.2222)		(0.3064)
Ln(AT)		0.0643		0.0878*
		(0.0404)		(0.0491)
Tangibility		-0.1629		-0.2281
		(0.1216)		(0.1535)
Labor/Capital		-0.0336		-0.1213
		(0.3405)		(0.3755)
Tobin's Q		0.0212		0.0130
		(0.0124)		(0.0272)
Firm Age		-0.0056		-0.0087
		(0.0068)		(0.0090)
Leverage		-0.0002		-0.0001
		(0.0004)		(0.0003)
ROA		-0.0633		-0.0323
		(0.0559)		(0.0617)
Cash/AT		-0.1635		-0.1923
		(0.1030)		(0.1266)
R&D Missing		-0.0489		-0.1225
		(0.0572)		(0.0808)
Observations	5,573	5,573	5,573	5,573
R-squared	0.896	0.897	0.918	0.919
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Table 9: Incumbents Collaborating with New-hired on Low-Carbon Patents

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on the likelihood of incumbent inventors collaborating with newly hired experts on low-carbon patents. The sample covers the period from 2002 to 2014. The dependent variable is the natural logarithm of one plus the unique count of incumbent co-inventors in a given year. An incumbent is defined as an inventor with a firm tenure of more than four years, and a new expert is defined as an inventor with a tenure of two years or less who has prior experience in low-carbon patenting. Therefore, the dependent variable captures the number of incumbents who collaborated with new experts on Y02 or BERT-based low-carbon patents within each firm-year observation. GHGRP is a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$,

Variables	(1) Y02 Low-Carbon Incumbent Co-Inventors	(2) Y02 Low-Carbon Incumbent Co-Inventors	(3) BERT Low-Carbon Incumbent Co-Inventors	(4) BERT Low-Carbon Incumbent Co-Inventors
GHGRP×Emitter	0.0158*	0.0168*	0.0233*	0.0237*
	(0.0087)	(0.0091)	(0.0120)	(0.0124)
R&D Intensity		0.0513		0.0470
		(0.1355)		(0.1260)
XAD/AT		-0.9062		-0.6084
		(0.9482)		(1.1765)
CAPX/AT		0.1620		0.0248
		(0.0951)		(0.1102)
Ln(AT)		0.0119		0.0131
		(0.0240)		(0.0230)
Tangibility		-0.1133*		-0.0768
		(0.0598)		(0.0796)
Labor/Capital		-0.0380		-0.0232
		(0.2375)		(0.2307)
Tobin's Q		-0.0023		0.0028
		(0.0124)		(0.0158)
Firm Age		-0.0040*		-0.0073**
		(0.0020)		(0.0032)
Leverage		-0.0001		-0.0001
		(0.0002)		(0.0002)
ROA		0.0186		0.0227
		(0.0361)		(0.0347)
Cash/AT		-0.2071*		-0.2747
		(0.1137)		(0.1562)
R&D Missing		0.0187		0.0000
		(0.0571)		(0.0665)
Observations	5,573	5,573	5,573	5,573
R-squared	0.667	0.668	0.693	0.694
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Table 10: Collaboration Outcomes in Low-Carbon Patents

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on collaboration outcomes in low-carbon patenting. The sample covers the period from 2002 to 2014. The dependent variable is the natural logarithm of one plus the number of Y02 or BERT-based low-carbon joint patents. A joint patent is defined as a low-carbon patent co-authored by at least one new expert (an inventor with a tenure of two years or less who has prior low-carbon patenting experience) and at least one incumbent (an inventor with a firm tenure of more than four years). GHGRP is a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Joint Patent Count	(2) Y02 Low-Carbon Joint Patent Count	(3) BERT Low-Carbon Joint Patent Count	(4) BERT Low-Carbon Joint Patent Count
GHGRP×Emitter	0.0108***	0.0115**	0.0150*	0.0153*
	(0.0035)	(0.0042)	(0.0071)	(0.0079)
R&D Intensity		0.0099		0.0062
		(0.0982)		(0.0869)
XAD/AT		-0.5422		-0.7537
		(0.6316)		(0.9570)
CAPX/AT		0.1508		0.0433
		(0.0940)		(0.1040)
Ln(AT)		0.0095		0.0165
		(0.0180)		(0.0191)
Tangibility		-0.0731		-0.0516
		(0.0478)		(0.0570)
Labor/Capital		-0.0289		-0.0521
		(0.0848)		(0.0962)
Tobin's Q		0.0017		0.0060
		(0.0089)		(0.0120)
Firm Age		-0.0019		-0.0038
		(0.0018)		(0.0022)
Leverage		-0.0001		-0.0001
		(0.0002)		(0.0002)
ROA		0.0159		0.0202
		(0.0267)		(0.0266)
Cash/AT		-0.1396*		-0.1738
		(0.0764)		(0.1182)
R&D Missing		0.0283		0.0118
		(0.0528)		(0.0631)
Observations	5,573	5,573	5,573	5,573
R-squared	0.681	0.682	0.713	0.714
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Table 11: Competition Pressure

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents for firms with high and low competition pressure. The sample period is from 2002 to 2014. The firm-level dependent variables are the logarithm of one plus (a) the number of CPC Y02 or BERT-based low-carbon patents, and (b) their citations. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. We classify firms into high and low competition pressure groups using two measures: (a) product market similarity and (b) climate risk analyst coverage. Firms with product market similarity (Hoberg and Phillips 2016) in 2006 above the sample median are classified as High Product Similarity, and the remainder as Low Product Similarity. Firms with climate risk analyst coverage above the sample median in 2006 are classified as High Climate Risk Analyst, and the remainder as Low Climate Risk Analyst. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Panel A. Product Similarity

Variables	(1) Y02 Low-Carbon Count	(2) Y02 Low-Carbon Count	(3) BERT Low-Carbon Count	(4) BERT Low-Carbon Count	(5) Y02 Low-Carbon Cite	(6) Y02 Low-Carbon Cite	(7) BERT Low-Carbon Cite	(8) BERT Low-Carbon Cite
Subsample	*Low Product Similarity*	*High Product Similarity*	*Low Product Similarity*	*High Product Similarity*	*Low Product Similarity*	*High Product Similarity*	*Low Product Similarity*	*High Product Similarity*
GHGRP×Emitter	0.0210	0.0505*	0.0216	0.0519*	0.0286	0.0538*	0.0172	0.0689*
	(0.0294)	(0.0243)	(0.0382)	(0.0266)	(0.0395)	(0.0260)	(0.0476)	(0.0328)
Observations	2,613	2,555	2,613	2,555	2,613	2,555	2,613	2,555
R-squared	0.912	0.914	0.923	0.934	0.872	0.867	0.892	0.907
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B. Climate Risk Analyst Coverage

Variables	(1) Y02 Low-Carbon Count	(2) Y02 Low-Carbon Count	(3) BERT Low-Carbon Count	(4) BERT Low-Carbon Count	(5) Y02 Low-Carbon Cite	(6) Y02 Low-Carbon Cite	(7) BERT Low-Carbon Cite	(8) BERT Low-Carbon Cite
Subsample	*Low Climate Risk Analyst*	*High Climate Risk Analyst*	*Low Climate Risk Analyst*	*High Climate Risk Analyst*	*Low Climate Risk Analyst*	*High Climate Risk Analyst*	*Low Climate Risk Analyst*	*High Climate Risk Analyst*
GHGRP×Emitter	-0.0084	0.0888**	-0.0033	0.0980*	-0.0172	0.1342***	-0.0201	0.1607***
	(0.0124)	(0.0377)	(0.0159)	(0.0490)	(0.0162)	(0.0353)	(0.0174)	(0.0422)
Observations	2,621	2,209	2,621	2,209	2,621	2,209	2,621	2,209
R-squared	0.869	0.903	0.893	0.923	0.816	0.848	0.843	0.884
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 12: Price Efficiency

This table reports the effect of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents for firms with high versus low price efficiency. The sample period is from 2002 to 2014. The firm-level dependent variables are the logarithm of one plus (a) the number of CPC Y02 or BERT-based low-carbon patents, and (b) their citations. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. We classify firms into high and low price efficiency groups based on two measures: (a) option trading volume and (b) the probability of informed trading (PIN). Firms with option trading volume in 2006 above the sample median are classified as High Option Trading, and the rest as Low Option Trading. Similarly, firms with PIN above the sample median are classified as High PIN, and the rest as Low PIN. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Panel A. Option Trading

Variables	(1) Y02 Low-Carbon Count	(2) Y02 Low-Carbon Count	(3) BERT Low-Carbon Count	(4) BERT Low-Carbon Count	(5) Y02 Low-Carbon Cite	(6) Y02 Low-Carbon Cite	(7) BERT Low-Carbon Cite	(8) BERT Low-Carbon Cite
Subsample	*Low Option Trading*	*High Option Trading*	*Low Option Trading*	*High Option Trading*	*Low Option Trading*	*High Option Trading*	*Low Option Trading*	*High Option Trading*
GHGRP×Emitter	0.0218	0.0931**	0.0400	0.0900*	0.0159	0.1342***	0.0327	0.1404***
	(0.0351)	(0.0382)	(0.0451)	(0.0453)	(0.0315)	(0.0354)	(0.0445)	(0.0398)
Observations	2,207	2,172	2,207	2,172	2,207	2,172	2,207	2,172
R-squared	0.809	0.924	0.845	0.943	0.738	0.874	0.783	0.907
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B. PIN

Variables	(1) Y02 Low-Carbon Count	(2) Y02 Low-Carbon Count	(3) BERT Low-Carbon Count	(4) BERT Low-Carbon Count	(5) Y02 Low-Carbon Cite	(6) Y02 Low-Carbon Cite	(7) BERT Low-Carbon Cite	(8) BERT Low-Carbon Cite
Subsample	*High PIN*	*Low PIN*	*High PIN*	*Low PIN*	*High PIN*	*Low PIN*	*High PIN*	*Low PIN*
GHGRP×Emitter	-0.0000	0.0625**	0.0146	0.0580*	-0.0095	0.0922***	0.0138	0.0833**
	(0.0207)	(0.0267)	(0.0236)	(0.0318)	(0.0184)	(0.0248)	(0.0208)	(0.0291)
Observations	2,702	2,726	2,702	2,726	2,702	2,726	2,702	2,726
R-squared	0.873	0.912	0.896	0.935	0.814	0.865	0.844	0.903
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES	YES	YES

REFERENCES

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous. 2012. "The Environment and Directed Technical Change." *American Economic Review*, 102: 131–166.

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

Aghion, Philippe, Antoine Dechezleprêtre, David Hémous, Ralf Martin, and John Van Reenen. 2016. "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry." *Journal of Political Economy*, 124: 1–51.

Aghion, Philippe, Christopher Harris, Peter Howitt, and John Vickers. 2001. "Competition, imitation and growth with step-by-step innovation." *The Review of Economic Studies*, 68: 467–492.

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

Amore, Mario Daniele, and Morten Bennedsen. 2016. "Corporate governance and green innovation." *Journal of Environmental Economics and Management*, 75: 54–72.

Angelucci, Simone, Francisco Javier Hurtado-Albir, and Alessandro Volpe. 2018. "Supporting global initiatives on climate change: The EPO's "Y02-Y04S" tagging scheme." *World Patent Information*, 54: S85–S92.

Arkhangelsky, Dmitry, Susan Athey, David A. Hirshberg, Guido W. Imbens, and Stefan Wager. 2021. "Synthetic difference-in-differences." *American Economic Review*, 111: 4088–4118.

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. "Measuring economic policy uncertainty." *The quarterly journal of economics*, 131(4): 1593–1636.

Bakke, Tor-Erik, and Toni M. Whited. 2010. "Which firms follow the market? An analysis of corporate investment decisions." *The Review of Financial Studies*, 23: 1941–1980.

Barwick, Patrick J., Shanjun Li, Ling Lin, and Eric Y. Zou. 2024. "From fog to smog: The value of pollution information." *American Economic Review*, 114: 1338–1381.

Berman, Eli, and Linda T. M. Bui. 2001. "Environmental regulation and labor demand: evidence from the South Coast Air Basin." *Journal of Public Economics*, 79: 265–295.

Berrone, Pascual, Andrea Fosfuri, Luis Gelabert, and Luis R. Gomez-Mejia. 2013. "Necessity as the mother of 'green' inventions: Institutional pressures and environmental innovations." *Strategic Management Journal*, 34: 891–909.

Blanco, Iván, and David Wehrheim. 2017. "The bright side of financial derivatives: Options trading and firm innovation." *Journal of Financial Economics*, 125: 99–119.

Bloom, Nicholas, Stephen Bond, and John Van Reenen. 2007. "Uncertainty and investment dynamics." *The Review of Economic Studies*, 74: 391–415.

Bollinger, Brian, Phillip Leslie, and Alan Sorensen. 2011. "Calorie posting in chain restaurants." *American Economic Journal: Economic Policy*, 3: 91–128.

Bolton, Patrick, and Marcin Kacperczyk. 2021. "Do investors care about carbon risk?" *Journal of Financial Economics*, 142: 517–549.

Bolton, Patrick, Marcin T. Kacperczyk, and Michael Wiedemann. 2023. "The co2 question: Technical progress and the climate crisis." *Available at SSRN 4212567*.

Boyer, Marcel, and Jean-Jacques Laffont. 1999. "Toward a political theory of the emergence of environmental incentive regulation." *The RAND Journal of Economics*, 137–157.

Brown, Jason R., Gustav Martinsson, and Christian Thomann. 2022. "Can environmental policy encourage technical change? Emissions taxes and R&D investment in polluting firms." *The Review of Financial Studies*, 35: 4518–4560.

Brown, Susan, Steven A. Hillegeist, and Kin Lo. 2004. "Conference calls and information asymmetry." *Journal of Accounting and Economics*, 37: 343–366.

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

Budish, Eric, Benjamin N. Roin, and Heidi Williams. 2016. "Patents and research investments: Assessing the empirical evidence." *American Economic Review*, 106: 183–187.

Calel, Raphael. 2020. "Adopt or Innovate: Understanding Technological Responses to Cap-and-Trade." *American Economic Journal: Economic Policy*, 12: 170–201.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma. 2018. "Manipulation testing based on density discontinuity." *The Stata Journal*, 18: 234–261.

Chava, Sudheer, and Nikhil Paradkar. 2024. "December doldrums, investor distraction, and the stock market reaction to unscheduled news events." *Journal of Financial Markets*, 71: 100928.

Chen, Qi, Itay Goldstein, and Wei Jiang. 2007. "Price informativeness and investment sensitivity to stock price." *The Review of Financial Studies*, 20: 619–650.

Chen, Yu-Chin, Mingyi Hung, and Yuyan Wang. 2018. "The effect of mandatory CSR disclosure on firm profitability and social externalities: Evidence from China." *Journal of Accounting and Economics*, 65: 169–190.

Christensen, Hans B., Eric Floyd, Liyan Liu, and Michelle Maffett. 2017. "The real effects of mandated information on social responsibility in financial reports: Evidence from mine-safety records." *Journal of Accounting and Economics*, 64: 284–304.

Christensen, Hans B., Luzi Hail, and Christian Leuz. 2013. "Mandatory IFRS reporting and changes in enforcement." *Journal of Accounting and Economics*, 56: 147–177.

Christensen, Hans B., Luzi Hail, and Christian Leuz. 2021. "Mandatory CSR and sustainability reporting: economic analysis and literature review." *Review of Accounting Studies*, 26: 1176–1248.

Cohen, Lauren, Umit G. Gurun, and Quoc H. Nguyen. 2024. "The ESG-innovation disconnect: Evidence from green patenting." National Bureau of Economic Research.

Darendeli, Aysa, Kevin K. Law, and Min Shen. 2022. "Green new hiring." *Review of Accounting Studies*, 27: 986–1037.

Downar, Benjamin, Jannis Ernstberger, Stefan Reichelstein, Sebastian Schwenen, and Aleksandra Zaklan. 2021. "The impact of carbon disclosure mandates on emissions and financial operating performance." *Review of Accounting Studies*, 26: 1137–1175.

Duchin, Rodolphe, Jie Gao, and Qing Xu. 2024. "Sustainability or greenwashing: Evidence from the asset market for industrial pollution." *Journal of Finance*. forthcoming.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara. 2002. "Is information risk a determinant of asset returns?" *The Journal of Finance*, 57: 2185–2221.

Edmans, Alex, and Gustavo Manso. 2011. "Governance through trading and intervention: A theory of multiple blockholders." *The Review of Financial Studies*, 24: 2395–2428.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist. 2020. "What is a patent worth? Evidence from the US patent "lottery"." *The Journal of Finance*, 75: 639–682.

Frankel, Robert, S.P. Kothari, and Anup Raghunandan. 2025. "The economics of ESG disclosure regulation." *Review of Accounting Studies*, 1–36.

Ganglmair, Bernhard, William K. Robinson, and Matthew Seeligson. 2022. "The rise of process claims: Evidence from a century of US patents." ZEW-Centre for European Economic Research Discussion Paper.

Gavriilidis, Konstantinos, Diego R Känzig, and JH Stock. 2023. "The Macroeconomic Effects of Climate Policy Uncertainty." *Unpublished working paper*.

Giannetti, Mariassunta, Martina Jasova, Maria Loumioti, and Caterina Mendicino. 2023. ""Glossy green" banks: the disconnect between environmental disclosures and lending activities." ECB Working Paper. Banks: The Disconnect between Environmental Disclosures and Lending Activities (December, 2023).

Gibbons, James B. 2023. "The financially material effects of mandatory nonfinancial disclosure." *Journal of Accounting Research*.

Greenstone, Michael. 2002. "The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures." *Journal of Political Economy*, 110: 1175–1219.

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu. 2022. "Can technology solve the principal-agent problem? Evidence from China's war on air pollution." *American Economic Review: Insights*, 4: 54–70.

Greenstone, Michael, John A. List, and Chad Syverson. 2012. "The effects of environmental regulation on the competitiveness of US manufacturing." National Bureau of Economic Research.

Grullon, Gustavo, and David L. Ikenberry. 2025. "Excess Capacity, Marginal q, and Corporate Investment." *The Journal of Finance*, 80: 1533–1592.

Gurney, Kevin R., Daniel L. Mendoza, Yuyu Zhou, Marc L. Fischer, Charles C. Miller, Saravanan Geethakumar, and Stephane de la Rue du Can. 2009. "High resolution fossil fuel combustion CO2 emission fluxes for the United States." *Environmental Science & Technology*, 43: 5535–5541.

Gurney, Kevin R., Daniel Mendoza, Yuyu Zhou, Marc Fisher, Chris Miller, Saravanan Geethakumar, and Stephane De La Rue Dy Can. 2010. "Vulcan science methods documentation, version 2.0." *Available at vulcan.project.asu.edu/pdf/Vulcan.documentation.v2.0.online.pdf*, Accessed September 1, 2014.

Hall, Bronwyn H., and Christian Helmers. 2010. "The role of patent protection in (clean/green) technology transfer." National Bureau of Economic Research.

Haščič, Ivan, and Matteo Migotto. 2015. "Measuring environmental innovation using patent data." OECD Environment Working Papers.

Hastings, Justine S., and Jeffrey M. Weinstein. 2008. "Information, school choice, and academic achievement: Evidence from two experiments." *The Quarterly Journal of Economics*, 123: 1373–1414.

Healy, Paul M., and Krishna G. Palepu. 2001. "Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature." *Journal of Accounting and Economics*, 31: 405–440.

Hege, Ulrich, Sebastien Pouget, and Yue Zhang. 2023. "The impact of corporate Climate action on financial markets: Evidence from climate-related patents."

Hermalin, Benjamin E., and Michael S. Weisbach. 2012. "Information disclosure and corporate governance." *The Journal of Finance*, 67: 195–233.

Huang, Shan, and Alexander Kopytov. 2023. "Sustainable finance under regulation." Available at SSRN 4231723.

Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura T. Starks. 2023. "Climate risk disclosure and institutional investors." *The Review of Financial Studies*, 36: 2617–2650.

Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins. 2003. "Technological change and the environment." In *Handbook of Environmental Economics*. 461–516. Elsevier.

Johnstone, Nick, Ivan Haščič, and David Popp. 2010. "Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts." *Environmental and Resource Economics*, 45: 133–155.

Jouvenot, Valentin, and Philipp Krueger. 2020. "Mandatory corporate carbon disclosure: Evidence from a natural experiment." Available at SSRN 3434490.

Kaltenberg, Mary, Adam B. Jaffe, and Margie E. Lachman. 2023. "Invention and the life course: Age differences in patenting." *Research Policy*, 52: 104629.

Keller, Wolfgang, and Arik Levinson. 2002. "Pollution abatement costs and foreign direct investment inflows to US states." *Review of Economics and Statistics*, 84: 691–703.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological innovation, resource allocation, and growth." *The Quarterly Journal of Economics*, 132: 665–712.

Krueger, Philipp, Zacharias Sautner, Dragon Yongjun Tang, and Ruicheng Zhong. 2024. "The effects of mandatory ESG disclosure around the world." *Journal of Accounting Research*, 62: 1795–1847.

Lanjouw, Jean O., and Ashoka Mody. 1996. "Innovation and the international diffusion of environmentally responsive technology." *Research Policy*, 25: 549–571.

Lanoie, Paul, Jérôme Laurent-Lucchetti, Nick Johnstone, and Stefan Ambec. 2011. "Environmental Policy, Innovation and Performance: New Insights on the Porter Hypothesis." *Journal of Economics & Management Strategy*, 20: 803–842.

Lanteri, Alessandro, and Adriano A. Rampini. 2023. "Financing the Adoption of Clean Technology."

Lin, Tzu-Chun, Qifei Liu, and Bo Sun. 2019. "Contractual managerial incentives with stock price feedback." *American Economic Review*, 109: 2446–2468.

Liu, Leo, Elvira Sojli, Wing Wah Tham, and Cara Vansteenkiste. 2024. "The Under-Disclosure of Environmental Innovation." *Available at SSRN*.

Luo, Xueming, and C.B. Bhattacharya. 2006. "Corporate social responsibility, customer satisfaction, and market value." *Journal of Marketing*, 70: 1–18.

Luo, Xueming, Christian Homburg, and Jan Wieseke. 2010. "Customer satisfaction, analyst stock recommendations, and firm value." *Journal of Marketing Research*, 47: 1041–1058.

Matsumura, Eileen M., Rahul Prakash, and Sandra C. Vera-Muñoz. 2014. "Firm-value effects of carbon emissions and carbon disclosures." *The Accounting Review*, 89: 695–724.

Myers, Emily, Steven L. Puller, and Jeremy West. 2022. "Mandatory energy efficiency disclosure in housing markets." *American Economic Journal: Economic Policy*, 14: 453–487.

Newell, Richard G., Adam B. Jaffe, and Robert N. Stavins. 1999. "The Induced Innovation Hypothesis and Energy-Saving Technological Change." *The Quarterly Journal of Economics*, 114: 941–975.

Palmer, Karen, Wallace E. Oates, and Paul R. Portney. 1995. "Tightening Environmental Standards: The Benefit-Cost or the No-Cost Paradigm?" *Journal of Economic Perspectives*, 9: 119–132.

Pástor, L'ubomír, Robert F. Stambaugh, and Lucian A. Taylor. 2021. "Sustainable investing in equilibrium." *Journal of Financial Economics*, 142: 550–571.

Popp, David. 2002. "Induced Innovation and Energy Prices." *American Economic Review*, 92: 160–180.

Popp, David. 2003. "Pollution control innovations and the Clean Air Act of 1990." *Journal of Policy Analysis and Management*, 22: 641–660.

Popp, David. 2006. "International innovation and diffusion of air pollution control technologies: the effects of NOX and SO2 regulation in the US, Japan, and Germany." *Journal of Environmental Economics and Management*, 51: 46–71.

Porter, Michael. 1991. "America's green strategy." *Business and the Environment: A Reader*, 33: 1072.

Porter, Michael E., and Claas van der Linde. 1995. "Toward a New Conception of the Environment-Competitiveness Relationship." *Journal of Economic Perspectives*, 9: 97–118.

Rambachan, Ashesh, and Jonathan Roth. 2023. "A more credible approach to parallel trends." *Review of Economic Studies*, 90: 2555–2591.

Reza, S. Wahidur, and Yuxing Wu. 2024. "The value of green innovation." Available at SSRN 4212739.

Rockett, Katharine E. 1990. "Choosing the competition and patent licensing." *The RAND Journal of Economics*, 161–171.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam. 2009. "Options trading activity and firm valuation." *Journal of Financial Economics*, 94: 345–360.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Rui Zhang. 2023*a*. "Firm-level climate change exposure." *The Journal of Finance*, 78: 1449–1498.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Rui Zhang. 2023*b*. "Pricing climate change exposure." *Management Science*, 69: 7540–7561.

Seira, Enrique, Alejandra Elizondo, and Elizabeth Laguna-Müggenburg. 2017. "Are information disclosures effective? Evidence from the credit card market." *American Economic Journal: Economic Policy*, 9: 277–307.

Shapiro, Adam Fox, and Gilbert E. Metcalf. 2023. "The macroeconomic effects of a carbon tax to meet the US Paris agreement target: The role of firm creation and technology adoption." *Journal of Public Economics*, 218: 104800.

Syverson, Chad. 2011. "What determines productivity?" *Journal of Economic Literature*, 49: 326–365.

Tarui, Nori, and Stephen Polasky. 2005. "Environmental regulation with technology adoption, learning and strategic behavior." *Journal of Environmental Economics and Management*, 50: 447–467.

Teece, David J. 1986. "Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy." *Research Policy*, 15: 285–305.

Tomar, Shivani. 2023. "Greenhouse gas disclosure and emissions benchmarking." *Journal of Accounting Research*, 61: 451–492.

Veefkind, V., J. Hurtado-Albir, S. Angelucci, K. Karachalios, and N. Thumm. 2012. "A new EPO classification scheme for climate change mitigation technologies." *World Patent Information*, 34: 106–111.

Wang, Mengyu, Jeffrey Wurgler, and Hong Zhang. 2026. "Policy uncertainty reduces green innovation." *Journal of Financial Economics*, 175: 104189.

Wang, Xiting, Seung-Hyun Cho, and Alan Scheller-Wolf. 2021. "Green technology development and adoption: competition, regulation, and uncertainty—a global game approach." *Management Science*, 67: 201–219.

Yang, Liyang, Nicholas Z. Muller, and Paul J. Liang. 2021. "The Real Effects of Mandatory CSR Disclosure on Emissions: Evidence from the Greenhouse Gas Reporting Program." National Bureau of Economic Research.

Yu, Meng Li Ting. 2024. "Are Green Innovations Priced? Evidence Beyond Patents." Swiss Finance Institute Research Paper 23-21.

Internet Appendix for "Grow in the Sun: Valuation and Development of Green Innovation under Mandatory Carbon Disclosure"

A1. Representative Public Comments on the GHGRP Proposal

This section of the internet appendix presents selected public comments on the EPA's initial GHGRP proposal. The comments highlight significant uncertainty and disagreement over key program elements at the time of the proposal.

Corporations express concerns about emissions calculations, continuous reporting requirements for facilities that reduce emissions, and ambiguous definitions, including those of natural gas and offshore production facilities. For example, William A. Collins, Jr., Senior Director of Regulatory Affairs at Occidental Petroleum Corporation, urges that EPA's mandatory GHG reporting rule should be based only on actual emissions, not potential or allowable emissions, and opposes the "once in, always in" policy that requires perpetual reporting even if emissions fall below thresholds. He requests clarifications in definitions, excluding gases without commercially significant hydrocarbons from "natural gas" and specifying that artificial islands are not "platform structures," and emphasizes that CO_2 captured for enhanced oil recovery, which is largely sequestered, should not be counted as emissions. Collins also recommends developing voluntary or demonstration reporting protocols for supplied CO_2 and sequestered CO_2 and supports annual rather than quarterly measurement to ensure accurate, practical, and legally sound reporting. Available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0452

Comment submitted by William W. Grygar II, Environmental & Regulatory Manager, Anadarko Petroleum Corporation, emphasized several concerns regarding the GHGRP proposal. Anadarko supported the 25,000 metric tons per year threshold, recommended delaying implementation by one year, and opposed the "once in, always in" policy. They requested extending the annual reporting deadline to June 30, excluding indirect emissions, and allowing self-certification rather than third-party verification. Anadarko also highlighted the disproportionate burden on onshore oil and gas facilities, urged clarifications for definitions such as "natural gas processing facilities" and "fugitive emissions," and recommended excluding CO_2 used for enhanced oil recovery and avoiding double-counting in NGL reporting. Available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0459

Some industry associations argue that the 25,000 metric ton CO_2e threshold is arbitrary. The comment submitted by Joseph J. Croce, Senior Vice President of the Virginia Manufacturers Association (VMA), discusses this issue on page 4 (available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0526). The VMA argues that the 25,000 tCO_2e threshold is arbitrary and not based on science. They note that it is unclear why 25,000 tCO_2e is preferred over 25,500 or 30,000 tCO_2e and that applying this threshold would impose burdens on facilities not classified as major sources under existing Clean Air Act programs. Similarly, Lauren E. Freeman and Norman W. Fichthorn, Hunton & Williams LLP, on behalf of the Utility Air Regulatory Group (UARG), address the threshold on pages 4–5 of their comment (available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0493). They note that EPA did not explain any legal or regulatory basis for setting the threshold at 25,000 tons, which appears far above the 250-ton-per-year level established under the Clean Air Act for PSD applicability, and they recommend that EPA clarify and justify this threshold before proceeding.

Different stakeholders express divergent views on the reporting scope. RiskMetrics Group recommends including Scope 2 emissions, whereas Teck Alaska Incorporated proposes limiting reporting to upstream emissions to prevent double-counting. Comment by Geri Kantor and Doug Cogan, RiskMetrics Group, is available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0369; comment by Jeffrey L. Clark, Environmental Coordinator, Teck Alaska Incorporated, is available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0142.

Many commenters from certain industries opposed the proposed rule, arguing that it would increase the regulatory burden. The Portland Cement Association notes that the rule would

create a massive new reporting system for greenhouse gases and impose requirements greater than any other EPA Clean Air Act information-gathering effort. The association emphasizes that the obligations go far beyond what is needed to understand national emissions and would impose disproportionately high costs on cement plants (Comment submitted by Andrew T. O'Hare, Vice President, Regulatory Affairs, PCA, p. 2, available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0509). Similarly, the California Cattlemen's Association argues that livestock operations would face unnecessary reporting obligations, even though agriculture accounts for a small share of national emissions, and that the rule applies arbitrary thresholds without reflecting the actual impact of emissions (Comment submitted by Justin Oldfield, Director, Industry Affairs, CCA, available at https://www.regulations.gov/comment/EPA-HQ-OAR-2008-0508-0383).

Data and Matching Details

B1. NEI Database

The National Emissions Inventory (NEI) is a national compilation of emissions sources that is created by combining data from various state, local and tribal air agencies (SLTs) with information from EPA emissions programs (e.g., Toxics Release Inventory (TRI), Acid Rain Program) and data gathered for EPA regulatory development aimed at reducing air toxic emissions. To create the NEI, the data from these different sources are blended together using quality assurance procedures. We use this section to show how we match NEI facilities with public firms.

Step 1: To access the NEI data, we visit the website https://www.epa.gov/air-emissions-inventories/2008-national-emissions-inventory-nei-data and download the "point" data. These data include process-level emissions information for various facilities.

The term "point" refers to large stationary sources (e.g., electric utilities, heavy industry) that have a distinct physical location. In contrast, "nonpoint" sources (e.g., field burning, residential wood combustion) have emissions that are distributed across a county area. Additionally, "mobile" category emissions, including "on-road" cars and trucks as well as "nonroad" sources such as aircraft and agricultural field equipment, are also typically estimated across county areas.

[Figure IA1 about here]

Step 2: In the NEI data, we utilize the "eis_facility_site_id," which is the identification number assigned to a facility in the EPA's Emissions Inventory System (EIS). We use this EIS ID to find the parent organization of a facility.

To find this information, we access the "National and State Comma Separated Value (CSV) files" available on the EPA website at https://www.epa.gov/frs/epa-state-combined-csv-download-files. The files include details of all Federal Reporting System (FRS) facilities.

Once we have downloaded these files, we use the "NATIONAL_ORGANIZATIO N_FILE.CSV" and select the rows where the "pgm_sys_acrnm" is "EIS" and "pgm_sys _id" matches the EIS ID of the facility. The "org_name" in this file provides the organization name (as shown in Figure IA2).

[Figure IA2 about here]

In some cases, an organization's name may be missing. In these instances, we extract the EIS ID from the "pgm_sys_acrnms" column of the "NATIONAL_FACI LITY_FILE.CSV" and use the "primary_name" to identify the facility name (as shown in Figure IA3). If the organization's name is not available, we then use the facility name.

[Figure IA3 about here]

Step 3: In this step, we prepare the data by cleaning any special characters, capitalizing all names, and standardizing the suffixes of the NEI and Compustat firms' names. This includes converting "CORPORATION" to "CORP," "INDUSTRY" to "IND," and "GROUP" to "GRP," among others.

Step 4: To match the names in the TRI and Compustat data sets, we utilize the SAS "compged()" function, which is a fuzzy name-matching algorithm. This function calculates the matching score (or edit distance) between two strings, with a score of 0 indicating that the strings are identical. To make the matching process more efficient, we first ensure that the initials of the names in the TRI and Compustat data sets are the same, and then calculate the edit distance. We keep outputs for cases in which the matching score is no more than 520, which yields a pool of potential matches.

Step 5: To verify the matches, we manually check the names from the output file. This includes checking the matching score, conducting a Google search of names, and visiting firms' websites to confirm that the two names refer to the same company.

B2. CO-to-CO_2 Conversion

To determine the amount of CO_2 emissions for each process at each facility, we employ conversion factors outlined in the literature (Gurney et al. 2009; Gurney et al. 2010) . These factors, detailed in the Vulcan Science Methods Documentation, can be found at: https://vulcan.rc.nau.edu/assets/files/Vulcan.documentation.v2.0.online.pdf

An overarching principle with respect to these factors is that when fuel is burned under consistent conditions in standard industrial processes, it will consistently produce CO_2 and CO in proportionate amounts. We use these conversion factors to calculate the CO_2 emissions for each process, and then add up the process-level estimates to arrive at the total CO_2 emissions for a company.

The process for converting CO emissions to CO_2 involves the following steps:

Step 1: We download the Source Classification Codes (SCCs) file from the website https://ofmpub.epa.gov/sccwebservices/sccsearch/, which contains a detailed description of each process. The file contains four levels of description for combustion processes that produce emissions. The higher levels contain more detailed information. For example, the SCC code 30500849 is for industrial processes (level 1), for mineral products (level 2), for clay ceramics manufacture (level 3), and is for a roller kiln: natural gas-fired (level 4).

[Figure IA4 about here]

Step 2: We match the detailed description by using the SCC code in the NEI CO emissions with the Source Classification Codes (SCCs) file. Therefore, we have a four-level description of SCCs.

Step 3: Following Table A.1 of the Vulcan Science Methods Documentation, we find key words in the four levels of the SCC description of each observation in the NEI. For example, we find the key words for materials "bituminous coal" and modifier for "pulverized" in the four levels of the SSC, and then assign the emission factors 0.021 for CO emissions.

[Figure IA5 about here]

Step 4: Following Table A.3 of the Vulcan Science Methods Documentation, we assign CO_2 factors for these materials. For example, the factor 0.0531 is for the material "natural gas," which SSCs include the key word "natural gas."

[Figure IA6 about here]

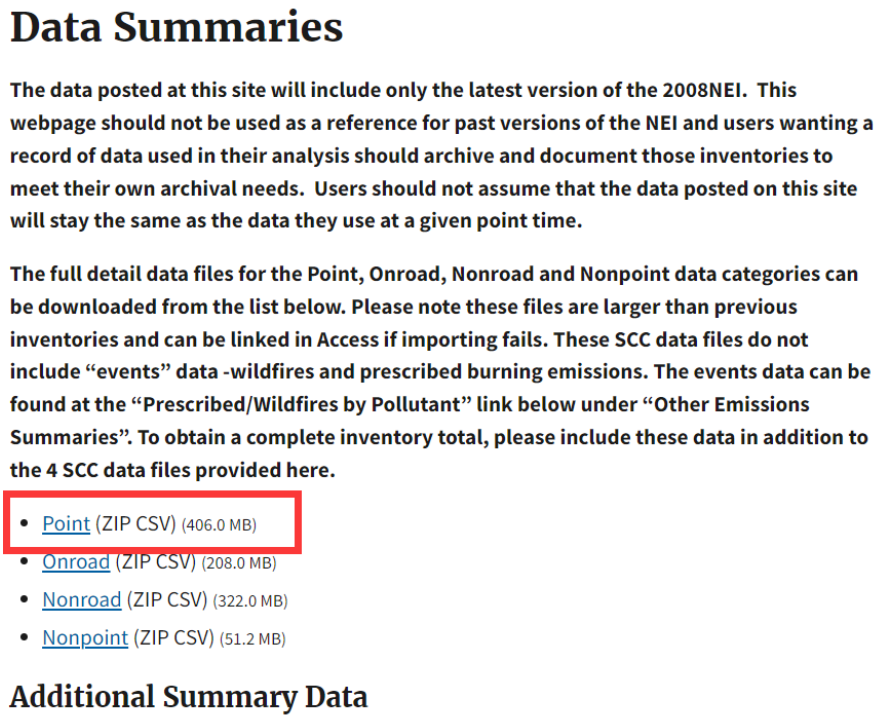
Step 5: We use the following formula provided by Gurney et al. (2010) to calculate the estimated CO_2 emissions for each CO observation in the NEI:

$$C_{pf} = \frac{12}{44} \frac{PE_{pf}}{PF_{pf}} CF_{pf}$$

In cases where p indexes combustion process (e.g., turbine and reciprocating engine), f is the fuel type such as distillate oil and natural gas, C is the emitted amount for carbon, PE is the amount of CO emissions, PF is the emission factor of CO, and CF is the emission factor of CO_2. Finally, we aggregate the process-level estimated CO_2 emissions at the firm-level.

Figure IA1: Data Download

We use the To access the NEI data, we visit the website and download the "point" data.



Data Summaries

The data posted at this site will include only the latest version of the 2008NEI. This webpage should not be used as a reference for past versions of the NEI and users wanting a record of data used in their analysis should archive and document those inventories to meet their own archival needs. Users should not assume that the data posted on this site will stay the same as the data they use at a given point time.

The full detail data files for the Point, Onroad, Nonroad and Nonpoint data categories can be downloaded from the list below. Please note these files are larger than previous inventories and can be linked in Access if importing fails. These SCC data files do not include "events" data -wildfires and prescribed burning emissions. The events data can be found at the "Prescribed/Wildfires by Pollutant" link below under "Other Emissions Summaries". To obtain a complete inventory total, please include these data in addition to the 4 SCC data files provided here.

- Point (ZIP CSV) (406.0 MB)
- Onroad (ZIP CSV) (208.0 MB)
- Nonroad (ZIP CSV) (322.0 MB)
- Nonpoint (ZIP CSV) (51.2 MB)

Additional Summary Data

Source: https://www.epa.gov/air-emissions-inventories/2008-national-emissions-inventory-nei-data

Figure IA2: National Organization File

We use the "NATIONAL_ORGANIZATION_FILE.CSV" and select the rows where the "pgm_sys_acrnm" is "EIS" and the "pgm_sys_id" matches the EIS ID of the facility. The "org_name" in this file provides the organization's name.

	registry_id	pgm_sys_acrnm	pgm_sys_id	org_name
1	110000491735	EIS	12663611	TESORO LOGISTICS OPERATIONS LLC
2	110000491780	EIS	680011	KOCH INDUSTRIES, INC.
3	110000498131	EIS	1075011	TO BE MERGED INTO 863511
4	110000498131	EIS	863511	PETRO STAR, INC.
5	110000507693	EIS	661411	ALYESKA SEAFOODS INC.
6	110000523595	EIS	12660411	ANCHORAGE WATER & WASTEWATER UTILITY
7	110000601705	EIS	542511	TECK ALASKA, INC. (TECK)
8	110000602250	EIS	12662311	GOLDEN VALLEY ELECTRIC ASSOC
9	110000707423	EIS	974811	TRIDENT SEAFOODS CORPORATION
10	110000908395	EIS	541511	ALYESKA PIPELINE SERVICE CO
11	110002003153	EIS	974911	TRIDENT SEAFOODS
12	110002003233	EIS	10564811	ALASKA POWER & TELEPHONE
13	110002003386	EIS	10591411	ALASKA ELECTRIC LIGHT AND POWER
14	110002151340	EIS	1134011	US AIR FORCE (CLEAR)
15	110002376679	EIS	10585911	KODIAK ELECTRIC ASSOCIATION
16	110002465779	EIS	542611	TECK ALASKA, INC. (TECK)
17	110003037883	EIS	679911	FAIRBANKS GOLD MINING INC
18	110003041994	EIS	680611	HILCORP ALASKA, LLC
19	110006002707	EIS	974611	US ARMY (FORT WAINWRIGHT)
20	110006002707	EIS	679211	DUPE IN 9746111
21	110006002707	EIS	12660811	DOYON UTILITIES LLC
22	110006377946	EIS	17987911	ALASKA POWER & TELEPHONE
23	110006532608	EIS	539611	PACIFIC ENERGY RESOURCES LTD.

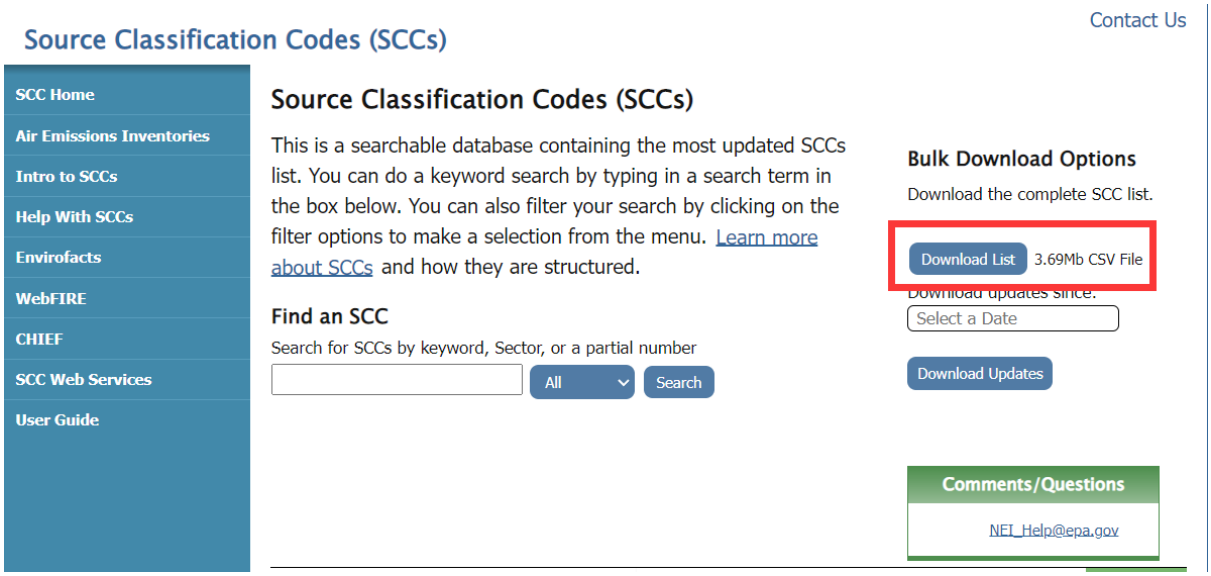
Figure IA3: National Facility File

In some cases, the organization's name may be missing. In these instances, we extract the EIS ID from the "pgm_sys_acrnms" column of the "NATIONAL_FACILITY_FILE.CSV" and use the "primary_name" to identify the facility name.

1C | AIR:AK0000000202000032, AIRS/AFS:0202000032, BR:AKD980987499, EIS:12663611, EPS:EPS10057094, ICIS:2336, ICIS:2

	registry_id	primary_name	pgm_sys_acrnms
1	110000491735	OCEAN DOCK TERMINAL AND …	AIR:AK0000000202000032, AIRS/AFS:0202000032, BR:AKD980987499, EIS:12663611, EPS:EPS10057094, ICIS:…
2	110000491744	INLET PERTROLEUM ANCHORA…	EIS:677611, ICIS:2600029860, ICIS:5870869, NPDES:AK0000370, OTAQREG:OTAQREG10027527, RCRAINFO:AKD0…
3	110000491762	UNIVAR USA	AIR:AK0000000202000105, BR:AKD981765902, EIS:677711, ICIS:1800046105, ICIS:3601086096, ICIS:360123…
4	110000491780	FAIRBANKS PETROLEUM TERM…	EIS:680011, ICIS:600007563, NPDES:AKR06AB58, NPDES:AKR06AF27, RCRAINFO:AKD000835033, TRIS:99707FRT…
5	110000491824	TESORO ALASKA KETCHIKAN …	EIS:540611, NPDES:AK0000523, RCRAINFO:AKD099832198, TRIS:99901TSRLS1010S
6	110000498131	ANCHORAGE TERMINALS I AN…	AIR:100000000003, AIR:AK0000000202000031, AIR:AK0000000202000070, AIRS/AFS:0202000031, AIRS/AFS:02…
7	110000507693	ALYESKA SEAFOOD UNALASKA…	AIR:AK0000000201600004, AIRS/AFS:0201600004, CEDRI:CEDRI3186, EIS:661411, EPS:EPS10056652, ICIS:77…
8	110000510215	EC PHILLIPS AND SON KETC…	AIR:AK0000000213000020, AIRS/AFS:0213000020, ICIS:3600200426, NPDES:AKG520001, OSHA-OIS:341887826
9	110000514079	KETCHIKAN CHLORINATION P…	
10	110000516558	GREAT WESTERN CHEMICAL A…	RCRAINFO:AKD983069568
11	110000517940	BRENNTAG PACIFIC	BR:AKR000000836, EIS:10594111, ICIS:3601086108, ICIS:6683850, RCRAINFO:AKR000000836, SSTS:066887AK…
12	110000523595	JOHN M ASPLUND WASTE WAT…	AIR:AK0000000202000023, AIRS/AFS:0202000023, BR:AKR000206219, CEDRI:CEDRI82441, EIS:12660411, ICIS…
13	110000526574	ALASKA PACIFIC SEAFOODS …	CEDRI:CEDRI3611, ICIS:1800019577, ICIS:6683849, NCDB:I10#198609111513 1, NCDB:I10#19960917AX002 1…
14	110000527920	ICICLE SEAFOODS SEWARD F…	AIR:AK0000000201000016, AIR:AK0000000212200016, AIRS/AFS:0201000016, CEDRI:CEDRI1428, NPDES:AK0001…
15	110000528947	CHANGEPOINT	NPDES:AKU000190
16	110000529599	TRIDENT SEAFOODS PILLAR …	ICIS:6683847, NPDES:AK0000825, NPDES:AKG528825, OSHA-OIS:314292434, OSHA-OIS:316898022, TRIS:9961W…
17	110000601705	RED DOG MINE	AIR:AK0000000218800002, AIRS/AFS:0218800002, EIS:10566811, EIS:542511, EPS:EPS10044885, ICIS:31546…
18	110000602250	HEALY POWER PLANT	AIR:AK0000000229000002, AIRS/AFS:0229000002, CAMDBS:6288, EGRID:6288, EIA-860:6288, EIS:12662311, …
19	110000608502	ALASKA RAILROAD CORP	BR:AKD981767403, ICIS:17055, ICIS:19977, ICIS:19978, ICIS:600035380, NCDB:C10#10-96344-01-NON, NCD…
20	110000707423	TRIDENT SEAFOODS SAND PO…	AIR:AK0000000201000025, AIRS/AFS:0201000025, CEDRI:CEDRI2619, EIS:974811, EPS:EPS10046876, ICIS:30…
21	110000710632	EKUK FISHERIES	AIR:AK0000000207000002, AIRS/AFS:0207000002, NPDES:AKG520037, SFDW:AK2261208, SFDW:AK2261208 32533
22	110000730193	NORTH PACIFIC SEAFOODS S…	NCDB:I10#198911170908 1, NPDES:AKG520065, NPDES:AKG523057
23	110000736151	NORQUEST SEAFOODS	NPDES:AK0045411
24	110000759162	SITKA WASTEWATER FACILITY	NPDES:AK0021474, NPDES:AKL021474
25	110000760917	PETERSBURG WWTP	NPDES:AK0021458, NPDES:AKL021458
26	110000761453	HAINES WWTP	NPDES:AK0021385, NPDES:AKL021385
27	110000779907	CCI INC	RCRAINFO:AK0000016709

Figure IA4: Source Classification Codes (SCCs)



Source: https://ofmpub.epa.gov/sccwebservices/sccsearch/

Figure IA5: Examples of CO Emission Factors

Mat id	unit	lbs CO/ unit	lbs CO/ 10^6 btu	material name	modifier
663	TON	0.5	0.021	bituminous coal	scc contains: "pulverized"
663	TON	0.5	0.021	bituminous coal	scc contains: "cyclone"
663	TON	0.6	0.025	bituminous coal	scc contains: "cogeneration"
663	TON	275	11.441	bituminous coal	scc contains: "hand-fired"
663	TON	6	0.250	bituminous coal	scc contains: "spreader stoker"
663	TON	6	0.250	bituminous coal	scc contains: "overfeed stoker"
663	TON	18	0.749	bituminous coal	scc contains: "atmospheric fluidized bed"
663	TON	11	0.458	bituminous coal	scc contains: "underfeed stoker"

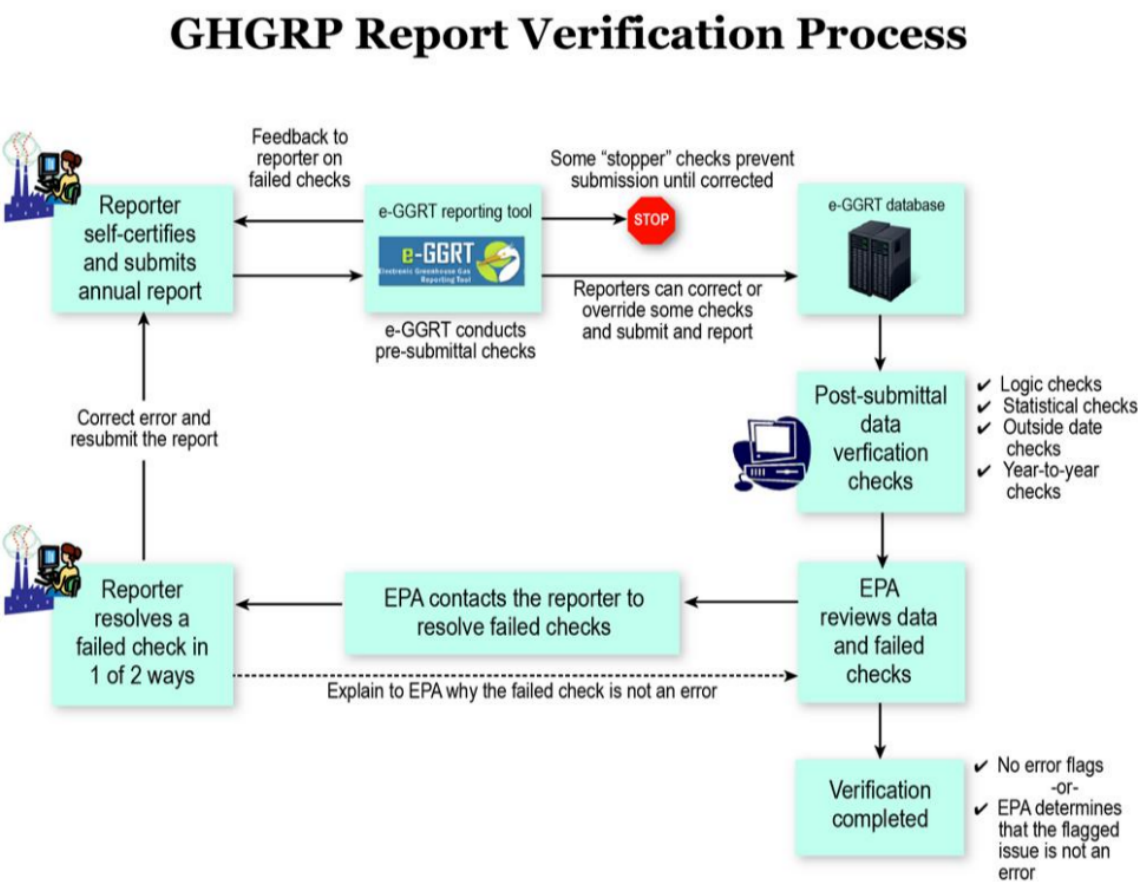
Source: Table A.1 of Vulcan Science Methods Documentation

Figure IA6: Examples of CO_2 Emission Factors

mat id	tonnes $CO_2/10^6$btu	material name	modifier	heat content	units
663	0.0931[1]	bituminous coal		24.04[3]	10^6BTU/TON
323	0.0967[1]	subbituminous coal		17.51[3]	10^6BTU/TON
664	0.0949[1]	bituminous/subbituminous	Average of previous two	20.77[3]	10^6BTU/TON
717	0.0949[1]	Coal	Use previous row	20.77[3]	10^6BTU/TON
640	0.1032[1]	Anthracite		24.94	10^6BTU/TON
639	0.1032[1]	anthracite culm	Use previous row	24.94	10^6BTU/TON
173	0.0961[1]	Lignite		12.97[3]	10^6BTU/TON
209	0.0531	natural gas	"natural gas pipeline"	1032[3]	10^6BTU/10^6FT^3
251	0.0561	process gas	"refinery fuel gas" entry	1068.6[1]	10^6BTU/10^6FT^3
553	0.0561	refinery gas	"refinery fuel gas" entry	1068.6[1]	10^6BTU/10^6FT^3
310	0.0561	sour gas	"refinery fuel gas" entry	1068.6[1]	10^6BTU/10^6FT^3
126	0.0561	Gas	"refinery fuel gas" entry	1068.6[1]	10^6BTU/10^6FT^3

Source: Source: Table A.3 of Vulcan Science Methods Documentation

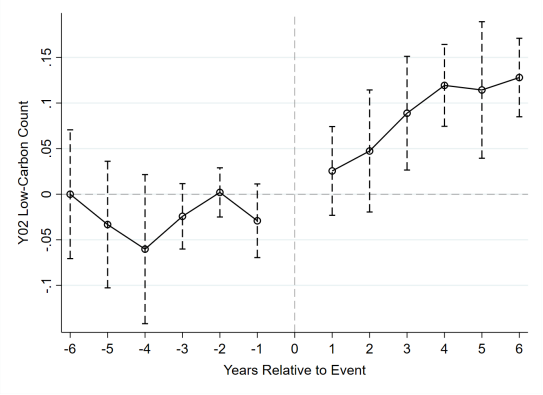
Figure IA7: GHGRP Report Verification Process



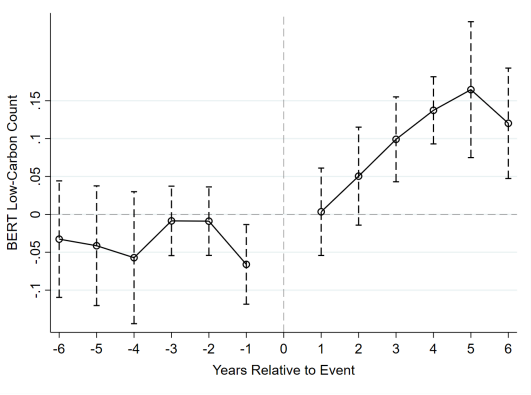
Source: https://www.epa.gov/sites/default/files/2017-12/documents/ghgrp_verification_factsheet.pdf

Figure IA8: Parallel Trend Plots – Two Groups

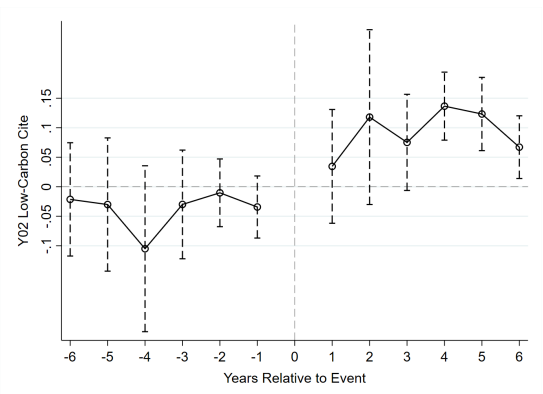
These plots show the evolution of low-carbon innovation over time for high- and low-CO_2 emitters. Panels A to C present results for the count, citations, and valuation of CPC Y_{02} or BERT-based low-carbon patents, respectively. Vertical lines indicate 90% confidence intervals for the estimated β values. The x-axis marks 2008 as year 0.



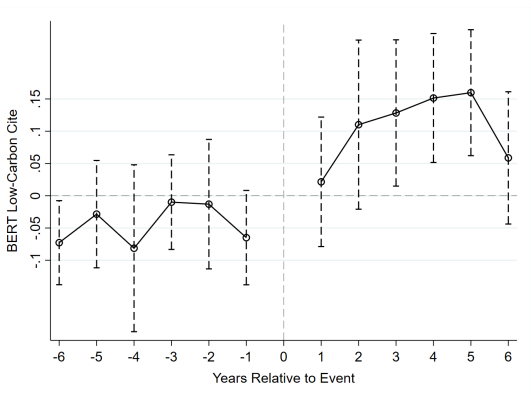
Panel A1. Y02 Count with Controls



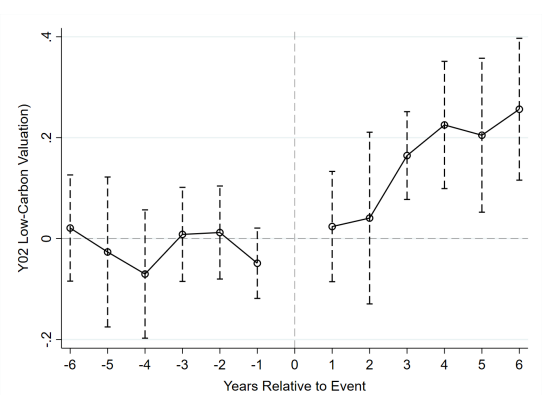
Panel A2. BERT Count with Controls



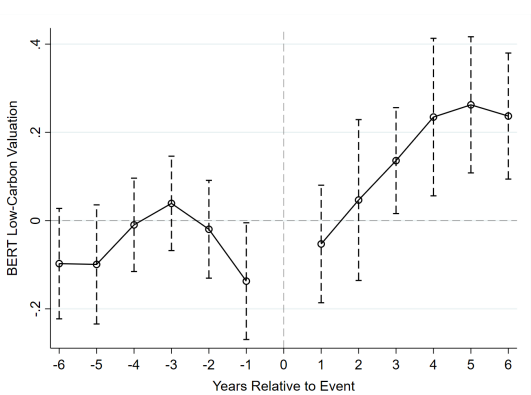
Panel B1. Y02 Cite with Controls



Panel B2. BERT Cite with Controls



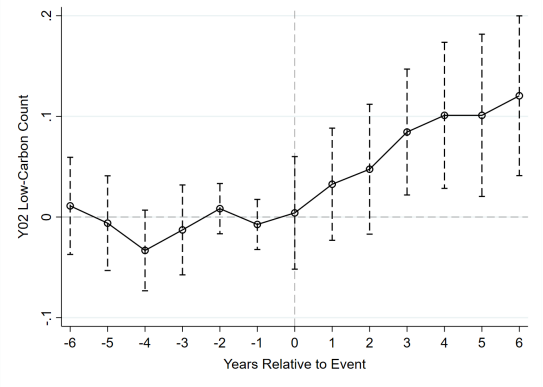
Panel C1. Y02 Valuation with Controls



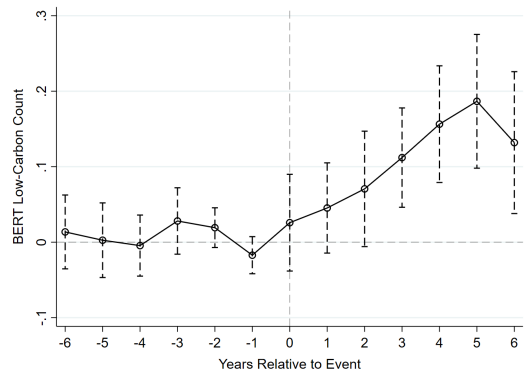
Panel C2. BERT Valuation with Controls

Figure IA9: Parallel Trend Plots – SDID

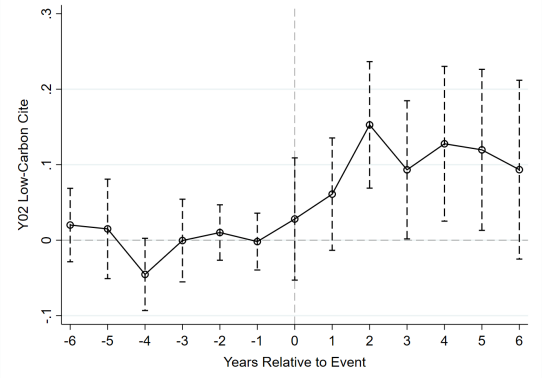
These plots display the variation in low-carbon innovation over time for high- and low-CO_2 emitters. Panels A to C report results from the SDID model for the count, citations, and valuation of CPC Y02 or BERT-based low-carbon patents, respectively. Vertical lines indicate 90% confidence intervals for the estimated β values.



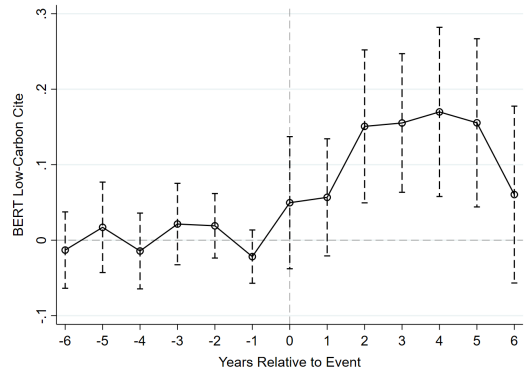
Panel A1. SDID Y02 Count with Controls



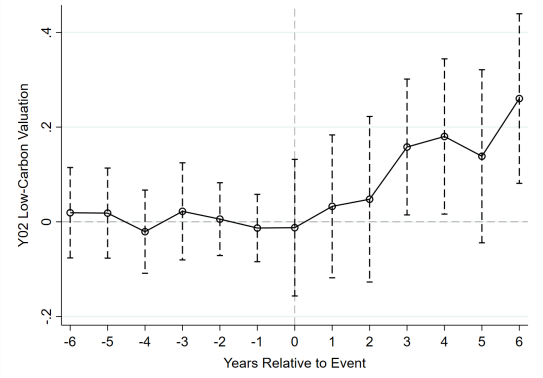
Panel A2. SDID BERT Count with Controls



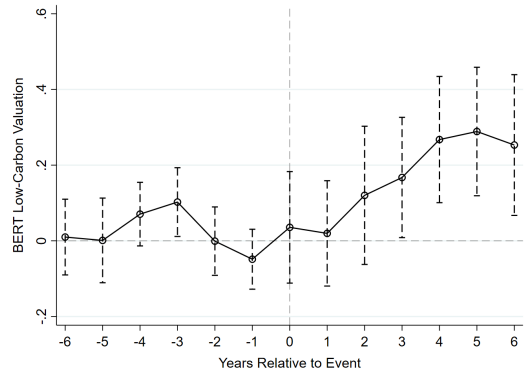
Panel B1. SDID Y02 Cite with Controls



Panel B2. SDID BERT Cite with Controls



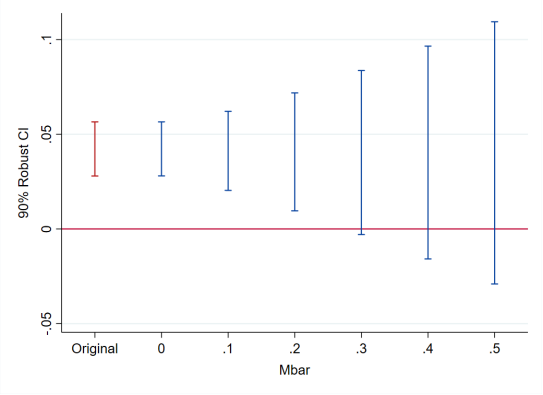
Panel C1. SDID Y02 Valuation with Controls



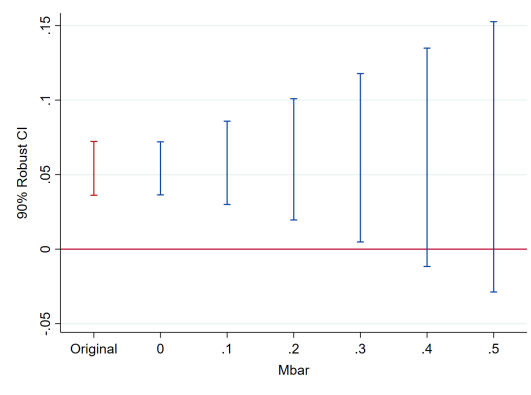
Panel C2. SDID BERT Valuation with Controls

Figure IA10: Sensitivity Analysis using HonestDiD

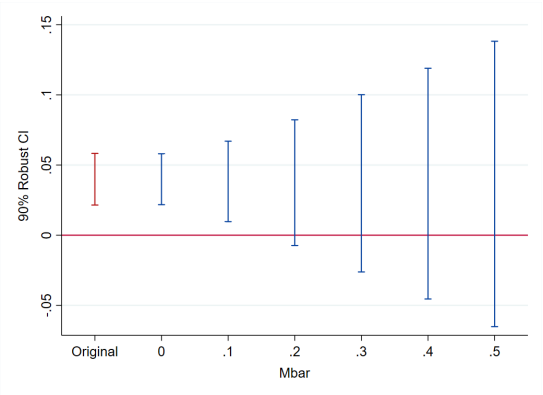
This figure displays the results of the HonestDiD approach applied to the dynamic analysis, highlighting stable confidence intervals for the average treatment effect in the post-treatment period. When Mbar = 0, we allow for violations of parallel trends that are approximately linear, whereas for Mbar > 0, we permit more nonlinearity violations.



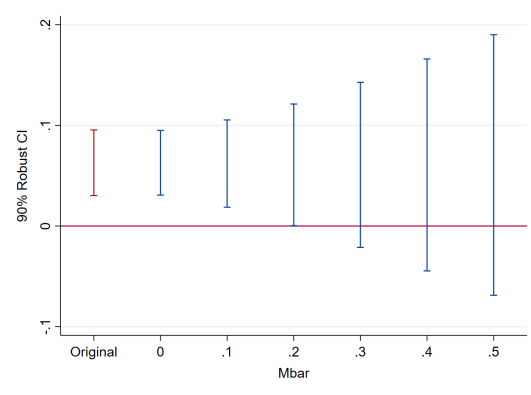
Panel A1. Y02 Count with Controls



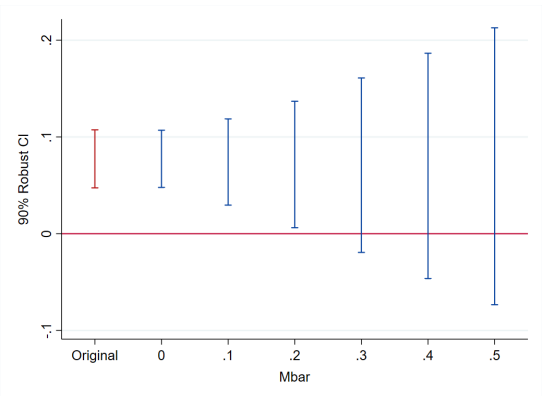
Panel A2. BERT Count with Controls



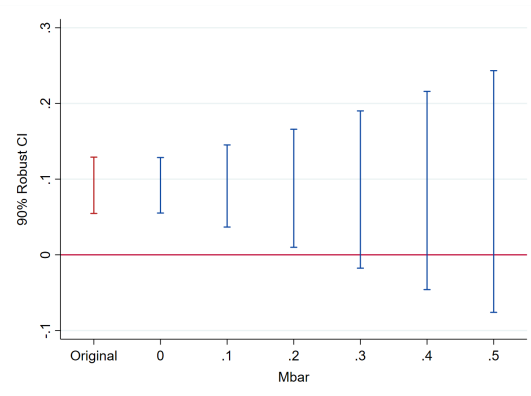
Panel B1. Y02 Cite with Controls



Panel B2. BERT Cite with Controls



Panel C1. Y02 Valuation with Controls



Panel C2. BERT Valuation with Controls

Table IA1: Keywords

The table presents keywords for locating Y02 patents covering subjects associated with carbon reduction, energy efficiency, and cleaner energy.

carbon dioxide emissions	carbon emissions	carbon emissions efficiency	carbon efficiency	climate change mitigation
carbon removal	carbon dioxide removal	removing carbon	remove carbon	carbon sequestration
carbon capture	carbon cycle	carbon-neutral	decarbonization	carbon footprint
carbon footprint reduction	carbon footprint reduce	carbon footprint management	carbon offset	greenhouse gas emissions
carbon neutral	climate positive	net zero	carbon reduction	greenhouse gas reduction
low carbon emission	low carbon dioxide	low-carbon emission	reduce carbon dioxide	reduce carbon emission
reduce carbon emissions	reducing carbon emission	reducing carbon emissions	reduce greenhouse gas	reducing greenhouse gas
carbon negative	net zero emission	carbon emission	carbon emission efficiency	carbon efficiency
combustion efficiency	greenhouse gas emission	carbon neutral	climate positive	carbon negative
reduce fuel consumption	reduce fuel consume	low fuel consumption	fuel efficient	fuel-efficient
fuel efficiency	fuel-efficiency	energy efficiency	energy efficient	energy-efficiency
power saving	power save	saving more power	saving power	saving energy
energy saving	saving fuel	energy save	fuel saving	fuel save
efficient power	reduce energy consumption	reduce energy consume	low energy consumption	low energy consume
energy consumption	energy consume	power consumption	power consume	net zero emission
net-zero emission	net-zero emissions	net-zero	renewable energy	renewable
regenerating	regenerate	regeneration	efficiency	efficient
efficiently	clean energy	controlling combustion processes	controlling combustion	control combustion
power efficient	switch mode	power supply	power density	sustainability
efficiently producing	conserve power	power conserve	power control	power loss
conserve energy	energy conserve	fuel conserve	conserve fuel	clean fuel
energy cycle	energy reuse	energy recycling	recycle	recycling
energy recovery	engine exhaust	exhaust purifying	exhaust gas	solar power
solar	zero waste	wind power	hydropower	geothermal energy
bioenergy	lowering the cost	lower the cost	energy conversion	energy storage
energy density	energy capacity	power capacity	photovoltaic power	photovoltaic
utilization rate	internal combustion	adsorption	fuel cell	fluid loss
efficient method	sustainable	efficient system	fuel economy	combustion efficient

Table IA2: Summary Statistics of Keyword-Based Low-Carbon Patents

This table provides summary statistics for keyword-based low-carbon patents across the sample firms. A patent is classified as a Keyword Low-Carbon Patent if its CPC class falls under the Y02 category and if it includes keywords related to carbon reduction, energy efficiency, and cleaner energy in the technical field, background, and summary of the inventions. Corresponding keywords can be found in Table IA1. For Count, Cite, or Valuation, this table reports the raw numbers without taking logarithms.

Variables	Obs	Mean	SD	p10	p50	p90
Panel A. Patent Level RDD Sample						
Keyword Low-Carbon Valuation	328	34.26	58.88	2.27	13.92	89.77
Brief Word Count	328	1.33	1.47	0.37	0.92	2.40
Cite Backward	328	18.17	27.82	3.00	10.00	32.00
Claims	328	3.07	1.99	1.00	3.00	5.00
Process Claim Ratio	328	0.40	0.37	0.00	0.33	1.00
Inventor Number	328	3.04	2.14	1.00	3.00	6.00
Inventor Average Age	328	44.14	7.35	35.50	44.00	53.00
Panel B. Firm Level DID Sample						
Keyword Low-Carbon Count	5573	3.26	18.44	0.00	0.00	4.00
Keyword Low-Carbon Cite	5573	3.65	21.71	0.00	0.00	4.05
Keyword Low-Carbon Valuation	5573	52.87	350.78	0.00	0.00	45.04

Table IA3: Results for Keyword-based Low-carbon Patents

This table examines the impact of the Greenhouse Gas Reporting Program (GHGRP) on keyword-based low-carbon patents. A patent is classified as keyword-based low-carbon if its CPC class includes Y02 and its keywords relate to carbon reduction, energy efficiency, or cleaner energy in the technical field, background, or summary of the invention. The list of keywords is provided in Internet Appendix Table IA1. Panel A shows the effect of the GHGRP on the market valuation of keyword-based low-carbon patents using RDD models. The sample consists of keyword-based low-carbon patents filed by sample firms between 2002 and 2006 and issued by the USPTO within 12 weeks before or after December 26, 2007, the passage date of the Consolidated Appropriations Act that established GHGRP funding. The dependent variable is the natural logarithm of patent valuation. The GHGRP is measured by a binary variable equal to one if a patent is issued on or after December 26, 2007. Regressions include fixed effects for patent parent firms and four-digit CPC codes. Column (1) reports results from local linear regressions with a 12-week bandwidth, and Column (2) uses a quadratic polynomial on each side of the GHGRP cutoff date with the same bandwidth. All models control for patent-level characteristics, including Brief Word Count, Cite Backward, Claims, Process Claim Ratio, Inventor Number, and Inventor Average Age. Standard errors are double-clustered by CPC industry and issue week. Panel B shows the effect of the GHGRP on keyword-based low-carbon patents using DID models over the 2002–2014 period. The dependent variables are the natural logarithm of one plus (a) the number of keyword-based low-carbon patents, (b) citations to these patents, and (c) their market valuation. The GHGRP is measured by a binary variable equal to one for 2008 and later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. All regressions include firm and industry-year fixed effects. Columns (2), (4), and (6) additionally control for R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and an indicator for missing R&D data. Standard errors are double-clustered by industry and year and reported in parentheses. Variable definitions are in Appendix A. Statistical significance is denoted as * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A. Patent Valuation (Keyword)

Variables	(1) Keyword Low-Carbon Valuation	(2) Keyword Low-Carbon Valuation
GHGRP	0.8076***	0.9054***
	(0.1080)	(0.1222)
Brief Word Count	-0.0112	-0.0071
	(0.0175)	(0.0174)
Cite Backward	-0.0015*	-0.0018*
	(0.0008)	(0.0010)
Claims	-0.0001	-0.0018
	(0.0145)	(0.0172)
Process Claim Ratio	-0.0290	-0.0243
	(0.0759)	(0.0796)
Inventor Number	0.0002	0.0029
	(0.0189)	(0.0185)
Inventor Average Age	0.0008	0.0014
	(0.0029)	(0.0034)
Constant	2.3555***	2.3795***
	(0.1637)	(0.1916)
Observations	328	328
R-squared	0.943	0.944
Specification	Local linear regression	Quadratic polynomial
Firm FE	YES	YES
CPC4 FE	YES	YES

Table IA3: Results for Keyword-based Low-carbon Patents (Continued)

Panel B. Firm Patenting Activities (Keyword)						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Keyword Low-Carbon Count	Keyword Low-Carbon Count	Keyword Low-Carbon Cite	Keyword Low-Carbon Cite	Keyword Low-Carbon Valuation	Keyword Low-Carbon Valuation
GHGRP×Emitter	0.0395**	0.0399**	0.0451**	0.0456***	0.0643*	0.0660**
	(0.0156)	(0.0147)	(0.0152)	(0.0147)	(0.0301)	(0.0281)
R&D Intensity		0.1617		0.0122		0.4716
		(0.1619)		(0.2877)		(0.3774)
XAD/AT		-1.1229		-0.0222		-2.0279
		(1.4458)		(1.0808)		(2.8741)
CAPX/AT		0.1804		0.0500		0.5187
		(0.2151)		(0.1907)		(0.4857)
Ln(AT)		0.0668		0.0810**		0.1538**
		(0.0393)		(0.0370)		(0.0609)
Tangibility		-0.1014		-0.0616		-0.1509
		(0.0924)		(0.0955)		(0.2023)
Labor/Capital		-0.4857		-0.6100		-0.5455
		(0.5502)		(0.6028)		(0.7004)
Tobin's Q		0.0111		0.0227		0.0078
		(0.0119)		(0.0157)		(0.0358)
Firm Age		-0.0039		0.0041		0.0098
		(0.0087)		(0.0073)		(0.0240)
Leverage		0.0001		-0.0000		0.0003
		(0.0002)		(0.0003)		(0.0003)
ROA		0.0488		0.0687		0.0218
		(0.0683)		(0.0563)		(0.1616)
Cash/AT		-0.2591**		-0.3339***		-0.1561
		(0.0927)		(0.0968)		(0.2065)
R&D Missing		-0.0348		-0.0013		-0.0653
		(0.0754)		(0.1016)		(0.1357)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.891	0.892	0.837	0.838	0.825	0.826
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Table IA4: Regression Discontinuity Design - Continuity in Patent Characteristics Across GHGRP

This table reports the characteristics of patents granted immediately before and after the GHGRP. Panel A presents results for CPC Y02 low-carbon patents, and Panel B for BERT-based low-carbon patents. In both panels, Column (1) reports summary statistics for patents granted before the GHGRP, Column (2) for those granted after, and Column (3) the difference between Columns (1) and (2) with corresponding t-statistics. The reported F-statistic is from a multivariate ANOVA (MANOVA) test, and the density test statistic (T) follows Cattaneo et al. (2018). Statistical significance is denoted as *** for 1%, ** for 5%, and * for 10%.

Panel A. Y02 low-carbon patents

	(1) Granted Before GHGRP	(2) Granted After GHGRP	(3) (1)-(2) t-value
Brief Word Count	1.36	1.14	-1.83*
Cite Backward	21.15	25.39	1.15
Claims	3.09	2.96	-0.78
Process Claim Ratio	0.40	0.39	-0.25
Inventor Number	3.11	3.06	-0.23
Inventor Average Age	44.93	43.86	-1.62
MANOVA test	F=1.40 (p-value=0.2122)		
Density test	T=-0.86 (p-value=0.3914)		

Panel B. BERT low-carbon patents

	(1) Granted Before GHGRP	(2) Granted After GHGRP	(3) (1)-(2) t-value
Brief Word Count	1.15	1.31	-1.95*
Cite Backward	22.66	19.75	1.18
Claims	3.04	3.02	0.17
Process Claim Ratio	0.39	0.39	-0.2
Inventor Number	3.03	2.95	0.58
Inventor Average Age	44.15	44.87	-1.44
MANOVA test	F=1.26 (p-value=0.2718)		
Density test	T=-0.42 (p-value=0.6716)		

Table IA5: Robust – Poisson Regression

This table shows robust test of our baseline results by using Poisson model. The sample period is from 2002 to 2014. The firm-level dependent variables are (a) the number of CPC Y02 or BERT-based low-carbon patents, and (b) their citations. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Columns also include the following variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT) Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. The definitions for these variables can be found in Appendix A. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Count	(2) Y02 Low-Carbon Cite	(3) BERT Low-Carbon Count	(4) BERT Low-Carbon Cite
GHGRP×Emitter	0.094*	0.2180**	0.0878*	0.1810***
	(0.0557)	(0.1036)	(0.0466)	(0.0676)
R&D Intensity	2.8453**	-0.7855	1.7092**	1.1161
	(1.1409)	(1.3712)	(0.7765)	(1.3153)
XAD/AT	4.0778	9.5971	7.2002	10.7759**
	(8.9987)	(9.7477)	(6.4458)	(5.4296)
CAPX/AT	4.6938***	3.6218***	1.6128*	1.2258
	(1.8157)	(1.3386)	(0.8263)	(1.1525)
Ln(AT)	0.4366**	0.3438*	0.4530**	0.4318**
	(0.1856)	(0.1861)	(0.1947)	(0.1998)
Tangibility	-0.5701	-0.8535	0.4174	0.1203
	(0.4100)	(0.6942)	(0.4927)	(0.7795)
Labor/Capital	-21.2843***	-37.7528***	-10.0447**	-16.3345**
	(7.6977)	(8.4749)	(4.4937)	(7.0092)
Tobin's Q	-0.0340	0.0373	0.0110	0.0583*
	(0.0313)	(0.0501)	(0.0181)	(0.0346)
Firm Age	-	-	0.0062	0.0858
			(0.1338)	(0.1284)
Leverage	-0.0019**	-0.0024**	-0.0020**	-0.0025***
	(0.0008)	(0.0010)	(0.0009)	(0.0008)
ROA	0.5816**	0.7038	0.7794***	0.6208
	(0.2372)	(0.5463)	(0.2307)	(0.4359)
Cash/AT	-0.5027	-0.3887**	-0.7090*	-1.0870***
	(0.3132)	(0.1563)	(0.3765)	(0.2824)
R&D Missing	0.1103	-0.3419	0.2060	0.4455
	(0.4497)	(0.6312)	(0.3236)	(0.4305)
Observations	2,455	2,290	2,838	2,633
Pseudo R2	0.896	0.874	0.925	0.903
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Table IA6: Robust – Firm Patenting Activities without Control Variables

This table reports the effect of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents without including control variables. The sample period is from 2002 to 2014. Patents are classified using either the CPC Y02 code or a BERT-based model. The firm-level dependent variables are the logarithm of one plus (a) the number of CPC Y02 or BERT-based low-carbon patents, (b) their citations, and (c) their valuation. We define a patent as BERT-based low-carbon if it either carries a Y02 code or is classified as low-carbon by our fine-tuned BERT model. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×Emitter	0.0364*	0.0443*	0.0449**	0.0512**	0.0631*	0.0782*
	(0.0181)	(0.0229)	(0.0176)	(0.0218)	(0.0339)	(0.0364)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.904	0.925	0.858	0.891	0.845	0.888
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Table IA7: Robust – Excluding Firms with High Foreign Income

This table reports the effect of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents by excluding firms with significant foreign income. We exclude firms with high foreign income, defined as those for which the ratio of foreign pretax income to firm total assets in 2006 exceeds the 80th percentile of the sample. The sample period is from 2002 to 2014. The firm-level dependent variables are the logarithm of one plus (a) the number of CPC Y02 or BERT-based low-carbon patents, (b) their citations, and (c) their valuation. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emittter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Indications are estimated from process-level CO emissions using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Columns also include the following variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. The definitions for these variables can be found in Appendix A. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Patents	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×Emittter	0.0386**	0.0461**	0.0304*	0.0400*	0.0741***	0.0687*
	(0.0174)	(0.0225)	(0.0172)	(0.0232)	(0.0260)	(0.0341)
R&D Intensity	0.4127**	0.1270	0.0136	-0.0062	0.8384**	-0.0353
	(0.1729)	(0.3057)	(0.3620)	(0.1599)	(0.4085)	(0.5666)
XAD/AT	-2.5694	-1.9630	-0.8834	-0.2680	-5.4228	-1.2382
	(2.3126)	(2.9357)	(1.8288)	(2.1549)	(4.4821)	(5.2179)
CAPX/AT	-0.0668	-0.1848	-0.1091	-0.2733	-0.2987	-0.2456
	(0.2005)	(0.2403)	(0.2401)	(0.2618)	(0.3628)	(0.4618)
Ln(AT)	0.0434	0.0771	0.0662	0.0749	0.1312	0.1943**
	(0.0435)	(0.0538)	(0.0473)	(0.0555)	(0.0786)	(0.0941)
Tangibility	-0.0195	-0.0873	0.0909	-0.0625	-0.0325	-0.2439
	(0.1723)	(0.2061)	(0.1875)	(0.2044)	(0.3637)	(0.4111)
Labor/Capital	-0.3486	0.8330	-0.4232	0.6440	-0.6246	1.1555
	(0.6129)	(0.9607)	(0.4194)	(1.0031)	(0.9806)	(1.3107)
Tobin's Q	0.0104	0.0021	0.0250	0.0325	0.0401	0.0233
	(0.0173)	(0.0209)	(0.0231)	(0.0288)	(0.0316)	(0.0398)
Firm Age	-0.0159*	-0.0137	-0.0119	-0.0079	-0.0142*	-0.0011
	(0.0079)	(0.0085)	(0.0071)	(0.0084)	(0.0075)	(0.0095)
Leverage	-0.0003	-0.0002	-0.0003	-0.0000	0.0001	0.0002
	(0.0006)	(0.0005)	(0.0006)	(0.0004)	(0.0008)	(0.0007)
ROA	0.0298	-0.0463	0.0339	-0.1190*	0.0528	-0.2346
	(0.0507)	(0.0586)	(0.0560)	(0.0662)	(0.1389)	(0.1749)
Cash/AT	-0.0288	-0.0204	0.0840	-0.0442	0.0810	0.1550
	(0.1193)	(0.1679)	(0.1049)	(0.1495)	(0.1704)	(0.2645)
R&D Missing	-0.0897	-0.0933	-0.1496	-0.1235	-0.1688	-0.1713
	(0.0903)	(0.0896)	(0.1189)	(0.0952)	(0.1514)	(0.1508)
Observations	4,440	4,440	4,440	4,440	4,440	4,440
R-squared	0.889	0.911	0.834	0.872	0.820	0.859
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Table IA8: Firm Patenting Activities – Two Groups

This table examines the impact of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents by dividing firms into two groups. The sample period covers 2002–2014. The firm-level dependent variables are the logarithm of one plus (a) the number of CPC Y02 or BERT-based low-carbon patents, (b) their citations, and (c) their valuation. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable "Emittter" is binary, where a value of one indicates that a firm's estimated CO_2 emissions in 2005 fall within the higher half of its industry (based on the three-digit NAICS code). Estimated CO_2 emissions are derived from process-level CO data in 2005, using the CO-to-CO_2 industry process conversion factors, and are then aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. Columns also include the following variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. The definitions for these variables can be found in Appendix A. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×Emittter	0.0949**	0.1129**	0.1154**	0.1316**	0.1399*	0.1668**
	(0.0414)	(0.0476)	(0.0471)	(0.0505)	(0.0673)	(0.0729)
R&D Intensity	0.3418	0.2591	0.0004	0.1856	0.9530**	0.1660
	(0.1933)	(0.2169)	(0.3473)	(0.2485)	(0.4180)	(0.5586)
XAD/AT	-0.8275	-0.5272	0.5826	0.6944	-0.5252	0.0879
	(2.4206)	(2.9720)	(1.4907)	(1.7949)	(5.6918)	(5.7370)
CAPX/AT	-0.0257	-0.1569	-0.1828	-0.2827	-0.0297	-0.1314
	(0.2310)	(0.2475)	(0.2730)	(0.2451)	(0.4344)	(0.5133)
Ln(AT)	0.1194**	0.1511**	0.1344**	0.1543**	0.2618***	0.2969***
	(0.0512)	(0.0641)	(0.0499)	(0.0588)	(0.0718)	(0.0901)
Tangibility	0.0292	0.0015	0.1797	0.0543	0.2066	-0.0088
	(0.1599)	(0.1824)	(0.1822)	(0.1852)	(0.3493)	(0.3420)
Labor/Capital	-0.3363	0.8482	-0.5132	0.4683	-0.3012	1.5237
	(0.6144)	(0.9776)	(0.5715)	(0.8909)	(0.8114)	(1.2972)
Tobin's Q	0.0360*	0.0314	0.0454*	0.0576**	0.0640*	0.0524
	(0.0173)	(0.0191)	(0.0209)	(0.0258)	(0.0355)	(0.0317)
Firm Age	-0.0029	-0.0075	0.0086	0.0054	0.0169	0.0005
	(0.0086)	(0.0081)	(0.0072)	(0.0076)	(0.0270)	(0.0096)
Leverage	-0.0002	-0.0001	-0.0001	0.0001	0.0000	0.0002
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
ROA	0.0439	0.0056	0.0712	-0.0246	0.0644	-0.1954
	(0.0778)	(0.0731)	(0.0743)	(0.0801)	(0.1747)	(0.1638)
Cash/AT	-0.1170*	-0.0775	-0.0596	-0.1657**	0.1372	0.2339
	(0.0626)	(0.0962)	(0.0828)	(0.0747)	(0.1922)	(0.2977)
R&D Missing	-0.0518	-0.0590	-0.0831	-0.0490	-0.1258	-0.1959
	(0.0816)	(0.0923)	(0.1094)	(0.1109)	(0.1467)	(0.1475)
Observations	5,573	5,573	5,573	5,573	5,573	5,573
R-squared	0.905	0.926	0.859	0.892	0.847	0.889
Firm FE	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES

Table IA9: Firm Patenting Activities – SDID

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents using the Synthetic Differences-in-Differences (SDID) method. The sample period is from 2002 to 2014. The firm-level dependent variables are the logarithm of one plus (a) the number of CPC Y02 or BERT-based low-carbon patents, (b) their citations, and (c) their valuation. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable "Emittter" is binary, where a value of one indicates that a firm's estimated CO_2 emissions in 2005 fall within the higher half of its industry (based on the three-digit NAICS code). Estimated CO_2 emissions are derived from process-level CO data in 2005, using the CO-to-CO_2 industry process conversion factors, and are then aggregated at the firm level. Columns also include the following variables: R&D Intensity, XAD/AT, CAPX/AT, Ln(AT), Tangibility, Labor/Capital, Tobin's Q, Firm Age, Leverage, ROA, Cash/AT, and R&D Missing. The definitions for these variables can be found in Appendix A. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Y02 Low-Carbon Count	(2) BERT Low-Carbon Count	(3) Y02 Low-Carbon Cite	(4) BERT Low-Carbon Cite	(5) Y02 Low-Carbon Valuation	(6) BERT Low-Carbon Valuation
GHGRP×Emittter	0.0700*	0.1023**	0.0966**	0.1105**	0.1143	0.1588*
	(0.0372)	(0.0403)	(0.0426)	(0.0450)	(0.0790)	(0.0820)
Controls	YES	YES	YES	YES	YES	YES
Observations	5,018	5,018	5,018	5,018	5,018	5,018

Table IA10: Robust – Real CO2 Emissions After 2010

This table presents the impact of the Greenhouse Gas Reporting Program (GHGRP) on firms' CO_2 emissions. The dependent variable includes the natural logarithm of one plus estimated CO_2 emissions for the pre-period of 2008, or the actual CO_2 emissions for the post-period between 2010 and 2014. The real CO_2 emissions data from 2010 to 2014 are obtained from the Greenhouse Gas Reporting Program. We aggregate facility-level real CO_2 emission data into firm-level data annually from 2010 to 2014. For firms lacking actual CO_2 data but with NEI data and estimated CO_2, we assigned a value of zero to represent actual CO_2 emissions in our sample. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. Regressions presented in this table include firm and industry-year fixed effects. The definitions for these variables can be found in Appendix A. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Variables	(1) Real CO_2	(2) Real CO_2
GHGRP×Emittter	-0.4709***	-0.4885***
	(0.0954)	(0.0972)
R&D Intensity		-3.4207
		(2.6056)
XAD/AT		-11.4716
		(10.5096)
CAPX/AT		-0.0112
		(1.3422)
Ln(AT)		0.0673
		(0.1901)
Tangibility		0.9269
		(1.7667)
Labor/Capital		8.1408
		(9.4800)
Tobin's Q		0.0873
		(0.1220)
Firm Age		-0.0744
		(0.1151)
Leverage		-0.0001
		(0.0023)
ROA		-1.0787*
		(0.5982)
Cash/AT		0.9020
		(1.0648)
R&D Missing		-0.2237
		(0.3830)
Observations	1,974	1,974
R-squared	0.947	0.947
Firm FE	YES	YES
Industry-Year FE	YES	YES

Table IA11: Competition Pressure (Patent Valuation)

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents for firms with high and low competition pressure. The sample period is from 2002 to 2014. The firm-level dependent variables are the logarithm of one plus the valuation of CPC Y02 or BERT-based low-carbon patents. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. We classify firms into high and low competition pressure groups using two measures: (a) product market similarity and (b) climate risk analyst coverage. Firms with product market similarity (Hoberg and Phillips 2016) in 2006 above the sample median are classified as High Product Similarity, and the remainder as Low Product Similarity. Firms with climate risk analyst coverage above the sample median in 2006 are classified as High Climate Risk Analyst, and the remainder as Low Climate Risk Analyst. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Panel A. Product Similarity

Variables	(1) Y02 Low-Carbon Valuation	(2) Y02 Low-Carbon Valuation	(3) BERT Low-Carbon Valuation	(4) BERT Low-Carbon Valuation
Subsample	*Low Product Similarity*	*High Product Similarity*	*Low Product Similarity*	*High Product Similarity*
GHGRP×Emittter	0.0248	0.0945*	0.0311	0.0842*
	(0.0603)	(0.0471)	(0.0619)	(0.0441)
Observations	2,613	2,555	2,613	2,555
R-squared	0.869	0.851	0.889	0.895
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Panel B. Analyst Coverage

Variables	(1) Y02 Low-Carbon Valuation	(2) Y02 Low-Carbon Valuation	(3) BERT Low-Carbon Valuation	(4) BERT Low-Carbon Valuation
Subsample	*Low Climate Risk Analyst*	*High Climate Risk Analyst*	*Low Climate Risk Analyst*	*High Climate Risk Analyst*
GHGRP×Emittter	-0.0083	0.1293*	-0.0044	0.1508*
	(0.0452)	(0.0653)	(0.0469)	(0.0779)
Observations	2,621	2,209	2,621	2,209
R-squared	0.731	0.843	0.785	0.889
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Table IA12: Price Efficiency (Patent Valuation)

This table reports the effect of the Greenhouse Gas Reporting Program (GHGRP) on low-carbon patents for firms with high versus low price efficiency. The sample period is from 2002 to 2014. The firm-level dependent variables are the logarithm of one plus the valuation of CPC Y02 or BERT-based low-carbon patents. GHGRP is represented by a binary variable, with a value of one indicating that the year is 2008 or later. The variable Emitter ranges from one to four, where one indicates that a firm's estimated 2005 CO_2 emissions fall in the first quartile of its three-digit NAICS industry. Emissions are estimated from process-level CO data using CO-to-CO_2 conversion factors and aggregated at the firm level. We classify firms into high and low price efficiency groups based on two measures: (a) option trading volume and (b) the probability of informed trading (PIN). Firms with option trading volume in 2006 above the sample median are classified as High Option Trading, and the rest as Low Option Trading. Similarly, firms with PIN above the sample median are classified as High PIN, and the rest as Low PIN. Regressions presented in this table include firm and industry-year fixed effects. Standard errors, double-clustered by industry and year, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Panel A. Option Trading

Variables	(1) Y02 Low-Carbon Valuation	(2) Y02 Low-Carbon Valuation	(3) BERT Low-Carbon Valuation	(4) BERT Low-Carbon Valuation
Subsample	*Low Option Trading*	*High Option Trading*	*Low Option Trading*	*High Option Trading*
GHGRP×Emittter	0.0313	0.1677**	0.0691	0.1496***
	(0.0651)	(0.0759)	(0.0726)	(0.0516)
Observations	2,207	2,172	2,207	2,172
R-squared	0.749	0.849	0.779	0.896
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Panel B. PIN

Variables	(1) Y02 Low-Carbon Valuation	(2) Y02 Low-Carbon Valuation	(3) BERT Low-Carbon Valuation	(4) BERT Low-Carbon Valuation
Subsample	*High PIN*	*Low PIN*	*High PIN*	*Low PIN*
GHGRP×Emittter	-0.0187	0.1138**	0.0013	0.1101**
	(0.0283)	(0.0506)	(0.0302)	(0.0470)
Observations	2,702	2,726	2,702	2,726
R-squared	0.797	0.849	0.853	0.890
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES

Table IA13: Impact of GHGRP on Firm Market Value by Pre-Event Low-Carbon Patents

This table reports the impact of the Greenhouse Gas Reporting Program (GHGRP) on firm market value, conditional on firms' pre-event accumulated low-carbon patent value. The analysis is conducted at the monthly level (from June 2007 to May 2008). The dependent variable is the natural logarithm of the firm's market value. GHGRP is a binary variable indicating the period equal to Dec 2007 or after. Y02 Pre-Low-Carbon and BERT Pre-Low-Carbon are indicator variables based on the quartiles of a firm's accumulated low-carbon patent valuations (Y02 and BERT-based, respectively) from 2002 to 2006 within its industry. Regressions presented in this table include firm and industry-month fixed effects. Standard errors, clustered by industry, are reported in parentheses. The estimated coefficient p-values are indicated using the following notation: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Variables	(1) Market Value	(2) Market Value
GHGRP×Y02 Pre-Low-Carbon	0.0124**	
	(0.0058)	
GHGRP×BERT Pre-Low-Carbon		0.0121*
		(0.0063)
Observations	5,339	5,339
R-squared	0.995	0.995
Firm FE	YES	YES
Industry-Month FE	YES	YES