The Price of Carbon Pricing: Climate Policies, Financial Constraints, and Green Innovation

Abstract

I show that carbon pricing can hurt green technology innovation due to firm financial constraints. I identify green technologies from patent filings through textual analysis of patent claims and construct a novel dataset that links firm green patenting to ownership of carbon-emitting plants. Focusing on firms with high emissions in California, I show that the California cap-and-trade program exacerbates financial difficulties in already constrained firms, forcing them to reduce R&D and, subsequently, green innovation. These effects offset the positive impact of cap-and-trade on green innovation in unconstrained firms, rendering the program less effective in stimulating much-needed green innovation.

I. Introduction

A key motivation behind the California cap-and-trade program is the expectation that the program "creates a powerful economic incentive for significant investment in cleaner, more efficient technologies," according to California Air Resources Board[1]. Compared to the short-term impact of reducing current carbon emissions, the impact of stimulating green innovation, such as renewable energy, energy efficiency, and carbon capture technologies, can provide viable, long-term solutions to combat climate change. The costs of energy from green technologies has fallen into the cost range of fossil fuel over the past decade, and a significant contributor to this trend is the rapid growth of green technology innovations (Figure 1). However, given the widening gap between global climate targets and reality[2], stronger policies and even more green innovation is needed to combat climate change. How effective is carbon pricing at incentivizing green innovation? My study examines how California cap-and-trade affects green innovation, and the role of financial constraints as the economic channel.

To empirically identify the effect of California cap-and-trade on green innovation, I assemble a new dataset that links firm green innovation to ownership of carbon-emitting plants. First, I match Compustat firms to plant parent companies in the Environmental Protection Agency plant dataset covering plant location and emission from 2010. Next, I merge the matched firm-plant data with patent data from USPTO Patentsview. I search through patent claim texts to find green technology keywords, including clean energy harvesting, energy efficiency systems, and carbon capture and emission reduction. Such granular data enables me to exploit firm-level variation in exposure to California cap-and-trade based on plant emissions in order to quantify the effects on firm green innovation. My data covers 5,541 firms, 4,679 greenhouse gas emitting plants, 249 California plants, 7,607 green patents, and 44,252 green patent claims. It provides the most detailed picture to date of how green innovations in U.S. firms have responded to the California cap-and-trade program.

My study specifically focuses on how a firm's financial constraints affect its green innova-

[1] California Air Resources Board: https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/about

[2] The world is heading for a temperature rise in excess of 3°C this century — far beyond the Paris Agreement goals of limiting global warming to 1.5°C over pre-industrial levels. United Nation Environment Programme Emission Gap Report 2021: https://www.unep.org/resources/emissions-gap-report-2021

tion response to carbon pricing. I exploit variation in firm carbon footprints as a proxy for exposure to California's cap-and-trade program in a difference-in-difference setting. That is, firms with a larger fraction of carbon emissions in California will be more intensely affected. I find that constrained firms with all of their carbon emissions in California reduce green patenting by 14% after the cap-and-trade program is launched. This surprising effect offsets the positive impact of cap-and-trade on unconstrained firms, rendering the program less effective in stimulating much-needed green innovation than intended.

The decline in green innovation is likely driven by exacerbated financial difficulties in already constrained firms. I show that California cap-and-trade causes a deterioration in balance sheets and income statements of treated constrained firms. Those firms reduce R&D investments after the program is launched.

Next, I show that the main results are robust to various alternative specifications and different groups of control firms. In addition, I conduct placebo tests with placebo years and placebo states. The treatment effects were only significant in 2013, and I do not find similar results in emission-heavy placebo states, such as Texas, Pennsylvania, Florida, and Illinois.

Constrained firms are economically important in green innovation. Over my sample period, constrained firms contributed to 26% of all green patent claims. Although they account for fewer than half of the green patents, the economic magnitude of the innovation decline in constrained firms is enough to offset the innovation stimulating effects in unconstrained firms: In a pooled regression including both constrained and unconstrained firms, I find that firms affected by cap-and-trade do not exhibit any statistically significant changes in green patenting.

In a second piece of analysis, I further extend the sample period to study the effects of green technology subsidies. I compare green innovation to non-green innovation within each firm before and after major U.S. environmental policies that introduce green subsidies: the Energy Policy Act of 1992, the Energy Policy Act of 2005, the Energy Independence and Security Act of 2007, and the Energy Improvement and Extension Act of 2008. I pick an event window around each of the relevant enactment dates and stack these event windows together to estimate an average treatment effect across the multiple events. After the introduction of green subsidies, constrained firms on average increase green innovation by 10%, and unconstrained firms increase green innovation by 3%. The 7% difference in treatment effects is statistically significant at the 1% level. Because constrained firms are more sensitive to green subsidies, combining green subsidies with carbon tax could reduce the unintended cost of climate policy through the financial constraint channel.

My economic hypothesis is that environmental constraints such as carbon taxes raise regulatory costs and reduce a firm's profits. While the cap-and-trade program provides incentives for firms to develop green technology, the cost of external capital for constrained firms renders new innovation opportunities inaccessible. Hence, after introducing a new environmental constraint, financially constrained firms have to bypass profitable opportunities in R&D and green patenting. I hypothesize that the optimal green innovation response to carbon tax is a function of a firm's financial constraints: Cap-and-trade stimulates green innovation in unconstrained firms and hinders green innovation in constrained firms.

Similarly, to the extent that investment at constrained firms is tied more closely to available cash flows, changes in tax policies and subsidies that affect internal finance will likely have a much greater effect on financially constrained firms (Fazzari, Hubbard, and Petersen, 1987; Campello, Graham, and Harvey, 2010). I hypothesize that green innovation in constrained firms is more sensitive to green subsidies compared with green innovation in unconstrained firms.

My paper contributes to the growing literature on environmental policy and green innovation. With the rise of interest in climate change, a considerable number of studies are exploring the idea that environmental regulations can induce technological changes (Newell, Jaffe, and Stavins, 1999; Popp, 2002; Brunnermeier and Cohen, 2003; Acemoglu, Aghion, Bursztyn, and Hemous, 2012; Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen, 2016). However, empirical evidence that speaks to the specific effects of cap-and-trade programs on green innovation is scarce.

A number of studies examine the effects of various U.S. climate policies, including California cap-and-trade (Bartram, Hou, and Kim, 2021; Ivanov, Kruttli, and Watugala, 2020), the cap-and-trade based Acid Rain Program (Schmalensee, Stoker, and Judson, 1998), the

Weatherization Assistance Program (Fowlie, Greenstone, and Wolfram, 2018), the Clean Air Act (Greenstone, 2002), as well as the failed Waxman-Markey bill (Meng, 2017). No study, however, has been able to evaluate the effects of U.S. carbon pricing policies on green innovation. My paper aims to fill this gap.

More academic evidence exists for the European cap-and-trade, the European Union Emission Trading Scheme, but empirical findings on green innovation are mixed. Aghion, Veugelers, and Serre (2009), Gagelmann and Frondel (2005), and Hoffmann (2007) show that firms are not investing in the development of green technologies. On the other hand, Martin, Muûls, and Wagner (2011), Calel and Dechezleprêtre (2016), and Calel (2020) find that firms increase investments in green technologies after the establishment of the European Union's Emissions Trading System.

My paper highlights the importance of firms' financial strength on their innovation response to carbon pricing and helps reconcile the contrasting findings of past cap-and-trade programs. I show that a firm's optimal innovation response to cap-and-trade is a function of its financial constraints. A related paper by Bartram et al. (2021) finds that financially constrained firms reallocate their emissions and plant ownership from California to other states in the face of heightened regulatory costs. Xu and Kim (2022) find that financial constraints increase firms' toxic emissions. My study focuses on the impact of financial constraints on much-needed green innovation. My paper also contributes to the literature on distortions arising from climate policy and the optimal form of carbon pricing (Nordhaus and Yang, 1996; Martin, Muûls, De Preux, and Wagner, 2014; Acemoglu et al., 2012; Fowlie, Reguant, and Ryan, 2016; Aghion et al., 2016).

A related paper by Calel (2020) studies firms' technological responses to the European Union Emission Trading Scheme and finds that the European carbon market has encouraged greater low-carbon patenting and R&D spending. I evaluate the California cap-and-trade and focus on the distortions arising from financial constraints. Interestingly, in a pooled regression, I do not find a statistically significant increase in green patenting after California cap-and-trade.

My paper is distinct from prior studies on cap-and-trade programs because (a) I focus on a firm's innovation response to carbon pricing as a function of its financial constraints, (b) I exploit variation in exposure to California cap-and-trade based on a firm's carbon footprint, utilizing plant ownership data and mandatory reported data on plant level greenhouse gas emissions from the U.S. Environmental Protection Agency, (c) I provide evidence relevant for policymakers in the United States, and (d) I identify green technology innovations by analyzing patent claim texts to find patents that are most relevant to climate change and carbon reduction.

The United States Patent and Trademark Office (USPTO) does not provide a patent classification for "low-carbon" technology such as the Y02 class developed by the European Patent Office (EPO) (Calel, 2020). My approach using textual analysis identifies a set of green patents that closely follow the definitions of green technology in the U.S. energy policies.

The remainder of the paper is organized as follows: Section II discusses the policy background on California cap-and-trade and green subsidies in U.S. Energy Policy Acts. Section III describes my data and sample construction. Section IV outlines my empirical strategies in the two quasi-natural experiments. Section V presents the main results. Section VI concludes.

II. Policy background

I use two quasi-natural experiments in my empirical strategy. The first explores the impacts of the California cap-and-trade program. The second studies the effects of green technology subsidies introduced in four major U.S. Energy Acts.

A. *California cap-and-trade*

The California cap-and-trade program, which had been set to end in 2020 and later extended to 2030, is the most important component of California's plan to meet its climate change target of reducing greenhouse gas emissions to 40% below 1990 levels by the year 2030. The program began in 2013 when the California Air Resources Board created a carbon emission allowance, the "cap," for industrial plants, power plants, and fuel distributors. The cap was set at two percent below the forecasted level of emissions for 2012. Under this program, firms that emit carbon dioxide over the cap must buy allowances in quarterly auctions from other firms willing to sell. This "trade" component sets a market price on carbon emissions. Each year, fewer allowances are created, and the annual cap declines. The motivation for creating this program is to both reduce current greenhouse gas emissions and to stimulate the development and use of green technologies[3].

Bartram et al. (2021) demonstrate that the California cap-and-trade program represents significant regulatory costs for firms with carbon-emitting plants in California, especially for those firms that are financially constrained. The carbon allowance futures trade between \$12 to \$23 per metric ton of carbon dioxide. Specifically, in all quarterly allowance auctions starting from 2013, the demand for allowances is always greater than the supply. To the extent that unused allowances can be traded, the market-based emission constraint is always binding for affected plants.

This environmental constraint that raises regulatory costs necessarily reduces a firm's profits. For financially constrained firms, investment spending is sensitive to the availability of internal finance. Hence, following the introduction of cap-and-trade, constrained firms likely have to bypass profitable R&D and green patenting opportunities. I hypothesize that while the cap-and-trade program provides incentives for firms to develop green technology, the cost of external capital for constrained firms renders new innovation opportunities inaccessible.

B. Green subsidies in U.S. Energy Policy Acts

This section includes a brief summary of four major U.S. Energy Acts that introduce green technology subsidies. These acts established the current energy tax structure that favors green energy over energy from conventional fossil fuels through both investment and production tax incentives. The four key acts in question are the Energy Policy Act of 1992, the Energy Policy Act of 2005, the Energy Independence and Security Act of 2007, and the

[3]California Air Resources Board: https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/about

Energy Improvement and Extension Act of 2008.

Investments in renewable energy was first incentivized in 1978 when the Energy Tax Act introduced a ten percent energy Investment Tax Credit (ITC) available to firms developing or investing in nuclear, solar, wind, geothermal, and other types of green energy equipment. This credit is in addition to the standard 10% investment tax credit, available on all types of equipment. The U.S. Congress passed the Energy Tax Act as part of the National Energy Act. The objective of this federal law is to stimulate alternative and renewable energy and promote energy efficiency through green subsidies.

B.1. Energy Policy Act of 1992

The Energy Policy Act of 1992 aims to reduce U.S. dependence on petroleum and improve air quality by addressing all aspects of energy supply and demand, including alternative fuels, renewable energy, and energy efficiency[4]. The act set goals and created mandates to increase clean energy use, provide clean and renewable energy incentives, and improve energy efficiency in the U.S.

The Energy Policy Act of 1992 introduced Production Tax Credit (PTC), which has been the primary incentive for renewable energy. The renewable electricity production tax credit is a per kilowatt-hour (kWh) federal tax credit included under Section 45 of the U.S. Internal Revenue Code (IRC)[5] for electricity generated by qualified renewable energy resources. The PTC provides a corporate tax credit of 1.5 cents per kWh of electricity produced by renewable sources.

Today, this production tax credit under IRC section 45 may be claimed on facilities utilizing the following sources of energy: wind, closed-loop biomass, open-loop biomass, geothermal, landfill gas, municipal solid waste, qualified hydropower, and certain marine and hydrokinetic technologies, among others. I closely follow this classification when constructing my sample of green technology patents.

[4] U.S. Department of Energy
https://afdc.energy.gov/laws/key_legislation

[5] U.S. Code §45 - Electricity produced from specific renewable resources, etc.
https://irc.bloombergtax.com/public/uscode/doc/irc/section_45

B.2. Energy Policy Act of 2005

The Energy Policy Act of 2005 includes additional renewable energy technologies eligible for the energy investment tax credits (ITC) under Section 48 of the IRC. The Section 48[6] ITC allows project owners or investors to be eligible for federal business energy investment tax credits for installing designated renewable energy generation equipment placed in service from 2006 to 2024.

The Energy Policy Act of 2005 contains about $15 billion in energy tax incentives favoring energy produced from alternative and renewable sources relative to energy from conventional fossil fuel. The tax package includes $1.3 billion for energy efficiency and conservation and $4.5 billion in renewable energy incentives (Lazzari, 2008).

B.3. Energy Independence and Security Act of 2007

The Energy Independence and Security Act (EISA) of 2007 aims to move the U.S. toward energy independence, to increase the production of clean renewable fuels, and to promote research in such areas as greenhouse gas capture and storage options. EISA also includes grant programs to encourage the research and development of green technologies. The law is projected to reduce greenhouse gas emissions by 9% by 2030[7].

B.4. Energy Improvement and Extension Act of 2008

The Energy Improvement and Extension Act of 2008 is Division B of the Emergency Economic Stabilization Act. On October 3, President Bush signed the Economic Stabilization Act of 2008, which includes $17 billion in energy tax incentives, primarily extensions of pre-existing provisions, but also includes several new energy tax incentives: $10.9 billion in renewable energy tax incentives aimed at clean energy production, $2.6 billion in incentives targeted toward cleaner vehicles and fuels, and $3.5 billion in tax breaks to promote energy conservation and energy efficiency (Lazzari, 2008). The cost of the energy tax extenders

[6] U.S. Code §48 - Energy credit
https://www.law.cornell.edu/uscode/text/26/48

[7] U.S. Department of Energy
https://afdc.energy.gov/laws/eisa.html

legislation is financed mostly by raising taxes on the oil and gas industry.

III. Data

To study the impact of California cap-and-trade on green innovation, I collected two datasets: U.S. plant emission data and green patent data. I hand-matched Compustat firms to plant parent companies in the Environmental Protection Agency plant dataset (FLIGHT) covering plant location and emission starting from 2010. Next, I merged the matched firm-plant dataset with green patent data.

I collected the patent claims and application data from Patentsview. I searched through patent claim texts to find green technology keywords. I use three general categories of green technology: renewable energy harvesting, energy efficiency systems, and carbon capture and emission reduction. Each category contains subcategories; for example, clean energy includes bio-energy, geothermal-energy, hydro-energy, solar energy, wind energy, and other types of clean energy. Carbon capture and emission reduction includes carbon dioxide reduction, capturing, recycling, and storage technologies[8]. Table A.1 shows the keywords I use for the textual analysis. Table A.2 shows examples of green patent and specific patent claims. The number before the patent claim text is the claim number in the corresponding patent. The definitions closely follow the green technology classification defined in the four major U.S. Energy Policy Acts discussed in Section II.B. To match patents to Compustat firms, I use the patent data from Kogan, Papanikolaou, Seru, and Stoffman (2017), which contains a match between patent number and CRSP "permco."

To measure firm innovation output, I use both the number of patents and the number of patent claims that are applied for and are eventually granted in a given year[9]. One patent generally contains multiple patent claims. In cases where a patent contains both green and non-green patent claims, I classify that patent as a green patent. Consequently, the

[8]These categories are not mutually exclusive. One patent claim can contain multiple keywords that fall into multiple categories. In that case, I assign the patent claim to the category according to the first occurring green technology keywords.

[9]The reason for using a patent's application year instead of its grant year is that previous studies (e.g. Griliches, Hall, and Pakes, 1988) have shown that the former is superior in capturing the actual time of innovation.

number of patent claims is a more refined outcome variable. Table 1 shows green technology innovation from 2010 to 2015. Table 2 shows green technology innovation by sector. Figure 2 shows the trend of green patenting.

I identify green technology innovations by searching through patent claim texts to find patents that are most relevant to carbon reduction. The United States Patent and Trademark Office (USPTO) does not provide a patent classification for 'low-carbon' technology like the Y02 class developed by the European Patent Office (EPO) (Calel, 2020). Compared with following a general classification, my approach using textual analysis identifies a set of green patents that closely follow the definitions of green technology in the U.S. energy policies.

My sample period is from 2010 to 2015, three years before and three years after the introduction of the California cap-and-trade program. I chose this window because (1) the FLIGHT dataset starts in 2010, (2) the Paris Agreement signed in 2016 affects both control and treated firms, and (3) the truncation problem of patent data becomes more severe after 2015 (Figure 2). Table 3 shows summary statistics of treated firms (Panel A), control firms (Panel B), and control firms with as least one plant (Panel C). Treated firms are those with at least one carbon-emitting plant in California. Control firms are those without a carbon-emitting plant in California.

By definition, treated firms have at least one plant. Restricting the number of plants owned by control firms generates a control group which has characteristics that more closely resemble those of the treated group. I show empirical results using the more broadly defined control group in the main analysis and results using the more refined control group in the robustness section.

My final sample includes firms with non-missing composite constraint measures. I replace missing R&D expenses with zeros. For firms with missing values for the state of incorporation, I replace the missing values with "NA." My extensive hand-check reveals that in every case, the firms with a missing state of incorporation are multinational firms operating in the U.S. I winsorize financial variables at the 1% tails. Consistent with the requirements of the California cap-and-trade program, I restrict affected plants to those emitting more than 25,000 metric tons of carbon dioxide equivalents in 2012, the year before the program started.

In the second quasi-natural experiment, I stack Compustat firm-years in four event windows into one event-time dataset. The key events are the Energy Policy Act of 1992, the Energy Policy Act of 2005, the Energy Independence and Security Act of 2007, and the Energy Improvement and Extension Act of 2008. I pick a six-year event window around each relevant enactment date and stack the event windows together to estimate an average treatment effect across the multiple events.

Unlike the California cap-and-trade program, the four major energy policies in question affect all firms in the U.S. In order to identify the effects of those policies on green innovation, I exploit variation within firms and use other innovation within the same firm as the counterfactual. To the extent that the green subsidies do not affect innovation in non-green technologies, changes in green innovation relative to non-green innovation after the four major environmental policies will capture the treatment effects.

In each of the two experiments, I focus on a firm's green innovation response to carbon pricing as a function of its financial constraints. I employ four measures of financial constraints that are widely accepted in the literature: the Hadlock-Pierce index (Hadlock and Pierce, 2010), the Whited-Wu index (Whited and Wu, 2006), the Ohlson's O Score (Ohlson, 1980), and payout ratio (Almeida, Campello, and Weisbach, 2004). I also construct a composite measure for financial constraint that is equal to 1 if the firm is constrained according to more than two of the four financial constraint measures.

IV. Empirical strategies

A. Carbon tax: California cap-and-trade

In the first quasi-natural experiment, I use a standard difference-in-difference approach to study effects of the 2013 California cap-and-trade. I look at changes in green innovation output for firms that have plants affected by cap-and-trade.

Treated firms are those with positive carbon emissions in California. The California cap-and-trade program sets emission caps and increases regulatory cost for those firms. Control firms are those without a carbon-emitting plant in California. They do not have immediate incentives to respond to California's cap-and-trade program as treated firms do. Table 3 shows summary statistics of treated firms (Panel A) and control firms (Panel B and Panel C).

I use an event window extending three years before and after the introduction of California cap-and-trade. My baseline specification is:

$$\begin{aligned} \textit{Green Innovation}_{it} &= \alpha_i + \delta \times \textit{California Share}_i \times \textit{After}_t \\ &\quad + \beta \times \textit{California Share}_i + \lambda \times \textit{After}_t + \gamma \cdot X_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where i and t index firms and years, respectively. *Green Innovation* stands for *Ln(1 + # Green Patents)* or *Ln(1 + # Green Patent Claims)*, natural logarithms of one plus the number of green technology claims and patents that are applied for and are eventually granted in a given year. To better match the timing of the innovation activities and the counting of the patents, I follow a standard practice in the literature and count patents by the application year. *California Share* is the total emissions by California plants divided by the total emissions by all plants by firm. California's cap-and-trade program has a stronger effect on firms with a larger share of emissions in California. *After* is an indicator for being after the introduction of the California cap-and-trade program. X are time-varying firm-level control variables including *Total Assets* and *Firm Age*. I cluster standard errors by state of incorporation and year to correct for correlation of the error terms within each state-year cell (Bertrand, Duflo, and Mullainathan, 2004). For all main analyses, I use control firms with *Number of Plants* ≥ 1. This set of control firms are all carbon-emitting firms and have characteristics that more closely resemble those of the treated firms, as shown by the summary statistics (Table 3, Panel C).

I estimate the above specification separately for financially constrained and unconstrained firms to show that a firm's optimal innovation response to carbon tax is a function of its financial constraints. Afterward, I formally test the heterogeneity in treatment effects between constrained firms and unconstrained firms with the following specification:

$$\begin{aligned}
\textit{Green Innovation}_{it} = \alpha_i + \delta \times \textit{California Share}_i \times \textit{After}_t + \beta \times \textit{California Share}_i \\
+ \theta \times \textit{California Share}_i \times \textit{After}_t \times \textit{Constrained}_i + \eta \times \textit{California Share}_i \times \textit{Constrained}_i \\
+ \kappa \times \textit{After}_t \times \textit{Constrained}_i + \lambda \times \textit{After}_t + \gamma \cdot X_{it} + \varepsilon_{it} \quad (2)
\end{aligned}$$

I use *Hadlock-Pierce Index, Whited-Wu Index, Ohlson's O score,* and *Payout ratio* to measure financial constraints. I also construct a composite measure for financial constraint that is equal to 1 if the firm is constrained according to more than two of all four financial constraint measures.

For all conditioning measures used in this section, I use ex-ante (pre-treatment) value to rank firms because these measures might be affected by treatment. I calculate the four measures for each firm in 2012, the year before the introduction of California cap-and-trade. I then rank the firms based on the pre-treatment values and construct indicators for having above-median measures of financial constraints.

B. Green subsidies: U.S. Energy Policy Act

In the second quasi-natural experiment, I compare green innovation to non-green innovation (all other types of patents) within each firm before and after major environmental policies that introduce green subsidies: the Energy Policy Act of 1992, the Energy Policy Act of 2005, the Energy Independence and Security Act of 2007, and the Energy Improvement and Extension Act of 2008. I pick an event window around each of the relevant enactment dates and stack the event windows together to estimate an average treatment effect across the multiple events.

These policies affect all U.S. firms. In order to identify the effect of green subsidies on a firm's green innovation, I use other innovation within the same firm as the counterfactual. The assumption is that the green subsidies do not directly affect innovation in non-green technologies. As such, changes in green innovation relative to non-green innovation after the four major environmental policies will capture the treatment effects.

This strategy does not rely on variation in plant location, so I do not need the plant emission dataset. This freedom allows me to extend the sample period back to the 1980s and include firms with no plants in the sample. My baseline specification to identify the effects of green subsidies is:

$$\textit{ln(1 + \# Patent claims)}_{itks} = \alpha_{ik} + \tau_t + \theta_s + \delta \times \textit{Greentech}_{itks} \times \textit{Green Subsidy}_{kt} + \gamma \cdot X_{itk} + \varepsilon_{itks} \tag{3}$$

where i indexes firms, t indexes years, $k \in \{1, 2, 3, 4\}$ indexes the four policy events, and s indexes patent type, i.e., green patents and other patents. *Greentech* is an indicator equal to 1 for green patent claims and 0 for all other types of patent claims. *Green Subsidy* is an indicator for being after the introduction of green subsidies in each of the four events. The coefficient δ captures the average treatment effect across the four events. X are time-varying firm-level control variables including *Total Assets* and *Firm Age*.

V. Results

A. Unintended consequences of carbon tax: California cap-and-trade

This section analyzes the impact of financial constraints on a firm's green innovation response to California cap-and-trade. I first show that California cap-and-trade causes a deterioration in balance sheets and income statements of treated constrained firms. I then focus on green innovation by estimating Specification (1) separately for financially constrained and unconstrained firms before formally testing the heterogeneity in treatment effect between these firms.

For all financial constraint measures, I use ex-ante (pre-treatment) value to rank firms because these measures might be affected by treatment. I calculate the four measures for each firm in 2012, the year before the introduction of California cap-and-trade. I then rank the firms based on the pre-treatment values and construct indicators for having above-median measures of financial constraints. A firm is classified as financially constrained if it has a high *Hadlock-Pierce Index*, high *Whited-Wu Index*, high *Ohlson's O score,* and low *Payout* *ratio*. I also construct a composite measure for financial constraint that is equal to 1 if firm is constrained according to more than two of all four financial constraint measures.

A.1. Effects on firm balance sheets and income statements

Table 4 presents the estimated effects of cap-and-trade on balance sheet and income statement items in financially constrained firms. Treated constrained firms experience decline in sales and increase in debt to asset ratio after California cap-and-trade is launched. They also decrease cash holdings and R&D investments. The evidence suggests that cap-and-trade caused a deterioration in balance sheets and income statement of firms that are already financially constrained.

The results confirm my hypothesis that environmental constraints raise regulatory costs and reduce a firm's production. California cap-and-trade introduces a new environmental constraint that further exacerbates financial difficulties in already constrained firms, forcing them to reduce investments in profitable green innovation projects.

A.2. Green innovation

Table 5 presents main results on green innovation from estimating Specification (1). The results reveal that treated firms which are unconstrained increase green innovation by 23.1% after the cap-and-trade program. In stark contrast, constrained firms reduce green innovation by 14.2% after treatment. The interpretation of the economic magnitude is as follows: A constrained firm with 100% of its carbon emissions in California reduces green patenting by 14.2% after the introduction of California cap-and-trade. These polarized results are consistent across all five measures of financial constraints. Table 6 shows results where the dependant variable is the natural logarithm of one plus the number of green technology patents. The results reveal the same pattern: Unconstrained firms and constrained firms move in opposite directions after cap-and-trade. This table provides strong evidence that cap-and-trade tightens financial constraints for innovating firms. Figure 3 and 4 provide a visualization of the treatment effects on green patent claims and green patents, respectively.

Table 7 presents treatment effects on different green technology clusters, including renewable energy, energy efficiency, and carbon capture. Innovations in renewable energy and energy efficiency decline the most.

In addition, I find that green patents are less valuable to firms compared with non-green patents, as demonstrated by Panel A of Figure 7. This complication could exacerbate the negative impact on green innovation because firms have to bypass the least profitable projects first when facing financial constraints.

Figure 5 presents the trend in green innovation in financially constrained firms. The figure shows that constrained treated firms do not produce any green patents after 2013. The trend in control firms is relatively more stable, and the treatment effects are driven by the changes in the treated firms. One assumption of my difference-in-difference strategy is that control firms do not change their green innovation after California cap-and-trade is launched. It's possible that firms with no carbon emission in California still responded to the program and increased their green innovation because of the increasing regulatory climate risk. However, compared with firms with at least one carbon-emitting plant, firms with no plants at all are less likely to change green innovation strategies. Figure 5 shows that the green innovation trend for all control firms is flatter compared with the trends for control firms with at least one plant. The concern that control firms responded to the shock is mitigated by using the full sample of control firms, which produce quantitatively similar results. I discuss the results using the full sample in Section V.D.

Figure 6 examines the parallel-trend assumption. I replace the *After* indicator in the main specification with a full set of year dummies and plot the regression coefficients on the interactions between *California Share* and year dummies. The differences in green innovation between treated and control firms were close to zero before 2013. The graphs are consistent with the parallel assumption that there is no significant difference in the evolution of green innovation between treated and control firms.

A.3. Pooled effects and heterogeneity in treatment effects

Column 3 in Table 8 shows the pooled treatment effects on green patent claims. This specification includes both constrained and unconstrained firms and shows the effects of cap-and-trade across all treated firms. With constrained firms counteracting the positive effects in unconstrained firms, the pooled effect is estimated at six percent, not statistically significant.

Similarly, Table 9 shows the effects on green patents. The estimated pooled treatment effect is 5.5% and not statistically significant. After the introduction of the cap-and-trade program, green innovation in constrained firms and unconstrained firms moves in different directions. The negative effects in constrained firms offset the positive impact in unconstrained firms, rendering the cap-and-trade program less effective in stimulating much-needed green innovation.

Column 4 in Table 8 shows results from a triple difference regression. The coefficient estimate on *California Share* × *After* × *Constrained* captures the heterogeneous treatment effect. Treated constrained firms reduce green innovation by a surprising 38 percentage points relative to treated unconstrained firms.

Overall, the results are consistent with the hypothesis that environmental constraints raise regulatory costs and force financially constrained firms to bypass profitable R&D and green patenting opportunities.

B. Mechanism

Section V.A.1 shows that California cap-and-trade likely raises regulatory cost and further exacerbates financial difficulties in already constrained firms. In this section, I demonstrate that the impact of California cap-and-trade channels through to a constrained firm's investments in research.

Table 10 presents results estimating a difference-in-difference regression across financially constrained firms. The dependant variable is R&D intensity, research and development expenses scaled by sales. Firms that are constrained according to the composite measure reduce R&D intensity by 18%. These results are consistent with the decrease in green patenting shown in Table 6. According to Hadlock-Pierce and Whited-Wu indexes, the point estimate for constrained firms is negative, although not statistically significant. Treated firms with a low payout ratio display the strongest reduction in research spending post cap-and-trade, showing an economically significant 17% decrease in R&D intensity.

C. Effects of green subsidies: U.S. Energy Policy Act

In the previous section I show that the unintended consequences of the cap-and-trade program on constrained firms offset its positive impact on green innovation in unconstrained firms, rendering the program less effective in stimulating much-needed green innovation. In this section, I show that green subsidies have different effects across firms with different financial constraints.

I compare green innovation to non-green innovation (all other types of patents) within each firm before and after major environmental policies that introduce green subsidies. The key events and decision times are listed in Table 11. I pick an event window around each of the relevant enactment dates and stack the event windows together to estimate an average treatment effect across the multiple events. The event window is six years. Table 12 shows green technology innovation by year in each of the four event windows.

Table 13 presents results from the event-stacked difference-in-difference regression. Column 1 shows that in financially constrained firms, green innovation increases by 10% relative to other types of innovation after the introduction of green subsidy. In unconstrained firms, the relative increase in green innovation is 3%. This estimated treatment effect is the average treatment effect across the four events. The pooled specification in Column 3 shows that the effect of green subsidy on green innovation is about 4.7% across all U.S. firms. A quick calculation from the first two columns reveals that constrained firms increase green innovation by 7% more relative to unconstrained firms. The last Column of Table 13 presents a formal test of heterogeneous treatment effects; the 7% difference is statistically significant at the 1% level. To the extent that financially constrained firms rely on internal finance, changes in tax policies and subsidies that affect internal finance will likely have a much greater effect on constrained firms.

Overall, both constrained and unconstrained firms increase green innovation after the introduction of green subsidies, with the constrained firms reacting much more strongly. The results suggest that combining green subsidies with carbon tax could reduce the unintended cost of climate policy through the financial constraint channel.

D. Robustness checks

To check the robustness of the main empirical specification, I repeat the analysis in Equation (1), first with two alternative specifications of difference-in-difference, and then with a larger group of control firms.

First, I replace the *California Share* variable with an indicator *Treat*, which equals one for having positive emissions in California. The resulting specification is a standard difference-in-difference with firm fixed effects:

$$\textit{Green Innovation}_{it} = \alpha_i + \delta \times \textit{Treat}_i \times \textit{After}_t + \lambda \times \textit{After}_t + \gamma \cdot X_{it} + \varepsilon_{it} \tag{4}$$

The results are demonstrated in Table 14. The economic interpretation of the difference-in-difference estimator is now different from the one in Equation (1): Constrained firms with positive emissions in California *on average* reduce green patenting by 10% after the introduction of California cap-and-trade. This magnitude is smaller than the 15% estimated in Table 8, which captures the treatment effect for firms that have *all* of their emissions in California.

Next, I replace the *California Share* variable with *California Plant Share* which is the number of plants in California divided by the total number of plants by firm. The resulting specification is:

$$\textit{Green Innovation}_{it} = \alpha_i + \delta \times \textit{California Plant Share}_i \times \textit{After}_t + \lambda \times \textit{After}_t + \gamma \cdot X_{it} + \varepsilon_{it} \tag{5}$$

The results are demonstrated in Table 15. The results are similar to those presented in Table 8. The interpretation of the economic magnitude is as follows: A constrained firm with 100% of its carbon-emitting plants in California reduces green patenting by 13.6% after the introduction of California cap-and-trade. An unconstrained firm with 100% of its carbon-emitting plants in California increases green patenting by 19.6%.

Finally, I repeat the analysis in Table 8 except for using the full sample, i.e., using control firms with no carbon-emitting plants. This strategy includes a much larger set of control firms, as shown by the summary statistics (Table 3, Panel B).

Table 16 shows that the results are robust to different specifications of the control group. Financially constrained firms reduced green patenting after the introduction of California cap-and-trade.

E. Spillover effects

One assumption of my difference-in-difference strategy is that control firms do not change their green innovation after California cap-and-trade is launched. It's possible that firms with no carbon emission in California still responded to the program and increased their green innovation because of the increasing regulatory climate risk. However, compared with firms with at least one carbon-emitting plant, firms with no plants at all are less likely to change green innovation strategies.

The above concern is mitigated by the tests presented in Table 16: The results using the full sample of control firms are quantitatively the same as that of the main specification. Figure 5 shows an upward trend in green innovation in control firms with at least one carbon-emitting plant. In contrast, the trend for all control firms is flatter. The advantage of the small control sample is that it includes firms having similar characteristics with the carbon-emitting treated firms. The advantage of the large control sample is that it is less susceptible to contamination of spillover effects.

Most importantly, Figure 5 shows that the negative treatment effects are mostly driven by the sharp decrease in treated firms.

F. Crowding-out effects

In this section, I investigate an alternative explanation that the California cap-and-trade program makes constrained firms less competitive in the product market, driving the increase in green innovation in unconstrained firms and crowding-out green innovation from constrained firms. One empirical prediction from the above hypothesis is that constrained firms in highly competitive industries should exhibit stronger treatment effects.

To explore the crowding-out effects, I examine the impact of product market competition on firm green innovation responses. I measure product market competition by the Herfindahl index, equal to the sum of the squared market share of each firm in the same industry. Table 17 shows the results that are inconsistent with the crowding-out hypothesis. As measured by low Herfindahl index in column 1, firms in more competitive industries do not show stronger effects. The green innovation response in both low and high Herfindahl firms are qualitatively similar.

G. *Placebo tests*

To confirm that the treatment effects are caused by the introduction of California cap-and-trade in 2013, I conduct two placebo tests.

First, I re-estimate Equation (1) with the following placebo years: 2012, 2014, and 2015. The coefficient estimates of the treatment effects are plotted in Figure 8. The analysis is the same as specification 1 in Tables 5 and 16, except I change the *After* indicator according to the placebo years. Estimates for the treatment effects are not significantly different from zero in the placebo years. The coefficients only show a significant effect in 2013, which is the true treatment year.

Next, I repeat the main analysis replacing California with alternative control states as the treatment state. The five U.S. states with the most energy-related carbon dioxide emissions in 2012 are Texas, California, Pennsylvania, Florida, and Illinois[10]. I run Equation (1) on financially constrained firms, replacing California with placebo states. Figure 9 shows the coefficient estimates of treatment effects estimated using Texas, California, Pennsylvania, Florida, and Illinois as treatment states, respectively. I do not find similar effects in placebo states as I find in California.

[10] U.S. Energy Information Administration: https://www.eia.gov/environment/emissions/state/

VI. Conclusion

I show novel evidence that carbon tax can hurt green technology innovation due to firm financial constraints. Constrained firms reduced R&D and, subsequently, green patenting after the introduction of the California cap-and-trade program. These effects offset the positive impact of cap-and-trade on green innovation in unconstrained firms, rendering the program less effective in stimulating much-needed green innovation. The results are consistent with the hypothesis that California cap-and-trade raises regulatory costs and further exacerbates financial difficulties in already constrained firms, forcing them to bypass profitable green innovation opportunities.

On the other hand, green innovation in constrained firms is more sensitive to green subsidies. Green technology subsidies introduced in the U.S. Energy Acts positively impact green innovation, especially in constrained firms. Together, the results suggest that combining green subsidies with carbon tax could reduce the unintended cost of climate policy through the financial constraint channel.

REFERENCES

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

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

Aghion, Philippe, Reinhilde Veugelers, and Clément Serre, 2009, Cold start for the green innovation machine, Technical report, Bruegel policy contribution.

Almeida, Heitor, Murillo Campello, and Michael S Weisbach, 2004, The cash flow sensitivity of cash, *The journal of finance* 59, 1777–1804.

Bartram, Söhnke M, Kewei Hou, and Sehoon Kim, 2021, Real effects of climate policy: Financial constraints and spillovers, *Journal of Financial Economics* .

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, 2004, How much should we trust differences-in-differences estimates?, *The Quarterly journal of economics* 119, 249–275.

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.

Calel, Raphael, 2020, Adopt or innovate: Understanding technological responses to cap-and-trade, *American Economic Journal: Economic Policy* 12, 170–201.

Calel, Raphael, and Antoine Dechezleprêtre, 2016, Environmental policy and directed technological change: evidence from the european carbon market, *Review of economics and statistics* 98, 173–191.

Campello, Murillo, John R Graham, and Campbell R Harvey, 2010, The real effects of financial constraints: Evidence from a financial crisis, *Journal of financial Economics* 97, 470–487.

Fazzari, Steven, R Glenn Hubbard, and Bruce C Petersen, 1987, Financing constraints and corporate investment.

Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram, 2018, Do energy efficiency investments deliver? evidence from the weatherization assistance program, *The Quarterly Journal of Economics* 133, 1597–1644.

Fowlie, Meredith, Mar Reguant, and Stephen P Ryan, 2016, Market-based emissions regulation and industry dynamics, *Journal of Political Economy* 124, 249–302.

Gagelmann, Frank, and Manuel Frondel, 2005, The impact of emission trading on innovation–science fiction or reality?, *European Environment* 15, 203–211.

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.

Griliches, Zvi, Bronwyn H Hall, and Ariel Pakes, 1988, R&d, patents, and market value revisited: Is there evidence of a secondtechnological opportunity related factor?, Technical report, National Bureau of Economic Research.

Hadlock, Charles J, and Joshua R Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the kz index, *The Review of Financial Studies* 23, 1909–1940.

Hoffmann, Volker H, 2007, Eu ets and investment decisions:: The case of the german electricity industry, *European Management Journal* 25, 464–474.

Ivanov, Ivan, Mathias S Kruttli, and Sumudu W Watugala, 2020, Banking on carbon: Corporate lending and cap-and-trade policy, *Available at SSRN 3650447* .

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

Lazzari, Salvatore, 2008, *Energy tax policy: History and current issues* (Congressional Research Service).

Martin, Ralf, Mirabelle Muûls, Laure B De Preux, and Ulrich J Wagner, 2014, Industry compensation under relocation risk: A firm-level analysis of the eu emissions trading scheme, *American Economic Review* 104, 2482–2508.

Martin, Ralf, Mirabelle Muûls, and Ulrich Wagner, 2011, Climate change, investment and carbon markets and prices–evidence from manager interviews, *Climate Strategies, Carbon Pricing for Low-Carbon Investment Project* 2011.

Meng, Kyle C, 2017, Using a free permit rule to forecast the marginal abatement cost of proposed climate policy, *American Economic Review* 107, 748–84.

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.

Nordhaus, William D, and Zili Yang, 1996, A regional dynamic general-equilibrium model of alternative climate-change strategies, *The American Economic Review* 741–765.

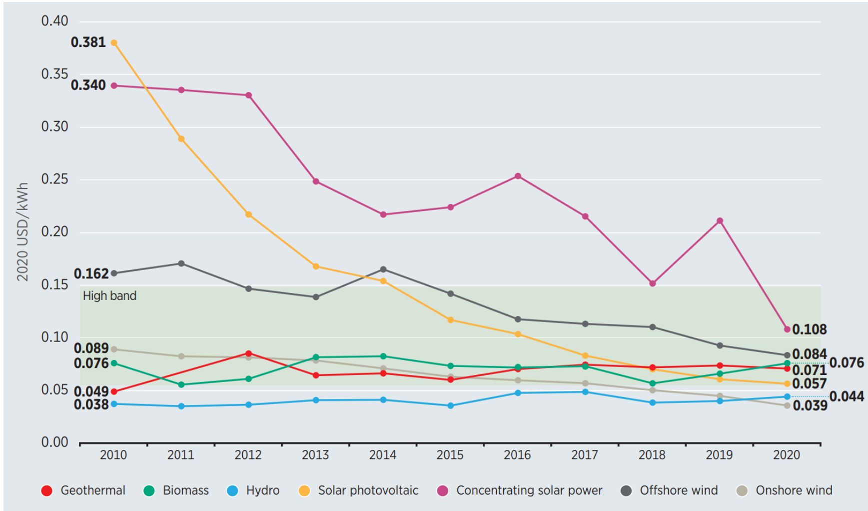
Ohlson, James A, 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of accounting research* 109–131.

Popp, David, 2002, Induced innovation and energy prices, *American economic review* 92, 160–180.

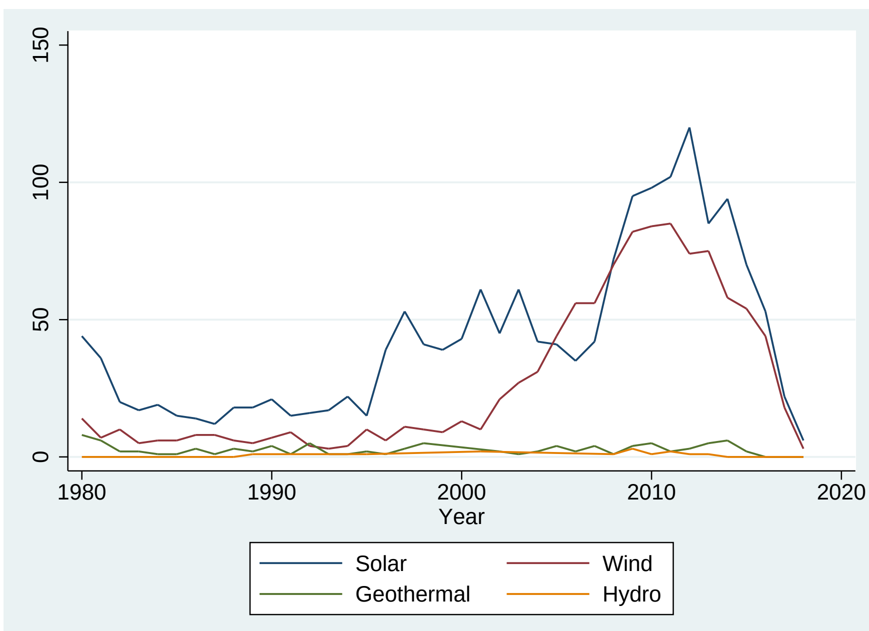
Schmalensee, Richard, Thomas M Stoker, and Ruth A Judson, 1998, World carbon dioxide emissions: 1950–2050, *Review of Economics and Statistics* 80, 15–27.

Whited, Toni M, and Guojun Wu, 2006, Financial constraints risk, *The Review of Financial Studies* 19, 531–559.

Xu, Qiping, and Taehyun Kim, 2022, Financial constraints and corporate environmental policies, *The Review of Financial Studies* 35, 576–635.



Panel A. Global average utility-scale levelized cost of energy by technology cluster compared with the cost of fossil fuel. Source: International Renewable Energy Agency (IRENA) Renewable Power Generation costs in 2020 (https://www.irena.org/publications/2021/Jun/Renewable-Power-Costs-in-2020)



Panel B. Number of green technology patents by technology cluster

Figure 1. Panel A shows the global average utility-scale levelized cost of energy by technology cluster. Panel B shows number of green patents that are applied for and eventually granted between 1980 and 2018 by technology cluster. The decline in costs of solar and wind energy coincides with the rapid growth of solar and wind technology.

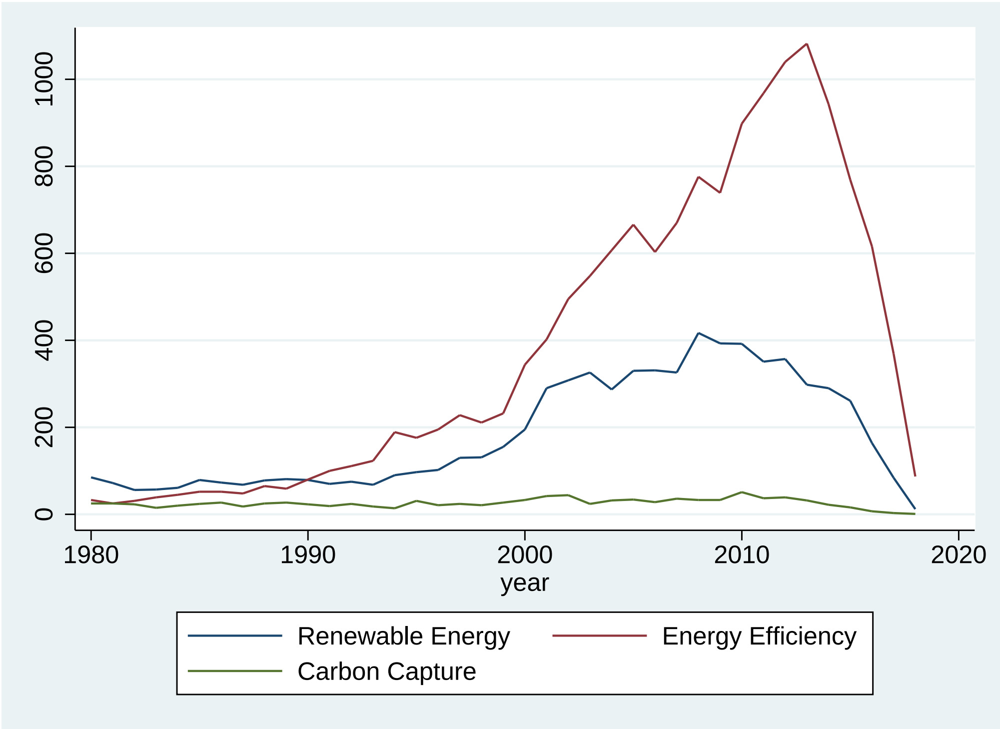


Figure 2. Number of green patents by technology cluster. The figure shows the number of green patents that are applied for and eventually granted between 1980 and 2018.

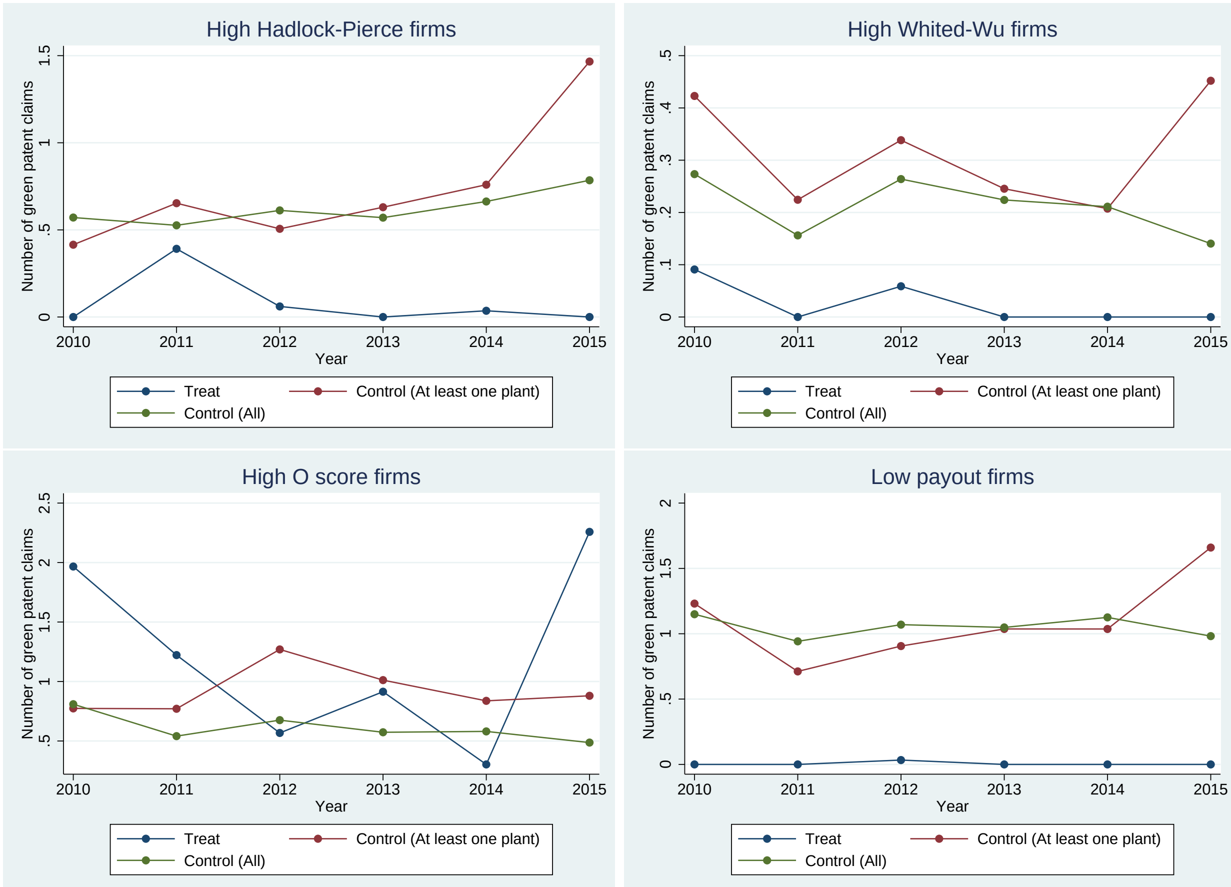


Figure 3. Average number of green patent claims produced by constrained firms. The figures include only firms that are financially constrained measured by Hadlock-Pierce Index, Whited-Wu Index, O score, and payout ratio, respectively. Treated firms are those with at least one plant in California emitting more than 25,000 metric tons of carbon dioxide equivalents in 2012. Control (At least one plant) are control firms with at least one carbon-emitting plant. Control (All) includes control firms with no plants.

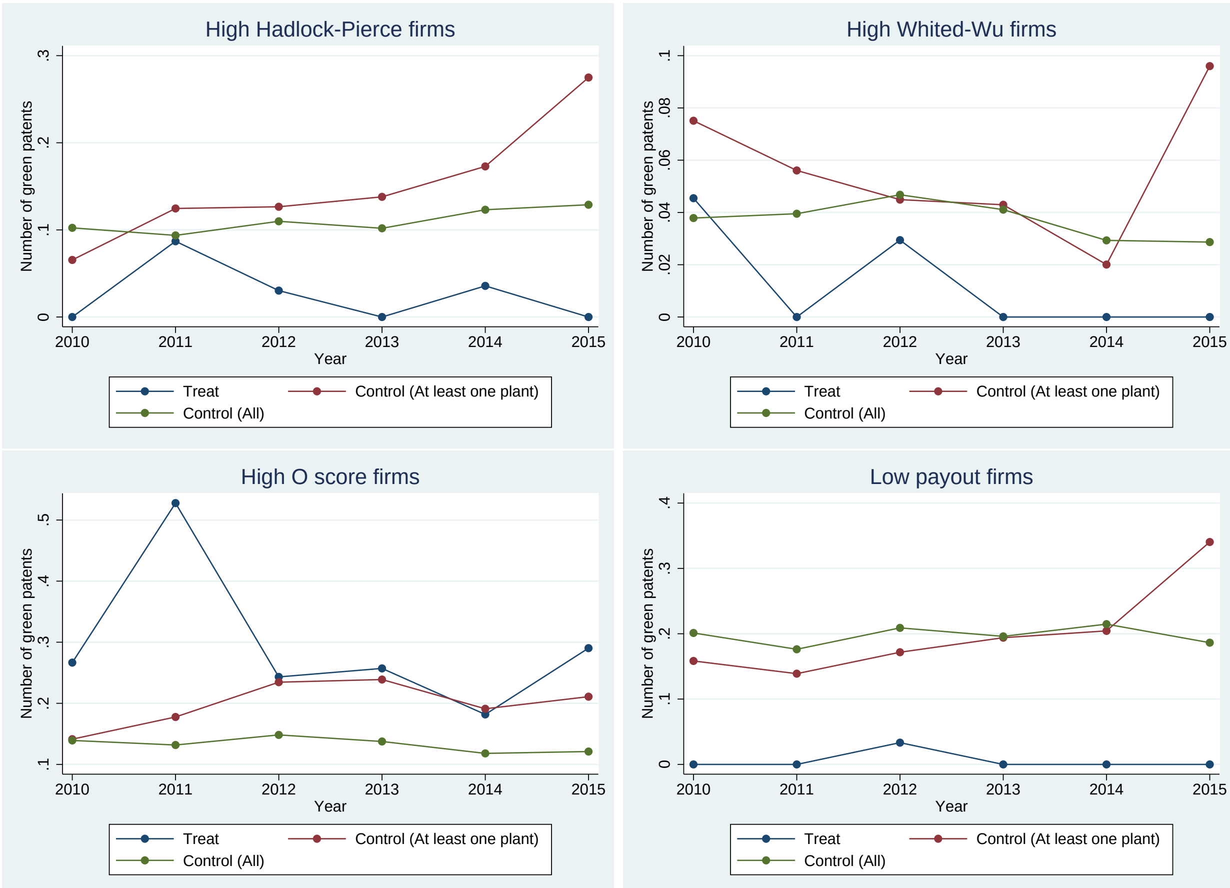
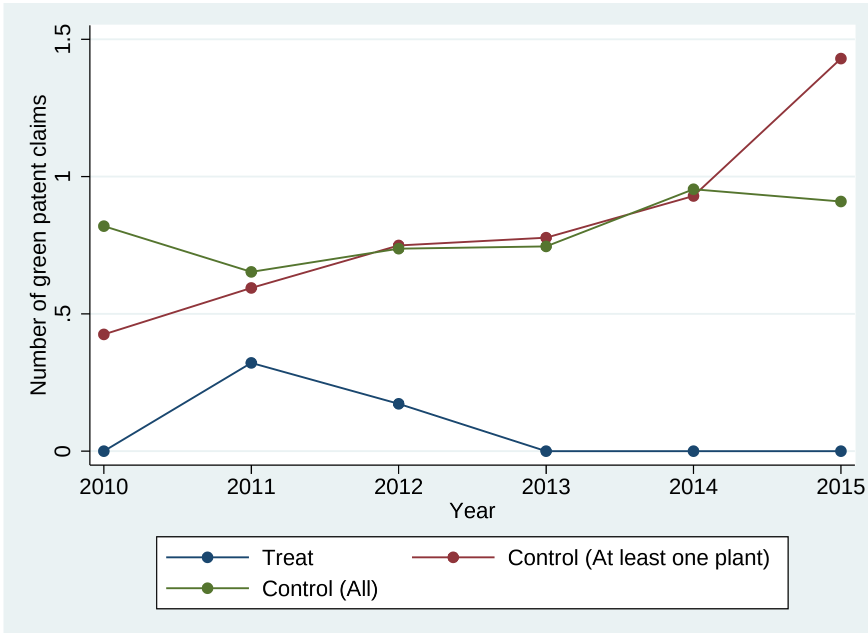
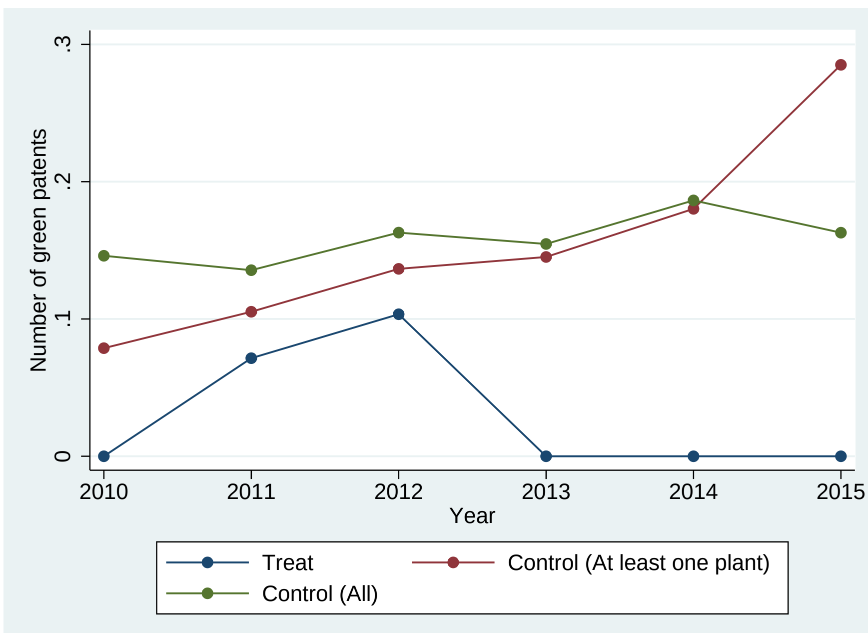


Figure 4. Average number of green patents produced by constrained firms. The figures include only firms that are financially constrained measured by Hadlock-Pierce Index, Whited-Wu Index, O score, and payout ratio, respectively. Treated firms are those with at least one plant in California emitting more than 25,000 metric tons of carbon dioxide equivalents in 2012. Control (At least one plant) are control firms with at least one carbon-emitting plant. Control (All) includes control firms with no plants.

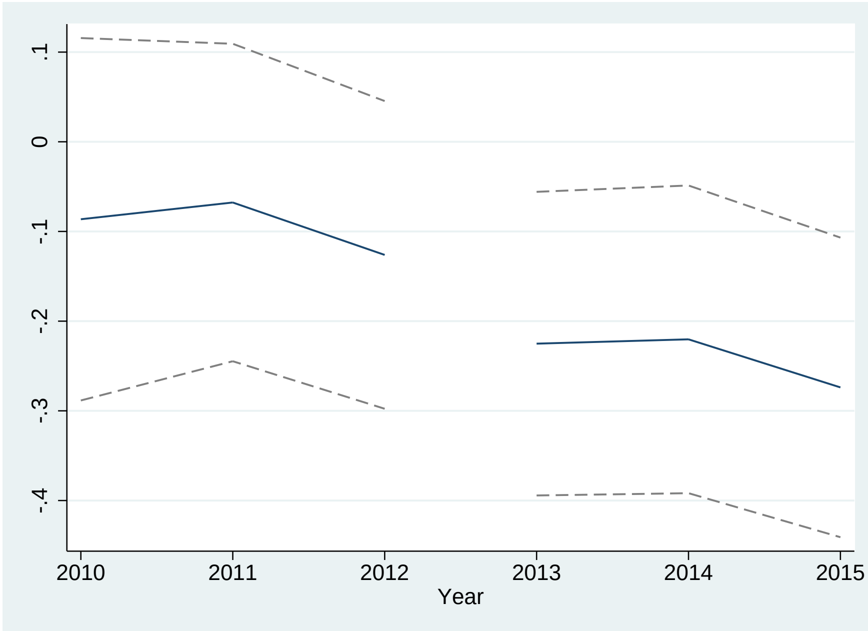


Panel A. Average number of green patent claims produced by constrained firms

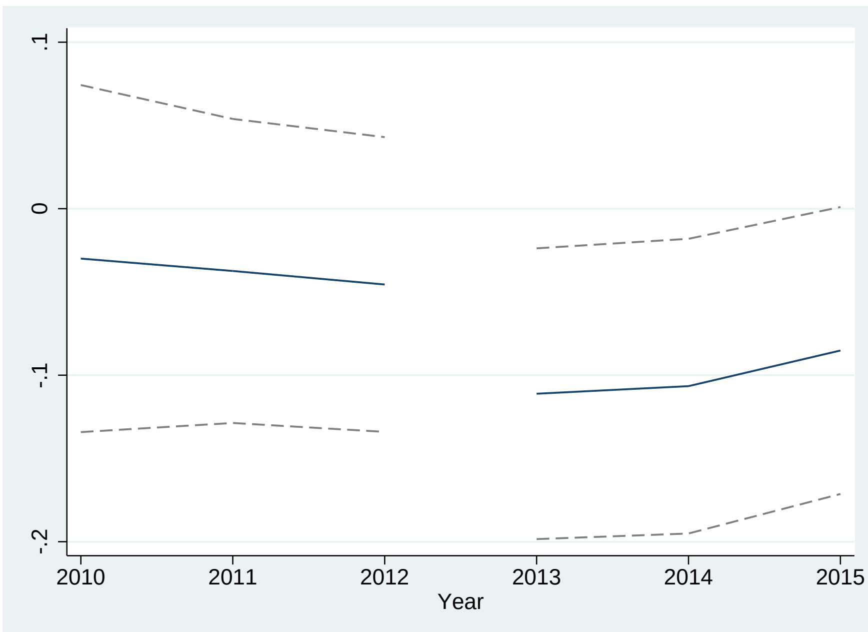


Panel B. Average number of green patents produced by constrained firms

Figure 5. Average number of green innovation produced by constrained firms. Treated firms are those with at least one plant in California emitting more than 25,000 metric tons of carbon dioxide equivalents in 2012. Control (At least one plant) are control firms with at least one carbon-emitting plant. Control (All) includes control firms with no plants.

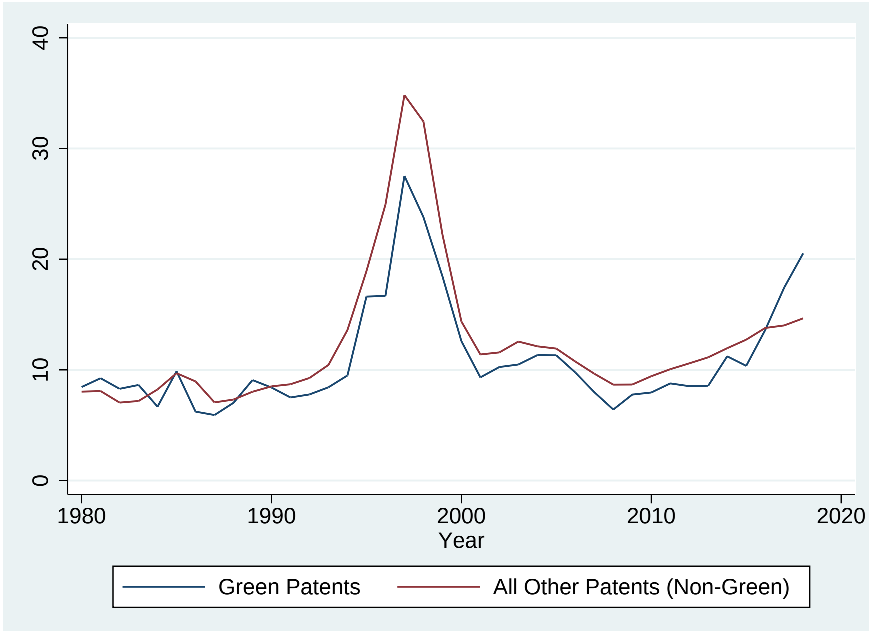


Panel A. Green technology claims coefficient trend in event time.

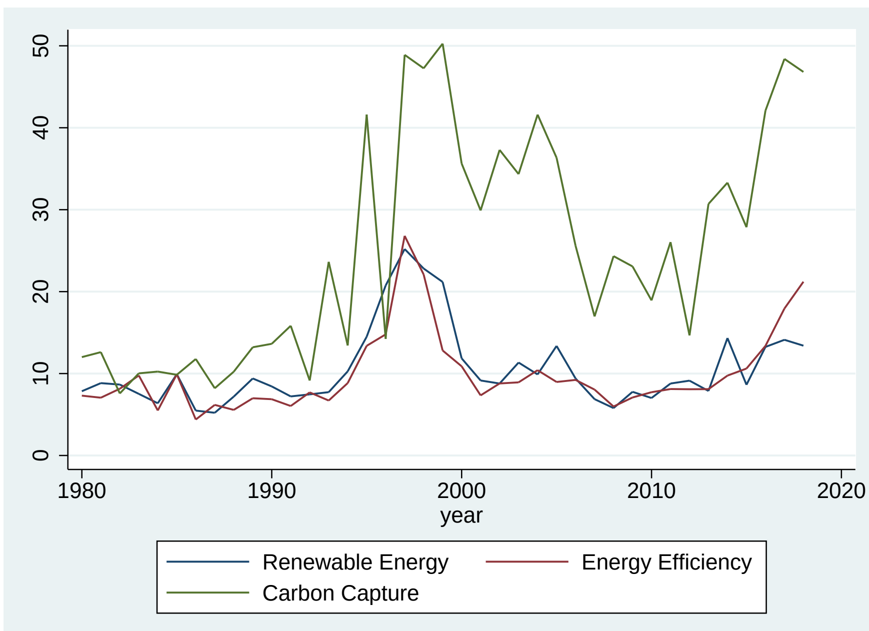


Panel B. Green technology patent coefficient trend in event time.

Figure 6. Green technology innovation coefficients trend in event time. The analysis is identical to specification 1 in Table 5 and Table 6, except that the *California Share* × *After* interaction is replaced with a full set of year dummies (2010, 2011, . . . , 2015) interacted with *California Share*. The figure shows the regression coefficients on the interactions between *California Share* and year dummies. The specification controls for number of plants, total assets, firm age, R&D expense, and firm fixed effects. The dashed lines show 95% confidence intervals.

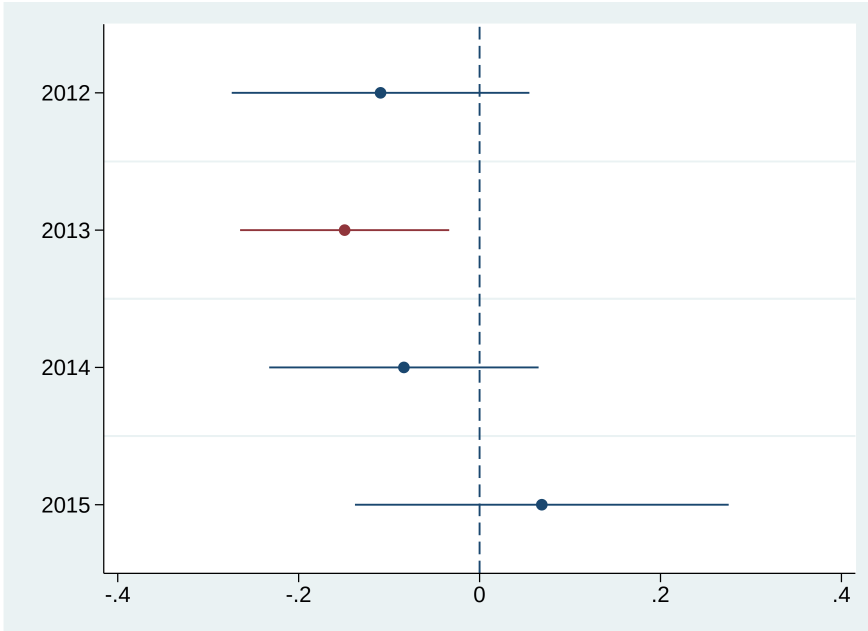


Panel A. Value of patents ($ millions)

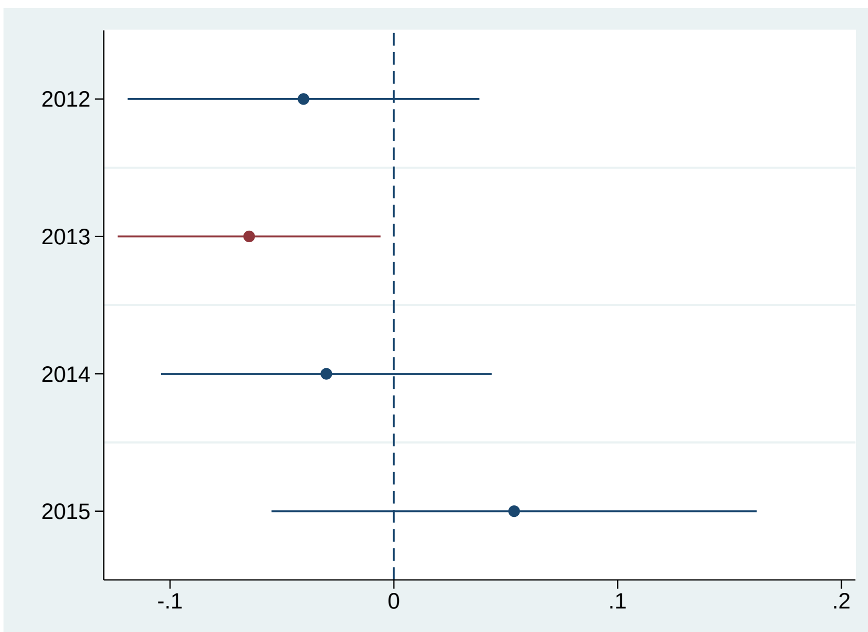


Panel B. Value of green patents ($ millions) by technology cluster

Figure 7. Panel A shows average green patent value and average non-green patent value ($ millions) between 1980 and 2018. Panel B shows green patent value ($ millions) by technology cluster. Patent value is the market value of newly granted patents, calculated using abnormal stock market responses to a patent's approval (Kogan et al., 2017). The abnormal return is defined as the difference between the firm's three-day return (CRSP holding period return) and the return of the CRSP value-weighted index.

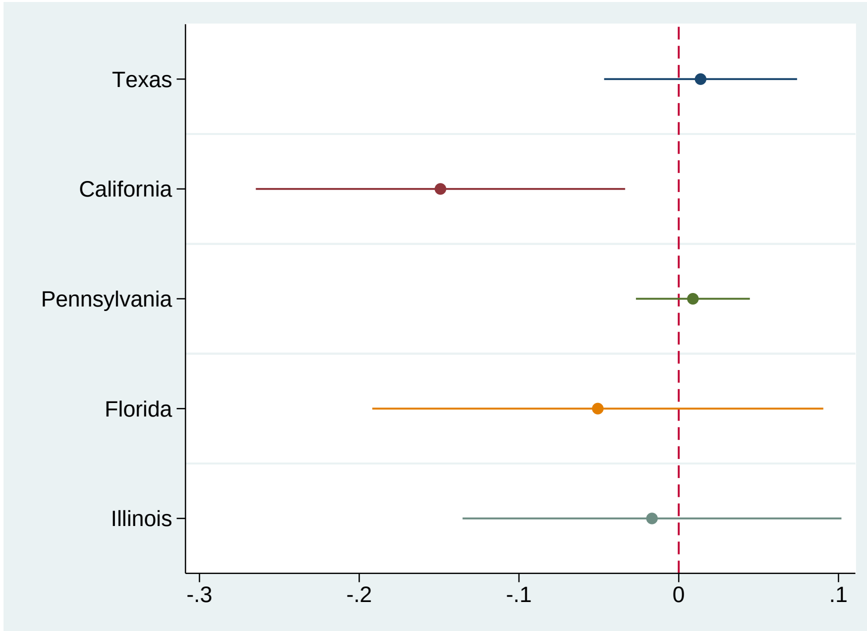


Panel A. Coefficient estimates on green patent claims

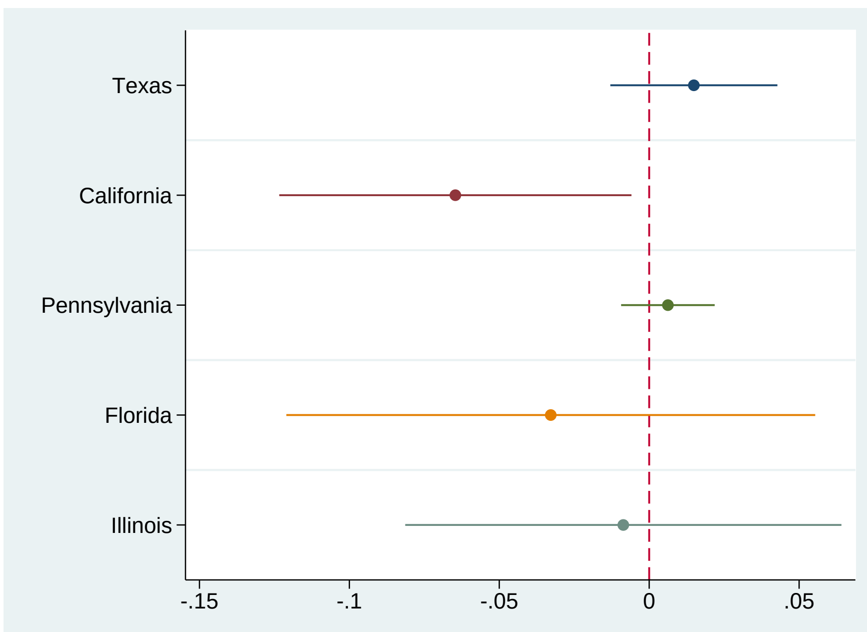


Panel B. Coefficient estimates on green patents

Figure 8. Placebo tests of main results on constrained firms. The figure shows coefficients estimates of treatment effects estimated using 2012, 2013, 2014, and 2015 as treatment year, respectively. The spikes display 95% confidence interval calculated using standard errors clustered at state-year level. The analysis is the same as specification 1 in Tables 5 and 6, except I change the *After* indicator according to the placebo years.



Panel A. Coefficient estimates on green patent claims



Panel B. Coefficient estimates on green patents

Figure 9. Placebo tests of main results on constrained firms. The figure shows coefficients estimates of treatment effects estimated using Texas, California, Pennsylvania, Florida, and Illinois as treatment state, respectively. The spikes display 95% confidence interval calculated using standard errors clustered at state-year level. The analysis is the same as specification 1 in Tables 5 and 6, except I replace California with alternative control states as the treatment state.

Table 1. Green technology innovation by year

This table shows the number of green technology patents and claims by year. I extract green technologies from patent filings through textual analysis of patent claims. I use three categories of green technology: renewable energy, energy efficiency, and carbon capture and emission reduction.

Year	Number of firms	Number of green patents	Number of green patent claims	# Renewable energy patents	# Energy efficiency patents	# Carbon capture patents
2010	5,511	1,267	7,319	367	870	30
2011	5,412	1,303	8,020	337	940	26
2012	5,334	1,387	8,354	341	1,018	28
2013	5,399	1,389	7,980	288	1,073	28
2014	5,541	1,225	7,102	279	928	18
2015	5,481	1,036	5,477	259	764	13

Table 2. Green technology innovation by sector

This table shows the number of green technology patents by sector. Sample period is 2010 to 2015. I extract green technologies from patent filings through textual analysis of patent claims. I use three categories of green technology: renewable energy, energy efficiency, and carbon capture and emission reduction.

Top-10 Industries (SIC2)	Total number of green patents
36, Electronic & Other Electric Equipment	2,880
37, Transportation Equipment	1,496
38, Instruments & Related Products	561
35, Industrial Machinery & Equipment	439
28, Chemical & Allied Products	267
26, Paper & Allied Products	107
48, Communications	86
49, Electric, Gas, & Sanitary Services	57
29, Petroleum & Coal Products	55
13, Oil & Gas Extraction	47

Table 3. Summary statistics

This table shows summary statistics of treated firms (Panel A), control firms (Panel B), and control firms with at least one plant (Panel C). Sample period is from 2010 to 2015. *California Share* is the total emission by California plants divided by the total emission by all plants by firm. *California Plant Share* is the number of plants in California divided by the total number of plants by firm. *California Emissions* is the total emissions by California plants by firm. *Total Emissions* is the total emission by all plants by firm. *Number of Plants* is the number of carbon-emitting plants with emissions more than 25,000 metric tons owned by a firm. *Number of California Plants* is the number of California plants owned by a firm. *Number of Green Patents* is the number of green patents a firm applies for that are eventually granted in a given year. *Number of Green Patent Claims* is the number of green patent claims a firm applies for that are eventually granted in a given year. *SD* is standard deviation. *N* is number of firm-year observations. Variables are winsorized at the one percent tails.

Panel A. Treated firms: firms with positive carbon emissions in California

	Mean	SD	Min	Max	N
Total Assets ($ Billions)	29.56	57.87	0.01	284.31	387
California Share	0.55	0.42	0.00	1.00	387
California Plant Share	0.58	0.39	0.04	1.00	387
California Emissions (Million Tons)	0.75	1.84	0.00	14.13	387
Total Emissions (Million Tons)	5.70	13.27	0.00	89.61	387
Number of Plants	15.68	38.89	1	260	387
Number of California Plants	2.76	4.14	1	23	387
Number of Green Patent Claims	3.75	18.36	0	277	387
Number of Green Patents	0.72	2.56	0	26	387
Age	34.50	21.46	2	66	387
R&D	0.31	0.80	0.00	5.49	387
Capital Expenditure	2.17	5.87	0.00	37.99	387
Sales	13.64	21.62	0.00	77.95	387
Net Income	1.15	2.09	-0.93	6.74	387

Panel B. Control firms: firms with no carbon emissions in California

	Mean	SD	Min	Max	N
Total Assets ($ Billions)	6.18	20.61	0.01	284.31	17,724
California Share	0.00	0.00	0.00	0.00	17,728
California Plant Share	0.00	0.02	0.00	1.00	17,728
California Emissions (Million Tons)	0.00	0.00	0.00	0.00	17,728
Total Emissions (Million Tons)	0.33	3.68	0.00	127.87	17,728
Number of Plants	0.66	3.43	0	142	17,728
Number of California Plants	0.00	0.02	0	1	17,728
Number of Green Patent Claims	1.98	30.40	0	1,901	17,728
Number of Green Patents	0.33	3.25	0	126	17,728
Age	23.18	15.95	1	66	17,728
R&D	0.12	0.66	0.00	12.54	17,728
Capital Expenditure	0.39	1.86	0.00	50.23	17,709
Sales	4.02	10.95	0.00	77.95	17,707
Net Income	0.27	0.93	-0.93	6.74	17,707

Panel C. Control firms (*Number of Plants* ≥ 1): firms with no carbon emissions in California

	Mean	SD	Min	Max	N
Total Assets ($ Billions)	10.82	25.10	0.01	284.31	3,462
California Share	0.00	0.00	0.00	0.00	3,462
California Plant Share	0.00	0.04	0.00	1.00	3,462
California Emissions (Million Tons)	0.00	0.00	0.00	0.00	3,462
Total Emissions (Million Tons)	1.70	8.19	0.00	127.87	3,462
Number of Plants	3.38	7.14	1	142	3,462
Number of California Plants	0.00	0.05	0	1	3,462
Number of Green Patent Claims	4.17	57.82	0	1,901	3,462
Number of Green Patents	0.60	4.67	0	126	3,462
Age	28.46	19.63	1	66	3,462
R&D	0.21	1.06	0.00	12.28	3,462
Capital Expenditure	0.76	2.28	0.00	45.11	3,458
Sales	6.29	13.72	0.00	77.95	3,459
Net Income	0.45	1.21	-0.93	6.74	3,459

Table 4. Impact of cap-and-trade on balance sheets and income statements in constrained firms

This table presents the effects of cap-and-trade on balance sheet and income statement items in financially constrained firms. Dependent variables are all scaled by firm total assets in 2012. *Sale*, *Cash*, *R&D*, and *Capex* are Compustat items *sale*, *ch*, *xrd*, and *capx*, respectively. Debt is the sum of debt in current liabilities (*dlc*) and long-term debt (*dltt*). *California Share* is the total emission by California plants divided by the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. A firm is classified as constrained if the firm is constrained according to more than two of all four financial constraint measures. The detailed definitions of *Hadlock-Pierce Index*, *Whited-Wu Index*, *O Score*, and *Payout* are provided in Appendix A. Variable definitions. Standard errors are clustered at state-year level.

Dependant variable =	Sale/Assets	Cash/Assets	R&D/Assets	Capex/Assets	Debt/Assets
California Share × After	-0.0970***	-0.0217**	-0.0112*	-0.00502	0.0618*
	(-3.17)	(-2.05)	(-1.87)	(-0.80)	(1.74)
California Share	0.0782	0.0624***	0.000774	-0.0141	-0.101***
	(1.63)	(4.97)	(0.13)	(-1.20)	(-2.99)
After	0.0169	0.0212**	0.00263	-0.00570	0.0322
	(0.90)	(2.24)	(0.57)	(-0.76)	(1.22)
Total Assets	0.131***	0.0972***	0.00219	0.0738***	0.365***
	(3.00)	(4.80)	(0.84)	(5.11)	(5.75)
Firm Age	0.0204	-0.100**	0.00231	0.0652*	-0.00731
	(0.30)	(-2.16)	(0.21)	(1.80)	(-0.05)
Firm FE	Yes	Yes	Yes	Yes	Yes
No. obs.	1816	1863	1886	1861	1599
R^2	0.936	0.767	0.824	0.730	0.845

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Green technology claims and financial constraints

This table presents results from difference-in-difference regressions separately for subsamples of financially constrained and unconstrained firms. Dependent variable is *Ln(1 + # Green Patent Claims)*, the natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year. *California Share* is the total emission by California plants divided the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. The detailed definitions of *Hadlock-Pierce Index*, *Whited-Wu Index*, *O Score*, and *Payout* are provided in Appendix A. Variable definitions. Standard errors are clustered at state-year level.

Dependant variable =	Ln(1 + # Green Patent Claims)									
	Composite		Hadlock-Pierce		Whited-Wu		O score		Payout	
	Constrained	Unconstrained	High	Low	High	Low	High	Low	Low	High
California Share × After	-0.142**	0.231***	-0.0826*	0.129**	0.00309	0.0663	-0.0262	0.123	-0.0477*	0.102
	(-2.40)	(2.81)	(-1.86)	(2.02)	(0.17)	(1.03)	(-0.26)	(1.60)	(-1.67)	(1.36)
California Share	0.0532	-0.203**	0.0475*	-0.132*	-0.0139	-0.119	-0.0451	-0.116	-0.0559	-0.0890
	(0.68)	(-2.01)	(1.82)	(-1.89)	(-0.27)	(-1.45)	(-0.42)	(-1.22)	(-0.73)	(-1.07)
After	-0.0173	-0.00875	-0.0171*	-0.00850	-0.0279*	-0.0160	-0.0109	-0.0195	-0.0298*	-0.00744
	(-1.30)	(-0.28)	(-1.76)	(-0.33)	(-1.94)	(-0.78)	(-0.74)	(-0.63)	(-1.82)	(-0.36)
Total Assets	0.0159	0.00501	0.0187*	-0.00137	0.00959	0.00360	0.00840	0.0122	0.00565	0.0211
	(1.27)	(0.13)	(1.92)	(-0.06)	(1.06)	(0.12)	(0.60)	(0.53)	(0.42)	(0.80)
Firm Age	0.0535	-0.222*	0.0541*	-0.174	0.0533	-0.00170	0.00848	-0.0587	0.128**	-0.133*
	(1.24)	(-1.88)	(1.77)	(-0.79)	(1.43)	(-0.02)	(0.16)	(-0.73)	(2.22)	(-1.78)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	1886	1963	1870	3094	1954	2862	2103	1984	1768	2548
R^2	0.784	0.846	0.832	0.861	0.726	0.867	0.798	0.861	0.815	0.865

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Green technology patents and financial constraints

This table presents results from difference-in-difference regressions separately for subsamples of financially constrained and unconstrained firms. Dependent variable is *Ln(1 + # Green Patents)*, the natural logarithm of one plus the number of green technology patents that are applied for and are eventually granted in a given year. *California Share* is the total emission by California plants divided the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. The detailed definitions of *Hadlock-Pierce Index*, *Whited-Wu Index*, *O Score*, and *Payout* are provided in Appendix A. Variable definitions. Standard errors are clustered at state-year level.

Dependant variable =	Ln(1 + # Green Patents)									
	Composite		Hadlock-Pierce		Whited-Wu		O score		Payout	
	Constrained	Unconstrained	High	Low	High	Low	High	Low	Low	High
California Share × After	-0.0604**	0.152***	-0.0412*	0.0921**	0.00224	0.0591	-0.00442	0.0961**	-0.0115	0.0736
	(-1.99)	(3.00)	(-1.94)	(2.38)	(0.23)	(1.54)	(-0.08)	(2.16)	(-0.74)	(1.64)
California Share	0.0598*	-0.0854	0.0246*	-0.0316	-0.00722	-0.0142	0.0265	-0.0550	0.00538	-0.0288
	(1.74)	(-1.56)	(1.86)	(-0.80)	(-0.22)	(-0.36)	(0.56)	(-1.13)	(0.35)	(-0.64)
After	-0.0106**	0.00138	-0.00981**	0.00309	-0.0150***	-0.00259	-0.00469	-0.00653	-0.0174**	0.000714
	(-2.12)	(0.06)	(-2.06)	(0.18)	(-2.75)	(-0.17)	(-0.71)	(-0.30)	(-2.60)	(0.05)
Total Assets	0.0195**	0.0172	0.0157**	0.0127	0.0124**	0.0155	0.0146	0.0174	0.0132	0.0248
	(2.18)	(0.75)	(2.50)	(1.02)	(2.22)	(0.85)	(1.51)	(1.18)	(1.39)	(1.53)
Firm Age	0.0241	-0.157*	0.0261	-0.154	0.0244	-0.0325	-0.0151	-0.0425	0.0653**	-0.103**
	(1.22)	(-1.83)	(1.64)	(-1.20)	(1.51)	(-0.59)	(-0.56)	(-0.69)	(2.40)	(-2.14)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	1886	1963	1870	3094	1954	2862	2103	1984	1768	2548
R^2	0.818	0.876	0.844	0.903	0.731	0.904	0.842	0.888	0.838	0.900

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Effects on different patent clusters

This table presents treatment effects on different patent clusters for constrained firms. Dependent variable is the natural logarithm of one plus the number of different green patent clusters. Sample includes constrained firms classified by the measure *Composite*. *California Share* is the total emission by California plants divided the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. Standard errors are clustered at state-year level.

Dependant variable =	ln(1 + # Patents)			
	Renewable energy patents	Energy efficiency patents	Carbon capture patents	All other patents (Non-green)
California Share × After	-0.0374**	-0.119**	0.00279	-0.0412
	(-1.98)	(-2.16)	(0.81)	(-0.55)
California Share	0.0633*	0.0657	-0.00251	-0.0813
	(1.66)	(1.46)	(-0.81)	(-0.88)
After	-0.0000591	0.0117	-0.00160	-0.0220
	(-0.00)	(0.94)	(-0.43)	(-1.00)
Total Assets	0.0698***	0.0605*	-0.00584	0.0202**
	(2.86)	(1.93)	(-0.81)	(1.98)
Firm Age	0.152***	0.108	-0.00142	-0.110
	(3.11)	(1.07)	(-0.11)	(-1.47)
Firm FE	Yes	Yes	Yes	Yes
No. obs.	1886	1886	1886	1886
R^2	0.706	0.813	0.190	0.926

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Treatment effects on green patent claims: pooled results and heterogeneous treatment effects

This table shows the impact of California cap-and-trade on green innovation for financially constrained and unconstrained firms as well as the heterogeneous treatment effects. Dependent variable is *Ln(1 + # Green Patent Claims)*, the natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year. *California Share* is the total emission by California plants divided by the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. Control variables are the same as defined in Table 5. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. Standard errors are clustered at state-year level.

Dependant variable =	ln(1 + # Green patent claims)			
	Constrained	Unconstrained	Pooled	Triple Difference
California Share × After	-0.142**	0.231***	0.0612	0.228***
	(-2.40)	(2.81)	(0.99)	(2.72)
California Share	0.0532	-0.203**	-0.0933	-0.203*
	(0.68)	(-2.01)	(-1.65)	(-1.97)
After	-0.0173	-0.00875	-0.0173	-0.0312
	(-1.30)	(-0.28)	(-0.83)	(-1.12)
Total Assets	0.0159	0.00501	0.0111	0.0117
	(1.27)	(0.13)	(0.74)	(0.73)
Firm Age	0.0535	-0.222*	-0.0201	-0.0275
	(1.24)	(-1.88)	(-0.31)	(-0.47)
California Share × After × Constrained				-0.367***
				(-3.93)
California Share × Constrained				0.254*
				(1.72)
After × Constrained				0.0306
				(1.21)
Firm FE	Yes	Yes	Yes	Yes
No. obs.	1886	1963	3849	3849
R^2	0.784	0.846	0.841	0.842

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Treatment effects on green patents: pooled results and heterogeneous treatment effects

This table shows the impact of California cap-and-trade on green innovation for financially constrained and unconstrained firms as well as the heterogeneous treatment effects. Dependent variable is *Ln(1 + # Green Patents)*, the natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year. *California Share* is the total emission by California plants divided by the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. Control variables are the same as defined in Table 5. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. Standard errors are clustered at state-year level.

Dependant variable =	ln(1 + # Green patents)			
	Constrained	Unconstrained	Pooled	Triple Difference
California Share × After	-0.0604**	0.152***	0.0553	0.149***
	(-1.99)	(3.00)	(1.51)	(2.90)
California Share	0.0598*	-0.0854	-0.0232	-0.0850
	(1.74)	(-1.56)	(-0.72)	(-1.53)
After	-0.0106**	0.00138	-0.00647	-0.0128
	(-2.12)	(0.06)	(-0.50)	(-0.67)
Total Assets	0.0195**	0.0172	0.0181*	0.0180*
	(2.18)	(0.75)	(1.82)	(1.69)
Firm Age	0.0241	-0.157*	-0.0286	-0.0287
	(1.22)	(-1.83)	(-0.70)	(-0.83)
California Share × After × Constrained				-0.208***
				(-3.85)
California Share × Constrained				0.144**
				(2.13)
After × Constrained				0.0128
				(0.69)
Firm FE	Yes	Yes	Yes	Yes
No. obs.	1886	1963	3849	3849
R^2	0.818	0.876	0.873	0.873

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. Impact of cap-and-trade on R&D intensity

This table presents results from difference-in-difference regressions for financially constrained firms. Dependent variable is *R&D / Sales*, research and development expense scaled by sales. *California Share* is the total emission by California plants divided by the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. Control variables are the same as defined in Table 5. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. The detailed definitions of *Hadlock-Pierce Index*, *Whited-Wu Index*, *O Score*, and *Payout* are provided in Appendix A. Variable definitions. Standard errors are clustered at state-year level.

Dependant variable =	R&D / Sales				
	Constrained (Composite)	High Hadlock-Pierce	High Whited-Wu	High O score	Low Payout
California Share × After	-0.181*	0.0197	-0.112	-0.0738	-0.172*
	(-1.77)	(0.21)	(-1.06)	(-1.04)	(-1.70)
California Share	0.0804	0.00690	0.0706	0.0124	0.0701
	(0.96)	(0.08)	(0.80)	(0.45)	(0.80)
After	0.0911	0.121	0.0838	0.0472	0.0995
	(0.76)	(0.64)	(0.65)	(0.56)	(0.77)
Total Assets	0.0608	0.0771	0.0463	0.0654	0.0978
	(0.42)	(0.39)	(0.28)	(0.34)	(0.65)
Firm Age	0.118	-0.230	-0.0203	0.0812	0.176
	(0.35)	(-0.53)	(-0.07)	(0.37)	(0.50)
Firm FE	Yes	Yes	Yes	Yes	Yes
No. obs.	1816	1672	1717	2036	1661
R^2	0.550	0.662	0.663	0.545	0.550

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11. U.S. Energy Acts used in the second quasi-natural experiment

Key Federal Legislation	Enacted on
Energy Policy Act of 1992	October 24, 1992
Energy Policy Act of 2005	August 8, 2005
Energy Independence and Security Act of 2007	December 19, 2007
Energy Improvement and Extension Act of 2008	October 3, 2008

Table 12. Green technology innovation by year stack specification

This table shows the number of green technology patents and claims by year.

Year	Number of firms	Number of green patent claims	Number of other claims	Number of green patents	Number of other patents
1989	6,261	528	396,947	169	28,845
1990	6,298	525	439,546	181	31,016
1991	6,410	651	455,011	193	32,942
1992	6,746	726	490,928	224	35,089
1993	7,471	869	525,188	225	35,874
1994	7,935	1,094	616,420	303	40,277
2002	6,797	3,892	1,642,547	848	80,230
2003	6,486	4,248	1,536,203	865	75,480
2004	6,487	4,445	1,505,741	912	75,366
2005	6,427	4,779	1,340,500	1,015	75,616
2006	6,324	3,896	1,342,564	922	74,558
2007	6,232	4,376	1,360,021	998	76,832
2008	5,907	5,386	1,343,206	1,169	76,605
2009	5,624	5,223	1,202,783	1,090	67,648
2010	5,519	6,364	1,295,019	1,319	70,513

Table 13. Impact of green subsidies on green innovation

This table presents results from the event-stacked difference-in-difference regressions. The four key acts in question are the Energy Policy Act of 1992, the Energy Policy Act of 2005, the Energy Independence and Security Act of 2007, and the Energy Improvement and Extension Act of 2008. I pick an event window (six years) around each of the relevant enactment dates and stack the event windows together to estimate an average treatment effect across the multiple events. I compare the number of green patent claims to the number of other patent claims in each firm around event date. Dependent variable is *Ln(1 + # Patent Claims)*, the natural logarithm of one plus the number of patent claims that are applied for and are eventually granted in a given year. *Greentech* is an indicator equal to 1 for green technology patents and patent claims. *Green Subsidy* is an indicator for being after the introduction of green subsidies by event. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. R^2 displayed is the within R^2. Standard errors are clustered by the state of incorporation.

Dependant variable =	ln(1 + # Patent claims)			
	Constrained	Unconstrained	Pooled	Triple Difference
Greentech × Green Subsidy	0.102***	0.0318*	0.0465***	0.0318*
	(5.54)	(1.76)	(3.55)	(1.76)
Total Assets	0.152***	0.200***	0.170***	0.163***
	(10.84)	(7.79)	(13.80)	(13.25)
Firm Age	-0.0302	0.00840**	-0.000993	0.000110
	(-0.64)	(2.26)	(-0.08)	(0.01)
Greentech × Subsidy × Constrained				0.0706***
				(2.73)
Firm * Event FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Patent Type FE	Yes	Yes	Yes	Yes
No. obs.	49024	46832	95856	95856
R^2	0.320	0.486	0.399	0.429

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14. Robustness of treatment effects on green patent claims (alternative specification of difference-in-difference using treatment group): pooled results and heterogeneous treatment effects

This table shows the impact of California cap-and-trade on green innovation for financially constrained and unconstrained firms as well as the heterogeneous treatment effects. Dependent variable is *Ln(1 + # Green Patent Claims)*, the natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year. *Treat* is an indicator for having at least one plant in California emitting more than 25,000 metric tons of carbon dioxide the year before treatment. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. Standard errors are clustered at state-year level.

Dependant variable =	ln(1 + # Green patent claims)			
	Constrained	Unconstrained	Pooled	Triple Difference
Treat × After	-0.0958**	0.0390	-0.0114	0.0302
	(-2.46)	(0.48)	(-0.21)	(0.40)
Treat	0.0364	-0.0392	-0.0124	-0.00703
	(0.78)	(-0.41)	(-0.23)	(-0.14)
After	-0.0160	-0.00157	-0.0130	-0.0215
	(-1.21)	(-0.05)	(-0.66)	(-0.82)
Total Assets	0.0159	0.00669	0.0115	0.0115
	(1.27)	(0.17)	(0.75)	(0.70)
Firm Age	0.0485	-0.207*	-0.0187	-0.0258
	(1.12)	(-1.81)	(-0.29)	(-0.44)
Treat × After × Constrained				-0.109
				(-1.36)
After × Constrained				0.0198
				(0.84)
Firm FE	Yes	Yes	Yes	Yes
No. obs.	1886	1963	3849	3849
R^2	0.784	0.845	0.841	0.841

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15. Robustness of treatment effects on green patent claims (alternative specification of difference-in-difference using plant share): pooled results and heterogeneous treatment effects

This table shows the impact of California cap-and-trade on green innovation for financially constrained and unconstrained firms as well as the heterogeneous treatment effects. Dependent variable is *Ln(1 + # Green Patent Claims)*, the natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year. *California Plant Share* or *CA Plant Share* is the number of plants in California divided by the total number of plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. Standard errors are clustered at state-year level.

Dependant variable =	ln(1 + # Green patent claims)			
	Constrained	Unconstrained	Pooled	Triple Difference
California Plant Share × After	-0.129**	0.191**	0.0465	0.188**
	(-2.33)	(2.18)	(0.76)	(2.12)
California Plant share	0.0351	-0.186	-0.0949*	-0.186
	(0.53)	(-1.59)	(-1.71)	(-1.56)
After	-0.0176	-0.00730	-0.0166	-0.0296
	(-1.32)	(-0.23)	(-0.81)	(-1.07)
Total Assets	0.0153	0.00535	0.0109	0.0113
	(1.21)	(0.14)	(0.72)	(0.70)
Firm Age	0.0556	-0.219*	-0.0183	-0.0251
	(1.30)	(-1.85)	(-0.29)	(-0.43)
CA Plant Share × After × Constrained				-0.315***
				(-3.22)
CA Plant Share × Constrained				0.220
				(1.41)
After × Constrained				0.0284
				(1.14)
Firm FE	Yes	Yes	Yes	Yes
No. obs.	1886	1963	3849	3849
R^2	0.784	0.846	0.841	0.842

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16. Robustness of treatment effects on green patent claims (full sample, control firms include firms with no carbon-emitting plants): pooled results and heterogeneous treatment effects

I repeat the analysis in Table 8 except for using control firms that include firms with no carbon-emitting plants. Dependent variable is *Ln(1 + # Green Patent Claims)*, the natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year. *California Share* is the total emission by California plants divided by the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. Standard errors are clustered at state-year level.

Dependant variable =	ln(1 + # Green patent claims)			
	Constrained	Unconstrained	Pooled	Triple Difference
California Share × After	-0.133**	0.231***	0.0634	0.233***
	(-2.29)	(3.23)	(1.09)	(3.21)
California Share	0.0571	-0.157**	-0.0582	-0.158**
	(1.05)	(-2.04)	(-1.09)	(-2.03)
After	-0.0107	-0.0181	-0.0196**	-0.0354**
	(-1.42)	(-1.08)	(-2.04)	(-2.54)
Total Assets	0.00322	0.0400**	0.00852	0.0108*
	(0.59)	(2.22)	(1.45)	(1.82)
Firm Age	0.00888	-0.226***	-0.0229	-0.0478**
	(0.40)	(-3.21)	(-1.01)	(-2.08)
California Share × After × Constrained				-0.366***
				(-4.37)
California Share × Constrained				0.215**
				(2.41)
After × Constrained				0.0361***
				(2.63)
Firm FE	Yes	Yes	Yes	Yes
No. obs.	10067	8044	18111	18111
R^2	0.765	0.804	0.798	0.798

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17. Impact of product market competition on firm green innovation responses

The table shows the impact of product market competition, as measured by the Herfindahl index, on green patent claims. Dependent variable is *Ln(1 + # Green Patent Claims)*, the natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year. Herfindahl index is equal to the sum of the squared market share of each firm in the same industry based on three-digit SIC code. *Low HHI* is equal to one if a firm is in industries with below median Herfindahl index. *High HHI* is equal to one if a firm is in industries with above-median Herfindahl index. *California Share* is the total emission by California plants divided by the total emission by all plants by firm. *After* is an indicator for being after the introduction of California cap-and-trade program. *Total Assets* is value of total book assets in millions (*at*). *Firm Age* is the difference between observation year and founding year. A firm is classified as constrained by the *Composite* measure if the firm is constrained according to more than two of all four financial constraint measures. Standard errors are clustered at state-year level.

Dependant variable =	ln(1 + # Green patent claims)		
	Low HHI	High HHI	All Constrained
California Share × After	-0.0909	-0.193*	-0.142**
	(-1.64)	(-1.75)	(-2.40)
California Share	0.00203	0.106	0.0532
	(0.02)	(1.41)	(0.68)
After	-0.0448	0.0135	-0.0173
	(-1.53)	(1.06)	(-1.30)
Total Assets	0.0128	0.00899	0.0159
	(0.82)	(0.38)	(1.27)
Firm Age	0.186**	-0.0893*	0.0535
	(2.19)	(-1.78)	(1.24)
Firm FE	Yes	Yes	Yes
No. obs.	976	910	1886
R^2	0.819	0.602	0.784

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A. Variable definitions

After	An indicator for being after the introduction of California cap-and-trade program
California Plant Share	Number of plants in California divided by the total number of plants by firm
California Share	The total emissions by California plants divided by the total emissions by all plants by firm
Constrained	Indicator equal to 1 if firm is constrained according to more than two of all four financial constraint measures
Firm Age	Difference between observation year and founding year
Greentech	An indicator equal to 1 for green technology patents and patent claims
Green Subsidy	An indicator for being after the introduction of green subsidies by event
Hadlock-Pierce Index	$-0.737 \times \textit{Total Assets} + 0.043 \times \textit{Total Assets}^2 - 0.040 \times \textit{Age}$
High Hadlock-Pierce	An indicator for having above-median *Hadlock-Pierce Index* in year 2012
High O Score	An indicator for having above-median *O Score* in year 2012
High Whited-Wu	An indicator for having above-median *Whited-Wu Index* in year 2012
Low Payout	An indicator for having below median *Payout* in year 2012
Ln(1 + # Green Patents)	Natural logarithm of one plus the number of green technology patents that are applied for and are eventually granted in a given year
Ln(1 + # Green Patent Claims)	Natural logarithm of one plus the number of green technology patent claims that are applied for and are eventually granted in a given year
Ln(1 + # Patents)	Natural logarithm of one plus the total number of patents that are applied for and are eventually granted in a given year
Ln(1 + # Patent Claims)	Natural logarithm of one plus the total number of patent claims that are applied for and are eventually granted in a given year
Number of Plants	Number of carbon-emitting plants with emissions more than 25,000 metric tons owned by a firm
Ohlson's O Score	The O score is computed using Compustat annual items: $-1.32 - 0.407 \times log(at/GNP) + 6.03 \times (lt/at) - 1.43 \times (wcap/at) + 0.076 \times (lct/act) - 1.72 \times (1\ if\ lt > at, else\ 0) - 2.37 \times (ni/at) - 1.83 \times (oancf/lt) + 0.258 \times (1\ if\ net\ loss\ for\ last\ two\ years, else\ 0) - 0.521 \times (ni_t - ni_{t-1})/(\lvert ni_t \rvert + \lvert ni_{t-1} \rvert)$.
Payout	$(\textit{Cash dividends} + \textit{repurchases})/\textit{Income before extraordinary items}$ $((dvp + dvc + prstkc)/ib)$
R&D Expense	Research and development expenditure (xrd)
Total Assets	Value of total book assets in millions (at)
Treat	An indicator for having positive *California Share*
Whited-Wu Index	$-0.091 \times \textit{Cash flow} - 0.062 \times \textit{Positive dividend dummy} + 0.021 \times \textit{Long-term debt} - 0.044 \times \textit{Total Assets} + 0.102 \times \textit{Industry sales growth} - 0.035 \times \textit{Sales growth}$

Appendix B. Examples of green patent

Table A.1 Green patent keywords used in the textual analysis

Green Patent Classification	Keywords
Renewable energy harvesting	Bio, Geothermal, Hydroelectric, Nuclear, Solar, Wind, Fuel cell, Energy, Power
Energy efficiency systems	Energy efficient, Energy efficiency, Electric vehicle, Energy distribution, LED, Energy management
Carbon capture and emission reduction	CO2, Carbon dioxide, Greenhouse gas, Reduction, Reducing, Capture, Capturing, Recycle, Recycling

Table A.2 Examples of green patents

Patent Number	Patent Claim
7042109	12. A wind turbine for generating electrical power from **wind energy** comprising: a turbine rotor mounted for rotation by capturing said wind energy and for converting said wind energy into rotational energy; a permanent magnet generator coupled with said turbine rotor such that said turbine rotor drives said generator; said generator comprising a stationary air core armature that is located in a magnetic airgap between two generator rotor portions mounted for co-rotation, said generator rotor portions comprising circumferential arrays of multiple alternating polarity magnetic poles attached to ferromagnetic back irons such that said permanent magnets magnetic flux back and forth between each rotor portion and through said stationary air core armature; said stationary air core armature comprising a substantially non-magnetic form having a support end, an opposite end, and intermediate portions between said support and opposite ends, said support end being attached to and supported by stationary structure of said wind turbine, and said intermediate portions lie in said magnetic airgap; said stationary air core armature further comprising windings having active length portions and end turn portions, wherein said end turn portions traverse predominantly in a circumferential direction, and said active length portions traverse inside said airgap in a direction transverse to said flux in said airgap and transverse to said circumferential direction to generate electromagnetically induced torque on said active length portions when said generator rotor portions rotate relative to said armature; said windings are wound onto and secured to said form such that said form reacts said electromagnetically induced torque to said stationary support structure at said support end of said form; said windings are wound in a serpentine path onto said form around the circumference of said magnetic airgap, wherein said serpentine undulates back and forth towards said support end and said opposite end, traversing said intermediate portions of said form; whereby, AC voltage is induced in said multiple phase windings as wind drives said turbine rotor to rotates.
7040108	49. A method of **thermal energy** recovery, comprising: absorbing thermal energy from a non-solar source with an evaporator plate exposed to the source; transferring the thermal energy absorbed by the evaporator plate to water so as to heat the water; and wherein the source is a liquid.
6868293	5. In a system for performing **energy** usage **management**, a software application for enabling remote monitoring and controlling of an energy management system within an energy consuming entity, comprising: an indoor temperature indicator module for monitoring the current temperature of the entity; a temperature setpoint module for establishing operating temperature points for the energy management system; a system setting module for activating the energy management system and for selecting the mode of operation of the energy management system; and a curtailment event override module for overriding an active curtailment event.
7479570	1. A **reducing** process of **carbon dioxide**, comprising mixing carbon dioxide and water with an organometallic complex represented by general formula (1) so as to reduce carbon dioxide so that formic acid or alkali salt thereof is formed, where R1, R2, R3, R4, R5, and R6 independently represent a hydrogen atom or a lower alkyl group, M represents an element that can be coordinated to the benzene ring, X1 and X2 represent nitrogen-containing ligands, X3 represents a hydrogen atom, a carboxylic acid residue, or H2O, X1 and X2 may be bonded to each other, Y represents an anion species, K represents a valency of a cation species, L represents a valency of an anion species, K and L independently represent 1 or 2, and K, m, L, and n are related to one another.

(*continued*)

Patent Number	Patent Claim
RE40143	1. A weather shield and solar heat collector per reflector, for **energy efficiency** and protecting the exterior unit of central air conditioning heat pump systems comprising: A) a cover of rigid material, of sufficient size and shape, to accommodate the complete surrounding of said exterior unit, B) having means for attachment as to form a protective shell, The weather shield and solar heat collector per reflector further including: A) a plurality of intake air vents to support an adequate air flow to reach and pass thru said exterior unit, B) a durable coating of black pigment, be applied to said cover for sufficient absorption of solar rays, C) a plurality of white panels, by means of attachment to, and with sufficient size and shape, to accommodate the complete surrounding of said cover, D) means for easy adjoining, of said white panels, with bolts, E) a portal hole of sufficient size, shape, and location on said cover, to accommodate the piping and wiring for the said exterior unit, by means of a flexible rubber bushing, insulator, to protect said piping and wiring, F) a plurality of air regulator panels, by means of attachment to, and with sufficient size and shape to accommodate the separation of air flow currents, by means of forced air, through said exterior unit, G) a plurality of air regulator panels, by means of attachment to, and with sufficient size, shape, and appropriate insulation, by means of attachment to said air regulator panels, to accommodate the complete coverage of area, by said insulation to said air regulator panels, H) a top cover diffuser, of adequate size and shape, to accommodate the exit flow of forced air current, having been passed through, the said exterior unit, The weather shield and solar heat collector per reflector further including: I) a bottom panel leveling plate of rigid material, of sufficient size and shape, as to accommodate a base and leveling platform, for said protective shell, with slide bolt holes, by means of attachment, J) a wing nut bolt per screw, with a wing nut per washer, by means of attachment, to a machine thread bolt, with hex head screw attached, in one, said wing nut bolt per screw.
7051529	1. A **solar power** system capable of storing heat energy wherein sun light is converted to electrical energy comprising: a light conversion system having an absorber and a concentrator, said absorber having a heat exchanger, an aperture, and a receiving cavity; said concentrator having a mirror and a sun-tracking system; said concentrator reflects the sun light into said absorber through said aperture, wherein the sun light warms said receiving cavity disposed within said absorber; said heat exchanger transfers heat from said receiving cavity to a fluid; a heat conversion system having a hot segment and a cold segment; said cold segment having said heat exchanger, a cold fluid hold, and a cold fluid pump; said hot segment having a hot fluid hold, a hot fluid pump and a heat engine; said hot fluid hold receives said fluid from said heat exchanger; said hot fluid pump impels said fluid to said heat engine and then to said cold fluid hold, wherein said heat engine converts heat to electricity; said cold fluid pump impels said fluid from said cold fluid hold to said heat exchanger then to said hot fluid hold, wherein said heat exchanger transfers the heat to said fluid; said hot segment operates under a power-demand condition; and said cold segment operates under a sunlight condition.
7493884	1. A system for **reducing** pollutant emissions of a power system, the system comprising: an engine; an intake system fluidly connected to the engine for supplying air into the engine; a **carbon dioxide** supply fluidly connected to the intake system; a valve connected to the intake system; and a controller operatively coupled to the carbon dioxide supply and the intake system valve, wherein the controller is configured to control the ratio of the carbon dioxide to air introduced into the engine by regulating the air intake valve to control the amount of air flowing into the engine.

(*continued*)

Patent Number	Patent Claim
7531144	1. A system for the **reduction** of **CO2** levels in an exhaust gas resulting from gas combustion in a combustion unit, said system comprising: one or more heat exchangers arranged for the transferral of heat energy from salt water and combustion air to liquefied natural gas to form cooled salt water and to evaporate said liquefied natural gas to fuel gas; means for mixing said fuel gas with said combustion air for gas combustion which generates exhaust gas containing CO2; and a process unit to which, subsequent to the gas combustion, the exhaust gas is furnished, and which is constructed and arranged to mix NH4OH with said cooled salt water to form cooled NH4OH comprising salt water; wherein said process unit is configured to cause said cooled NH4OH comprising salt water to contact said exhaust gas, such that at least a portion of the CO2 contained in said exhaust gas reacts with the cooled NH4OH comprising salt water such that the CO2 level is reduced in said exhaust gas which is output from said process unit, and further configured to cause formation of a mix of process unit products NaHCO3, NH4Cl and fresh water, said process unit comprising a first outlet for said exhaust gas with said reduced CO2 level and a second outlet for said mix of process unit products.
6868677	5. A combined **fuel cell** and fuel combustion **power** generation system, comprising in combination: a source of a first fuel, the first fuel containing hydrogen; a source of oxygen; a fuel cell downstream from said source of fuel and said source of oxygen, said fuel cell having a discharge for at least fuel cell products produced within said fuel cell including water, said fuel cell having an output for electrical power, and said fuel cell adapted to convert at least a portion of the first fuel and the oxygen into the fuel cell products while releasing electrical power from said output; a combustor downstream from said fuel cell discharge, said combustor adapted to combust a second fuel with oxygen in the presence of the fuel cell products from said discharge, the second fuel including hydrogen, said combustor adapted to produce elevated temperature and elevated pressure combustion products including water, said combustor including an exhaust for a mixture of the combustion products and the fuel cell products, the mixture including water; an expander downstream from said combustor exhaust, said expander having a power outlet, said expander adapted to produce power by expanding the mixture of the combustion products and the fuel cell products, and release the power through said power outlet; wherein at least one of said fuels includes carbon therein and a portion of the mixture of the fuel cell products and the combustion products includes carbon dioxide at said combustor exhaust; wherein a separator is located downstream from said combustor, said separator separating at least a portion of the water from a portion of the carbon dioxide within the mixture of the fuel cell products and the combustion products; wherein said separator is located downstream from said expander; and wherein a compressor is located downstream from a CO2 outlet of said separator, said compressor sufficiently compressing the CO2 for injection of the CO2 into a terrestrial formation spaced from the atmosphere.