The effect of the California cap-and-trade on green innovation

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Abstract

Current environmental policies have not performed effectively enough to mitigate climate change. Continuous evaluation of economic policy is imperative to close the gap between projected emission reductions and actual performance. This study examines California cap-and-trade, a market-based policy aiming to reduce emissions of heavy emitting firms in California. It evaluates its effects on green technological innovation – an important driver of green technological growth and decreased emission intensity. Doing this, it uses green technology patents as a proxy for green innovation, and applies a Synthetic Control Method (SCM) which creates a counterfactual outcome of California by a combination of other US states. The findings of this thesis suggest that the California cap-and-trade has significantly enhanced green innovation in California, compared with its synthetic counterfactual. However, the effect is merely short-term, which points out the importance of policy makers' consideration of temporal dynamics of outcomes to ensure optimal policy effect. This requires continuous evaluation of the California cap-and-trade, to realize proper stringency and effectiveness in inducing green innovation. If doing so, cap-and-trade policy may be considered an efficient environmental policy in mitigating climate change and helping achieve long-term sustainability.

Keywords: Green innovation, California cap-and-trade, policy evaluation, green technology patents, directed technological change, synthetic control method

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Abbreviations

SCM	Synthetic Control Method
CPC	Cooperative Patent Classification
USPTO	United States Patent and Trademark Office
DTC	Directed Technological Change
IPCC	Intergovernmental Panel on Climate Change
EPO	European Patent Office
EU ETS	European Emissions Trading Scheme
DiD	Difference in differences

1. Introduction

Environmental regulatory frameworks have been insufficient in mitigating climate change, and a 1.5°C temperature rise will likely be reached during the 21st century (IPCC 2023). There is a gap between projected emissions from implemented environmental policies and stated emission reduction efforts made by countries to achieve sustainable development. Consequently, unsustainable energy use, consumption, production, and lifestyles of humans have brought a 1.1°C temperature rise above 1859–1900 levels in the period of 2011–2020. Thus, it is imperative to undertake further actions of implementation and improvement of environmental regulatory frameworks, to effectively reduce emissions. These frameworks should encompass economic policies, financial incentives, or other regulations. Moreover, as stated by Acemoglu et al. (2012) in the economic theory of Directed Technological Change (DTC), an important outcome of environmental policy is to stimulate green technological growth, to increase effectiveness in producers and making them less emission intensive. This is imperative to enable decreased emissions from production processes and achieve long-term sustainable growth. This points out the relevance of continuous evaluation and improvement of ongoing climate policies, to ensure its effectiveness in steering the rate and direction of green technological change. Such regulatory framework includes cap-and-trade policy, an often applied market-based economic program that sets a cap on the allowed quantity of emissions for heavy-emitting firms (Shammin & Bullard 2009).

As green technological growth is prompted by innovation, this thesis will assess the effect of cap-and-trade policy on innovation for green technology. Doing this, it will assess the California cap-and-trade, the largest cap-and-trade policy in America and the fourth greatest cap-and-trade policy in the world (C2ES n.d.). Specifically, this thesis aims to assess the effect of the California cap-and-trade on green technology patents in California. The thesis answer the following research question:

"How has the California cap-and-trade affected green technology patents in California?"

By addressing the research question, this study contributes with enhanced understanding of the effectiveness of cap-and-trade policies in stimulating innovation for green technological growth. Consequently, it provides insights into the policy's efficacy in achieving long-term sustainability goals.

The California cap-and-trade was implemented 2013 in California and covers approximately 450 heavy-emitting firms, responsible for 85% of California's total greenhouse gas emissions (C2ES n.d.). Emission allowances may be traded on a market for allowances, where supply and demand determine an emission allowance price (Shammin & Bullard 2009). The California cap-and-trade is selected for assessment in this thesis due to it being a key element of California's strategy to reduce emissions. Moreover, its effects are confined exclusively in California, making it feasible to assess and compare with other economies. Additionally, other states within the United States may serve as homogenous comparison units to evaluate policy effects. Doing this, the study applies the synthetic control method (SCM) which creates a synthetic counterfactual outcome of California by the combination of other US states. This enables a comparison between California and the counterfactual outcome, to assess the potential effects on green innovation following the introduction of the policy.

The theory of Porter Hypothesis created by Porter (1991), and of DTC created by Acemoglu et al. (2012), suggests that environmental policy induce innovation in green technology. This affects the direction and rate of green technological change and thus improve competitiveness of regarded firms. However, previous studies have shown ambiguous results when assessing such outcomes, which underlines a need for further policy evaluation. For instance, Popp (2003) and Taylor (2012) assess the effect of the Clean Air Act (CAA) on green innovation, presenting varying results. Popp (2003) states a positive effect on innovation, whilst Taylor (2012) suggests a less noticeable effect, as the unclear and unbalanced market for allowances has resulted in decreasing effects on innovation. Similar findings are discovered regarding the European Emission Trading Scheme (EU ETS) cap-and-trade policy, as discussed by Calel & Dechezleprêtre (2016) and Calel (2020). Furthermore, assessment of the California cap-and-trade effect on green innovation has been sparse, with yet only one study approaching this. In a working paper, da Cruz (2022) finds a positive effect of the California cap-and-trade on green innovation. However, a single study with a limited timeframe of assessment is insufficient to determine conclusive findings, and further evaluation of the policy is needed.

Overall, there have been varied findings when assessing the effect of cap-and-trade policy on green innovation, and sparse evaluation of the California cap-and-trade specifically. Nonetheless, considering the theory of DTC and the Porter Hypothesis, the California cap-and-trade have most likely had an inducing effect on green technology patents. This thesis presents an assessment of a longer time-period than previously provided, contributing significantly with additional knowledge about the temporal dynamics of the effects of the California cap-and-trade. Furthermore, it contributes with insights to the literature regarding the effect of market-based policy on green innovation. Specifically, it contributes with deeper knowledge about the inducing effect of the California cap-and-trade on green technology patents. The results of the study indicate that there has been a short-term positive effect of the California cap-and-trade on green innovation. This indicates that cap-and-trade policy may have an inducing effect on green innovation, however policy makers need to take temporal variations of outcomes into consideration to achieve optimal policy effect. If doing so, implementation of cap-and-trade policy may be an effective strategy to achieve long-term advances in green technological change and mitigate climate change.

This thesis is structured as follows. Section 2 describes the background of the California cap-and-trade, as well as other environmental policies in California. Section 3 reviews and discusses previous literature of cap-and-trade policy and green innovation. Section 4 describes what fundamental economic theory the testable hypothesis and empirical analysis of this thesis builds upon. Section 5 describes the methodological framework and data applied in the study. Section 6 presents the results from the empirical assessment. Section 7 discusses the results of the study. Section 8 summarizes the key findings and presents the fundamental implications and conclusions made from the study.

2. Background

2.1 California cap-and-trade

The California cap-and-trade is a market-based regulatory framework aiming to reduce greenhouse gas emissions and mitigate climate change in California (C2ES n.d.). The policy was implemented in 2013 and the California Air Resources Board (CARB) adopted final regulations of the law of the California cap-and-trade in 2011 (Taylor 2012). The aim of the policy is to lower the greenhouse gas emissions to 1990-levels by 2020, 40% below 1990-levels by 2030, and 80% below 1990-levels by 2050 (C2ES n.d.). California also aims to reach 100% carbon-free electricity by 2045 and economy-wide carbon neutrality by 2045. The California cap-and-trade program sets a cap on the total amount of emissions that various industries and producers may emit. The cap is gradually lowered each year to continue inciting participating firms to adjust their production towards less emission-intensity and decreased emissions. The firms affected by the program are thereby allocated a certain number of emission allowances which act as permits for emitting a specific quantity of greenhouse gases. Such allowances may either be purchased from the state or state-run auctions where companies can buy or sell allowances. Otherwise, they may opt to purchase emission offsets, which are credits earned by indirectly reducing emissions in other ways, for example by investing in renewable energy projects. If a firm does not require their full allowed share of emissions they may sell their permits on the trading market, creating a market-based regulation in which the demand and supply of permits determines the allowance price. As the allowance cap is gradually lowered, the decreased supply of allowances will, if the demand of permits is unchanged, result in an increased allowance price. Furthermore, if participating companies exceed their level of allowed emissions, heavy fines will be set.

The program was first applied on large industrial facilities and electrical power generators emitting 25 000 tons of carbon dioxide equivalents or more annually (CEPA 2015). In 2015, the program widened to also cover distributors of transports, natural gas, and other fuels that met the yearly 25 000 ton limit. The 2023 total sectorial shares of allocated allowances in the policy are presented in Table 1. The number of total allocations exclude any stored allowances from previous years.

Table 1. Summary of 2023 allowance allocation in tons of CO2 equivalents (CARB 2022).

	Total Allocation	Percentage share
Electrical Distribution Utilities	69 646 354	49.4%
Natural Gas Suppliers	35 987 704	25.5%
Total Industrial	34 614 621	24.5%
Other	830 889	0.6%
Total	141 079 568	100%

2.2 Other policies

Besides the cap-and-trade program, California has additional policies targeting greenhouse gas reductions, that have been active since the implementation of the cap-and-trade policy (Taylor et al. 2018). Such policies may also have exerted an effect on advancements of green innovation. The largest additional policies in California are The Short-Lived Climate Pollutants, the Renewable Portfolio Standard (RPS), a bulk of regulations targeting Energy Efficiency, the Low Carbon Fuel Standard (LCFS), the Vehicle-Related Programs, and the Vehicle Miles Traveled (VMT). Such incentive programs are indicated as important tools to improve California's low carbon future in various sectors. In the 2022 Scoping Plan Update the California Air Resource Board (n.d.) stated that some of these programs have performed better, such as the RPS and the LCFS, and others may not meet the expectations, such as the VMT. Since the California cap-and-trade is multisectoral, potential effects indicated by the results of this study may be partly mixed with the effects of other policies. There is a challenge to assess causality in effects of environmental policy and attribute changes in innovation or emissions to specific policies. However, as approximately 75% of the emissions covered by the California Cap-and-Trade are ascribed to electrical distribution utilities and natural gas suppliers, the effects of the cap-and-trade could be joint with the effects of alternative policies for increased energy efficiency.

3. Literature review

The evaluation of the California Cap-and-Trade and its impact on innovation has so far received limited attention in previous academic studies. In a recent study, da Cruz (2022), investigates the effect of the California Cap-and-Trade program on innovation, using the Synthetic Control Method (SCM). The paper uses the International Patent Classification (IPC) system to identify patents related to green technology and assess the potential effect of the policy on green innovation. The results of the study show that the number of patents related to green technologies increased significantly by 22.5% in California following the introduction of the policy, compared with the counterfactual outcome of synthetic California. Furthermore, the results show an increase in patenting activity in 2011, two years prior to actual policy treatment, which is discussed to be due to an anticipation effect. This eventuality agrees with the study of Barbieri (2015), which assess the effect of environmental policy on green patent activity. Barbieri (2015) find that assignees anticipates the introduction of regulatory instruments by filing patents before the effective implementation of regulations when legislation is announced. However, the study of da Cruz (2022) applies analysis on years 2000–2015 which gives merely three post-treatment years to assess any treatment effects. Such short time period is inadequate to assess mid-term or long-term policy effects of the California cap-and-trade. Thus, assessment of longer time period is needed to comprehend the prospective of the policy in achieving long-term sustainability. Furthermore, da Cruz (2022) applies averaging over the entire time period. This practice is questionable in the application of the SCM as it makes the model include predictor data of post-treatment years when averaging and estimating pre-treatment outcomes of synthetic California. This is controlled for in this thesis, which should provide less bias in results of the effect of the California cap-and-trade on green innovation.

The empirical assessments of market-based policy and its effect on innovation of green technology has so far been relatively sparse. Popp (2003) evaluates the important link between emission trading schemes and innovation. The study applies regression analyses to evaluate the changes in innovation in flue gas desulfurization units following the implementation of the Clean Air Act (CAA) in 1990. The CAA is a vast cap-and-trade policy made for greenhouse gas emissions such as sulfur dioxide, SO_2. The results of the study indicate that the outcomes of patenting changed following initiation of the policy. Also, the policy did not only seem to improve innovation in the regarding area, but the new innovations have also improved the efficiency of the technologies, in contrast to innovations prior to 1990. However, Taylor (2012) conduct an independent evaluation of the CAA cap-and-trade, yielding inconsistent findings compared to those of Popp (2003). The results suggest an overall less positive effect of the policy. The initiation of the program demonstrate a starting period with an overestimation of the compliance costs and value of allowances. When the price of allowances is subsequently lower than expected due to improved mitigating strategies from the emitters, many firms bank allowances and thereby change their future abatement approaches. Also, the study shows that the commercial innovation for climate change-mitigating technologies eventually decrease due to uncertain and unbalanced market of allowances. This uncertainty make it challenging for participating firms in the program to assess the allowance market and realize optimal financial investments.

In further assessment of the effects of cap-and-trade policy on innovation, Calel and Dechezleprêtre (2016) investigate the European Emissions Trading System (EU ETS). The study measures how the affected firms' innovation patterns change due to the trading program initiation in 2005. The study, using a comparison approach in a Difference-in-Difference (DiD) analysis, find indicators of a positive causal effect in the starting period of the EU ETS. Affected firms' patents in low-carbon technology increased by approximately 10%, without crowding out patenting activity for other technologies. They also find that the trading scheme did not affect innovation in other companies but those regulated. However, putting the increased innovation in relation to all registered patents in the European Patent Office (EPO) following 2005, the EU ETS account for merely a 1% increase of environmentally friendly patenting in total in Europe. This is probably due to the policy design of the EU ETS, targeting a limited group of firms with an overallocation of allowances in the starting trading phase of the program. Thus, even though the policy may have had a causal effect on the affected firms, the economy-wide effects on the direction and pace of green technological change is negligible. In a more recent study, Calel (2020) applies a DiD methodology to investigate the changes in innovation of cap-and-trade regulated British firms, to see any possible technical responses to the policy. The paper say that firms may respond to cap-and-trade programs either by adopting existing low-carbon technologies or by innovating new ones. Furthermore, the study found that firms already using low-carbon technologies are more prone to innovate further, whilst others may prefer adopting already existing technologies to comply with regulations. Some technologies may progress faster than others due to varying technological maturity in different sectors. The paper acknowledges that cap-and-trade policies can be an effective tool for reducing emissions and may also trigger further innovation in industries not covered by the policy.

As noted, there are ambiguous results in previous empirical studies regarding the effect of cap-and-trade policies on innovation. Several studies applies the DiD methodology to enable comparison when assessing the effect of cap-and-trade policies on innovation. This study will apply a SCM to create a counterfactual scenario when assessing the California Cap-and-Trade. This is due to several benefits of the SCM compared to the DiD, clearly motivated by Bueno and Valente (2019). They assess the effect of a unit pricing system on the disposal of municipal solid waste in Trento, Italy. The authors underline the benefits of the SCM by its performance in accounting for time-varying effects on unobservables, contrary to the conventional DiD approach. They emphasize the weakness of the DiD assumption of having parallel trends in the pre-treatment period, and thereby state a clear benefit in applying the SCM. Also, the SCM enables a reasonable comparison of the counterfactual outcome when there is unsatisfactory homogeneity in individual comparative regions. This agrees with the reality of the state of California, which is a unique state in the US in several macroeconomic aspects. This includes its economic size, high-technology industry, extensive trade, and environmental leadership (Budget & Policy Center 2022; BC n.d.; EDF n.d.), circumstances that motivate the use of the SCM before the DiD. Following the previous research of induced innovation (Popp 2002, 2003; Taylor 2012; Calel & Dechezleprêtre 2016; Calel 2020), green technology patents will be used as a proxy for measuring green innovation.

In conclusion, there has so far been few empirical evaluations of patent activity following the California Cap-and-Trade, and only one applying the SCM in the analysis. This thesis contributes to previous literature by further testing the inducement effect of the policy on innovation in green technology. Thereby, the findings of this study bring further understandings about the impacts of market-based policies on the rate and direction of technological change. Furthermore, it contributes significantly with additional assessment of the temporal variations in policy effects, as it provides the so far longest assessed time period of the California cap-and-trade. This bring additional knowledge to literature regarding the potential of the California cap-and-trade in mitigating climate change and achieving long-term sustainability.

4. Theory

This section describes what fundamental economic theory this thesis builds upon. These economic concepts are utilized to establish a testable hypothesis and lays the groundwork for the analysis of the empirical data.

4.1 The Porter Hypothesis

The view on environmental regulation and its effect on competitive advantages have been controversial. The Porter hypothesis argues against the dictated conflict between environmental protection and economic performance. The hypothesis says that even in a larger economy, strict environmental regulations may actually foster competitiveness (Porter 1991; Porter & van der Linde 1995). The arguments against environmental policy originates from the perception that it raises the costs and makes firms less competitive. Porter (1991) argues that this may be true, if everything stays the same except for the very expensive additional pollution-control equipment. However, this is not the case. Instead, environmental regulatory standards that target outcomes and not methods will encourage firms to change their technology. This is due to an increase in innovation and productivity that improves the returns of investments in technology, as pollution costs increase with regulation. The result of this is, in most cases, a production or process that pollutes less whilst achieving lowered costs or improved quality. Also, it may push companies towards innovation for a less emission-intensive or an increased resource-efficient production, which is highly valued internationally. However, not all companies are content with strict regulations as it increase short-term costs and require unsettling redesigns in products and processes (ibid). Also, industries competing with international actors are especially averse towards tough regulations even though meeting them would induce innovation, making the products more competitive. Porter (1991), as well as Porter and Van der Linde (1995), conclude that the negative mindset towards environmental regulation, and the argument that it simply leads to higher costs, must be discarded. Thus, the Porter hypothesis state that through innovation, environmental protection may benefit competitiveness if approached properly. Polluting firms can thus benefit from well-designed and stringent environmental policies, as it may stimulate innovations that in turn improve the productivity of firms or the product value for end users.

4.2 Directed Technological Change

The concept of Directed Technological Change (DTC) was formally introduced by Acemoglu (2002). Although it relates to the broader concept of the Porter Hypothesis, the theory of DTC focus on how policies and incentives can influence the direction of technological change towards more sustainable outcomes. For this, a theoretical framework is presented for analyzing DTC and how it can impact economic growth and welfare. Since then, the concept of DTC has been applied and expanded into various fields. In following work, Acemoglu et al. (2012) introduce endogenous and directed technological change in a growth model with environmental constraints. The authors state that environmental policy may have a significant impact on the direction of technological change. The framework specifically suggest that stringent environmental policies or regulations may encourage participating firms to invest in cleaner technologies, stimulating a rapid technological progress in the area. The theoretical model illustrate this idea by first stating the assumption that economic growth is driven by technological progress, increasing productivity. Moreover, this technological progress is driven by research and development (R&D) investments by companies, increasing the knowledge stock, which results in innovation. However, the direction of the technological progress may not only be determined by market forces alone but also affected by incentives and policies that affect investment strategies in certain types of technologies. The model shows that stringent environmental policies may incentivize firms to invest in cleaner technologies that reduce emissions and increase resource-efficiency. This is due to firms facing a trade-off between complying with environmental regulations and maintaining profitability. Cleaner technologies can help achieve these objectives simultaneously. The model further show that the quality of intellectual property rights (IPR) and the availability of R&D funding are important factors to determine the effectiveness of the environmental policy in driving green technological progress. Examples of IPR are patents, trademarks, or trade secrets. Effective IPR protection, such as green technology patents, is crucial for incentivizing firms to invest in R&D and thereby achieve green innovation, as it allows the firms to receive profits on their intellectual property. This in turn, may stimulate more innovation. These factors must be considered by policymakers when designing and implementing efficient environmental policies.

The original model of Acemoglu (2002) show that when the inputs of the production are sufficiently substitutable there can be long-run growth using temporary policy intervention. This is supported by a quantitative evaluation performed by Acemoglu et al. (2012) showing that, provided a sufficiently high elasticity of substitution between dirty and clean input factors, an immediate switch in R&D investments in clean technology should be observed following optimal policy regulation. This should then be followed by a gradual switch of all production towards clean input factors. Overall, the theory of DTC suggest that environmental policy may play an important role in shaping the direction of technological change, which should be considered by policymakers when designing optimal policies to address environmental challenges.

4.3 Testable hypothesis

Given the theory of DTC and the Porter hypothesis, a cap-and-trade policy like the California cap-and-trade should have a positive effect on innovation of green technology. However, underlying mechanisms following policy implementations may not be straightforward. If participating firms of the policy have high elasticity of substitution between dirty and clean input factors, it could be likely to observe an initial increase in green innovation followed by a decrease in the mid- or long-term perspective. This may be as, for high-elasticity firms, adoption of already existing green technologies is a faster and more cost-efficient solution to reduce emissions than research and development (R&D) investments for green innovation. This eventuality might ultimately buffer any initial inducing effect on innovation caused by the policy. However, this can vary depending on various factors, such as policy design, the extent of technological advancements, or market dynamics. Also, potential adoption of already existing technologies may not necessarily mean that green innovation will continually decline, as other factors related to policy, market forces, or demands might reignite the need for further innovation. Thus, it is precarious to determine the exact underlying mechanisms playing out following the implementation of the California cap-and-trade, based solely on theory. Such evaluation would require additional empirical examination that goes beyond the scope of this thesis. Nevertheless, based on the presented theoretical framework it is anticipated that the results of this thesis will show a significant positive effect of the California cap-and-trade policy on green innovation.

The research hypothesis of this thesis posits that the implementation of a cap-and-trade policy fosters innovation of green technology. Accordingly, the introduction of the California cap-and-trade will show a positive effect on the number of green technology patents in California.

5. Methodology

This section describes the applied methodology and utilized empirical data that estimate the effect of the California cap-and-trade on green innovation.

5.1 Synthetic Control Method

To assess the effect of the California cap-and-trade on green innovation this study applies the Synthetic Control Method (SCM), developed by Abadie and Gardeazabal (2003), Abadie et al. (2010), and Abadie et al. (2015). The SCM is a statistical technique that can be used to estimate causal effects of interventions or other treatments when a randomized control trial is not feasible or ethical. The method constructs a synthetic control group that represents the counterfactual situation, which shows what would have happened if the policy or intervention did not take place. This is done by combining information from several untreated control units that are similar to the treated unit in terms of pre-intervention patterns and other characteristics. The term "treated" and "untreated" refers to states exposed and not exposed to the intervention, respectively.

The SCM is depending on data availability on pre-intervention outcomes as well as homogeneity in the control units and the treated unit. An advantage of using SCM estimators compared with alternative methods is its transparency of model fit. Also, Abadie et al. (2015) argues, one of the greatest appeals of the SCM lies in its interpretability of the estimated counterfactuals. This is due to the weighted average nature of estimators and from the sparsity of unit weights. Another benefit of the SCM, in contrast to the often applied Difference-in-Differences (DiD) method, is its less restrictive assumptions of having parallel pre-treatment period trends. This is due to the DiD's assumption that the effects of unobserved variables are constant, whilst the SCM allows for these to vary over time. Furthermore, the SCM is refraining from extrapolation, in contrast to regression analyses. Extrapolation allows for estimation of predictors outside the support of data. While regressions uses extrapolation, which may estimate values beyond the range of known datapoints, the SCM applies interpolation, as well as ensuring weights to be nonnegative and summing to one. Interpolation is when the estimated weights are set between known data points, which may reduce any extrapolation biases. There are, however, contextual requirements under which the SCM is an appropriate tool for policy evaluation. This includes having units in the control group with similar pre-treatment periods as the treated group. This is important when constructing estimates in the pre-treatment period of the synthetic control group. If the units in the donor pool are dissimilar to the treated unit in the pre-treatment period, the interpolation may cause bias to the results. Therefore, only states with similar pre-treatment patterns in green technology patents are included in the donor pool. Furthermore, the treated unit must be unique, which means that the intervention must be set to a single unit only and not affect multiple units simultaneously.

5.1.1 The setting

This thesis is using the SCM setting defined by Abadie et al. (2015). Data is obtained for units $J+1: j = 1,2,\ldots,J+1$, which are the states of USA, where the first unit $(j = 1)$ is assumed to be the treated unit, California. The set of potential comparison units, which are other US states than California creating the donor pool, are $j = 2,\ldots,J+1$. This is formally a collection of untreated units not affected by the policy intervention. As California is the only state in USA covered by the cap-and-trade policy, states in the donor pool are consequently the untreated units. Also, the data spans over T periods where T_0 are the periods before the intervention. As the California cap-and-trade was implemented 2013, all years prior to 2013 are considered as time period T_0. For each unit, j, and time, t, the outcome of interest is observed, Y_{jt}. This is consequently the number of approved green technology patent applications made in each state for each year. Also, for each state, j, a set of k predictors of the outcome are observed, $X_{1j},\ldots,X_{kj}$. These are variables that predicts and explain the dynamics of green technology patents in the states. These predictors are unaffected by the California cap-and-trade policy. However, the set of explanatory variables may include a variable of pre-intervention values of Y_{jt}, green technology patents. The $k \times 1$ vectors $X_1,\ldots,X_{J+1}$ includes the values of the predictors for units $j = 1,\ldots,J+1$, respectively. For each unit, j, and time period, t, Y_{it}^N is defined to be the potential response without intervention. For the treated unit California, $j = 1$, in the post-intervention period, $t > T_0$, Y_{1t}^I is defined to be the outcome under the intervention of California cap-and-trade. The effect of the intervention for the treated unit in period t, where $t > T_0$, is therefore:

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

where Y_{1t}^N represents the synthetically created California, demonstrating the counterfactual outcome of the policy not being implemented in California. This shows the potential outcome of the intervention for California under the post-intervention period. Simply put, it shows how the green technology patents would have evolved in California in the absence of the California cap-and-trade policy.

The challenge with the SCM is to estimate Y_{1t}^{N} (Abadie et al. 2015). The equation allows for the temporal variability of treatment effects, acknowledging that intervention impacts may not be immediate and could fluctuate over time. This is a crucial consideration in treatment assessment.

A synthetic control is defined as a weighted average of the units in the donor pool (Abadie et al. 2015). This can be represented by a $J \times 1$ vector of weights, $W = (w_2, \ldots, w_{J+1})'$. Having a set of weights, W, the synthetic control estimators of the synthetic California, $Y_{1t,}^{N}$ and the treatment effect, τ_{1t}, are respectively:

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

and

$$\hat{\tau}_{1t} = Y_{1t} - \hat{Y}_{1t}^{N}$$

The weights are nonnegative and restricted to sum to one, so that the synthetic California is a weighted average of the states in the donor pool (Abadie et al. 2015). Weighted synthetic controls that sums to one are warranted only if the variables in the model are rescaled to adjust for differences in size between units. Therefore, the patent data in this thesis is presented as patents per 100 000 capita, as well as some explanatory variables are presented as per capita measures. Such corrections are not needed in variables where the data do not scale with size, as in prices.

The SCM uses a data driven process when formalizing the selection of comparison units (Abadie et al. 2015). This opens the door to quantitative inference for comparative case studies. To provide such inference in the SCM analysis it is possible to run placebo tests (Galiani & Quistorff 2017). The in-space placebo test is a technique used to assess the validity of a causal inference in a study that uses a specific intervention. The basic idea is to test whether the same statistical methodology applied to a placebo intervention, which is known to not have any causal effect, produces the same result as for the actual intervention. To perform an in-space placebo test, one would apply the same intervention, methodology, and analysis to a placebo population that is similar to the actual population but did not receive the actual intervention. In this thesis, this is done by in-space placebo estimates for the same treatment period but on all the other states in the donor pool. The inference, providing p-values, is given by comparing the estimated main effect of California with the distribution of placebo effects.

5.2 Data

The data consists of a panel dataset for all US states throughout years 1980–2019. The California Cap-and-Trade was enacted in 2013, which gives 33 pre-treatment years and six post-treatment years.

5.2.1 Patent data

The patent data is annual data gathered from the United States Patent and Trademark Office (USPTO) and covers year 1980-2019 (USPTO 2023b). The data applied in this thesis account for innovation by using patents registered in the Cooperative Patent Classification (CPC) system. The CPC system is jointly managed by the European Patent Office (EPO) and the USPTO (USPTO 2023a). It is sectioned into nine sectors, A-H and Y, which are in turn divided into classes, subclasses, groups, and sub-groups. This thesis measures green innovation by patents registered in the CPC class Y02. This class includes patents defined as technologies or applications for mitigation or adaptation against climate change. Those are technologies that reduce, control, or prevent anthropogenic emissions of greenhouse gases. It also cover technologies that allow for adaption to negative effects of climate change. One patent may be registered in several CPC classification groups or subgroups simultaneously due to diverse areas of utility or characteristics. Therefore, extensive cleaning of the datasets is completed to eliminate any duplicate patents causing double counting in the Y02 group.

To overview the changes of green innovation, an illustration of green technology patent filings, Y02, is presented in Figure 1. The figure show the trends of approved green patent applications in California and all other US states combined, respectively. The graph is presented as patents per 100 000 population to enable a comparison of patenting in the USA, considering the large differences in population sizes of US states. The figure indicate that the level and rate of green innovation has increased significantly in California throughout the sample period, compared with the rest of USA.

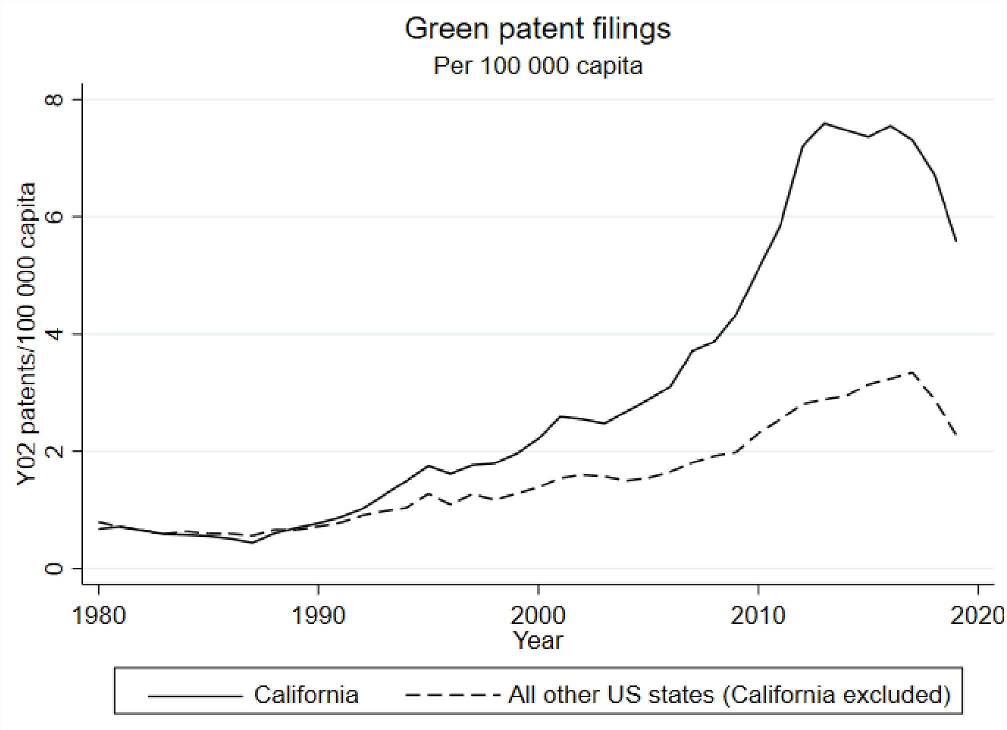

Figure 1. Applications of green technology patents per 100 000 capita, California versus all other US states (US Census Bureau 2023; USPTO 2023b).

The location of the patent is defined by its assignee, which is a person, company, or organization that has been assigned or transferred the legal right to use, sell or license the patent as an intellectual property (USPTO 2023c). Hence, the assignee is the party that receives ownership rights to the patent. If a patent has two or more assignees located in different states, the patent count is shared equally over those concerning states. The assignee may not necessarily be the original inventor of the patent, as a company may acquire a patent from an individual inventor in exchange for a single payment or other agreements. The designation of the origin of the patent play an important role to this study, as the inventors, applicants, and assignees may be located in different states. In this study, the assignees are considered to be the most relevant indicator of location of the innovation. This is for the reason that the assignee plays an important role in the intellectual property system, as they are highly affected by economic policies and therefore may initiate and commercialize innovation due to the California cap-and-trade. Only patents granted to American assignees is included in the data, since foreign inventors and firms are likely to be influenced by conditions not included in the applied data.

The timeframe 1980–2019 is settled due to data availability in patents and other explanatory variables during this time period. Patent applications are made public only when the patent is granted (USPTO 2023d). The average time-period from filing a patent application to approval in USA is approximately two years but may be longer, sometimes more than 10 years. Therefore, the dataset in this study reaches until 2019 even though data availability in patents is longer, to reduce the risk of bias in results. Additionally, this minimize any distortion effect from the Covid-19 pandemic.

5.2.2 Other data

Except for data of green technology patents, this study also includes data of explanatory variables for the synthetic California. This data creates explanatory variables to the model of Synthetic California and thereby describe the changes in green technology patents. The data of the explanatory variables cover all states of USA, with varying timeframes.

As stated by Abadie and Gardeazabal (2003) and Abadie et al. (2010), the inclusion of lagged outcomes in the model can help control for unobserved factors that affect both the treatment and control units over time. Therefore, it is suggested to include a lag of the outcome variable to improve the accuracy of the synthetic control and reducing the bias in the estimated treatment effect. Hence, a three-year lag of Y02 patents is included in the model, with data reaching over years 1983–2019.

Data of GDP per capita is included in millions of chained 2012 US dollars (BEA 2023). This data covers each state and range years 1998–2019. Furthermore, as research and development (R&D) investments may likely be a significant driver of innovation, a variable of R&D as percentage of GDP is included in the model (NCSES 2022b). This indicator represents to which extent R&D play a role in a state's economy, where a high value suggests that a state has a high intensity of R&D activity. The data refers to R&D activities conducted by federal and state agencies, universities, nonprofit organizations, or businesses, during years 1991–2019. A variable of state-agency R&D is also included in the dataset (NCSES 2022c). This is done to further include the perspective of a state's governmental efforts in boosting R&D by funding, which may positively affect innovation activities. This data represents the ratio of state agency R&D funding to the size of a state's economy, by the expenditures per $1 million of GDP, and reaches throughout years 2006–2019.

Data of employment in high Science, Engineering, and Technology (SET) establishments creates a variable that represents the extent to which a state's workforce are employed in industries with a high level of such occupations (NCSES 2019). High SET employment industries are defined as those with a proportion of SET occupations of at least twice as the average proportion for all industries. SET occupations includes scientific, engineering, and technical occupations with employees who possesses deep knowledge of theories and principles of science, engineering, and mathematics at a postsecondary level. The data reach throughout years 2003–2016. Also, data of bachelor's degree holders aged 25–44 is included to create a variable accounting for the research-intensity of the population (NCSES 2022a). The indicator shows the percentage of the early- to mid-career population with a bachelor's degree or higher, covering years 2005–2019.

As an attempt to account for the effect of other policies or regulations on green technology innovation, this study seek to include the data of scores of the State Energy Efficiency Scorecard in the analysis. The Energy Efficiency scorecard, created by the American Council for an Energy-Efficient Economy (ACEEE), is an annual report aiming to assess and rank the efforts and performance of energy efficiency measures in US states (ACEEE 2023). The scorecard evaluates and assign points to the states based on their performance in various policies and programs implemented across different sectors. This includes programs improving energy efficiency in buildings, transportation, industry, and utility sectors. It examines a wide range of factors, such as state-level energy efficiency policies, transportation policies, utility programs, building energy codes, appliance standards, and achieved energy savings. The states receive points in each category which are then aggregated to a sum score of maximum 50 points. In this thesis, this score is included in the dataset as a ratio for each state throughout years 2006–2019. The attempt of including the Energy Efficiency scorecard variable is an effort to separate the potential effect of other environmental policies from the California cap-and-trade. As California have had ambitious policy enactments for improving energy efficiency (CPUC 2021), its effects may otherwise be embedded in any treatment effect indicated by the results in this study.

5.3 Model

In accordance with Abadie et al. (2010), the optimal model in this thesis has been created with explanatory variables, by the systematical testing of various model constellations and covariate adjustments. The choice of the best combination of explanatory variables have been done by using indicators of pre-treatment model fit, measures of covariate balance and optimal covariate weights. Such indicators are all provided by the SCM code in Stata (Galiani & Quistorff 2017; Peri & Yasenov 2019; Yan & Chen 2023). Also, it has undergone a graphical analysis of model fit. The choice of the optimal covariate combination is done by assessing the optimal covariate balance, shown in Figure 2. This figure depicts what biasing effect each variable bring across covariates, graphically shown by the red marks. Covariates having their red marks close to the vertical line of 0 are indicating a low standardized percentual bias across covariates. The variables with least standardized percentual bias of the synthetic control have been kept in the model, whilst those who bring a large amount of bias to synthetic California are systematically excluded from the model. This methodology is supported by the graphical cross-checking assessment of synthetic outcomes when building the model. The specific combination of the variables seen in Figure 2 generate the best possible pre-intervention model fit of synthetic California, given the available data in the dataset.

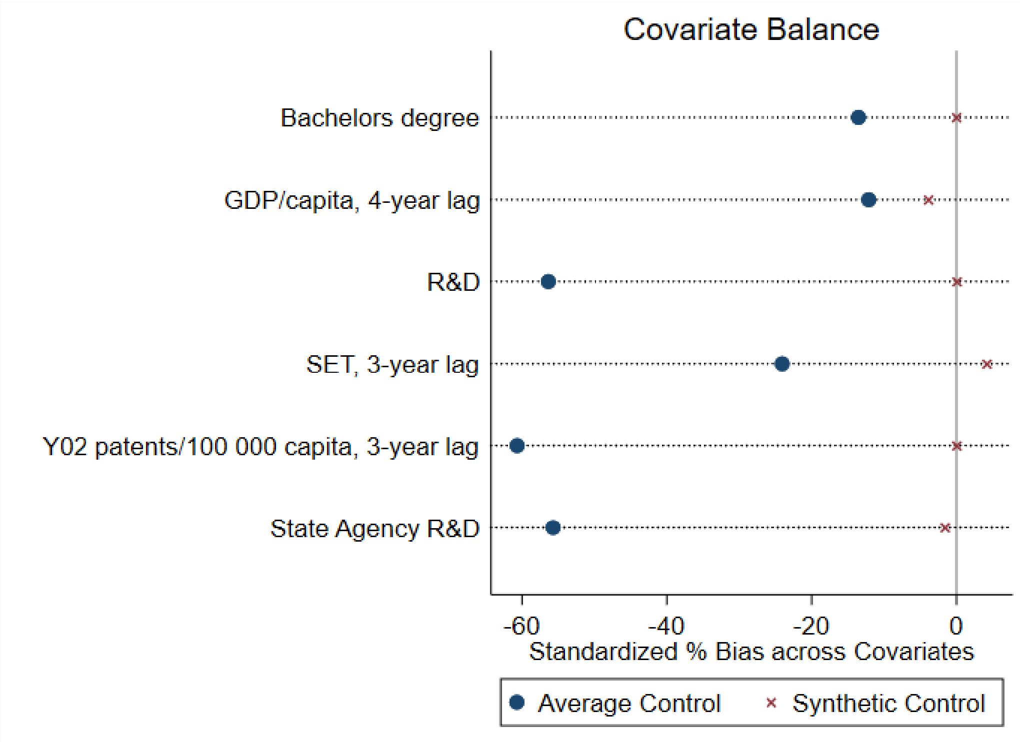

Figure 2. Covariate Balance.

Table 2 presents the descriptive statistics for the predictors included in the analysis. These statistics provide an overview of the dataset, presenting a summary of the covariates and its number of observations, mean values, standard deviations, minimum values, and maximum values. The numbers of observations varies for each predictor, as the accessible time period of predictor data varies.

Table 2. Descriptive statistics.[1]

VARIABLE	N	Mean	Std. Dev.	Min	Max
Y02 Patents (per 100 000 capita, outcome variable)	1 560	1.03	1.41	0.00	13.66
Y02 Patents (per 100 000 capita, 3-year lag)	1 443	0.94	1.27	0.00	13.66
State-agency R&D (Expenditure/1 million $ GDP)	701	1.93	1.39	0.27	8.11
GDP per capita (4-year lag)	858	0.05	0.0088	0.03	0.08
Bachelor's degree holders (% of 25-44 years old)	585	28.02	3.98	19.91	42.55
SET (High Science, Engineering, and Technology establishments, % of Total Employment, 3-year lag)	546	10.49	2.48	5.42	18.07
R&D (% of GDP)	966	1.87	1.39	0.23	8.55

5.3.1 Choosing of lags

The choosing of time lags for the explanatory variables in the model has been done by systematic inclusion and exclusion of lags and evaluation of its effects on the model fit. This is consistent with the methodology of choosing variables in general. Each variable has been lagged up until 5 years, and each lag have been tested in the model until the optimal alternative is found. Thus, the choices of lags are consistent with the methodology of choosing predictors in general, as inclusion of a variable or its lag is decided based on its standardized percentual bias across covariates. The variable, lagged or not, with the lowest biasing effect is used in the model. For the model explaining the effect of the California Cap-and-Trade on Y02 patents, there are 3 lagged variables; Y02 patents (3-year lag), GDP per capita (4-year lag), and SET (3-year lag). The combination of included variables is of high importance when creating the optimal model. If some other variable are used, the optimal choice of lags may change. Many model constellations have been tested, and the model applied in this thesis is chosen as it creates the most accurate synthetic California, given the data availability and time-scope of this thesis.

[1]A variable of energy-efficiency scorecards was initially included in the model but brought a high level of percentual bias to the results. Therefore, it was excluded from the model. This biasing effect is presented in Figure 9 and Figure 10 in Appendix.

5.4 Donor pool

California cap-and-trade is solely in effect within the state of California in the US, whereas California is the treated unit. The donor pool in this thesis includes all US states, except for the states participating in the Regional Greenhouse Gas Initiative (RGGI). This excludes the states of Connecticut, Delaware, Massachusetts, Maryland, Maine, New Hampshire, New Jersey, New York, Rhode Island, Virginia, and Vermont. The exclusion of these states is done to avoid any biasing effects from the RGGI policy in the donor pool, and to maintain homogeneity for the units in the pre-treatment period. Furthermore, District of Columbia is omitted from the dataset due to it being an outlier in pre-treatment patent data. This may be attributed to the presence of the national capital Washington DC in the region, as well as a high concentration of corporate headquarters in the area. The changes in green technology patents for California and states included in the donor pool are illustrated in Figure 3, presented as patents per 100 000 capita. The dotted vertical line indicates the introduction of the California cap-and-trade.

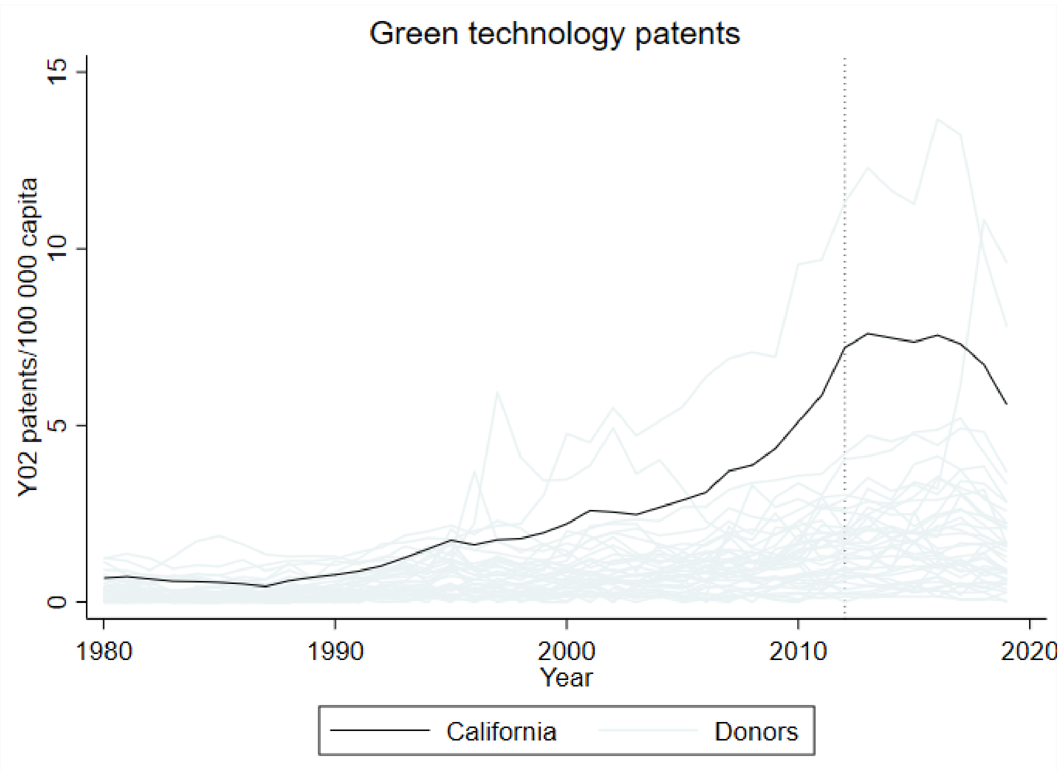

Figure 3. The changes in green technology patents in California and states of the Donor pool.

5.5 Comparison to prior research

This thesis embarks upon further assessment of the California cap-and-trade and differs from the single previous study of da Cruz (2022) in several methodological aspects. First, it applies a longer time-period, giving additional pre-treatment and post-treatment years to assess. Therefore, this thesis contributes to the field of study by elongating the assessed time period to 1980–2019, creating 33 years of pre-treatment period and seven years of post-treatment period. This offers 20 additional years of pre-treatment years for the SCM model to utilize when modelling synthetic California, and four additional years of post-treatment period to evaluate treatment effects. Second, the model of this thesis contains a unique set of explanatory variables, utilizing alternative predictors for synthetic California. Third, it applies averaging of the synthetic control predictors until 2013 when treatment was implemented. This is contrary to da Cruz (2022) which applies averaging over the entire assessment period, a questionable practice in the application of the SCM as it includes post-treatment predictor data when estimating the counterfactual outcome of California. This is controlled for in this thesis, to avoid bias in results. Fourth, it includes a different set of states in the donor pool. Finally, it uses the patent classification system of CPC instead of the IPC. Overall, these methodological considerations should provide more conclusive results of the effect of the California cap-and-trade on green innovation.

6. Results

The following section presents the results of the empirical analysis, which aims to assess the effect of the California cap-and-trade on green innovation, using a Synthetic Control Method (SCM). To enable an assessment of the counterfactual conditional outcome of the California Cap-and-Trade policy, a synthetic California is created. To generate a synthetic California that matches the pre-intervention trajectories of California, a weighted combination of US states of the donor pool is utilized. This allocation of weights is presented in Table 3. The weights show that a combination of Colorado, Michigan, New Mexico, and Washington are the most optimal components when creating the synthetic California. Other states in the donor pool are hence assigned a weight of zero.

Table 3. Unit weights in Donor pool.

State	Weight	State	Weight
Alabama (AL)	0	Montana (MT)	0
Alaska (AK)	0	Nebraska (NE)	0
Arizona (AZ)	0	Nevada (NV)	0
Arkansas (AR)	0	**New Mexico (NM)**	**0.051**
Colorado (CO)	**0.235**	North Carolina (NC)	0
Florida (FL)	0	North Dakota (ND)	0
Georgia (GA)	0	Ohio (OH)	0
Hawaii (HI)	0	Oklahoma (OK)	0
Idaho (ID)	0	Oregon (OR)	0
Illinois (IL)	0	Pennsylvania (PA)	0
Indiana (IN)	0	South Carolina (SC)	0
Iowa (IA)	0	South Dakota (SD)	0
Kansas (KS)	0	Tennessee (TN)	0
Kentucky (KY)	0	Texas (TX)	0
Louisiana (LA)	0	Utah (UT)	0
Michigan (MI)	**0.325**	**Washington (WA)**	**0.389**
Minnesota (MN)	0	West Virginia (WV)	0
Mississippi (MS)	0	Wisconsin (WI)	0
Montana (MO)	0	Wyoming (WY)	0

The per 100 000 capita patenting patterns of the weighted units in the donor pool are presented in Figure 4. The black graph represents California, and the colored graphs represent the states that have received weights by the SCM. The outcomes of these states are hence combined and used by the SCM to construct the synthetic California, as they have similar pre-treatment characteristics as California and jointly create a well-fitted counterfactual outcome.

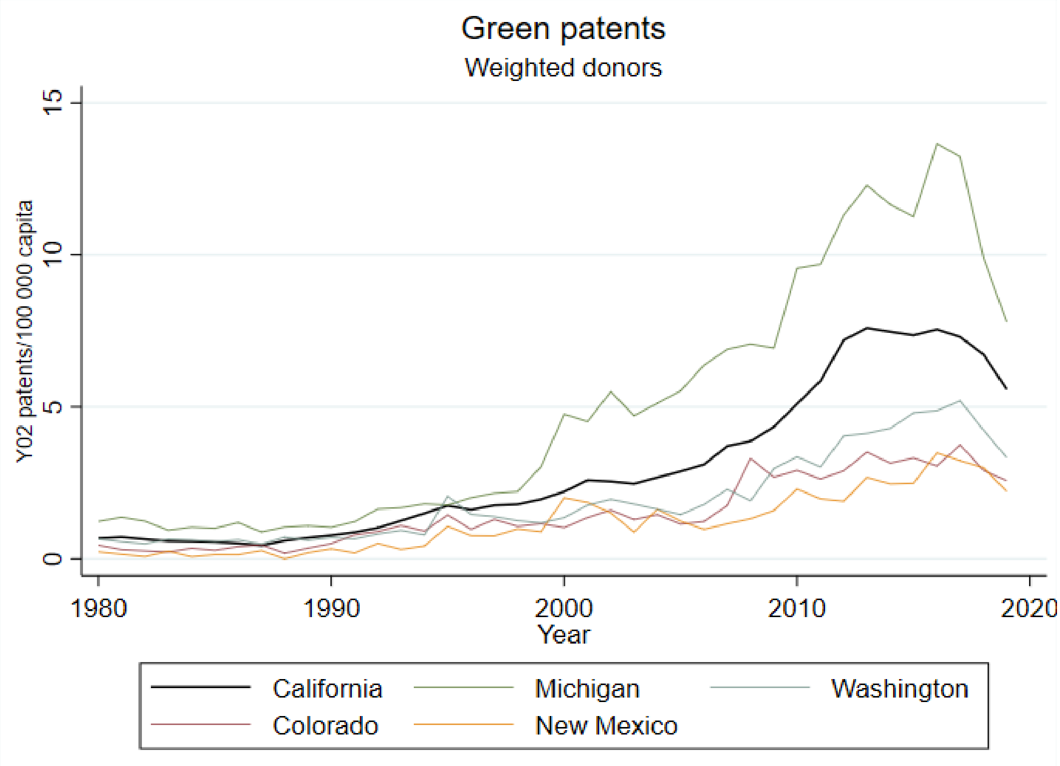

Figure 4. Green technology patents in the weighted units of the donor pool, compared with California.

Table 4 presents the weights of the predictors included in the model creating the synthetic California. It also presents the mean values of the predictors of actual California, synthetic California, and the simple average of all control units with equal weights. The covariate with the highest weight is the percentual share R&D of GDP, followed by a 3-year lag of the outcome variable. Clearly, research and development (R&D) activities are important predictors of innovation output. It is common within the modelling of synthetic controls that the lag of the outcome variable is a substantially weighted predictor in the synthetic unit, as shown by these results (Abadie et al. 2015). Additionally, the level of bachelor's degree holders in the workforce aged 25–44 receives a minor weight of predicting green innovation output. In contrast, GDP per capita, state agency R&D expenditures, and the share of high science-, engineering-, and technology- (SET) employment in the total workforce does not receive any weights in predicting the changes of environmentally friendly patents. Furthermore, the average control indicators show that a state average is not a suitable control group, as states in USA differ greatly in pre-treatment characteristics. This is indicated by the strong bias in the average control. The synthetic control, however, provides a better approximation of the actual California and creates a better model fit.

Table 4. Covariate balance in pre-treatment periods.

Covariate*	Weight**	Treated	Synthetic Control***		Average Control****	
			Value	Bias	Value	Bias
Y02 patents (3-year lag)	0.228	1.799	1.799	0.01%	0.707	-60.68%
GDP per capita (4-year lag)	0.000	0.052	0.049	-3.95%	0.0454	-12.14%
Bachelor’s degree	0.001	30.671	30.661	-0.03%	26.515	-13.55%
R&D % of GDP	0.771	4.042	4.043	0.03%	1.763	-56.38%
State Agency R&D	0.000	4.128	4.062	-1.61%	1.828	-55.72%
SET (3-year lag)	0.000	13.407	13.964	4.16%	10.182	-24.06%

Note: *The covariates are averaged over years with available data until treatment. For Y02 patents (3-year lag) this period is 1982-2013, for GDP/capita (4-year lag) this period is 2002–2013, for Bachelor’s degree holders this period is 2005–2013, for R&D investments of GDP this period is 1991–2013, for state agency R&D investments this period is 2002–2013, and for SET (3-year lag) this period is 2006–2013; **”Weight” is the optimal covariate weight; ***”Synthetic Control” is the weighted average of donor units with optimal weights; ****"Average Control" is the simple average of all control units with equal weights.

The credibility of the synthetic control outcome depends on the pre-treatment fit of synthetic California. This is described by the Root Mean Prediction Error (RMSE), which calculates the square root of the average squared differences between predicted and actual values, presenting an absolute measure of the error (Abadie et al. 2015). The RMSE in this analysis is 0.292, presented in Table 5, which is the lowest value encountered. Also, the effectiveness of the synthetic control estimator relies on how closely the trajectory of the outcome in the counterfactual state aligns with that of the treated state. This is further presented in Figure 5.

Table 5. Fitting results in the pre-treatment periods.

Treated Unit: California Treated Time: 2013	
Number of Control Units	38
Number of Covariates	6
Root Mean Squared Error	0.292
R-squared	0.962

Figure 5 illustrates the result of the synthetic control. It presents the outcome of approved patent applications of environmentally friendly technology during years 1980–2019. California is presented by the black line and synthetic California by the dashed line. The dotted vertical line indicates policy implementation. The line of synthetic California follows the trajectory of California well during the pre-treatment period, indicating a good model fit. However, starting 2011 the graphs diverge, as California shows a comparably higher level of green innovation. This indicates a positive treatment effect, however, beginning two years prior to policy implementation. This observation aligns with the adoption of the final regulations of the policy in 2011, suggesting a potential anticipation effect of the policy. The gap between the two graphs in the post-treatment period are according to Abadie et al. (2015) the indicated treatment effect. This gap is clearly visible in Figure 5 following 2011 but is then notably decreased after 2015.

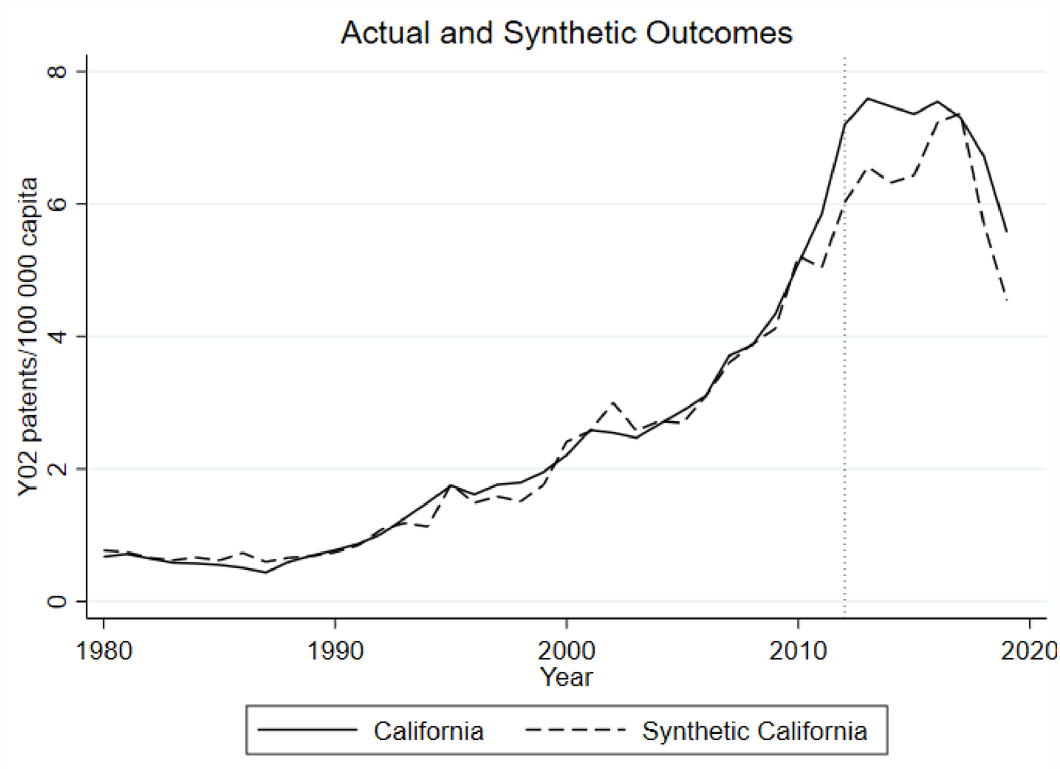

Figure 5. Outcomes of synthetic California and actual California.

The treatment effect is further illustrated in Figure 6. This figure enables a straightforward assessment of treatment effects, as it presents the differentials between synthetic California and actual California. Synthetic California is illustrated by the horizontal dotted line of 0, and California is illustrated by the black line. The dotted vertical line indicates policy implementation. The black line of California follow synthetic California fairly consistently in the pretreatment period, which confirms a satisfactory model fit. Thereafter, a clear structural break is shown in 2011 as the gap in green technology patents increase significantly. This indicates a treatment effect in California starting 2011, which supports the interpretation made in Figure 5. However, this treatment effect decline after 2015 before recovering years 2018–2019. This fluctuation may be due to temporal variations in policy effects, or to biases in the estimated outcome of Synthetic California.

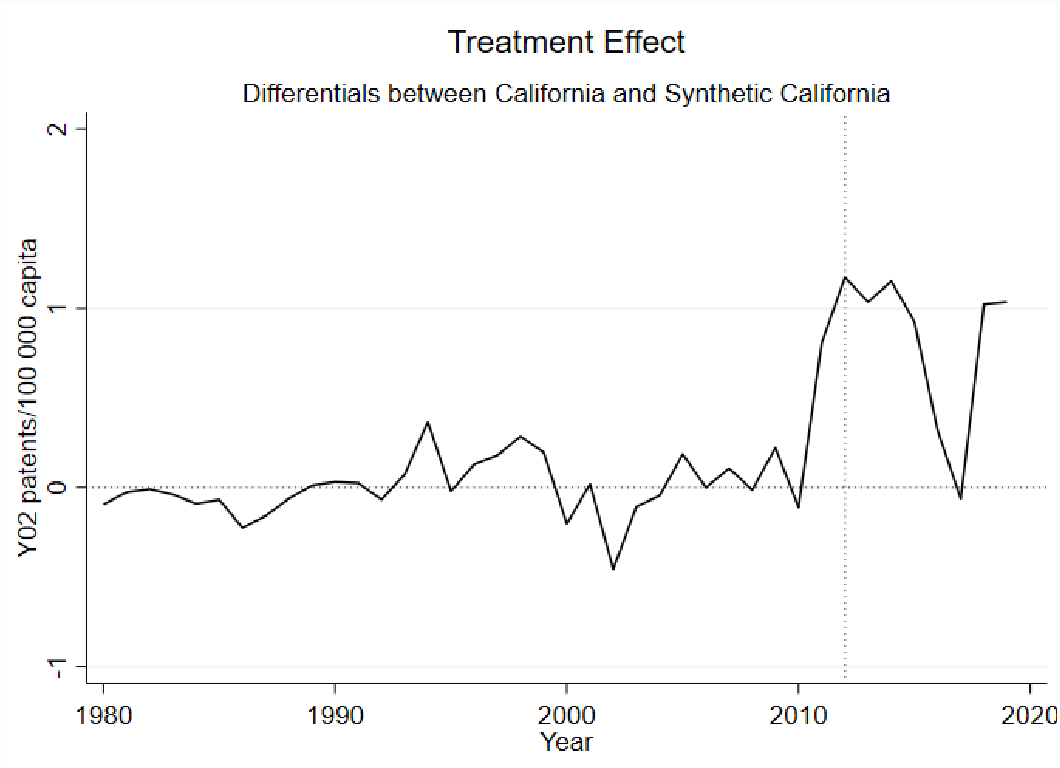

Figure 6. Treatment effect of the policy intervention, shown by the differentials between California and synthetic California.

6.1 Robustness checks

6.1.1 In-space placebo test

To further assess the significance of the treatment effect, a robustness check is conducted. This is completed by an in-space placebo test, where treatment is assigned to all other units in the donor pool respectively. The in-space placebo test generates p-values that indicate the statistical significance of the indicated treatment effect in California, for each post-treatment estimate respectively. This explores the uniqueness of the indicated treatment effect in California in relation to other US states. The results of the in-space robustness test are presented in Table 6. The test show a short-term statistical significance of treatment effects. The first two years after treatment are assigned estimates of a positive treatment effect statistically significant at 10% level, followed by statistically insignificant estimates.

Table 6. Prediction results in the posttreatment periods.

Time	Actual Outcome	Synthetic Outcome	Treatment Effect	P-value Standardized
2013	7.594	6.560	1.033*	0.057
2014	7.472	6.322	1.149*	0.085
2015	7.360	6.436	0.924	0.257
2016	7.548	7.231	0.317	0.771
2017	7.304	7.369	-0.064	0.971
2018	6.723	5.703	1.020	0.285
2019	5.575	4.542	1.033	0.171
Mean	7.082	6.309	0.773	

Note: The average treatment effect over the posttreatment period is 0.7734; *P<0.1; **P<0.05; ***P<0.01

The decreasing statistical significance of a treatment effect in California is graphically visible in Figure 7. The black line represents California, and the horizontal value of 0 synthetic California. The black graph show the gap between California and synthetic California, similar to the treatment effects presented in Figure 6. The bundle of grey lines represent the effects of the states in the donor pool when respectively assigned a false policy treatment by the placebo test. This figure enables a comparison of the treatment effect of California with the indicated treatment effects of other states in the donor pool. This range of effects is illustrated by a bundle of grey graphs. California is in the first years after treatment located in the upper parts of the effect-range. This displays an initial statistical significance of a positive treatment effect. Subsequently, the effect of California decreases and additionally traces closer to the center part of the effect-range. This shows the decreased treatment effect in California, as well as depicts the decreasing statistical significance of estimated effects presented in Table 6. The SCM is accordingly suggesting a treatment effect on green innovation in several states in the donor pool, even though there has been no actual treatment.

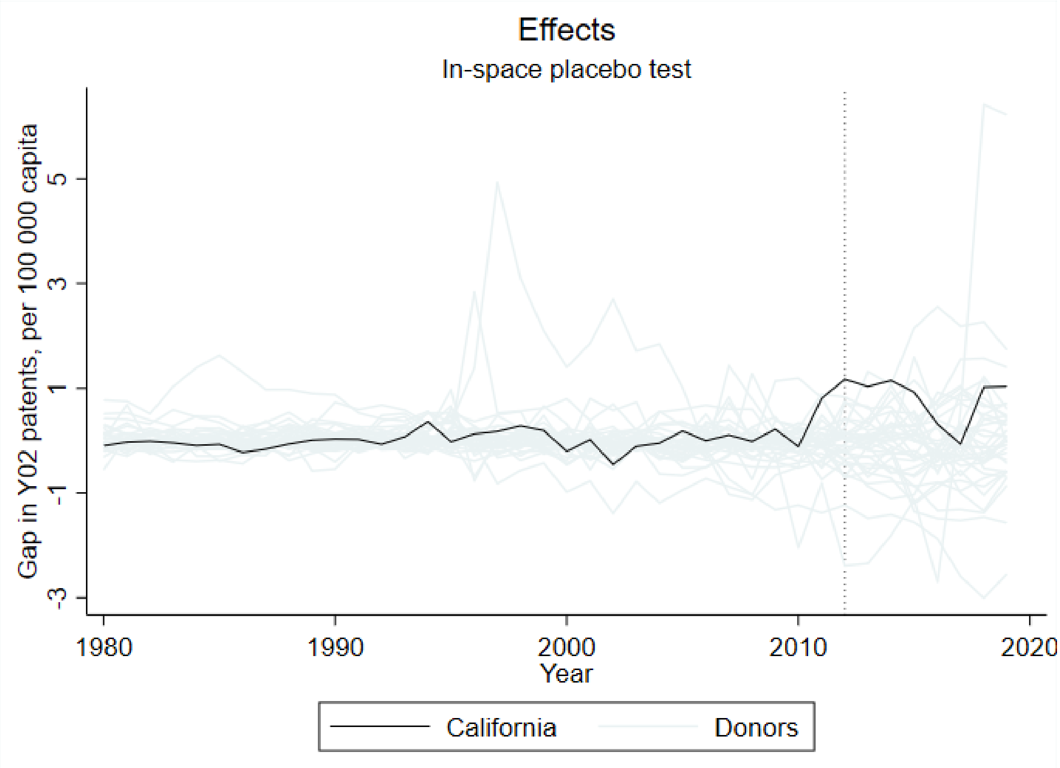

Figure 7. In-space placebo test, effects of assignation of treatment to each unit in donor pool.

6.1.2 Energy-related patents

To rule out any possible biasing crowding-out effects due to the multi-sectoral nature of the California cap-and-trade policy, the share of energy-related patents is further examined. This is of relevance as approximately 75 percent of the allowances carried out by the California cap-and-trade are assigned to energy industries. This may have caused a higher inducement of innovation in this specific subsector of Y02 patents, relative to other subsectors. Such eventuality could imply a potential bias in the results of the SCM analysis in this thesis. To assess this further, the ratio of patents for green energy generation technologies, CPC subsector Y02E, to all Y02 patents is illustrated in Figure 8. The figure shows a significant decrease in the share of Y02E patents following 1993, finding a new steady level in 1996. The ratio is then slightly increased years 2006–2013 before again setting the post-1996 steady level. These relatively minor changes in energy-related patents oppose the factuality of any great overlooked crowding-out effect within the Y02 group following the implementation of the California cap-and-trade.

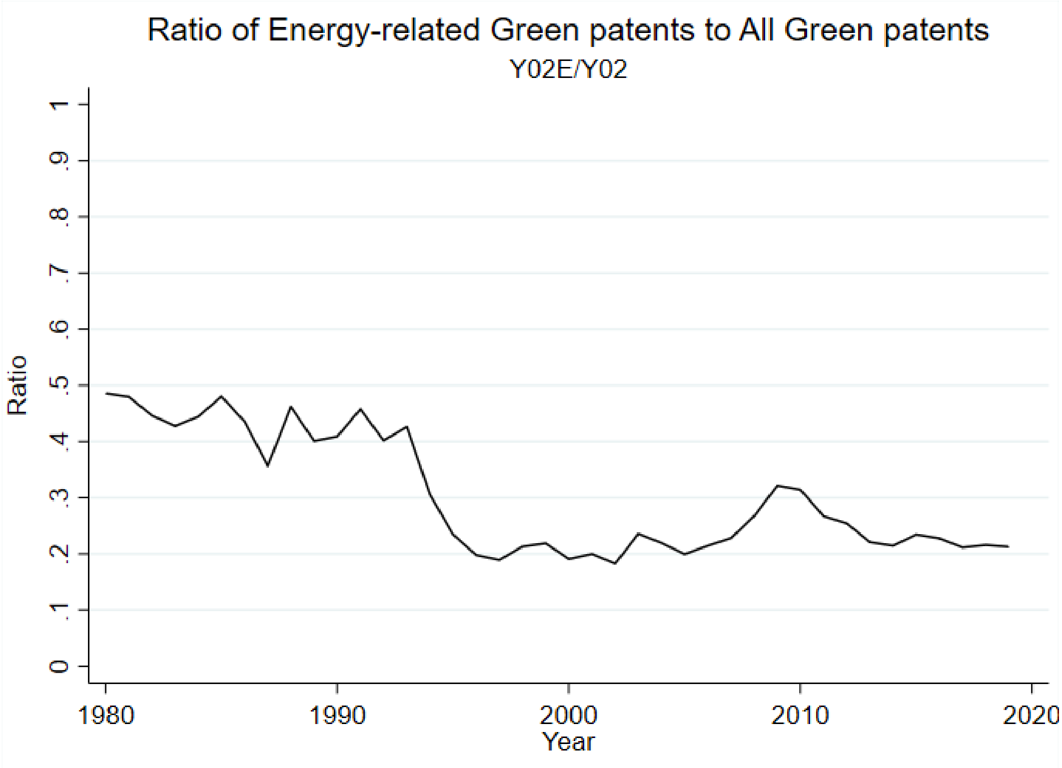

Figure 8. Share of energy-related patents among all green technology patents in California.

7. Discussion

This study aims to assess the effect of the California cap-and-trade on green innovation, by answering the following research question: *How has the California cap-and-trade affected green technology patents in California?.* This is done by applying a Synthetic Control Method (SCM) when assessing the dynamics of green technology patents. The theory of the Porter Hypothesis and Directed Technological Change (DTC) say that firms affected by an environmental policy can benefit from innovation, due to its positive effect on increased competitiveness. Furthermore, environmental policy may shape the direction and rate of technological change. Thus, I hypothesized that the California cap-and-trade have increased the level of innovation for environmentally friendly technologies in California. The results of this thesis suggests that there has been a positive short-term effect of the California cap-and-trade policy on green innovation. Specifically, the analysis shows statistical significance of a positive treatment effect in years 2013–2014, followed by statistically insignificant treatment effects. This inference is given by the in-place placebo test which in later years shows similar or even larger gaps in green technology patents in the control states than California, compared with their respective synthetic versions. It is important to note that these differences exist despite the absence of any, to my knowledge, additional intervention made in the donor pool states. The reasons for this outcome can be many, which will be further discussed in this section.

The findings of this thesis align with previous research made by da Cruz (2022), which also discovers a positive effect of the policy on green innovation until year 2015. This despite there being several differences in the studies, in terms of applied data and details in methodology. The positive effect on innovation starts to show 2011, two years prior to policy implementation. This shift in green technology patents correlates strongly with the California Air Resources Board (CARB) adoption of final legal regulations of the California cap-and-trade in 2011. This early treatment effect could thus potentially be due to an anticipation effect. In such early stages of the policy there may have been readily accessible technology improvements, quickly implemented by the firms to reduce emissions. This reasoning is consistent with the conclusions made by Barbieri (2015), and agrees with the discussion made by da Cruz (2022), also observing an increase in green innovation prior to policy implementation. However, the results of this thesis show a decreased treatment effect following year 2014, indicating an isolated short-term effect of the policy.

There are several aspects suggesting that a positive short-term effect of the policy on green innovation is true. One of these could be the realization of early market opportunities. The introduction of the policy may have created an urgency for immediate action, leading to an initial wave of green innovation in the affected firms. This is due to firms covered by the policy striving to comply with the new regulations and taking advantage of early prospects of less emission-intensive technologies. This aligns with the theory of the Porter Hypothesis. Porter (1991), says that firms covered by a policy may improve their competitiveness by green innovation, as it would improve their productivity, boost comparative advantages, and increase end-value of products. Furthermore, a short-term effect could be due to the actuality of initially low-hanging fruit in green technology innovation. As companies initially implements relatively cost-effective measures for emission reductions, the remaining opportunities for innovation can be costly or challenging. Thus, there may be diminishing marginal returns in realizing innovation for the firms covered by the California cap-and-trade, causing a declining rate of green innovation. Similarly, the theory of Directed Technological Change (DTC) by Acemoglu et al. (2012) supports the findings of a positive inducing effect on innovation. Underlying mechanisms of policy effects described by DTC may also help explain a potential short-term effect on green innovation. This includes the mechanisms of substitution effects of participating firms. A short-term effect could indicate a high elasticity of substitution in input factors or technology of the affected firms. An initial response to the policy of firms with high elasticity of substitution would be adjustments in input factors, initial cost-effective green technology investments, or adoption of sustainable production processes to comply with policy requirements. However, the firms may thereafter prioritise cost-savings over mid- or long-term innovation. Thus, they would continue by adopting existing technologies or make other changes to ensure emission reductions without pursuing innovation. Such responses would lead to a short-term effect on green innovation and explain the diminished treatment effect and decreased statistical significance.

While economic theory can help explain the mechanisms of green technological change, many other factors also affect how well a cap-and-trade policy performs. This includes policy design or other market dynamics. If the California cap-and-trade policy perform with lower stringency than first expected by the market, it may subsequently decrease the firms' ambitions and force in green innovation efforts. This is a frequent case in cap-and-trade policy, as previously noted by Calel and Dechezleprêtre (2016), as firms subsequently adjust their initially substantial efforts to a more appropriate level of compliance. This eventuality could explain a short-term effect of the California cap-and-trade on innovation. Furthermore, as pointed out by Popp (2002) and Calel (2020), there can be technological limitations or maturity slowing down the process after an initial surge of innovation. Green technological development may have relied on emerging technologies still in the early stages when the policy was implemented. This would cause a decrease in the rate of green technology patenting after an initial stage of quick introductions to the market. Accordingly, there may be some bottlenecks apparent in the technological growth, leading to a momentary slowdown in progress. Although, it is important to acknowledge that while there is temporary slowdown in innovation, it does not imply a complete stop. Also, this study does not measure the changes in emissions following the introduction of the policy. Even if the policy has not brought any great significant mid- or long-term inducing effect on green innovation, the affected sectors may have performed alternative measures to reduce emissions, still making it an efficient climate policy.

7.1 Limitations

Although the findings of this study are in line with theory and previous literature, there are limitations that needs to be discussed. This includes the possibility of the SCM structure and methodology bringing biased results. This points out the importance of accurate model specification, which if misspecified may not adequately capture the relevant factors driving green innovation. Such factors could for instance affect temporary increases in the rate of innovation, which the model may not then adequately capture. Likewise, the interpolating and averaging nature of the SCM brings a risk of overestimation of effects. This means that any temporal changes in the rate of innovation years prior to policy implementation may be overlooked by the SCM, and unaccounted for in synthetic California. As the synthetic control rely on interpolation and averaging when creating the synthetic California, it cannot go beyond historic data when predicting the synthetic outcomes. This may smooth out any sudden shifts or discontinuities in the rate of innovation, which would bring bias to the results. This implies that the effect suggested by the findings in this thesis, as well as of da Cruz (2022), may be greater than the actual counterfactual outcome would be. Furthermore, the study does not assess sector-level effects, neither across firm sizes, which may overlook any heterogeneity across such units. The SCM assumes a homogenous treatment effect, but if having differences in responses, the results may not completely reflect the true impact.

Another important factor that may have brought bias to the results is other policies or regulations in California uncontrolled for in this study. A temporary rise in innovation is seen in energy-related green technologies in years 2008–2012. This may be due to the ambitious efforts for increased energy efficiency in California uncontrolled for in this thesis, indicating a possibility of bias in results. I made an attempt to include a predictor of Energy Efficiency scorecards in the model, explaining the efforts in policies related to energy efficiency. However, the variable brought a high level of percentual bias across covariates. This signals that it did not perform well in predicting green technology patent filings in synthetic California and was therefore excluded from the model.

Furthermore, it is possible that the results of this thesis do not perfectly explain the effect of the California cap-and-trade on firms covered by the policy. This is due to the study not applying firm-level data for the concerned firms, but aggregated patent activity for green technologies in general. Thus, the results of this study show the combination of the direct effect of the policy and any potential indirect effects on other actors. California cap-and-trade might therefore have had a higher causal effect on the involved firms than shown by this study. This means that the spill-over effect on economy-wide green innovation is not specified by this study, an important factor to assess as discussed by Calel and Dechezleprêtre (2016). It is also important to note that there is a possibility of missing data in the latter years of the assessed time-period. This is due to the varying time-lengths for approval of filed patent applications. Hence, there could exist not yet approved patent applications filed during the assessed time-period that are not included in the dataset.

8. Conclusions

The California cap-and-trade is a market-based environmental policy initiated 2013, aiming to reduce emissions of heavy-emitting firms in California. The objective of this study is to assess the effect of the California cap-and-trade on green innovation, an important driver of green technological growth, reduced emission-intensity, and long-term sustainable growth. This is done by assessing the dynamics of green technology patents in California, applying a Synthetic Control Method (SCM) that creates a synthetic counterfactual outcome of California by using a combination of US states. The results indicate a short-term increase in green technology patents in California, with an associated anticipation effect starting 2011, two years prior to policy implementation. In years following 2014 there is decreased statistical significance of an indicated positive treatment effect, as other US states tend to show similar increases in green innovation. These findings help realize the objective of the study, as it brings further insights on how green innovation has been affected by the California cap-and-trade. The findings suggest that the California cap-and-trade has fostered green innovation. However, it confirms that policy makers and stakeholders involved in policy design should consider the temporal dynamics of policy effects. This requires continuous evaluation of the California cap-and-trade, to ensure proper stringency and effectiveness in inducing green innovation. If doing so, the policy may have the potential to be an efficient environmental regulation by decreasing emission-intensity, mitigating climate change, and realizing long-term sustainability.

Future research of the California cap-and-trade should seek to control for other policies. This could help disentangle what effects should be directly attributed to the California cap-and-trade. Also, firm-level data should be applied to enable a more detailed assessment of the underlying mechanisms and responses of the regulated sectors and firms. Furthermore, it would be valuable to further investigate the ratio of green technology patents to total patents, to see whether the California cap-and-trade has significantly increased the share of green innovation in California.

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Appendix 1

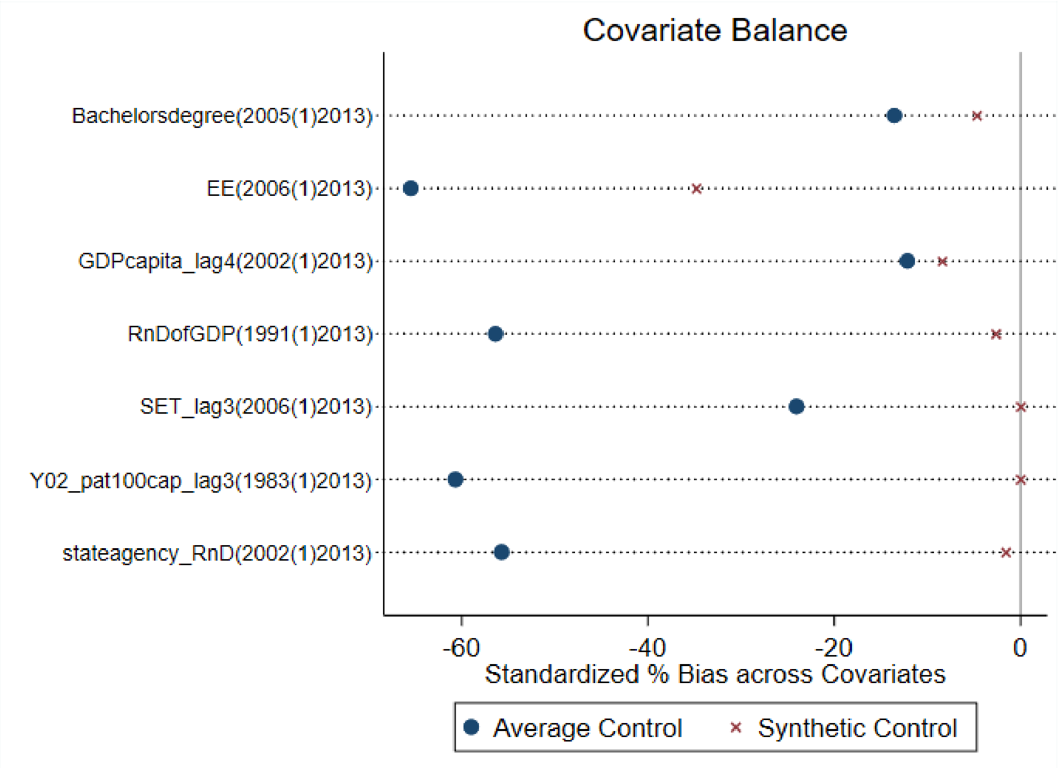

Figure 9. Covariate balance with the Energy Efficiency scorecard included as a predictor in the model.

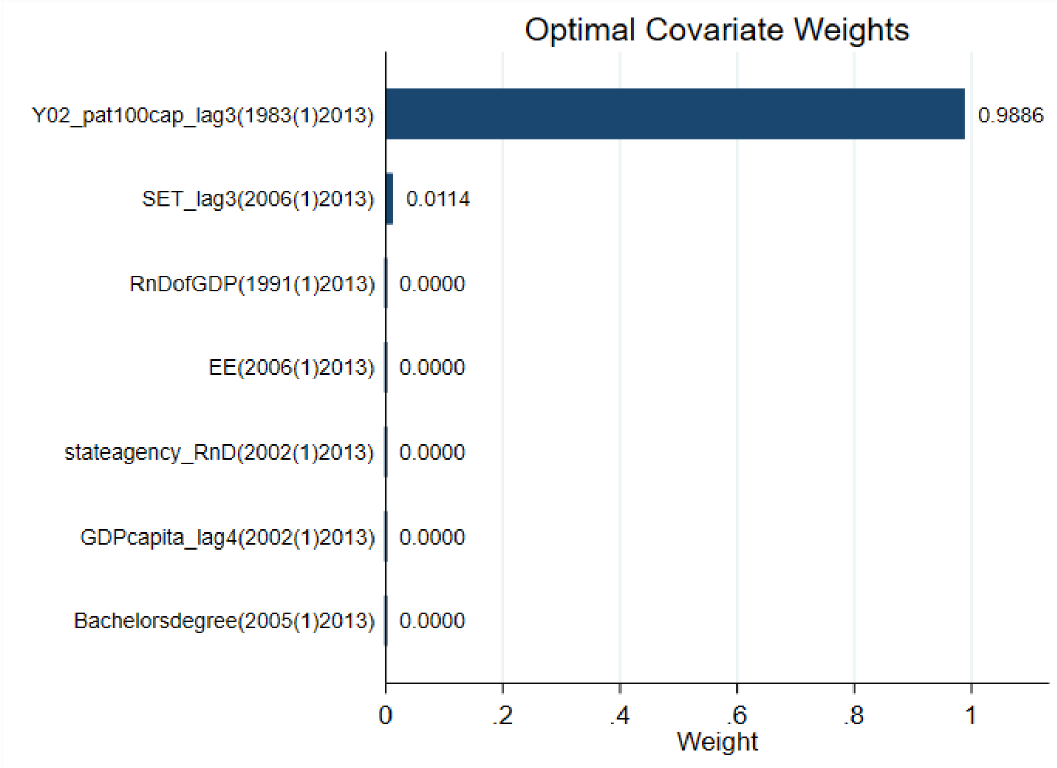

Figure 10. Optimal covariate weights when including the Energy Efficiency scorecard as a predictor in the model.

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