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Abstract

The paper applies the synthetic control method to examine the effects of California's Cap-and-Trade Program on environmental innovation. The analysis exploits the International Patent Classification system to identify patents relating to environmentally sound technologies. This enables the study to focus on the effects of the policy intervention on green patent filings. A counterfactual is constructed by the combination of other states in the US which allows the comparison of patent applications in California to the estimated counterfactual situation in the absence of a Cap-and-Trade program. The study finds that the number of patents related to green technologies increased by approximately 22.5% after the passing of the Cap-and-Trade regulation. This result is robust to alternative specifications of the synthetic control method.

Keywords: Induced Innovation, Environmental Policy, Climate Change, California Cap-and-Trade Program
JEL*: Q55, Q58, O31, O38*

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1 Introduction

Humanity is increasingly affecting the climate through the use of fossil fuels, deforestation and farming. The IPCC's Sixth Assessment Report 2021 highlights that increasing emission levels in the atmosphere and rising global surface temperature call for urgent action to limit warming to 1.5°C above pre-industrial levels. Effectively mitigating climate change requires a technological shift from current fossil and resource-intensive production to climate-friendly alternatives. Consequently, creating incentives to encourage the development of new energy-efficient technologies comes into focus for environmental policy makers. The impact of environmental policy on the development and diffusion of alternative technologies may be a critical determinant in environmental protection (Kneese & Schultze, 1975). Thus, understanding technological developments and assessing the incentive mechanisms of different policy instruments is essential to policy makers in designing policies that foster environmental sustainability in the long-run.

In *The Theory of Wages*, published in 1932, Hicks established the idea that "[a] change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind — directed to economizing the use of a factor which has become relatively expensive". In other words, it is argued that making a production factor more costly will reduce its use and associated technological innovations will be developed. In 1991, Porter introduced the notion of regulation-induced innovation which states that stringent environmental regulation may spur innovation as firms seek to achieve competitive advantage through technological advances. Against this background, the inducement effect of environmental policy has received considerable attention in the recent environmental economics literature. Various quantitative applications of this hypothesis examining the linkage between innovation and varying policy instruments can be found in the relevant literature.

The present paper contributes to the existing literature by evaluating the linkage between regional climate policy and innovation activity at a narrower level. This contrasts with much of the previous literature which focuses on country-specific or cross-border regulations. An in-depth understanding of this relationship is particularly important for regions that are severely at risk from future climate change such as California. The coastal state is anticipated to be largely affected by environmental threats stemming from climate change. Sea level rise, coastal flooding, erosion as well as droughts and wild fires call for urgent action to reduce greenhouse gas emissions.

Over the past few decades, California has passed some of the strongest environmental policies among the states to tackle these challenges, taking a climate leadership role at the subnational level. In 2006, the California legislature passed the California Global Warming Solutions Act, also known as the Assembly Bill 32 (AB 32), which marked the beginning of an comprehensive climate change plan. The law requires the California Air Resource Board (CARB) to develop regulations and market-based instruments to reduce the state's total GHG emissions to 40 percent below 1990 levels by 2030. A core component of the state's climate plan is the California Cap-and-Trade Program that was approved by the CARB in October 2011 (CARB, 2011). The compliance obligation took effect on January 1, 2013 scheduled after the first quarterly auction of allowances in the preceding calendar year (CARB, 2013).[1] Proceeds from the state's allowance auctions fund the California Climate Investments program as reported by the (CARB, 2019). The state's overall emission cap set under the program decreased on average by 3% per year from 2015 through 2020 and is set to decline further by 5% up until 2030.[2]

California's program is the first multi-sector Cap-and-Trade system in North America, offering a new opportunity to analyse the effects of regional policies. In light of this, the present study empirically evaluates the impact of emission trading systems on innovation in environmentally-friendly technologies by analyzing the effect of the introduction of the Cap-and-Trade program in California.[3] The aim is to bring new insights into the effectiveness of policy-induced incentives in encouraging business and institutions to develop new and green technologies. On a broader level, the paper seeks to reflect on the policy implications of environmental regulations. As there are different policy approaches and various policy instruments available to policy makers, the design of interventions to achieve certain goals is critical. The type of approach and instrument retained has the potential to impact both the direction and the speed of technological development. With innovation being a key element to reaching environmental objectives, it is indispensable to further our understanding of the role of the regulatory framework in encouraging the development of green technology.

Only a small number of papers have empirically assessed the inducement effect of emissions trading policies. One of the few studies that make a direct link between emissions trading schemes and innovation performance is provided by Popp (2003). Alike the present study, Popp analyzes the level of innovation measured by the annual number of successful patent applications before and after the introduction of the Acid Rain Program — a major Cap-and-Trade program for SO_2 emissions created by the Clean Air Act (CAA) of 1990. Despite the decrease in the level of overall innovative activity after the passage of the CAA, the study finds that the implementation of the market-based policy in 1990 did lead to more environmentally-friendly innovation in the form of increased patenting for higher-efficiency scrubbers.[4] Taylor (2012), however, shows that patenting

[1] The system consists of emission allowances that are distributed via both free allocation and quarterly auctions and is structured into multi-year compliance periods. The first compliance period from 2013–2014 covered large industrial facilities (e.g. cement, glass, iron and steel, etc.) as well as industries involved with the generation and importation of electricity. Hence, upon implementation, the emissions cap addressed only emissions in the energy and industrial sectors — accounting for approximately 36% of total emissions. Beginning with the second compliance period in 2015, the scheme expanded to include natural gas suppliers and the transport sector (ICAP, 2020). As of 2015, the coverage expanded to approximately 87% of California's GHG emissions and 360 businesses representing 600 facilities, respectively. Initially, the program started with a cap of 162.8 Mt CO_2e in 2013. With additional emitters subject to the system in the second and third compliance period, the cap rose to 394.5 Mt CO_2e (ICAP, 2020).

[2] The legislation covers carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulfur hexafluoride (SF_6), and hydrofluorocarbons (HFCs).

[3] Innovation in environmentally-friendly technologies refers to the development of products and processes that will aid the sustainable development such as low-carbon solutions. Throughout the paper, the terms eco-innovation, environmentally-friendly innovation and green innovation will be used interchangeably.

[4] A scrubber is a flue-gas desulfurization technology to remove SO_2 from flue gases.

for low-sulfur technologies in the US declined after traditional regulation was replaced by the Cap-and-Trade. Thus, the findings suggest that the Acid Rain Program failed to create long-term incentives for technological advancement. Taylor finds a similar pattern for the Southern California NO_x Budget Trading Program, demonstrating falling patent activities for NO_x-control technologies after the implementation of emission trading program.

More recently, Calel & Dechezleprêtre (2016) investigated the European Union Emissions Trading System (EU ETS). The EU ETS constitutes the largest Cap-and-Trade program in the world, regulating nearly half of the European greenhouse gas (GHG) emissions. Exploiting patents filed with the European Patent Office (EPO), the authors of the study estimate that the EU ETS is responsible for a 10% increase in low-carbon innovation among regulated firms.

In conclusion, the empirical evidence reveals ambiguous results with respect to the inducement effect of emissions trading schemes. Thus, there is a need to undertake additional examination to determine the link between allowance trading and innovative output.

Following previous induced innovation research (Brunnermeier & Cohen 2003; Calel & Dechezleprêtre 2016; Carrión-Flores & Innes 2010; Lanjouw & Mody 1996; Noailly 2012; Popp 2002), I rely on patents as proxy to measure innovation. To estimate the impact of the policy intervention, I employ the synthetic control method (SCM) exposed in Abadie & Gardeazabal (2003) and expanded in Abadie et al. (2010). The idea behind this econometric technique is to construct a counterfactual — a "synthetic California" — with a weighted combination of selected US states to obtain a comparable unit. The counterfactual allows the assessment of how green patent activity would have evolved in the absence of the treatment. The empirical findings of this paper imply that the implementation of the Cap-and-Trade program spurred innovation of green technologies in the chosen post-treatment period. Thus, the findings indicate that the policy intervention incentivized the private sector to develop alternative and renewable energy technologies. This result bears important implications for regional governments in climate policy discussions.

The study makes two new contributions to the empirical literature on the effects of environmental policy on innovative activity. On the one hand, to the best of my knowledge, the analysis provides the first empirical assessment of the impact of California's emissions trading program on the state's innovative output, thereby granting insights on the effects of regional environmental policies. On the other hand, the present study offers additional empirical evidence on the positive impact of government regulation on the direction and rate of technology. Insights on the driving forces of innovation can support the development of government policies that effectively address environmental problems, provide incentives for firms to mitigate pollution activities and help meet environmental goals.

The remainder of this paper is organized as follows. Section 2 describes the empirical design and data used to estimate the impact of the policy on innovation. Subsequently, Section 3 presents the results of the analysis. Section 4 discusses the obtained results and Section 5 concludes.

2 Empirical Analysis

2.1 Method

The analysis makes use of the synthetic control approach originally devised by Abadie & Gardeazabal (2003) and Abadie et al. (2010). This method is chosen because the case setting is not suitable for traditional techniques such as the commonly used randomized control trial (RCT) which relies on randomly selecting a subset of people or entities in which the intervention being assessed is introduced. In evaluating regional policy, it is generally impossible to randomize states, making non-randomised approaches more suited for analyzing the effect of the emissions trading program. Moreover, the SCM improves on the standard difference-in-differences (DiD) approach by accounting for unobserved determinants with potentially time-varying effects.

On account of this, a growing number of studies evaluating policy interventions apply the synthetic control method (Andersson 2019; Bretscher & Grieg 2020; Bueno & Valente 2019; Kreif et al. 2016; Leroutier 2019). The basic idea of this method is to estimate an unobserved counterfactual of the treated unit. This involves constructing a synthetic control unit as a weighted average of untreated states that is comparable with California before the policy intervention. This approach allows to compare trends in green patent filings between California and a synthetic counterfactual over time. The notation and proceeding of the paper follows the approach of Abadie et al. (2010).

Let $t = 1, ..., T$ be the observed time period. The year 2000 is selected as the starting point of the study because a large part of the collected state-level data is only available from this point onwards. The length of the sample period is further constrained by the duration of the patent examination process. It may take several years from filing a patent application until patent approval. Moreover, patent filings are made public only when the patent is granted. Therefore, data on recent years deliver an incomplete and inaccurate picture due to pending patent applications awaiting a final decision by the USPTO. In light of this, the method is applied for the sample period 2000 through 2015.

Let T_0 denote the number of pre-intervention periods with $1 \leq T_0 < T$. Whilst the Cap-and-Trade program enters into force in January 2013, the treatment period begins with the passing of the bill in 2011. The treatment is defined to start in the said prescribed year in consideration of previous findings by Barbieri (2015) and Taylor et al. (2003) that indicate a rise in patent applications even before regulations were implemented, implying that anticipated regulations can encourage firms and organizations to invest in R&D upon implementation. Due to regulations being published before the effective implementation, inventions are developed beforehand to ensure that the requirements can be met. In such a case where forward looking economic agents react in advance of the policy intervention and there are signs of anticipation, Abadie (2021) recommends to "[...] backdate the intervention in the data set to a period before any anticipation effect can be expected, so the full extent of the effect of the intervention can be estimated".

Let $J+1$ be the states observed over the time period t and let $J=1$ be the state of California. The remaining J states will be referred to as the "donor pool". The donor pool is not affected by the implementation of the policy under investigation for any period t. The observed outcome variable of interest for a state $i = 1, ..., J+1$ at time t is given by Y_{it}. Correspondingly, Y_{1t}^N and Y_{1t}^I constitute the weighted number of successful environmental patent filings granted by the USPTO for California under no treatment and under treatment, respectively. Subsequently, the treatment effect can be denoted as:

$$\alpha_t = Y_{1t}^I - Y_{1t}^N \tag{1}$$

While the outcome with treatment Y_{1t}^I can be observed, the counterfactual Y_{1t}^N has to be estimated. The estimation of the counterfactual is derived from the weighted average of control units Y_{jt} $(j = 2, ..., J+1)$ in the donor pool. Therefore:

$$\hat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j Y_{jt} \tag{2}$$

where $\sum_{j=2}^{J+1} w_j = 1$ and $0 \leq w_j \leq 1$.

Further following the approach by Abadie et al. (2010), $\sum_{j=2}^{J+1} w_j$ is defined as a $(J \times 1)$ vector W of weights, such that each value of W represents a potential synthetic California. The vector W is obtained by minimizing the discrepancy of the pre-treatment characteristics of California and the donor pool. Formally, W is derived such that:

$$\|X_1 - X_0W\|v = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{3}$$

where $X_1 = (Z_1^{'}, Y_{11}, ..., Y_{1T_0})$ denotes a $(k \times 1)$ vector of pre-treatment characteristics for California and $X_0 = (Z_j^{'}, Y_{j1}, ..., Y_{jT_0})$ is a $(k \times J)$ matrix for the untreated states. Z_i denotes the vector of predictors of Y_{it}. Analogous to Abadie & Gardeazabal (2003), let V be some $(k \times k)$ symmetric and positive semi definite matrix that assigns weights to pre-treatment variables in such a way as to minimize the mean square error for the pre-treatment periods.

There are numerous advantages associated with the chosen statistical framework. For one thing, it offers a feasible method to assess the effects of an intervention or policy change that is unique to a single region. Unlike traditional regression methods that require variation in key variables across multiple observational units, synthetic control allows for the identification of policy impacts on an outcome of interest over time for a single or a small number of treated units. Moreover, in contrast to the DiD approach, SCM makes less restrictive assumptions by relaxing the parallel trends assumption and allowing for the effects of unobserved variables to change over time (Kreif et al., 2016). Another advantage of the method as pointed out in Abadie et al. (2015) lies in the transparency of the weights assigned to each unit of the control group.

This enables a comprehensible and transparent construction of the estimated counterfactual of interest.

There are, however, a number of difficulties and drawbacks that arise with the synthetic control methodology as a tool for policy evaluation, as it relies on significant restrictions. First of all, the SCM approach presupposes the availability of potential controls for the donor pool that did not adopt similar interventions. Thus, control units affected by similar policy changes in either the pre-intervention or post-intervention period are excluded from the donor pool. Another requirement necessary for the success of the method is that pre-intervention characteristics of the treated and synthetic unit are similar. Additionally, the outcome trajectory of the synthetic control must approximate that of the treated state during the pre-treatment period (Abadie, 2021). On account of this, other US states are more appropriate potential control units than European countries in this setting. Further, Abadie notes that the method does not allow for the existence of spillovers. As this is a severe restriction, it should be account for in the analysis of the results. Lastly, if the unit affected by the intervention shows extreme values in the outcome variable during the pre-treatment period, there may not be a weighted average of the untreated units that can approximate the trajectory of the outcome variable. In such a case, the method cannot be applied. As a result, I measure the outcome variable per 100'000 population to increase the comparability of units.[5]

In summary, the SCM offers various advantages for the estimation of the effects of policy interventions. Despite the challenges listed above, the SCM is a valuable, beneficial method for policy evaluation. The credibility of the results relies on achieving a good pre-intervention fit and on the fulfilment of the requirements. The closeness of pre-intervention outcomes can either be assessed graphically or by computing the Mean Squared Prediction Error (MSPE).[6] A good fit allows to interpret the discrepancy in the outcome variable during the post-treatment period as an intervention effect.

The results of the synthetic control method provide empirical evidence on the impact of the policy intervention on the innovation trend in California measured in terms of patent activity. In order to test the validity of the findings, a series of robustness checks are performed. Inference can be derived by running "in-time", "in-space" and "leave-one-out" placebo tests (Abadie et al., 2010). The in-time placebo consists of assigning the treatment to another date prior to 2011. For the in-space placebo, the intervention is iteratively reassigned to each of the states in the donor pool. For the leave-one-out test, the analysis is done by iteratively leaving out one of the states in the donor pool to examine whether the results are highly sensitive to the exclusion of one control unit. These methods of inference are based on the premise that the credibility of the synthetic control estimator would be severely undermined if effects of similar magnitudes could

[5]California is extreme in the values of green patent counts compared to the states in the donor pool as can be seen in Figure 3a.

[6]The MSPE is defined as the average of the squared discrepancies between the outcome of the treated unit and the outcome of the synthetic counterpart.

be obtained from the placebo runs. Thus, the placebo tests are used to rule out the possibility that the effects of the treatment do not depend on the treatment itself.

2.2 Data

A. Patent Data

This paper makes use of the number of patent applications to measure innovative activities. This metric is a common approach in the relevant literature, which is attributable to patents being "[...] a means of protecting inventions developed by firms, institutions or individuals, and as such they may be interpreted as indicators of invention" OECD (1994). In the survey *Patent Statistics as Economic Indicators*, Griliches (1990) puts forth benefits of patents as indicator for inventive output. These include the availability of data over a long period of time as well as the fact that patents are only granted by a patent office if they pass an objective standard. The latter implies that a technology protected by a patent does constitute as an invention, as there is a standard of novelty and utility imposed on the granting of such a right. Moreover, Archibugi (1992) argues that due to the lengthy and costly process of obtaining the grant of a patent, only innovations which are expected to provide future benefits to compensate for these costs are being filed for application. These are key features in the frequently applied distinction between the terms "innovation" and "invention" by Schumpeter (1939).[7] A further major advantage of patent indicators is the accessibility of detailed information on the inventive activity and the respective inventor. In addition, the patent description specifies the technical field to which the invention relates, thus providing information not only on the rate but also on the direction of technological innovation (Archibugi, 1992).

Despite the many positive aspects, there are also a number of drawbacks associated with patents as a measure of innovation. First of all, not all inventions are patentable and not all inventions are patented as it is only one out of several ways to protect successful research results. However, concerning this point Dernis et al. (2001) note that there are very few examples of significant inventions that have not been patented. Secondly, the propensity to file patents varies between sectors, industries and type of inventions (Archibugi 1992; Desrochers 1998). Certain fields in the industry experience more patent registrations than others, which may lead to a skewed view of the rate of innovation. Lastly, the skewed distribution of patent value presents a further disadvantage. Patents differ significantly in regards to their economic value (Archibugi 1992; Griliches 1990; Lanjouw et al. 1998). Aggregation of patents with heterogeneous values implies that highly valuable innovations and innovations of minor value are placed under the same umbrella. Thus, when applying an indicator derived by merely counting the number of patents, all innovations are weighted equally, regardless of their economic value.

[7] Schumpeter defines invention as the act of “intellectual creativity” with no economic significance, whereas an innovation refers to the introduction of a novel technical idea with commercial purpose. By this definition, granted patent applications are an appropriate indicator to capture technological innovation.

In sum, irrespective of the above mentioned limitations, the OECD's manual on the measurement of scientific and technological activities (1994) considers patent-based indicators as useful means for studying the innovation process, as they provide more detailed information compared to other indicators and are available at a highly disaggregated technological level. To this end, the analysis makes use of US patent data, drawing upon detailed information on published patent filings directly relevant to clean technologies.

The patent data is collected from the U.S. Patent and Trademark Office (USPTO) online database. The USPTO provides a publicly available data set, consisting of a complete history of patent applications for all states as of 1976.[8][9] The present analysis restricts the data to successful patent applications (i.e. granted patents). Only including granted patents ensures that the applications meet the requirements of novelty and marketability.

To account for differences in importance and value of inventions, the patents are weighted using a logarithmic transformation of the number of forward citations.[10] This citation-weighted indicator overcomes the issue of the skewed distribution of patent values (OECD, 2009).[11] Further, I compute the patent count per 100'000 inhabitants to make it comparable across states. Consequently, the outcome variable is given by the citation-weighted annual count of granted green patent applications per 100'000 inhabitants per state.

Since the core of this analysis rests on environmentally-friendly technology, a specific search for relevant patents is required. For this, I rely on the International Patent Classification (IPC). This classification system was developed at the World Intellectual Property Organisation (WIPO), classifying inventions into over 70'000 classification groups and subgroups. In order to identify the relevant patents, I adopt the "IPC Green Inventory".[12] The tool was developed to facilitate searches for patents relating to Environmentally Sound Technologies (ESTs) and contains 200 topics organized into seven major areas: a) administrative, regulatory or design aspects; b) alternative energy production; c) agriculture/ forestry; d) energy conservation; e) transportation; f) nuclear power generation; and g) waste management. Further details are given in Appendix A.3, Table A.3.

[8] Documentation updated on March 30, 2021.

[9] All patents originating outside the US are eliminated from the data set along with incorporated and unincorporated territories as well as military states. Additionally, I remove all patent documents with faulty or incomplete information.

[10] Each patent application is multiplied by ln(2 + #forward citations). Because the number of citations increases over time as older patents have had more time to accumulate citations, only citations within the first five years of publication are counted to avoid bias (OECD, 2009). Studies have found that a citation window of the first five years following publication is a reasonable indicator for the number of citations received for each patent application as the majority of all citations occur during this period (Narin & Olivastro 1993; Breschi et al. 2006).

[11] Several studies provide evidence that the number of citations a patent receives is a valid measure of the technological importance and value of an invention (Carpenter et al. 1981; Lanjouw & Schankerman 1999; Trajtenberg 1990).

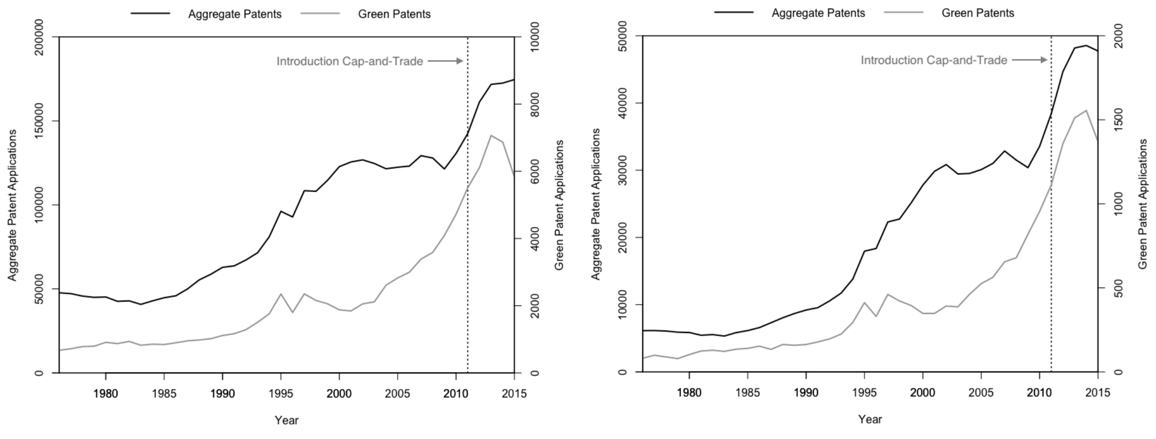
[12] The Green Inventory is one of several green patent classification systems. It is adopted in this paper due to being the most widely used classification in academic literature (Tanner et al. 2019).

For each relevant patent, I retrieve several bibliographic data including filing date, grant date, IPC code as well as details of the inventor and assignee.[13] The patent origin is determined by the residence of the inventor and the assignee. In the case of two or more entities residing in different states, analysts suggest "sharing" the patent among the respective states (fractional counting), avoiding double counting (OECD, 1994).[14] It has to be noted, however, that this approach can result in over- or underestimation of some states, as the different contributions to the inventive output of several inventors may not have equal weight.

Further, to capture the point of emergence of innovation, the present analysis follows previous research that has found that the date of application is a good indicator of R&D activity (Griliches, 1990).[15] Accordingly, I determine the weighted number of patents per year for each US state and calculate the corresponding rates per 100'000 population.

Figure 1a depicts the evolution of patent filings from 1976 until 2015 distributed by year of application in the US. During the observed period, the US exhibits a strong increase in the number of both total and green patent filings. Figure 1b graphs the development of patent filings for California. The state shows similar trends in patent filings to the US.

Figure 1: Patent Filing Trends, 1976-2015



(a) US Patent Trends

(b) California Patent Trends

[13]Inventorship is independent of the assignment of a patent. The person(s) listed as an inventor on a patent application is determined by who conceived of the invention. In contrast, the assignee is defined as the entity that holds the property rights to the patent. By United States patent law, a patent application is required to be in the name of the inventor, a company cannot be the inventive entity. Thus, in the case of an independent inventor, the inventor and the assignee is one and the same. In the case where an employee of a firm or organization produces an innovation, typically, that inventor's patent rights are assigned to the company.

[14]This case can occur if either (i) there are two or more inventors; (ii) inventor and assignee differ; or (iii) there are multiple partial assignees of the patent property. For example, when two inventors residing in the same state have assigned the property right to a third party of a different state, two-thirds of the patent is credited to the resident state of the inventors and one-third is ascribed to the assignee's state of residency.

[15]As Griliches notes, the date of application is a more accurate approximation than the date of grant due to the duration of the patent grant procedure.

At the beginning of the century, both the US and California experience an increase in green patent applications. Towards the end of the observed period, however, the number of green patent application declines. A comparison of the development in the USA and California shows that this downward trend sets in earlier in the USA.

This decreasing trend in environment-related patent applications is in line with previous published results on the development of environmental who recorded a decline in the number of patent applications (León et al. 2018; OECD 2021; Urbaniec et al. 2021). The studies report that patent filings in the field have declined for some technologies, notably patenting activity in alternative energy technologies. This development is not exclusive to the US but can also be observed in countries such as Germany, Japan and China. The reasons for this development are not entirely clear.

B. Other Data

Beyond the patent data provided by the USPTO, I include data on variables predicting green patent activity into the research framework to build the synthetic counterfactual.[16] The values of the chosen predictor variables are included in the pre-intervention characteristics of the treated unit X_1 and the untreated unit X_0, respectively. For each predictor, annual US state-level data from several federal bureaus was collected. The data are described below and summarized in Appendix A.4, Table A.4.

As mentioned in the introduction, Hicks (1963) put forward the notion that changes of relative factor prices impact the direction of technological progress. From this it follows that rising energy prices may induce energy-saving innovation. This underscores the importance of energy prices on technological change. As a consequence, total energy average prices published by the US Energy Information Administration are included. State energy prices are available since 1970 and are measured in 2020 USD per million Btus.

In view of the importance of science and engineering (S&E) in creating innovation, the analysis includes three state-level S&E indicators. As an indicator for higher educational attainment in the field of S&E, the number of bachelor's degrees awarded in S&E fields conferred per 1'000 individuals 18 to 24 years old is included.[17] The variable is lagged by three years, as I expect that its effects on patent activity take a few years to unfold. The data is drawn from the US Department of Education and indicates educational attainment in S&E fields. Similarly, a state indicator of business establishments in high science, engineering, and technology (SET) is used as a predictor of S&E in the economy.[18] The indicator is measured in percentage of total business establishments. In addition, to account for the concentration of scientific and technical jobs,

[16]Macroeconomic variables and crude oil prices affecting the entire national economy can be disregarded due to the empirical framework.

[17]S&E fields include the physical, life, earth, ocean, atmospheric, computer, and social sciences; mathematics; engineering; and psychology.

[18]High SET employment industries are defined as industries in which the proportion of employees in technology-oriented occupations is at least twice the average proportion for all industries.

a predictor measuring the employment in High SET establishments as a percentage of total employment is also included. The predictor captures the extent to which a state's workforce is employed in these industries. Data is provided by the US Census Bureau.

Considering that technological innovations may have a positive effect on a firm's exports, a predictor representing the state exports measured in total global merchandise exports in millions of 2020 USD is included. Further, R&D expenditures are likely to be a significant driver of innovative, environmentally-friendly output. Thus, to account for investments in R&D, I include a one-year lagged indicator using data collected from the National Center for Science and Engineering Statistics. The variable is measured in total state-level performed R&D as a percentage of GDP. Finally, annual state-level GDP per capita measured in 2020 USD and one-year lagged real GDP growth are included as predictor variables. GDP data and population estimates are drawn from the US Bureau of Economic Analysis and the US Census Bureau, respectively.

Descriptive statistics for all predictor variables based on the estimation sample are presented in Table 1.

Table 1: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Max	Min
(ln) GDP per Capita	544	3.78	0.32	5.22	3.14
Real GDP Growth (1-year lag)	544	1.94	2.83	22.30	-8.80
Total Energy Average Price	544	16.39	5.10	40.15	6.69
R&D expenditure (% of GDP, 1-year lag)	510	1.70	1.03	5.98	0.27
Exports (% of GDP)	544	6.97	3.88	27.66	0.75
S&E Indicators:					
High SET Establishments	442	8.03	2.16	17.77	4.68
Employment in High SET (% of Total)	442	10.58	2.69	18.21	5.42
S&E BA Degrees (3-year lag)	442	15.73	7.93	62.65	5.13

Notes: Differences in the number of observations are due to heterogenous time periods. The variable R&D expenditures and the S&E Indicators are only available as of 2001 and 2003, respectively.

2.3 The Donor Pool

In the selection of the control units it is essential to choose regions of high comparability to California in terms of green innovation activity in the pre-treatment period so as to create a counterfactual that closely resembles the state. Thus, the resulting set of control units ought to consist of regions with pre-treatment predictor variables X_0 comparable to those of the treated state X_1. In addition, care must be taken to ensure that the states in the donor pool did not adopt any statewide interventions similar to the Cap-and-Trade during the period of the study.[19]

The present research restricts the donor pool to states in the US. Ten states (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Vermont) are excluded from the sample due to being members of the mandatory Cap-and-Trade program Regional Greenhouse Gas Initiative (RGGI) established in the year 2009.[20] Further discarded are states that initially joined the Western Climate Initiative (WCI) (Arizona, Montana, New Mexico, Oregon, Utah and Washington), a non-profit cooperation established in 2007 with the goal to collectively evaluate and implement emission policies to reduce GHG emissions to 15% below 2005 levels by 2020 (Warren & Tomashefsky, 2009). To achieve this reduction goal, the WCI jurisdictions developed design recommendations for the WCI Regional Cap-and-Trade Program which were released in July 2010, calling for implementation of the program by January 1, 2012. With the passage of AB 32, which authorized the creation of California's Cap-and-Trade, California implemented its Cap-and-Trade program under guidelines of the WCI. The other US jurisdictions, however, withdrew in November 2011. Although the WCI is limited to California and several Canadian provinces at the present moment, the aforementioned states are excluded from the donor pool on the grounds that the anticipated implementation of the WCI Cap-and-Trade Program prior to the official withdrawal by the states may bias the estimation.

I further drop the state of Missouri due to incomplete data on R&D expenditures. Consequently, the final donor pool consists of the remaining 33 states (including the District of Columbia).

[19]The SCM allows to disregard nationwide policy interventions in this setting as the outcome path of each state is uniformly affected.

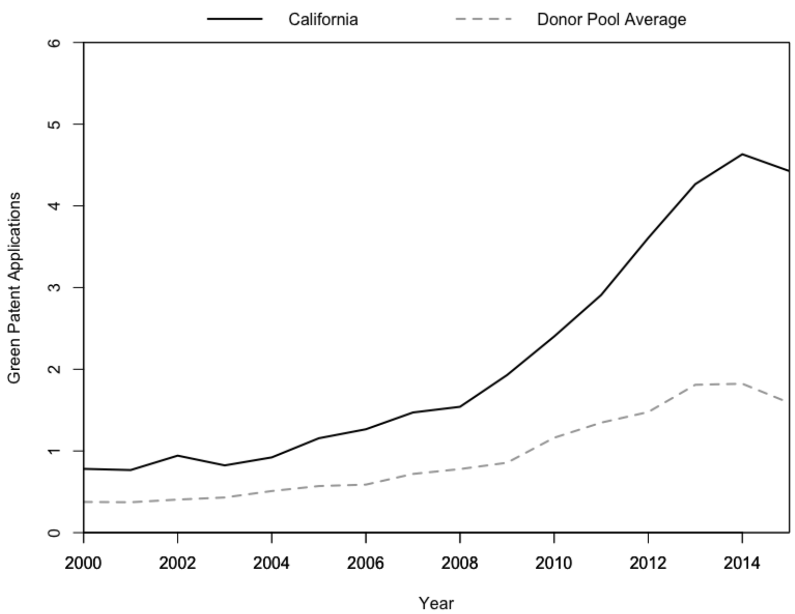
[20]The state of Virginia effectively joined the RRGI on January, 2021. As the state was not yet a member of the initiative during the observation period and a possible anticipation effect does not reach back to the observed time period, Virginia is not eliminated from the donor pool.

3 Results

3.1 The Synthetic Counterfactual

As a first step, Figure 2 depicts the trends in green patent filings in California compared to a naive counterfactual, which is constructed using the simple average of the donor pool. The figure shows that California and the donor pool average experience different paths throughout the entire sample period. In contrast to the naive counterfactual, California exhibits a significantly higher level of environmental patent activity before as well as after the policy implementation and records stronger growth beyond 2004, whereby the gap becomes larger each year.

Figure 2: Trends in Green Patent Filings: California vs. Donor Pool Average



These differing trends demonstrate that the state's average does not provide a suitable comparison unit for evaluating the intervention effects on patent activity. Hence, to recreate the pre-intervention path of California, a synthetic control is constructed as the weighted combination of US states in the donor pool to match the pre-treatment outcome. The weights w_j are estimated according to the algorithm developed by Abadie et al. (2010) and reported in Table 2. The displayed values represent the vector of weights W of each control state in the donor pool and indicate that the synthetic California is best reproduced by a combination of the District of Columbia, Hawaii, Idaho, Michigan, Texas and Virginia. The remaining states in the donor pool are assigned a weight of zero.

Figure 3 provides insight into state-level trends in green patent activity. The figure includes trajectories for California and the six states that make up the synthetic counterfactual. For the pre-treatment period, the figure shows that California's patent application trend features a similar pattern as the trends in Michigan and Texas, albeit at a higher level. That is, at the end of the observation period, the USPTO granted nearly three times as many patents to California than to Michigan and Texas. For the other four states, the figure depicts a consistently low level of green patent activity and hardly any increase throughout the entire period.

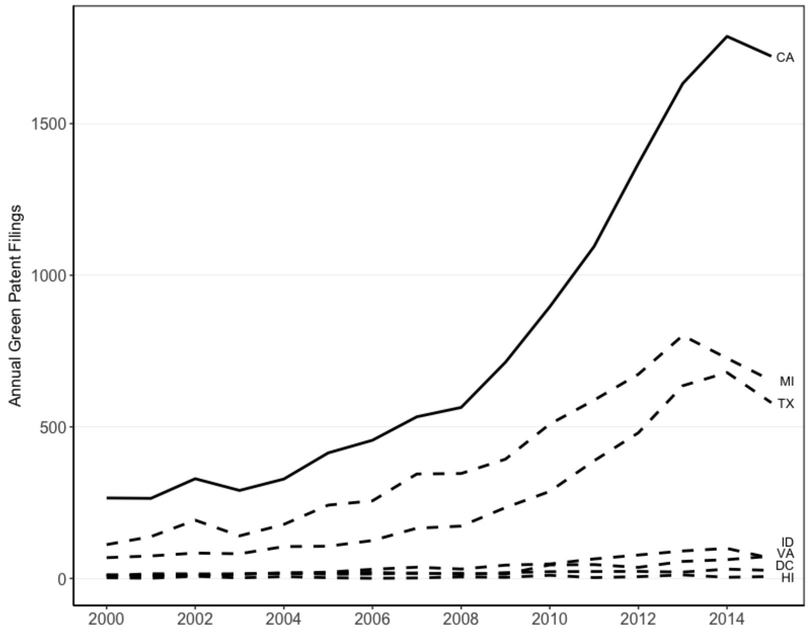
Considering that the US states differ wildly in terms of population size, the number of patents granted in absolute terms as presented in Figure 3a do not provide an accurate comparison. Thus, population size is taken into account. The results are depicted in Figure 3b, which plots the trajectories of green patent applications per 100'000 population for the sample period. The generally increasing trend during the pre-treatment period as seen in the previous graph remains. Yet, the differences between California and the six donor states are less pronounced, as the consideration of population size narrows the differences between the states. Michigan, the state with the highest relative patent count, undergoes a significant rise from 2000 until 2013. Moreover, the District of Columbia and Idaho stand out with volatile movements. In contrast, the remaining three states in the donor pool, Hawaii, Texas and Virginia, show a fairly low overall increase in patent activity. It is also striking to see that all depicted states except for Idaho experience a decline in green patent activity towards the end of the observation period.[21]

Table 2: State Weights in Synthetic California

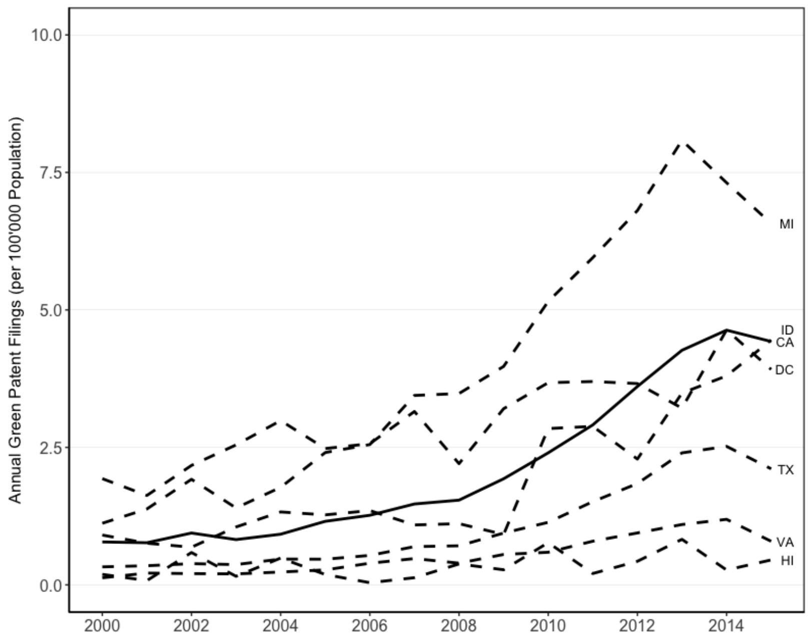
Weight	State	Weight	State
0.000	Alabama	0.000	Mississippi
0.000	Alaska	0.000	Nebraska
0.000	Arkansas	0.000	Nevada
0.000	Colorado	0.000	North Carolina
0.074	District of Columbia	0.000	North Dakota
0.000	Florida	0.000	Ohio
0.000	Georgia	0.000	Oklahoma
0.086	Hawaii	0.000	Pennsylvania
0.058	Idaho	0.000	South Carolina
0.000	Illinois	0.000	South Dakota
0.000	Iowa	0.000	Tennessee
0.000	Indiana	0.146	Texas
0.000	Kansas	0.335	Virginia
0.000	Kentucky	0.000	West Virginia
0.000	Louisiana	0.000	Wisconsin
0.300	Michigan	0.000	Wyoming
0.000	Minnesota		

[21]see Section 2.2

Figure 3: State-level Trends in Green Patent Activity, 2000–2015



(a) Total Number of Green Patent Filings



(b) Green Patent Filings (per 100'000 Population)

Lastly, Table 3 displays the relative weights corresponding to each of the key predictor in the V matrix and compares the mean values of key predictors for California (X_1), the synthetic California (X_0) and the sample average for the control units in the donor pool in the pre-treatment period. The predictor with the highest weight is exports, followed by the three S&E indicators and (ln) GDP per capita. This highlights the importance of including predictors related to science and engineering education, workforce and knowledge-intensive industries. In contrast, GDP growth, R&D expenditure and total energy average price do not have substantial power in predicting the number of green patent applications.

Table 3: Predictor Means for Green Patent Filings

Variables	Weights	Treated	Synth.	Sample Mean
(ln) GDP per Capita	0.128	3.86	3.82	3.70
GDP Growth (1-year lag)	0.035	2.46	1.66	1.95
Total Energy Average Price	0.057	16.93	15.38	14.43
R&D expenditure (% of GDP, 1-year lag)	0.047	4.22	2.82	1.62
Exports (% of GDP)	0.246	6.99	6.92	6.23
S&E Indicators:				
High SET Establishments	0.124	10.02	9.77	7.97
Employment in High SET (% of Total)	0.205	13.56	13.51	10.48
S&E BA Degrees (3-year lag)	0.159	15.78	18.77	15.73

Notes: The predictor variable R&D expenditure is averaged over the period 2001–2015. High SET Establishments, Employment in Hgh SET, and S&E BA degrees are averaged for the period 2003-2015. All remaining predictors are averaged for the 2000-2015 period. Data measurements are presented in Appendix A.4, Table A.4. The values of the sample mean are simple averages with equal weights assigned to each donor pool unit.

The predictor values prior to the treatment illustrated in Table 3 further confirm that the state average does not provide a suitable control group due to large differences in pre-treatment characteristics. In contrast, the table indicates that the synthetic counterfactual provides a better approximation of the factual situation and a good fit.

3.2 California vs. Synthetic California

The preceding visualizations give a descriptive indication of the evolution of patenting activity from 2000 onwards. However, it is unfeasible to derive any conclusions on the relation between environmental policy and patenting activity based on the descriptive statistics above. To obtain an accurate policy evaluation, the synthetic control method is used to analyze the effects of the Cap-and-Trade.

Figure 4 plots the trajectories of patent applications relating to environmentally-friendly technologies for both California and its synthetic counterfactual during the period 2000–2015. As noted in Section 2.1, the credibility of the synthetic control estimator depends on the mean squared prediction error and how closely the outcome path of the counterfactual follows that of the treated state. As can be seen from the picture, the treated and synthetic California have a similar trajectory of the outcome variable before the treatment in 2011, with a pre-treatment MSPE of 0.005. These findings suggest that the synthetic state provides a good approximation to the number of filed green patents applications in California. Further, the figure shows that while the synthetic California tracks the trajectory of California closely for the entire pre-treatment period, the trends begin to diverge noticeably after 2011. The discrepancy between the two trajectories right after the passage of the law indicates a positive effect of the Cap-and-Trade on patenting activity relating to environmentally-friendly technology in California.

Though both California and its counterfactual display a decline in green patent filings towards the end of the post-treatment period, the decline occurs later for California. This suggests that the introduction of the emission trading system counteracted the decline in green patent activity in early years by incentivizing businesses under the cap to develop environmentally sound technologies.

The estimated effect of the intervention is given by the difference between the number of patent filings in California and its synthetic version in the post-treatment period which can be interpreted as the annual increase in successful green patent filings resulting from the passing of the bill. Figure 5 visualizes this gap between the synthetic and treated California. The findings suggest that in the post-treatment period, the green patent filings in California increased by about 22.5% on average relative to the synthetic control.

Figure 4: Trends in Green Patent Filings: California vs. Synthetic California

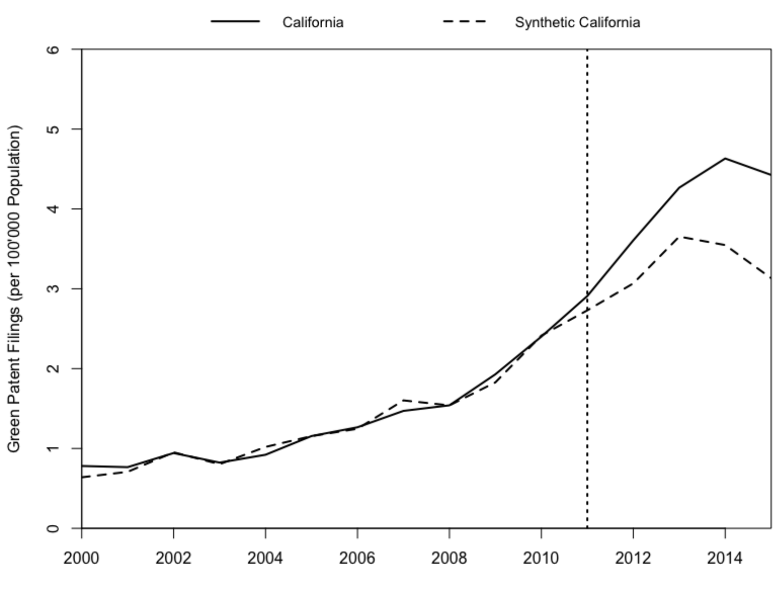
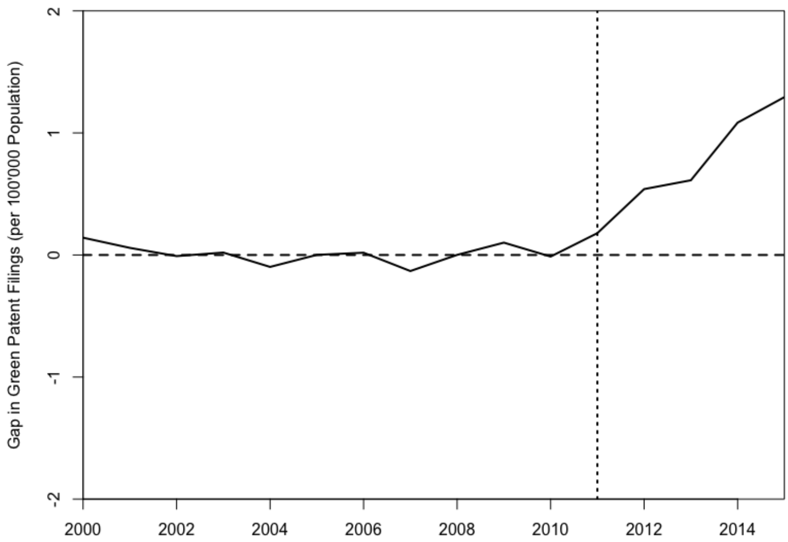


Figure 5: Green Patent Filings Gap between California and Synthetic California

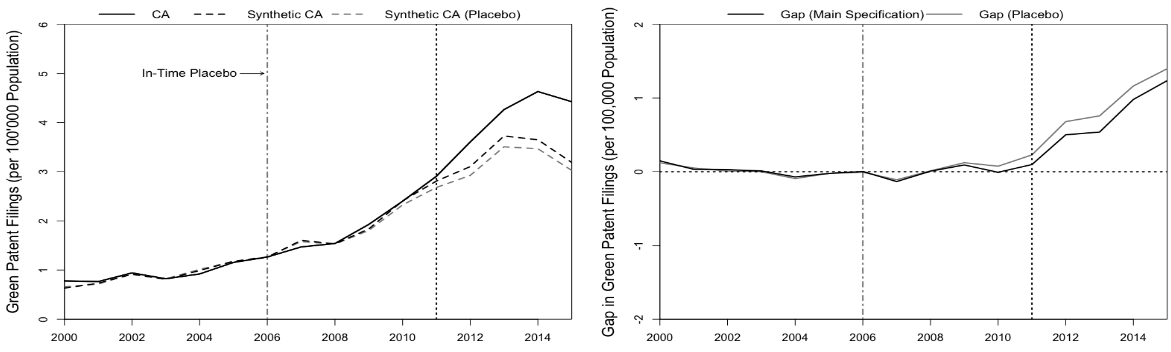


3.3 Inference

As previously mentioned, inference is conducted by running a series of placebo tests. For the in-time placebo test, the year of treatment is shifted to a date prior to the intervention. If assigning the treatment to a date before the introduction of the Cap-and-Trade resulted in a large difference between the synthetic and observed California, this would cast doubt on the claim that the effect found in the main analysis results from the policy intervention. To verify that the observed results are not caused by the passage of AB 32, the treatment is assigned to 2006. Figure 6 shows the resulting synthetic California and the new patent filings gap. As can be seen in the figure, the resulting synthetic counterfactual closely reproduces the synthetic counterpart obtained in the main analysis. Most importantly, the green patent filings trajectories of California and its synthetic counterfactual do not diverge after 2006. That is, in contrast to the actual implementation of the intervention in 2011, randomly assigning the intervention to 2006 has no perceivable effect. Thus, this suggests that the gap estimated in Figure 5 reflects the impact of the Cap-and-Trade, ruling out the possibility that the effect arises for reasons other than the treatment.

For the in-space placebo test, the synthetic control method is iteratively applied to every control unit in the sample and compared to the main specification. The gaps associated with each of the 33 runs of the test determine whether the gap associated with the actual synthetic control unit differentiates itself from the other estimated gaps. Thus, the conception is to test

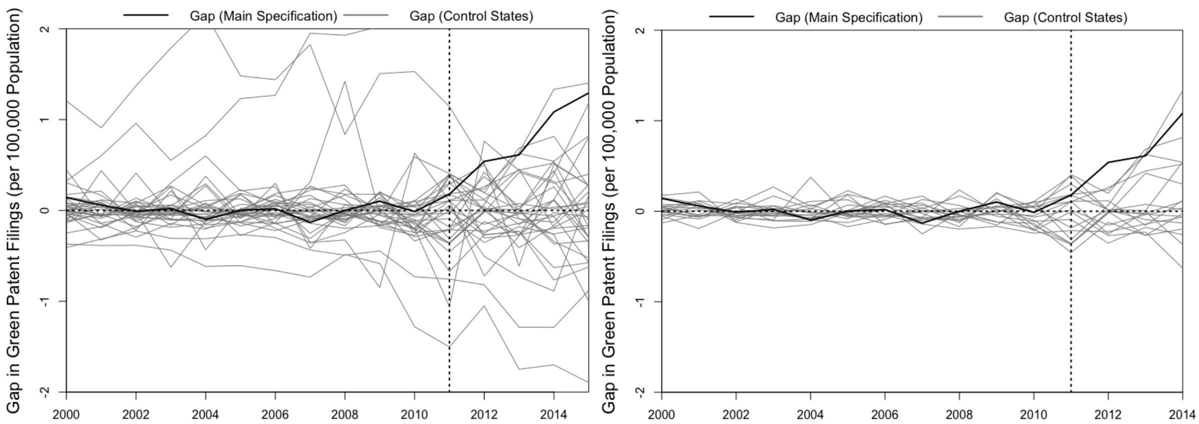
Figure 6: Green Patent Filings: In-Time Placebo Test



(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

Figure 7: Green Patent Filings Gaps in California and Placebo Gaps in Control States



(a) Including all 33 Control States

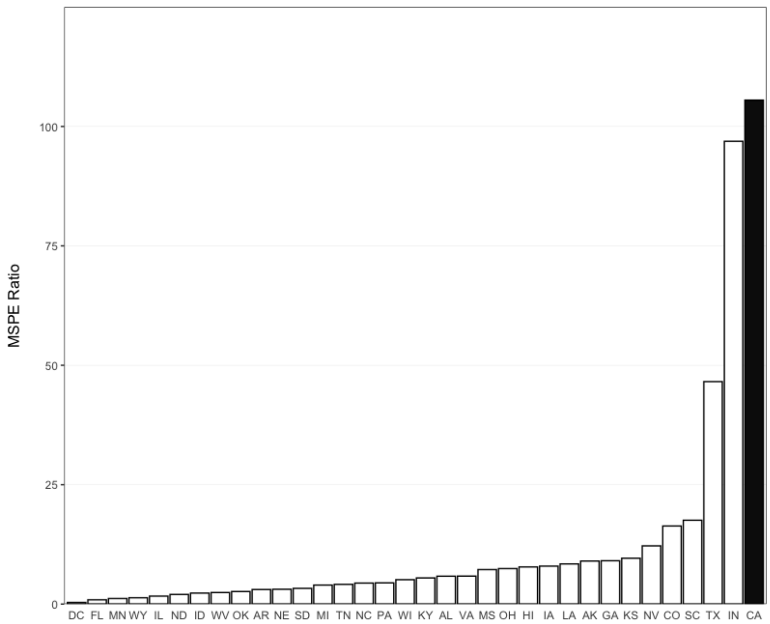
(b) Including States with Small Pre-Intervention MSPE

whether any control unit experiences similar or even larger increases in patent applications relative to its respective synthetic version. If this were the case, inspite of the fact that no intervention took place, such an outcome would indicate that the results illustrated in Figure 4 and 5 may be driven by other factors than the introduction of the emissions trading system. The results of the in-space placebo are displayed in Figure 7. The grey lines denote the estimated gaps between the control units in the donor pool and the corresponding counterfactual. The bold black line represents the gap between the treated and synthetic California. Figure 7a depicts the gaps for California and all 34 control states. The grey lines indicate that for some states in the donor pool the synthetic control method is unable to accurately replicate the path of green patent filings in the period before 2011. The states with the worst fit in the pre-intervention period are Michigan and Washington with a MSPE of 2.237 and 2.268, respectively. The two states exhibit a very large MSPE relative to the median MSPE among the 33 control states in the pre-intervention period with a value of 0.02. This demonstrates that for those states there is no combination of control units in the sample that will accurately replicate the path of patent filings before the treatment period.

Abadie et al. (2010) recommend the exclusion of control units with a high MSPE due to poor pre-treatment fit to achieve a meaningful comparison. In consequence, Figure 7b discards states with a MSPE equal or higher than four times the MSPE of California. Among the eighteen states remaining, the solid line from the main specification clearly stands out, depicting the largest increase in patent applications from 2011 onwards.

Further, the ratios of post/pre-2011 MSPE for California and all states in the donor pool are computed to evaluate the estimated gap in the main specification relative to the gaps of the states in the donor pool. The underlying assumption is that a large ratio is indicative of a casual effect from treatment. The ratios serve to illustrate the differences in the magnitude of the pre- and post-intervention gap for California relative to the gaps obtained in the placebo tests. This juxtaposition allows to calculate the probability of obtaining results of the magnitude of those obtained for California by measuring the fraction of control states with MSPE ratios larger than (or as large) as California (Abadie et al., 2010). Figure 8 shows that California differentiates itself notably from most of the 33 control states and exhibits the largest MSPE ratio among the observed states. That is, if one were to assign treatment at random, the probability of attaining a post/pre-intervention ratio this large is $1/34 = 2.94\%$. Thus, this ratio can be interpreted as

Figure 8: Post-/Pre-Intervention Ratios of the MSPE



the p-value at which the null hypothesis can be rejected.

For the leave-one-out placebo test, the six control states with a positive weight w_j are iteratively eliminated from the donor pool to examine whether the main results are sensitive to the exclusion of one donor pool state. The objective is to assess the extent to which the results in Section 3.2 are driven by any particular control unit. Thus, I re-estimate the model excluding at each iteration one of the six states used to construct the synthetic counterfactual, namely Washington, Hawaii, Idaho, Michigan, Texas and Virginia. Figure 9 displays the results of the placebo test.

As can be seen from the figure, eliminating Michigan deteriorates the pre-treatment fit. A potential explanation for this outcome can be found in Table 4 which presents the detailed results of the placebo test. When omitting Michigan, the synthetic control assigns a high weight to the state of Minnesota which is not present in the baseline estimation. This impairs the predictive ability of the model (MSPE of 0.034) and the magnitude of the estimated effect is likely overestimated (29%). The remaining leave-one-out estimations yield good fits. Further, the obtained state weights assigned to the donor pool are comparable to those in the main specification. This suggests that the leave-one-out estimates are robust to changes in the synthetic control state weights. The elimination of Washington, Idaho, Hawaii, Texas and Virginia provides us with a range for the estimated treatment effect, from an average increase in green patent filings of 17.1% (for the elimination of Washington) to 24.7% (for the elimination of Idaho).

Figure 9: Green Patent Filings: Leave-One-Out Placebo Test

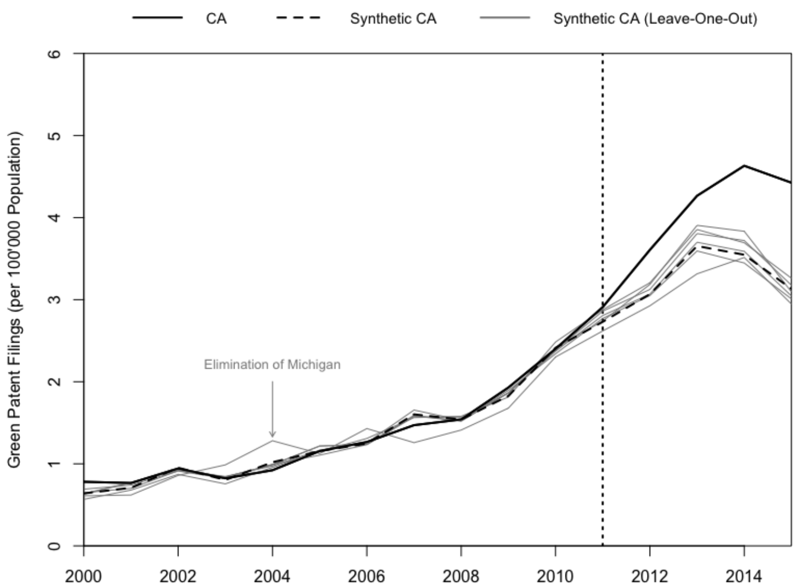


Table 4: State Weights from the Leave-One-Out Placebo Test

	Washington	Hawaii	Idaho	Michigan	Texas	Virginia
Alabama	0.000	0.000	0.000	0.000	0.000	0.000
Alaska	0.000	0.000	0.000	0.000	0.000	0.000
Arkansas	0.000	0.000	0.000	0.000	0.000	0.000
Colorado	0.000	0.000	0.000	0.000	0.000	0.349
Washington	—	0.067	0.100	0.090	0.075	0.052
Florida	0.000	0.000	0.000	0.000	0.000	0.000
Georgia	0.000	0.000	0.000	0.000	0.000	0.000
Hawaii	0.000	—	0.000	0.000	0.032	0.071
Idaho	0.126	0.047	—	0.179	0.035	0.001
Illinois	0.000	0.000	0.000	0.000	0.000	0.000
Iowa	0.000	0.000	0.000	0.000	0.000	0.000
Indiana	0.146	0.000	0.000	0.000	0.000	0.000
Kansas	0.335	0.000	0.000	0.000	0.000	0.000
Kentucky	0.000	0.000	0.000	0.000	0.000	0.000
Louisiana	0.000	0.000	0.000	0.000	0.000	0.000
Michigan	0.317	0.316	0.302	—	0.327	0.241
Minnesota	0.103	0.000	0.001	0.600	0.000	0.045
Mississippi	0.000	0.000	0.000	0.000	0.000	0.000
Nebraska	0.000	0.000	0.000	0.000	0.000	0.000
Nevada	0.000	0.241	0.000	0.000	0.242	0.000
North Carolina	0.000	0.000	0.000	0.000	0.000	0.000
North Dakota	0.000	0.000	0.143	0.000	0.000	0.000
Ohio	0.000	0.000	0.000	0.000	0.000	0.000
Oklahoma	0.000	0.000	0.000	0.000	0.000	0.000
Pennsylvania	0.000	0.000	0.000	0.000	0.000	0.000
South Carolina	0.000	0.000	0.000	0.000	0.000	0.000
South Dakota	0.000	0.000	0.000	0.000	0.000	0.000
Tennessee	0.000	0.000	0.000	0.000	0.000	0.000
Texas	0.000	0.127	0.115	0.131	—	0.241
Virginia	0.455	0.201	0.337	0.000	0.288	—
West Virginia	0.000	0.000	0.000	0.000	0.000	0.000
Wisconsin	0.000	0.000	0.000	0.000	0.000	0.000
Wyoming	0.000	0.000	0.000	0.000	0.000	0.000
Estimated Effect	17.1%	18.6%	24.7%	29.0%	22.2%	18.5%
MSPE	0.009	0.004	0.006	0.034	0.005	0.003

I undertake several further sensitivity checks to examine the validity of the synthetic control estimates. In a first step, I extend the donor pool to include all US states. The resulting synthetic control estimates presented in Figure A.1 produce a fairly similar outcome. As can be seen in the figure, the path and gap plot are comparable to those obtained in the baseline specification. Note that the inclusion of the full sample changes the assigned weights considerably. Nevertheless, the treatment effect is not significantly affected.

In a second step, I assess the initial donor pool selection. The main criterion for dropping WCI and RRGI states is to avoid the inclusion of units that adopted similar policy changes during the sample period. To reproduce the estimation with changes to the donor pool, I re-run the estimation by including the six states initially discarded due to the WCI membership when constructing the counterfactual. Subsequently, I re-run the estimation by expanding the initial donor pool to include the the member states of the RGGI. The results are presented in Figure A.2 and A.3, respectively.

The inclusion of the WCI leads to a poor pre-treatment match indicating that there is no weighted average of untreated units in the donor pool that can approximate the pre-treatment trajectory of the outcome variable for the treated unit due to the high value assigned to the state of Washington. In contrast, the re-estimation with the RGGI produces a very similar outcome as the baseline results despite a notable change in the distribution of state weights. This suggests that in the case of a good pre-treatment fit, the main results are fairly robust to the undertaken modifications in the donor pool which is an encouraging finding, as it indicates that the counterfactual outcome trajectory is not dependent on a particular combination of states.

As a final robustness check, I re-run the baseline model using a data set constructed by employing a different green patent classification system to ensure that the results do not depend on the chosen classification system. The reason for this lies in the fact that the identification of patents related to environmentally-sound technologies is not flawless. Filter-approaches for identifying green patent documents on the basis of classification systems such as WIPO's IPC Green Inventory present certain challenges. Veefkind et al. (2012) characterize the main disadvantages related to the usage of patent filters by two categories: Type I and Type II errors. The former refers to the erroneous inclusion of patent applications that are not related to green technologies. The latter refers to the failure of capturing all relevant patents, which leads to incomplete results.

Due to the susceptibility to Type I and Type II errors, data sets can differ greatly depending on the patent classification systems used for the identification of relevant patents. To evaluate whether the results are robust to other classification systems, the analysis is repeated using green patent applications as identified by the Cooperative Patent Classification (CPC).[22] The results of the robustness check can be found in Appendix A.1.2, Figure A.4 illustrating a similar gap in green patent filings as shown in Figure 5.

[22]The CPC is an extension of the IPC, a jointly developed system by the European Patent Office (EPO) and the USPTO. The classification system contains 250'000 classification symbols including a Y02 tagging scheme corresponding to "technologies or applications for mitigation or adaptation against climate change" (EPO, 2003).

In any case, the placebo tests and the sensitivity analysis to the choice of donor pool states and classification system provide evidence that the main results are not driven by the selection of specific control units.

4 Discussion

The empirical analysis of this paper sheds light on the relationship between environmental innovation and regional climate policy. Overall, I find that the introduction of the Cap-and-Trade system resulted in an increase in the annual number of successful patent filings related to environmentally-friendly technologies over the 2011–2015 period. On the basis of these results, it can be concluded that the introduction of the program spurred eco-innovation in California. Further, I find that the anticipation of the regional Cap-and-Trade program has triggered environmental patent production before the implementation in 2013. The increase in patent filings from 2011 onwards corresponds to the idea that an enhancement in innovative activities precede the compliance obligation due to the anticipation of legislation. This result is consistent with previous studies which drew a similar conclusion in regards to the anticipation of policy interventions (Barbieri 2015; Taylor et al. 2003). Consequently, this finding indicates that even anticipated environmental regulations can affect the nature of technological progress.

There are a few key limitations that need to be addressed. First, as the program was only recently introduced, it is not feasible to take a long-term perspective. Data constraints further restrict the observation period. Thus, a longer temporal perspective is needed considering that previous research on the effects of emissions trading schemes unearths evidence that the innovation inducement effect is confined to early years of the trading scheme Taylor (2012). Second, as mentioned in Section 1, patents are imperfect measure of innovative output. Thus, while a patent analysis provides an adequate approximation of innovative output, it is important to be aware of the drawbacks of patent counts as indicators of innovative activity. Along with this, there is the probability of incurring Type I or Type II errors when using patent filters such as the IPC or CPC for the retrieval of green patent documents. Therefore, one should be careful when interpreting the estimated magnitude of the effect on innovative activity found in this paper. In a similar vain, one must bear in mind that the validity of the synthetic control estimator depends on whether the contextual and data requirements are met. A specific concern is that the synthetic control method precludes the possibility of spillover effects. In cases where spillovers are present, i.e. the outcomes of control units are affected by the treatment, the estimate of the counterfactual outcome may be biased. In the present case, however, it may be assumed that the introduction of the policy intervention did not lead to spillovers as the cap only covers industries located in California. Given that businesses which are not affected by the regulation are not incentivised to undertake innovative activity, the assumption is met in the empirical application at hand. Last, the isolation of the Cap-and-Trade effect is hampered by the large number of climate mitigation policies implemented in California. Nevertheless, the analysis on a sectorial level indicates that the treatment effect can be attributed to the implementation of the Cap-and-Trade program (see Appendix A.2).

While this study explores the policy-inducement effect on innovation, it falls short in addressing further advantages and disadvantages associated with the program. Other variables must be taken into consideration when choosing among valid policy instruments. This includes, inter alia, administrative costs and complexity, total abatement costs as well as government revenues. The key advantage of the Cap-and-Trade lies in the ability of setting specific emission targets that provide a persistent incentive to reduce carbon levels over time through a declining cap. However, even though a Cap-and-Trade system can generate revenue (assuming allowances are auctioned), the implementation is associated with high cost. Additionally, the system is more complex and the implementation process takes longer than other policy instruments such as the carbon tax. In brief, governments have various instruments at their disposal to achieve emission reductions. The policy instrument choice involves weighing the advantages and disadvantages of each instrument. Ultimately, identifying the most suitable instrument depends on the characteristics of the region concerned and the actors involved.

5 Conclusion

Due to the ability to induce innovative activity, environmental policy not only affects the quality of the environment today, but also impacts the nature of technological progress. In consideration of the upcoming challenges posed by climate change, many states implement policies to promote the investment in greener technological development. Understanding the potential of policy instruments to influence the rate and direction with which knowledge is produced is crucial to guide policy makers towards instruments that induce advances in environmental or energy-efficient technologies.

California‘s Cap-and-Trade program adopted in 2011 is aimed at reducing GHG emissions throughout the state as well as creating an economic incentive for investments in cleaner, more efficient technologies. The present paper empirically investigated the program's effect on the development of environmentally-friendly technologies during the four years subsequent to its passage. The results of the synthetic control approach imply that, at least in the short-term, the introduction of the emissions trading system increased the number of green patent filings originating from California. This result is robust to alternative specifications of the synthetic control method.

Thus, this paper provides evidence that the Cap-and-Trade program has had an impact on the environmental innovation activity in California, thereby bringing new insights into the relationship between regional climate policies and environmental innovation. It shows empirically that among the available options, the emissions trading instrument can serve as a framework for reducing emissions and be successful in significantly increasing environmentally-friendly technology.

From the mere point of view of environmentally-friendly innovation, the Cap-and-Trade program implemented by the state of California can be regarded as an effective climate change mitigation policy. Future research should further develop and validate these initial findings. Long-term effects of the emissions trading scheme need to be evaluated taking into account declines in the annual cap on the region's emissions. One feasible extension of the present analysis would be to include Canadian provinces seeing that California has formally linked its system with Québec and Ontario in 2014 and 2018, respectively. In addition, further efforts should be undertaken to separate the effect of the Cap-and-Trade on patent activity from other policy enactments.

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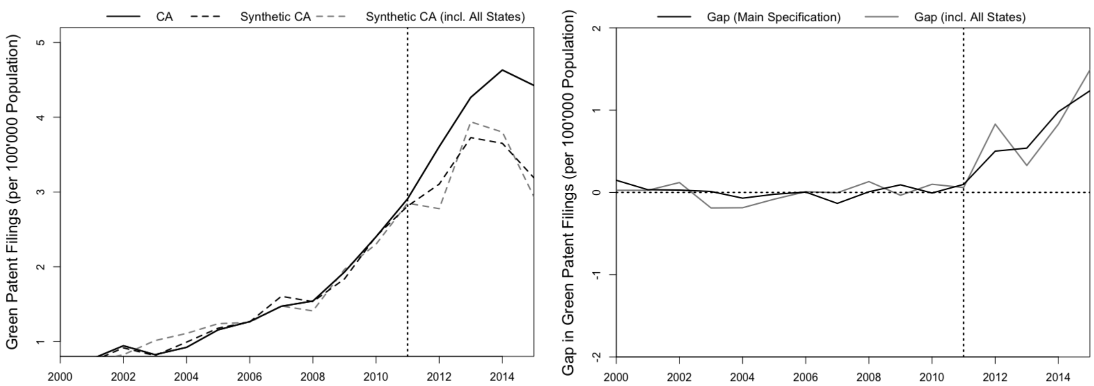
A Appendix

A.1 Further Robustness Checks

A.1.1 Choice of Donor Pool

For further robustness checks, modifications are made in terms of the donor pool from which the synthetic California is constructed. Predictor variables are chosen as for the main specification discussed in Section 2.2.[23] The corresponding weights of control units can be found in Table A.1.

Figure A.1: Robustness Check: Including All US States

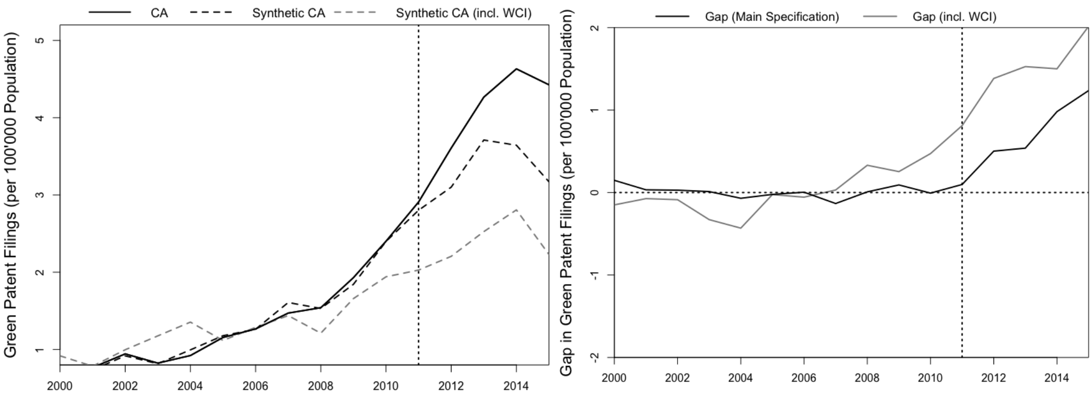


(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

[23]There is no data on R&D for the state of Minnesota in the year 2010. The NA value is ignored in the estimation.

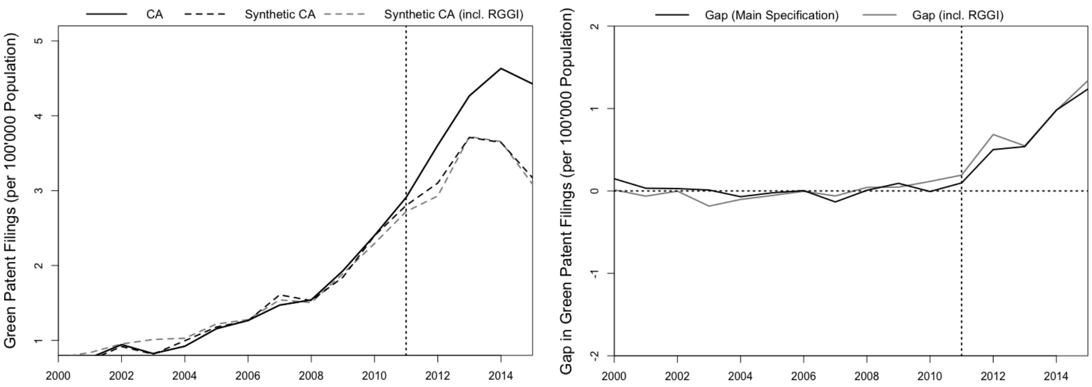
Figure A.2: Robustness Check: Including Former Members of the WCI in the Donor Pool



(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

Figure A.3: Robustness Check: Including Members of the RGGI in the Donor Pool



(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

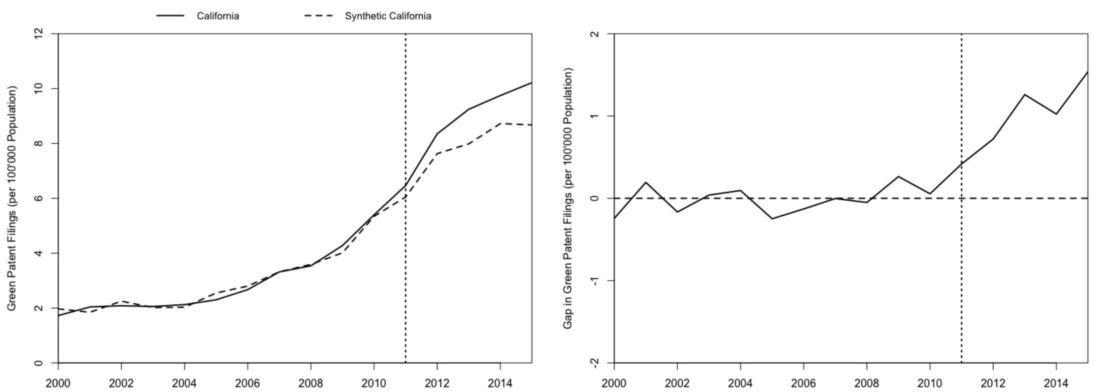
Table A.1: State Weights in Synthetic California (Robustness Checks)

	Weights		
State	Incl. All US States	Incl. WCI	Incl. RGGI
Alabama	0.001	0.000	0.000
Alaska	0.002	0.000	0.000
Arizona	0.001	0.000	—
Arkansas	0.001	0.000	0.000
Colorado	0.001	0.000	0.000
Connecticut	0.006	—	0.001
Delaware	0.061	—	0.000
District of Columbia	0.012	0.337	0.000
Florida	0.001	0.000	0.000
Georgia	0.001	0.000	0.000
Hawaii	0.00	0.117	0.000
Idaho	0.001	0.000	0.000
Illinois	0.001	0.000	0.000
Indiana	0.001	0.000	0.000
Iowa	0.001	0.000	0.000
Kansas	0.001	0.000	0.000
Kentucky	0.000	0.000	0.000
Louisiana	0.001	0.000	0.000
Maine	0.000	—	0.000
Maryland	0.099	—	0.279
Massachusetts	0.363	—	0.311
Michigan	0.001	0.000	0.155
Minnesota	0.001	0.000	0.000
Mississippi	0.000	0.000	0.000
Missouri	0.001	0.000	0.000
Montana	0.001	0.000	—
Nebraska	0.001	0.000	0.000
Nevada	0.056	0.000	0.107
New Hampshire	0.001	—	0.000
New Jersey	0.001	—	0.000
New Mexico	0.142	0.013	—
New York	0.001	—	0.000
North Carolina	0.001	0.000	0.000
North Dakota	0.001	0.109	0.000
Ohio	0.001	0.000	0.000
Oklahoma	0.001	0.000	0.000
Oregon	0.001	0.000	—
Pennsylvania	0.001	0.000	0.000
Rhode Island	0.001	—	0.000
South Carolina	0.001	0.000	0.000
South Dakota	0.001	0.001	0.000
Tennessee	0.001	0.000	0.000
Texas	0.231	0.000	0.146
Utah	0.001	0.000	—
Vermont	0.000	—	0.000
Virginia	0.001	0.000	0.000
Washington	0.000	0.422	—
West Virginia	0.000	0.000	0.000
Wisconsin	0.001	0.000	0.000
Wyomning	0.001	0.000	0.000

A.1.2 Choice of Patent Classification System

For the robustness check, I select all patents issued between 2000 and 2015 that pertain to the Y02 class and re-estimate the synthetic control model using the resulting data set. Figure A.4 reports the results of the estimation. It is evident that the CPC Y02-tags schema returns significantly more results than the Green Inventory. Nevertheless, the illustrations show that the number of green patent filings of California and its synthetic counterpart show a similar progression as those in the main specification.

Figure A.4: Robustness Check: Identifying Green Patents Using the CPC



(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

A.2 Disentangling the Effect of the Cap-and-Trade

The main critical issue in evaluating the impact of the Cap-and-Trade scheme is to isolate the effects of the program from other policy interventions. The isolation of the Cap-and-Trade effect is hampered by the large number of climate mitigation policies implemented in California. Thus, it has to be assessed whether the estimated differences in the outcome variable are mainly due to the intervention of interest. The previously conducted in-time placebo test where the treatment is shifted to 2006 resulted in no significant divergence in the trajectories. This placebo test provided evidence that the mere passing of the legislation had no perceivable effect on the number of green patent filings. There is a risk, however, that the results are biased because of GHG reduction measures in the AB 32 Scoping Plan approved in the years following its enactment. Pursuant to AB 32, the CARB has made endeavours to clean the air and curb the worst effects of climate change by implementing the Low Carbon Fuel Standard (LCFS) and the Advanced Clean Cars program taking effect in 2011 and 2012, respectively.[24] The programs were designed to reduce emissions stemming from transportation with an ultimate goal to improve vehicle technology and increase alternative transportation mobility options.

To assess whether the observed changes in outcomes can be attributed to the introduction of the Cap-and-Trade rather than to the closely coinciding fuel standards, the policy intervention is re-evaluated on a disaggregated sectorial level. For this purpose, I draw on the seven technological categories as presented in Appendix A.3, Table A.3. The organization of relevant patents into different subject areas permits the distinction of patents in EST related to transportation from those related to other technological fields. This, in turn, permits the individual categories to be analyzed separately. This approach is similar to empirical work by Barbieri (2015) who relies on patenting at the EPO in the Y02T category to analyse the impact of environmental regulation on environmental road transport technologies. The study finds that instruments such as post-tax fuel prices and environmental vehicle taxes positively influence technological development in this field.

The sectorial disaggregation starts on the premise that the confidence that the increase in green patent activity as estimated by the synthetic control reflects the effect of the Cap-and-Trade intervention would disappear if the increase is mostly concentrated in the transportation sector. Similar or larger estimates arising in other sectors would confirm the validity of the empirical results. For patents from industries not covered by the Cap-and-Trade, on the other hand, one would expect no treatment effect.

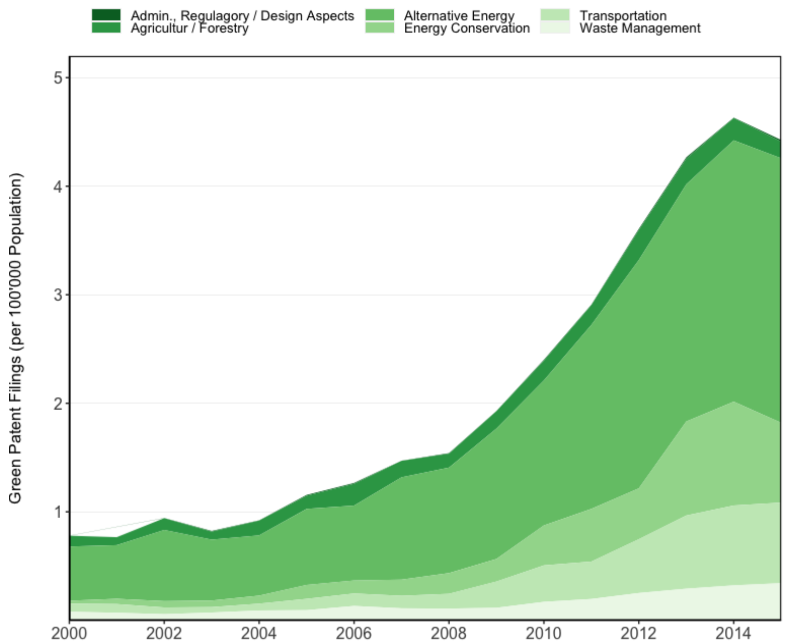
Figure A.5 depicts the distribution of patenting activity in California across the seven technology categories for the period 2000–2015 as captured by the Green Inventory.[25] No-

[24] The dominant theory of environmental policy states that general command-and-control instruments (e.g. emission standards) do not set innovation incentives given their nature (Downing & White, 1986; Jaffe & Stavins 1995; Milliman & Prince 1989). Based on this presumption, it would be reasonable to assume that businesses to which the two standards set by the CARB are applicable are not incentivized to pursue innovation. This in turn would suggest that the treatment effect can be fully ascribed to the introduction of the Cap-and-Trade. Despite this presumption, the issue merits further examination.

[25] Nuclear Energy Generation is not represented in the graph, as no patents were found for this category in the data set.

tably, over the whole period 2000–2015 patents related to alternative energy production represent the largest share of patent filings. This can most likely be explained by the growing interest in technological advancements in this field such as solar, wind and hydro power since the late 1990s (WIPO, 2009). By contrast, the category in which the fewest patents have been filed is related to administrative, regulatory or design aspects and represented by the thin outer line of the color scheme. As illustrated in the figure, patent activity across all categories grew over the observed period, albeit at different rates.

Figure A.5: Green Patent Filings in California by Technological Area, 2000–2015



For the disaggregated analysis, I decompose the data set according to this classification and set up the following model:

$$y_{it} = \beta_0 + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 Treated_i \times Post_t + \beta_4 X_{it} + \varepsilon_{it} \qquad (4)$$

where y_{it} is the dependent variable indicating the number of green patent filings per 100'000 population for state i at time t. $Treated_i$ is a dummy variable indicating the exposed state. The variable is equal to one if state i is exposed to the treatment and equal to zero otherwise. Similarly, $Post_t$ is an indicator variable for time t after the policy change and is equal to one if the observation occurs after the policy change and equal to zero in the previous periods. Thus, the interaction term $Treated_i \times Post_t$ equals one for observations that are in the exposed state after the policy intervention. The corresponding estimated coefficient β_3 represents the net effect of the emissions trading policy on green patent filings for the exposed state in the post-intervention period. X_{it} represents the control variables as specified in the main analysis and ε_{it} is the error term. The number of observations N is given by the number of states $i = 1, ..., J+1$ times the number of observed time periods.

For each subset, I analyze the effects of the treatment separately. Consequently, the DiD is applied to each subset to evaluate the effect of the policy on each technological area.[26] The regression results are presented in Table A.2.

For patents relating to the technological area administrative, regulatory or design aspects as well as agriculture/forestry, the interaction term is insignificant at a 5% level. This suggests that patent activity in those areas is not affected by the policy change and therefore exhibits no treatment effect. Further, although for patents relating to waste management the coefficient is significant at a 10% level, the sign of the coefficient is negative, indicating no increase in patents relating to waste management after the introduction of the emission trading system. This is in line with the statistical expectation, as the initial cap does not directly cover agricultural and forestry nor waste management sources of emissions (ICAP, 2020).

The third and fourth columns in Table A.2 the coefficients of the interaction term are significantly positive, which suggests that the policy intervention stimulated innovation in these technological areas. These results indicate that the treatment effect found in Figure 4 is at least partially driven by an increase in patent filings relating to alternative energy technologies and energy conservation. For patents relating to transportation, however, the interaction coefficient is not significant. In other words, patent activity related to transportation is not significantly affected by the policy change, which is consistent with the presumption that the results of the main specification are not related to the the vehicle emission standards. As mentioned above, the cap coverage expanded to transportation fuels only at the beginning of the second compliance period in 2015. This may have delayed the incentive to improve transportation technologies, whereby the anticipatory effects on

[26]Disaggregated analysis on patents related to nuclear power generation is unfeasible due to lack of patents in this area.

innovation set in later for the particular technological area.

In the last column, I run the same regression model for the entire data set. The obtained DiD estimates of the average treatment effect are positive and statistically significant at a 5% level. According to the model estimates, the policy change leads to an estimated average increase in environmentally-friendly patent filings of 0.849 (per 100'000 population).
The treatment effect as estimated using the synthetic control method corresponds the an average annual increase in patent filings by approximately 0.74 patent filings per 100'000 population.[27] Thus, the estimated average treatment effects obtained by the DiD present plausible magnitudes. Note, however, that the estimates obtained by DiD are larger than the SCM estimate. This difference in the estimated treatment effects may be attributable to the violation of the parallel trends assumption.

In a nutshell, the results of the DiD are consistent with the theoretical impact of the Cap-and-Trade on California's green patent output. Although additional positive impacts from the LCFS and the Advanced Clean Cars program can not be fully ruled out, the results suggest that the standards are not the driving forces in the increase of environmentally-friendly patents in California.

[27] The average treatment effect is computed as $\frac{1}{T-T_0} = \sum_{t>T_0} Y_{1t}^I - \hat{Y}_{1t}^N$

Table A.2: Difference-in-Differences Regression Estimates

	Admin., Regulatory / Design Aspects	Agriculture / Forestry	Alternative Energy	Energy Conser- vation	Transpor- tation	Waste	Total
Treated × Post	−0.003	0.014	0.750***	0.237**	0.020	−0.172*	0.849***
	(0.002)	(0.047)	(0.078)	(0.060)	(0.204)	(0.098)	(0.314)
Treated	−0.002	−0.008	0.068	−0.157**	−0.616*	−0.456***	−1.172**
	(0.005)	(0.032)	(0.108)	(0.076)	(0.345)	(0.176)	(0.512)
Post	0.006	−0.050**	0.056	0.103**	0.203***	0.068*	0.386***
	(0.005)	(0.020)	(0.063)	(0.031)	(0.070)	(0.040)	(0.125)
ln GDP per Capita	0.017**	0.090***	0.230	−0.047	0.177*	0.408***	0.874**
	(0.008)	(0.024)	(0.175)	(0.066)	(0.107)	(0.157)	(0.373)
GDP Growth (1-year lag)	−0.001*	−0.001	0.005	0.005	0.007	0.007	0.022
	(0.001)	(0.002)	(0.008)	(0.004)	(0.006)	(0.006)	(0.019)
Total Energy Average Price	0.001	−0.002	−0.020**	−0.004	0.001	−0.020**	−0.046**
	(0.001)	(0.002)	(0.009)	(0.005)	(0.006)	(0.008)	(0.020)
R&D expenditure (% of GDP, 1-year lag)	0.003	0.026***	0.238***	0.318*	0.127***	0.189**	0.852***
	(0.002)	(0.006)	(0.057)	(0.039)	(0.165)	(0.080)	(0.243)
Exports (% of GDP)	−0.0001	0.0001	−0.014*	−0.007**	0.009	0.004	−0.008
	(0.002)	(0.001)	(0.008)	(0.003)	(0.007)	(0.007)	(0.015)
High SET Establishments	−0.002	0.012***	0.022	0.012**	0.002	0.003	0.048
	(0.001)	(0.003)	(0.021)	(0.005)	(0.010)	(0.015)	(0.030)
Employment in High SET (% of Total)	0.001	−0.008***	−0.034***	−0.012*	−0.031	−0.013	−0.098***
	(0.001)	(0.002)	(0.013)	(0.006)	(0.021)	(0.013)	(0.036)
S&E BA Degrees (3-year lag)	0.00003	0.007***	0.013**	−0.004*	−0.017*	−0.015**	−0.016
	(0.0004)	(0.001)	(0.005)	(0.002)	(0.009)	(0.006)	(0.016)
Constant	−0.059	−0.346***	−0.299	0.334	−0.595	−0.981**	−1.939**
	(0.037)	(0.082)	(0.490)	(0.252)	(0.391)	(0.496)	(0.832)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	377	442	442	442	442	442	442
Period	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015
Adjusted R^2	0.065	0.582	0.573	0.448	0.349	0.440	0.677

Notes: Heteroskedasticity-consistent standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01. Patent applications relating to administrative, regulatory or design aspects were only found for 45 states resulting in a lower number of observations in the first column. No patents related to that technological area were found in Arkansas, Hawaii, Mississippi, Vermont, West Virginia and Wyoming.

A.3 IPC Green Inventory

Table A.3: Topics of WIPO's Green Inventory (WIPO, 2020)

Topic	Sub-Topic
Administrative, Regulatory or Design Aspects	Commuting (e.g. High-occupancy vehicle lanes, teleworking, etc.); Carbon / emissions trading (e.g. pollution credits); Static structure design
Alternative Energy Production	Bio-fuels; Integrated gasification combined cycle; Fuel cells; Pyrolysis or gasification of biomass; Harnessing energy from manmade waste; Hydro energy; Ocean thermal energy conversion; Wind energy; Solar energy; Geothermal energy; Other production or use of heat, not derived from combustion (e.g. natural heat); Using waste heat; Devices for producing mechanical power from muscle energy
Agriculture/ Forestry	Forestry techniques; Alternative irrigation techniques; Pesticide alternatives; Soil improvement
Energy Conservation	Storage of electrical energy; Power supply circuitry; Measurement of electricity consumption; Storage of thermal energy; Low energy lighting; Thermal building insulation, in general; Recovering mechanical energy
Nuclear Power Generation	Nuclear engineering; Gas turbine power plants using heat source of nuclear origin
Transportation	Vehicles in general; Vehicles other than rail vehicles; Rail vehicles; Marine vessel propulsion; Cosmonautic vehicles using solar energy
Waste Management	Waste disposal; Treatment of waste; Consuming waste by combustion; Reuse of waste materials; Pollution control

A.4 Data Sources

Table A.4: Data Sources

Variable	Measured in	Source
Employment in High SET Establishments	Percentage of Total Employment	US Census Bureau
Available at: `https://ncses.nsf.gov/indicators/states/indicator/high-set-employment-to-total-employment`		
Exports (Total Merchandise)	Percentage of GDP	Foreign Trade Division, U.S. Census Bureau
Available at: `http://tse.export.gov/tse/`		
GDP per Capita	Thousands of 2020 USD	US Bureau of Economic Analysis
Available at: `https://www.bea.gov/data/gdp/gdp-state`		
High SET Establishments	Percentage of All Business Establishments	US Census Bureau
Available at: `https://ncses.nsf.gov/indicators/states/indicator/high-set-to-all-business-establishments`		
Patent Data	Citation-Weighted Count	United States Patent and Trademark Office
Available at: `https://www.patentsview.org/download/`		
Real GDP growth (1-year lagged)	Percent change from preceding period	US Bureau of Economic Analysis
Available at: `https://www.bea.gov/data/gdp/gdp-state`		
R&D performed	(% of GDP)	National Center for Science and Engineering Statistics
Available at: `https://ncses.nsf.gov/indicators/states/indicator/rd-performance-to-state-gdp`		
S&E BA Degrees (3-years lagged)	Per 1'000 Individuals 18–24 Years Old	US Department of Education
Available at: `https://ncses.nsf.gov/indicators/states/indicator/se-bachelors-degrees-per-1000-18-24-year-olds`		
State Population Estimates	Count	US Census Bureau
Available at: `https://www.census.gov/programs-surveys/popest.html`		
Total Energy Average Price	2020 USD per Million Btu	US Energy Information Administration
Available at: `https://www.eia.gov/state/seds/seds-data-complete.php?sid=US`		

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