The Effects of Carbon Trading: Evidence from California's ETS

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Abstract

We study the impact of California's emission trading scheme on carbon emissions and economic outcomes. We use panel data for all US states and apply the synthetic control method to construct an optimal counterfactual for CO2 emissions, GDP, employment, and industry turnover as outcome variables. We find evidence for a modest decline in emissions and a net positive aggregate economic effect. While we estimate overall emissions to fall relative to the counterfactual by 0.9% annually and by 6.3% in total between 2013 and 2019, the effect is most evident in the electricity and buildings sector, accounting for an annual abatement of 6.2% and 1.4%, respectively. Our estimates suggest that California's carbon trading scheme has so far not caused large reductions in overall CO2 emissions and has positively affected macroeconomic outcomes in the short run.

Keywords: Carbon pricing, emission trading, cap and trade, economic effects, emission reduction, synthetic control
JEL Classification: Q58, O44, Q52, Q48

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1 Introduction

While global emissions are still rising and the chances of not surpassing 1.5 degrees Celsius of global warming are shrinking, the debate about the appropriate measures to tackle climate change remains unresolved. Economists argue that carbon pricing is a highly efficient and effective instrument to reduce emissions.[1] However, there is an unresolved debate around the effectiveness and efficiency of carbon pricing that might hamper its broader implementation. Currently, only one-quarter of global GHG emissions are covered by carbon pricing mechanisms (World Bank, 2022). This might be explained by the fact that while such measures induce immediate costs on businesses and consumers, the benefits of a climate-preserving economy only materialize in the future (Karapin, 2016). Furthermore, polls show that public support for market-based environmental policy is generally low. People tend to distrust the capacity of carbon taxes and cap-and-trade systems to reduce emissions effectively without imposing high social and economic costs (Maestre-Andres et al., 2019). This suggests that more evidence on the effects of carbon pricing is urgently needed.

Our study contributes to filling this gap by estimating the emission abatement induced by the emissions trading system (ETS) in California and its macroeconomic effects. We use the synthetic control method introduced by Abadie and Gardeazabal (2003) and Abadie et al. (2010) to construct a counterfactual assessing the causal effect on energy-related CO2 emissions, real GDP, employment, and industry turnover. We find that the ETS-induced overall emissions fall by less than 1% (0.92) annually in comparison to the counterfactual. A sectoral analysis shows that the emission abatement is strongest in the electricity and buildings sectors, having caused an estimated annual reduction of 6.2% and 1.4%, respectively. Furthermore, we find no evidence of adverse economic effects. We even identify a net positive effect on growth, employment, and firm turnover.

However, the evidence from this case study should not be overestimated as California is one of the richest US states in terms of GDP per capita and already emitted a relatively low carbon dioxide per capita level in 2013 before the ETS was enacted. The conditions for implementing carbon pricing were advantageous for California limiting the external validity of our results. Since the effectiveness of an ETS, by definition, depends on the emission cap defined, we also cannot make a statement about the economic effects of a much stricter cap with higher environmental goals. One could still assume that a more stringent policy design would have adverse economic effects. However, the results are in line with literature indicating that the economic and social costs of carbon pricing might, in fact, be much smaller than suggested by theory (see, e.g., Bernard and Kichian, 2021; Dechezleprêtre et al., 2023; Metcalf and Stock, 2020). While imposing market-based environmental policies can negatively affect competitiveness in the short term for certain industries, it generally incentivizes low-carbon investments having a net positive effect on the economy (Dechezlepretre and Sato, 2017). This questions popular claims discrediting carbon pricing as being too costly. However, our results add to evidence suggesting that existing carbon pricing measures are too lax in accomplishing significant emission

[1]In 2019, The Wall Street Journal published a letter signed by 3,640 US economists proposing the introduction of a carbon tax arguing that this is "the most cost-effective lever to reduce carbon emissions" and the only remedy in line with "sound economic principles". Source: Climate Leadership Council. (2019, January 17). Economists' Statement. https://clcouncil.org/economists-statement/ Critics, however, question market-based approaches for being unjust, politically unfeasible, and most of all, costly.

reductions (see, e.g., Tvinnereim and Mehling, 2018; World Bank, 2022).

The paper is organized as follows. Section 1 briefly summarizes the existing literature on the impacts of carbon pricing on emissions and economic outcomes. Section 2 shortly presents background information on the cap-and-trade system in California and then introduces the methodological approach and our data. The empirical evidence is discussed in Section 3 and Section 4 concludes the paper.

2 Related Literature

While a comprehensive global attempt to price carbon waits to be seen, multiple national and regional carbon taxes or ETS have been implemented worldwide. In 2021, 64 regional, national, and supranational carbon pricing schemes were in action, representing 23% of global GHG emissions (World Bank, 2022). However, it is difficult to empirically estimate the effectiveness of these measures as they are often implemented together with other environmental policies, and their effects on emissions tend to be hard to distinguish from exogenous factors such as energy prices or economic shocks. Still, several studies have conducted ex-post analyses of carbon pricing schemes.

Schaefer (2019) shows that the European Union's ETS (EU ETS) had a low but significant negative impact on emissions from electricity in Germany and Colmer et al. (2022) demonstrate an effect on manufacturing in France. However, most of the literature focuses on the EU ETS (e.g., Bayer and Aklin, 2020; Cheze et al., 2020; Jaraite and Di Maria, 2016). The Regional Greenhouse Gas Initiative, a cap-and-trade system introduced in 2009 by nine northeastern US states is also widely analyzed (see, e.g., Fell and Maniloff, 2018; Murray and Maniloff, 2015; Yan, 2021). It was the first ETS addressing CO2 emissions in the US; however, it covers only the power sector and therefore represents a much less comprehensive approach than California's ETS. The recent implementation of emission trading in China and the preceding pilot projects were of particular interest to researchers as well (see, e.g., Hu et al., 2020; H. J. Zhang et al., 2019; W. Zhang et al., 2020). In addition to these case studies applying mostly firm-level data, some studies have used cross-country data to estimate the environmental effects of pricing carbon. Best et al. (2020) estimated that the annual CO2 emissions growth rate for fuel combustion is around two percentage points lower in countries with some form of carbon tax than those without. Similar results obtained by Rafaty et al. (2020) find that introducing a carbon price reduces the annual growth rate of CO2 emissions by roughly 1% to 2.5%.

Several studies have also been conducted on the aggregate economic effects of carbon pricing. Metcalf and Stock (2020), who analyze the impact of European carbon taxes on employment and GDP, find no significant adverse economic effects. Yamazaki (2017) and Bernard and Kichian (2021) come to a similar result evaluating the British Columbia carbon tax. Concerning ETS, there is evidence that the introduction of cap-and-trade policies has no negative effect on GDP (Dong et al., 2019) and does not impact total employment, while it does even positively affect firm turnovers (Dechezleprêtre et al., 2023). Reviewing existing ex-post empirical assessments, Ellis et al. (2020) conclude that there seems to be no significant relationship between economic performance and carbon pricing. However, most of the studies analyzed were done on the EU ETS, meaning that the external validity of the results is low, mainly because this highly depends on the stringency of the concrete measure. A related concern deals with the danger of carbon leakage. If firms face strict environmental regulations in one place, they are incentivized to relocate to another where regulation is less stringent. So far, most studies have not detected significant carbon leakage effects. But these mainly focused on the EU ETS in the early phase with low cap (see, e.g., Naegele and Zaklan, 2019; Schaefer, 2019). However, the vulnerability to carbon leakage depends on economic and geographical preconditions. For regional cap-and-trade systems, there is some evidence for significant leakage effects (see, e.g., Cullenward, 2014b; Fell and Maniloff, 2018).

3 Estimating the Effects of California's ETS

3.1 Background on California's ETS

Even though California does not sit at the table when international climate policies are discussed, it represents the 5th largest economy in the world, by scale.[2] Therefore, it is an important player in global climate policy. The state is not just home to many of the world's largest enterprises; it is also highly affected by the consequences of global warming. In recent years it experienced an unseen wave of devastating wildfires, floods, and extreme droughts. In response to this, its parliament passed the Global Warming Solutions Act in 2006, also known as Assembly Bill 32 (AB-32), which introduced several environmental policy measures, such as energy efficiency standards for electricity producers, a low carbon fuel standard for motor vehicle fuels, and most significantly an emission trading scheme (Schmalensee and Stavins, 2017). The Bill aimed to reduce GHG emissions to their 1990 level by 2020. This means a reduction of approximately 15% according to official estimates of the California Air Resource Board (CARB), which is responsible for monitoring the ETS (CARB, 2008). While most other measures came into effect much earlier, the compliance obligations for the ETS started seven years later, in 2013. In 2015 the trading scheme was extended to cover fuels. In the same year, the CARB's chair, which is responsible for monitoring the system, already called it "officially a success."[3] The state reached its goal for 2020 four years ahead of schedule, in 2016.[4] Subsequently, the emission reduction target for 2030 was set to 40 percent below the 1990 levels in Senate Bill 32 (SB-32). Carbon neutrality is to be achieved in 2045 (Executive Order B-55-18). Due to its compliance with emission reduction targets and the comparably high sectoral coverage of 74% of overall emissions, California's ETS is considered one of the most comprehensive in the world (ICAP, 2022). With its ambitious climate policies, California is often seen as a model case for environmental action. The empirical evidence, however, remains scarce.

It is still unclear what share of the emission reduction can be attributed to the ETS and what economic implications its adoption entailed. Researchers have so far been skeptical about the measure's effectiveness. Several studies deal with the issue of carbon leakage: Caron et al. (2015) apply a general equilibrium model to predict 9% carbon leakage from total emission reduction. They argue that the design of

[2] CBS. (2018, May 4). California now has the world's 5th largest economy. CBS News. https://www.cbsnews.com/news/california-now-has-the-worlds-5th-largest-economy/

[3] Camuzeaux, J. (2015, November 5). Cap and Trade under AB 32 – Now it's an "Official Success." Market Forces. https://blogs.edf.org/markets/2015/11/05/cap-and-trade-under-ab-32-now-its-an-official-success/

[4] California Air Resources Board. (2021, November 3). 100% of companies in cap-and-trade program meet 2020 compliance obligations. https://ww2.arb.ca.gov/news/100-companies-cap-and-trade-program-meet-2020-compliance-obligations

California's ETS only allows for small leakage effects, as it covers imported electricity and bans resource shuffling. Cullenward (2014b) questions this claim stating that the prohibition of resource shuffling was relaxed in 2014, allowing for more extensive carbon leakage. Other studies indicate issues of oversupply: Cullenward and Coghlan (2016) analyze allowance prices, arguing that they have stayed low since the system's implementation, while Cullenward et al. (2019) show that firms have practiced excessive banking, meaning that they have purchased more allowances than needed which could endanger future emission reductions.

Still, no study has so far attempted to estimate the overall emission abatement induced by the cap-and-trade system. The effect on regulated firms was quantified by Hernandez-Cortes and Meng (2023) using a differential trend-break model. They find that CO2 emissions have fallen by 9% annually between 2012 and 2017 compared to unregulated firms. Making several restrictions, they exclude all firms which are also subject to other environmental regulations. This largely rules out interaction effects; however, the firms considered in their analysis are only responsible for 5% of total emissions questioning the external validity of the results. Mastrandrea et al. (2020) use index decomposition methods assessing to what degree economic activity, environmental policies, and market forces have contributed to emission reductions. Their findings suggest that the financial crisis has played a major role in reaching emission targets early, while climate policies have become increasingly important over time. They do not, however, estimate how single policies have contributed to emission abatement. Therefore, the controversy about the ETS's effectiveness remains unresolved. Our study builds on the existing evidence to develop a broader picture of the measure's effects.

3.2 Method & Data

In recent years, California was not the only state able to reduce its carbon emissions. In fact, between 2010 and 2015, only eight states registered rising emissions, while in all other states, average carbon emissions fell.[5] Consequently, we should not simply attribute the decrease in emissions observed in California to any environmental policy, let alone to a particular one. Hence, the methodological challenge is to build a reliable counterfactual. Commonly used forecasting techniques relying on a business-as-usual scenario similarly do not consider general trends in emissions and are therefore not viable to assess the effect of single policies. Measuring the instrument's performance by looking at emission reduction targets the state sets is also highly problematic. The AB-32 defined the aim of reducing GHG emissions to their 1990 level by 2020. While California peaked in 2004, the referred-to threshold was passed in 2016.[6] This early achievement might have also been due to recession effects (Mastrandrea et al., 2020). Hence, the impact of the cap-and-trade system seems to be at least questionable and needs to be further scrutinized. Comparing California to the average of all other US states is problematic since most states have a very different industry structure. Therefore, we apply the Synthetic Control Method (SCM) to analyze the case.

The method provides multiple advantages in our case. First, it does not presuppose the parallel trends assumption as Difference-in-Difference approaches do, allowing us to analyze anticipation effects instead of assuming they are irrelevant.

[5] Calculations based on own dataset.

[6] California Air Resources Board. (2018, July 11). Climate pollutants fall below 1990 levels for first time. https://ww2.arb.ca.gov/news/climate-pollutants-fall-below-1990-levels-first-time

The counterfactual is constructed to minimize the distance function between the pre-treatment outcomes of the treated unit and the synthetic control. This reduces the selection bias, as the comparison units are not selected by the researcher, but are estimated algorithmically. Another advantage is the possibility of integrating covariates which are then considered in calculating the weights. We use real GDP, employment in manufacturing, and turnover in the private goods-producing industry (all in per capita terms).[7] We also include other potential covariates, namely energy intensity and carbon intensity, but they dropped in the final specification, as they did not add explanatory power to the model. Lastly, the synthetic control method is highly transparent, as both, the weights for the control units and the weights for the predictors can be revisited.

We use US state-level panel data from 2003 to 2019. California's cap-and-trade system was enacted in 2013. Hence, the pre-treatment period spans over ten years. The sample ends in 2019. Although newer data is already available, we did not include it in the analysis as we intended to exclude possibly distorting effects of the Covid-19 pandemic. However, this means that long-term effects can neither be analyzed nor predicted with this sample. Our data includes all 50 US states (excluding District of Colombia), although not all of them are considered in the donor pool. First, we exclude neighboring states (Oregon, Nevada, and Arizona) to rule out possible spill-over effects. Second, all states participating in the RGGI program are excluded, as they have implemented emission trading as well (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont). Virginia is included even though it is part of the RGGI since it only joined in 2021. The remaining 37 states represent the donor pool for the study.

In the first step, we estimate the effect on annual energy-related carbon dioxide emissions measured in metric tons per person. This seems to be the most appropriate measure for the policy's effectiveness. In the second step, we assess the aggregate economic effects considering real GDP per capita, turnover in the private goods-producing industry, and total employment as dependent variables. All variables are expressed in per capita terms making the treated unit more comparable. As we consider it necessary to use covariates, we only use three years of lagged outcome variables as additional predictors, so that the covariates are still considered by the algorithm (Ferman et al., 2020; Kaul et al., 2022). All other predictors are averaged over the entire pre-treatment period. To check the results' validity, we conduct placebo tests and plot the post/pre-MSPE (mean squared prediction error) ratios of all individual placebo tests. The MSPE of the treated unit should be particularly low for the pre-treatment period and high for the period after the intervention, so its post/pre-MSPE ratio should be one of the highest in the sample. On the basis of the ranked post/pre-MSPE ratios, we calculate p-values as proposed by Abadie et al. (2010) dividing the rank of the treatment unit by the number of units in the sample.

Although the ETS only took effect in 2013, the measure was already decided on in 2006. This left companies with much time to prepare for its implementation. Therefore, it seems reasonable to assume anticipation effects. We consider this by defining a second specification with 2009 as the treatment year for each experiment. It is hard to argue that all anticipation effects have occurred within one year, particularly considering the large period between decision and installation. However,

[7]real GDP and industry turnover are only used as covariates in those models in which they are not the outcome variable themselves.

the year 2009 seems most appropriate for the placebo in time since it lies halfway between 2006 and 2013, but still leaves a large enough pre-treatment period.

3.3 Emission Abatement

3.3.1 Results

We present our results in Figure 1 finding that California has reduced its emissions stronger than its synthetic counterfactual. Both trends are on a reduction path until 2009, then the emissions of the treated unit keep on falling while the trend for the synthetic control stabilizes and even records a slow rise in emissions. At first sight, it seems that the difference between treatment and control does not change much after 2013 (panel A). The graph plotting the gap between both functions (panel B), however, shows that even after the introduction of the ETS the emission trends further diverge. The second interesting finding is that the effect kicks in earlier than the measure's enactment. The graphs in which 2009 is defined as the treatment year (Figure C.1 in the appendix) show that the parallel trend reverses at this point in time. This could be interpreted as evidence for the occurrence of an anticipation effect. Firms might have reduced investments in carbon-intensive technology and shifted funds to finance greener production in advance, as they were already aware of the introduction of the ETS in 2006. We will further test this hypothesis in the next sections.

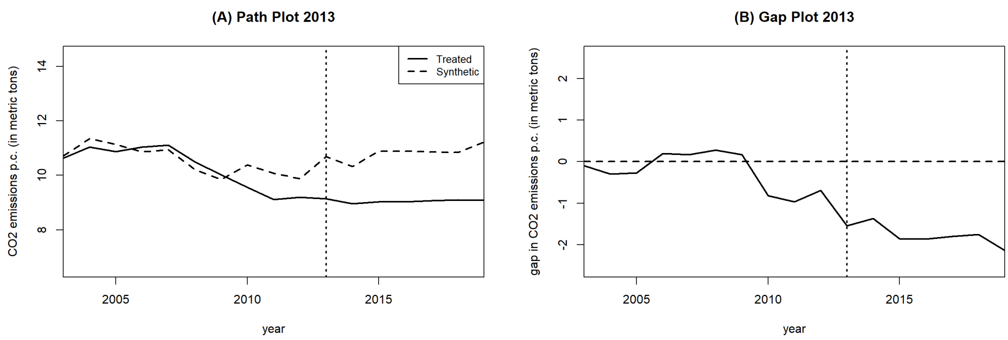

FIGURE 1: TRENDS IN TOTAL CO2 EMISSIONS P.C. 2003-2019: CALIFORNIA VERSUS SYNTHETIC CALIFORNIA

3.3.2 Robustness

Two issues occur needing further scrutiny. First, the covariates are barely considered as the weights are almost exclusively distributed between the three lagged emission values (see, Table B.3 in the appendix). This is a common problem with synthetic controls. The trade-off between finding a well-suited pre-treatment fit and taking into consideration unobserved confounders is often resolved in favor of the former (Kaul et al., 2022), also because the algorithm used[8] has a tendency to do so. Abadie (2021) argues that all weights should, in practice, be chosen to best resemble the pre-treatment trajectory of the treated unit, meaning that only under this condition, should covariates be considered. Hence, disregard for the covariates does not delegitimize the results. Second, synthetic California is almost entirely composed of one state (see Table B.2 in the appendix). In a comparative case study, this is

[8]We use the Synth package in R proposed by Abadie et al. (2011).

not problematic as such, but it strengthens the argument if the weights are more evenly distributed. However, the "sparsity of the weights" (p. 398) for the donor pool is a common characteristic of synthetic controls (Abadie, 2021). More important than the even distribution of weights is that the states forming the synthetic control seem comparable to the treated unit. In our case, the synthetic California consists of Idaho and Washington. Although both states are much smaller in terms of population size,[9] they are geographically close, while still not sharing a common border.

To further investigate the robustness of our estimates, we conduct placebo tests for all units in the donor pool and plot the results and the corresponding ranked post/pre-MSPE ratios in Figure 2.

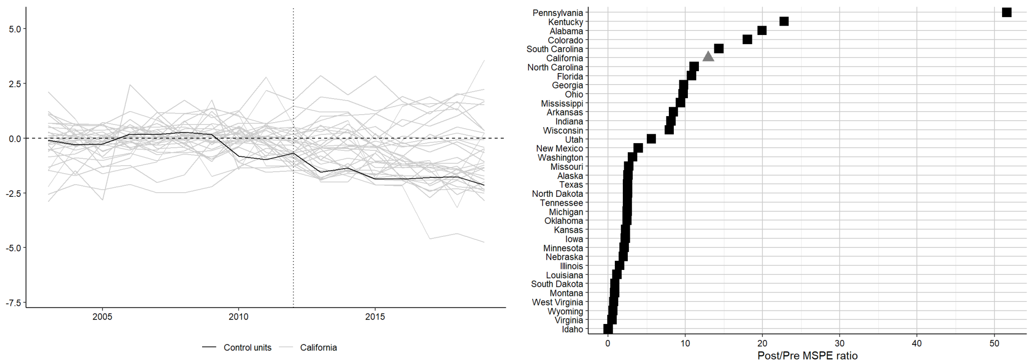

Figure 2: Placebo test and post/pre-MSPE ranking for total CO2 emissions p.c.

The results show that California ranks among those states that have reduced their emissions more intensively from 2013 onward. California has the 6th highest post/pre-MSPE ratio out of a sample of 36 states which is equivalent to a p-value of 0.167. The robustness test for the treatment year 2009 (Figure C.7 in the appendix) confirms the visual evidence suggesting that California's relative emission reduction has taken off earlier. Here, California ranks third corresponding to a p-value of 0.083. There are three possible explanations: First, the fact that the state's legislature already decided on the AB-32 entailing the introduction of the ETS in 2006 suggests that firms had enough time to prepare for the intervention. This implies that there could have been significant anticipation effects. Second, it could be that California was affected stronger than other states by the financial crisis causing emissions to fall below the counterfactual without any policy intervention. Mastrandrea et al. (2020) account the major part of emission abatement in the period between 2009 and 2013 to changes in GDP. Still, it could be that the emission reduction that occurred before the actual implementation of the ETS is at least partly attributable to other policy measures. With the adoption of AB-32, California implemented additional environmental policies, so-called "complementary policies"[10], which are predicted to contribute a significant amount of emission reduction (Mazmanian et

[9] California has 39.4 million inhabitants, while Idaho and Colorado have 1.8 and 7.6 million, respectively.

[10] Four policy instruments next to the ETS are considered as most significant for reaching emission reduction targets in California: (1) tailpipe emission standards for cars and trucks; (2) Low carbon fuel standards for gasoline; (3) Energy efficiency standards for new buildings; and (4) renewable portfolio standards for electricity utilities (Wara, 2014). While (1) became a national standard shortly after its implementation, meaning that it cannot account for differences in emissions between states, all other measures potentially affect the outcome.

al., 2020; Wara, 2014). To assess whether there actually is an anticipation effect and to further elaborate on the effect of the ETS we examine heterogeneous treatment effects between the affected sectors.

3.3.3 Treatment heterogeneity

We assume that not all sectors are similarly affected by the carbon pricing measure as some rely less on carbon-intensive technologies than others. Therefore we conduct a synthetic control analysis for all sectors included in the ETS, namely electricity, industry, buildings, commercial, and transportation[11] (ICAP, 2022). We only receive meaningful results for the electricity and the buildings sector. In all other sectors, the effect is either too small or the data does not allow for building a suitable synthetic counterfactual. While the effect for electricity emissions is particularly strong with annual emission reductions of 6.2% (Figure 3), we examine residential emissions to fall by 1.4% (Figure 4). The placebo tests for both experiments reveal that California ranks among the highest states in the donor pool (Figures C.8 and C.9 in the appendix). We estimate p-values of 0.111 for electricity and 0.056 for residential emissions. In both cases analyzed, the abatement effect only emerges after 2013, while the alternative treatment year 2009 shows no effect on CO2 emissions. This suggests that anticipation effects might have not caused previous relative reductions in overall carbon emissions.

FIGURE 3: TRENDS IN CO2 EMISSIONS P.C. IN ELECTRICITY SECTOR 2003-2019: CALIFORNIA VERSUS SYNTHETIC CALIFORNIA

FIGURE 4: TRENDS IN CO2 EMISSIONS P.C. IN BUILDINGS SECTOR 2003-2019: CALIFORNIA VERSUS SYNTHETIC CALIFORNIA

[11] The ETS was expanded in 2015, additionally covering the distribution of fuels and natural gas.

3.4 Economic Effects

It is much more difficult to assess the causal impact of a policy measure that explicitly aims to reduce emissions on economic performance than on the target variable itself. Many factors determine growth, employment, and firm turnovers; we cannot control them simultaneously. However, researchers struggled to make a causal link between aggregate emission reductions and carbon pricing (see, e.g., Pretis, 2022). In a study on the EU ETS, Dechezleprêtre et al. (2023) argue that it seems more difficult to assess the emission effects than the economic effects of policy instruments. Our estimates confirm these assumptions.

3.4.1 Results

Figure 5 illustrates GDP trends for California and the synthetic counterfactual. The pre-treatment fit is highly precise, and we can observe a clear divergence in 2013. California's GDP rises continuously faster after the introduction of the ETS. Figure C.4 in the appendix shows that the choice of the treatment year is not arbitrary (The same is true for Figure C.5 and C.6 in the appendix). If we define 2009 as the treatment year, we observe that the state grows slower than its counterfactual and only reaches higher growth rates after 2013.

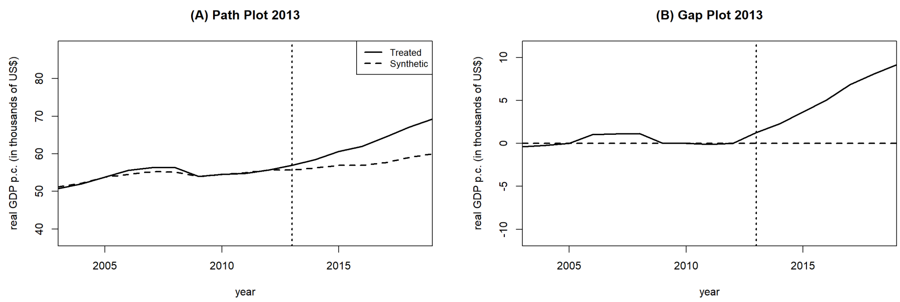

Figure 5: Trends in real GDP p.c. 2003-2019: California versus synthetic California

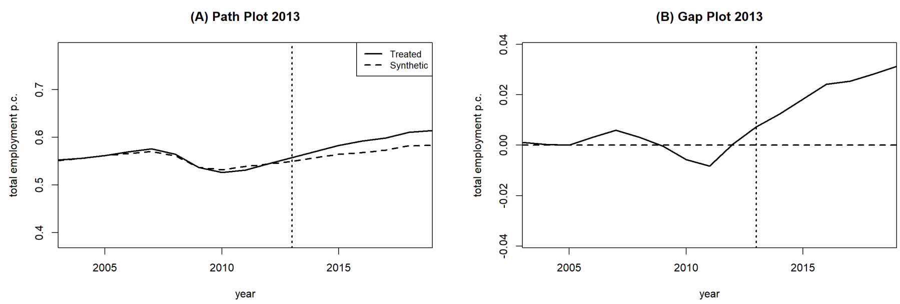

Figure 6: Trends in total employment p.c. 2003-2019: California versus synthetic California

The estimates for employment (Figure 6) and firm turnovers (Figure 7) show similar patterns. In both cases, the trend for the treated unit surpasses the synthetic control from the treatment 2013 year onward. The fits for both outcome variables are good, and in either case, California falls behind in the anticipation period before catching back up and surpassing its synthetic equivalent.

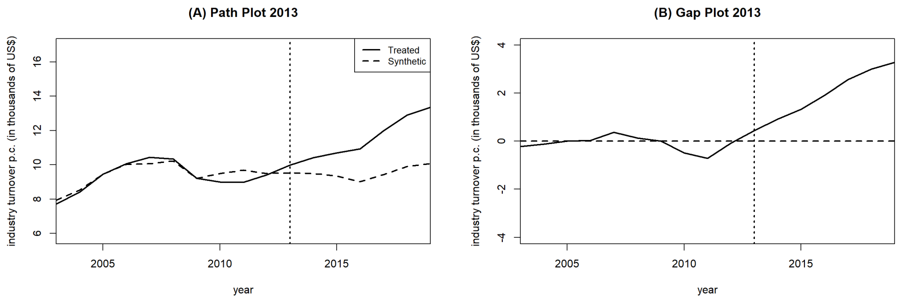

FIGURE 7: TRENDS IN INDUSTRY TURNOVERS P.C. 2003-2019: CALIFORNIA VERSUS SYNTHETIC CALIFORNIA

3.4.2 Robustness

In all three analyses, the counterfactual is composed of a large variety of states (see, Tables B.20, B.26, and B.32 in the appendix). This rules out far-fetched comparisons and speaks in favor of the results. Similarly, the algorithm considers the covariates, making the synthetic control even more reliable (see, Tables B.21, B.27, and B.33 in the appendix). The placebo tests also strongly support our results. For industry turnover and employment, California has the second highest post/pre-MSPE ratio out of the 36 states in the donor pool, for GDP even the highest (Figures 8, 9 and 10).[12] This proves that the outcome is statistically significant.

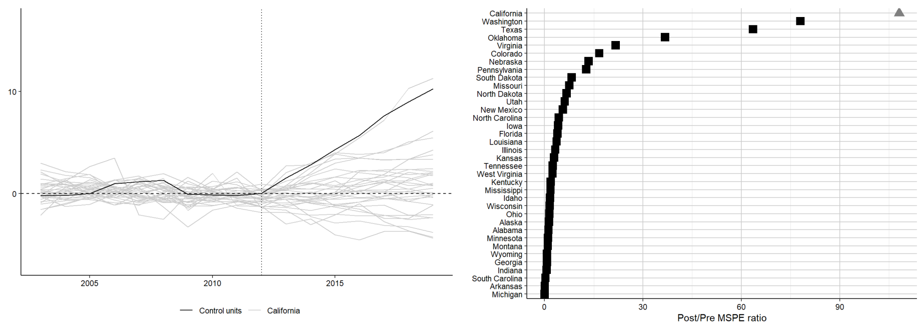

FIGURE 8: PLACEBO TEST AND PRE/POST-MSPE RANKING FOR GDP P.C.

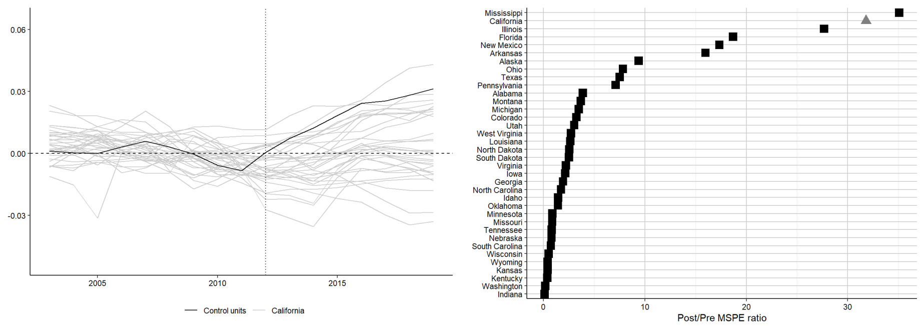

FIGURE 9: PLACEBO TEST AND PRE/POST-MSPE RANKING FOR TOTAL EMPLOYMENT P.C.

[12]These results equal p-values of 0.056 for industry turnover and employment, and 0.028 for GDP.

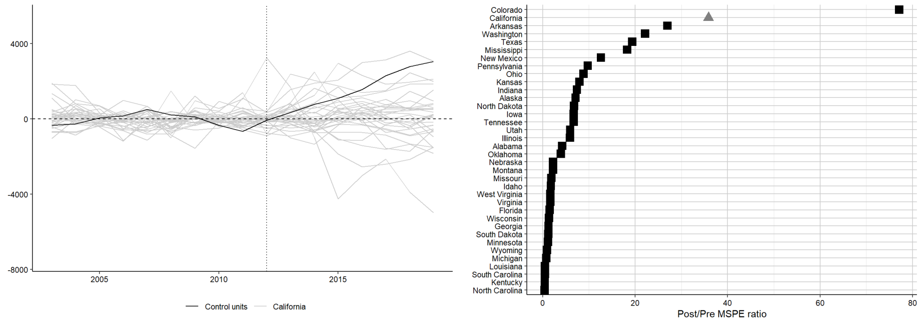

Figure 10: Placebo test and Pre/post-MSPE ranking for industry turnover p.c.

However, we have to consider reverse causality. Metcalf and Stock (2020) argue that governments could decide to implement carbon pricing or lower the emission cap during economic growth. Then the measure would not cause growth but simply be enacted because of growth. This can, however, be ruled out in the case of California since the policy framework AB-32 was adopted in 2006. At that time, the economic conditions for the policy's implementation were unforeseeable. The emission reduction level in place until 2016 was also decided on in 2006. One could argue that the more ambitious goal to reduce emissions by 40% below its 1990 level until 2030 could have been impacted by good economic performance. This, however, does not interfere with our results, as the positive trend clearly started with the measure's implementation in 2013.

The timing of the measure comes with another issue. One could argue that the drop in all three outcome variables after 2009 was an effect of the financial crisis and the bounce-back in 2013 then simply a recovery effect. We cannot rule out that the first part of the argument is at least partly right. California might have been more affected by the financial crisis than other US states, and this is not controlled for when 2009 is defined as treatment year. However, it is unlikely that the second part of the argument is also true. The synthetic control is created by minimizing the distance to the pre-treatment trend of the observed case, meaning that if it is true that California suffered a stronger downturn after the financial crisis, then the counterfactual should encompass states that were strongly affected too. Even if our results show that for firm turnover and employment, this is not fully accomplished, as the curve for California falls below the synthetic control in the recession years, the gains after 2013 far outgrow these differences. We are, therefore, confident that California's strong economic performance after 2013 relative to that of the synthetic control is not solely attributable to the recovery from the financial crisis. Still, more evidence would be necessary to disentangle the effects of the ETS and the financial crisis, particularly in its anticipation phase.

3.5 Discussion

We show that California's cap-and-trade system has not hurt the economy and seems to have even spurred growth. Recent evidence from da Cruz (2022) analyzing the ETS' impact on green patents suggests that this effect might have been inferred by low-carbon innovation. We should, however, consider that California's preconditions for implementing carbon pricing were quite good, considering that its economy is characterized by low carbon intensity and a large service sector.[13] Therefore, one should be cautious about extrapolating the estimates to other states or countries with different economic structures. However, as stated before, there is too little diversity in empirical assessments of carbon pricing schemes. Therefore, our study serves as additional evidence to the fairly one-sided body of literature on the EU ETS. A diversification of comparative case studies could, in the next step, help to understand under which circumstances carbon pricing is successful.

Moreover, the effectiveness of carbon pricing highly depends on the design, particularly the price, or in the case of ETS, the cap applied. These differences always need to be considered when making inferences about the effects of carbon pricing in general. Similarly, the economic impact depends on the stringency of the measure. As we argued, we estimate overall annual emission abatement to be below 1%, and we only find a large effect in the electricity sector. This confirms existing evidence suggesting that other policy measures might have been more important than the ETS in reducing carbon emissions in California, in the anticipation phase of the measure (Cullenward, 2014a; Wara, 2014). After 2013, we still need to assume some interaction effects occurred between the ETS and complementary policies. However, implementing a cap-and-trade system makes most other policy instruments in those sectors covered toothless, at least on an aggregate level (Goulder and Stavins, 2011). All emission reductions induced by other measures free emission certificates, which can then be sold, and carbon is emitted elsewhere. Complementary policies are therefore doomed to cause leakage to other sectors. So, the cap of an ETS strictly regulates emissions by setting a limit and making reductions beyond this limit highly unattractive. As California's ETS covers about three-quarters of the state's CO2 emissions, it seems reasonable to assume that the large majority of reductions in the post-2013 period are attributable to carbon pricing. Furthermore, we need to consider that sub-national environmental policy measures are particularly prone to carbon leakage (Fell and Maniloff, 2018). While no study - to the best of our knowledge - has estimated leakage effects for California's carbon market, Cullenward (2014b) provides selected evidence that leakage might be a significant problem. Hence, these objections suggest that our estimates should rather be interpreted as an upper limit of the actual treatment effect.

One should not stretch our results to argue that carbon pricing in general has no adverse economic effects. According to estimates by the High-Level Commission on Carbon Prices, the necessary price to limit global warming to 1.5°C solely by means of carbon pricing, lies between 170 and 290 USD2015/tCO2 (Stieglitz and Stern, 2017). No carbon pricing scheme so far fulfills this condition (World Bank, 2022). Therefore, it remains open how large the aggregate economic effects of sufficiently strict pricing policies would be. The same applies to a policy mix combining carbon pricing with other environmental policy measures.

4 Conclusion

To the best of our knowledge, our paper is the first comprehensive quantitative ex-post analysis of emission abatement and economic effects induced by California's ETS. In the first step, we assess the overall emission reduction using the synthetic control method. Our evidence suggests that between 2013 and 2019 CO2 emissions

[13] California ranks 7th for turnover in services per capita in 2019 (9th in 2000) and 48th for carbon intensity of the economy in 2019 (47th in 2000). Calculations based on own data set.

have fallen by 0.9% annually and by 6.4% in total compared to an optimal counterfactual. This reduction is most visible in the buildings and electricity sector, while the latter comprises the largest share of emission abatement. Although relative emissions dropped significantly in the period leading up to the implementation of the ETS, we assume that this can be accredited to a stronger exposure to the financial crisis or alternative environmental policies dismissing the hypothesis that firms have anticipated the introduction of the measure. Furthermore, we cannot rule out that carbon leakage has occurred, further depressing the actual treatment effect, and we need to assume that at least some interaction effect with other environmental policies has taken place. Second, we analyze the macroeconomic effects of the policy and find that the ETS has had a positive effect on GDP, employment, and firm turnover. This contradicts the widespread belief that carbon pricing comes at a high economic price. Although this does not mean that any price on carbon boosts the economy, our evidence suggests that low prices can have a net positive effect on aggregate economic outcomes in the short run. However, as more stringent measures are desperately needed, it remains unclear if those would still entail net positive economic effects. Comparative studies also need to further analyze the conditions under which carbon pricing is successful. Considering that still far too few environmental policy measures have been implemented and those in place are mostly too weak, there is an urgent need to study the political barriers and political economy constraints hindering the necessary policies to be installed. Citizens' concerns about emission trading and carbon taxes (c.f. Kallbekken and Sælen, 2011, Maestre-Andres et al., 2019) have to be taken seriously. Hence, researchers need to develop a practical interdisciplinary approach to climate politics considering political economy perspectives and feasibility aspects.

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Appendices

A Data Sources

Carbon-dioxide emissions: The measure comprises all energy-related CO2 emissions by state and refers to emissions released at the location where fossil fuels are consumed. The data was obtained from the US Energy Information Administration available at https://www.eia.gov/environment/emissions/state/.

GDP: Real GDP by state is measured in chained 2012 dollars. The data is available Bureau of Economic Analysis (BEA) at the US Department of Commerce (https://apps.bea.gov/regional/downloadzip.cfm).

Employment: The employment measure counts all state-wide full-time and half-time jobs by NAICS Industry. Employment in manufacturing is used as covariate. Manufacturing comprises all establishments engaged in the mechanical, physical, or chemical transformation of materials, substances, or components into new products. The data can be obtained from the BEA at https://apps.bea.gov/regional/downloadzip.cfm.

Industry turnover: Private goods-producing industry consists of agriculture, forestry, fishing and hunting; mining; construction; and manufacturing. The data is from the BEA (https://apps.bea.gov/regional/downloadzip.cfm).

Population: Resident population data was provided by the Federal Reserve Economic Database available at https://fred.stlouisfed.org/release/tables?rid=118&eid=259194.

B Descriptive Statistics

	Treated	Synthetic	Sample Mean
Real GDP p.c.	54.387	38.655	47.408
Employment manufacturing p.c.	0.041	0.044	0.049
Industry turnover p.c.	9303.591	8468.394	10730.077
Emissions p.c. 2012	9.191	9.879	26.722
Emissions p.c. 2010	9.555	10.378	28.413
Emissions p.c. 2005	10.873	11.143	31.183

Figure B.1: Total CO2 emissions (2013) predictor means

Weight	State	Weight	State
0.000	Alabama	0.000	Nebraska
0.000	Alaska	0.000	New Mexico
0.000	Arkansas	0.000	North Carolina
0.000	Colorado	0.000	North Dakota
0.000	Florida	0.000	Ohio
0.000	Georgia	0.000	Oklahoma
0.946	Idaho	0.000	Pennsylvania
0.000	Illinois	0.000	South Carolina
0.000	Indiana	0.000	South Dakota
0.000	Iowa	0.000	Tennessee
0.000	Kansas	0.000	Texas
0.000	Kentucky	0.000	Utah
0.000	Louisiana	0.000	Virginia
0.000	Michigan	0.054	Washington
0.000	Minnesota	0.000	West Virginia
0.000	Mississippi	0.000	Wisconsin
0.000	Missouri	0.000	Wyoming
0.000	Montana		

Figure B.2: Total CO2 emissions (2013) state weights in synthetic control

Predictor	Weight
Real GDP p.c.	0
Employment manufacturing p.c.	0.015
Industry turnover p.c.	0.017
Emissions p.c. 2012	0.079
Emissions p.c. 2010	0.889
Emissions p.c. 2005	0

Figure B.3: Total CO2 emissions (2013) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Real GDP p.c.	54.134	39.723	47.087
Employment manufacturing p.c.	0.044	0.047	0.052
Industry turnover p.c.	9402.515	8501.460	10337.639
Emissions p.c. 2008	10.491	10.278	29.980
Emissions p.c. 2005	10.873	11.197	31.205
Emissions p.c. 2003	10.627	10.784	31.076

Figure B.4: Total CO2 emissions (2009) predictor means

Weight	State	Weight	State
0.000	Alabama	0.000	Nebraska
0.000	Alaska	0.000	New Mexico
0.000	Arkansas	0.000	North Carolina
0.000	Colorado	0.000	North Dakota
0.000	Florida	0.000	Ohio
0.000	Georgia	0.000	Oklahoma
0.912	Idaho	0.000	Pennsylvania
0.000	Illinois	0.000	South Carolina
0.000	Indiana	0.000	South Dakota
0.000	Iowa	0.000	Tennessee
0.000	Kansas	0.000	Texas
0.000	Kentucky	0.000	Utah
0.000	Louisiana	0.000	Virginia
0.000	Michigan	0.088	Washington
0.000	Minnesota	0.000	West Virginia
0.000	Mississippi	0.000	Wisconsin
0.000	Missouri	0.000	Wyoming
0.000	Montana		

Figure B.5: Total CO2 emissions (2009) state weights in synthetic control

Predictor	Weight
Real GDP p.c.	0
Employment manufacturing p.c.	0.002
Industry turnover p.c.	0.001
Emissions p.c. 2008	0.387
Emissions p.c. 2005	0.321
Emissions p.c. 2003	0.288

Figure B.6: Total CO2 emissions (2009) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Real GDP p.c.	54.387	44.759	47.408
Employment manufacturing p.c.	0.041	0.039	0.049
Industry turnover p.c.	9303.591	11710.116	10730.077
Electricity Emissions p.c. 2012	1.265	1.206	12.398
Electricity Emissions p.c. 2010	1.165	1.184	13.603
Electricity Emissions p.c. 2005	1.171	1.307	14.878

Figure B.7: Electricity emissions (2013) predictor means

Weight	State	Weight	State
0.000	Alabama	0.000	Nebraska
0.193	Alaska	0.000	New Mexico
0.000	Arkansas	0.000	North Carolina
0.000	Colorado	0.000	North Dakota
0.000	Florida	0.000	Ohio
0.000	Georgia	0.000	Oklahoma
0.800	Idaho	0.000	Pennsylvania
0.000	Illinois	0.000	South Carolina
0.000	Indiana	0.000	South Dakota
0.000	Iowa	0.000	Tennessee
0.000	Kansas	0.000	Texas
0.000	Kentucky	0.000	Utah
0.000	Louisiana	0.000	Virginia
0.000	Michigan	0.007	Washington
0.000	Minnesota	0.000	West Virginia
0.000	Mississippi	0.000	Wisconsin
0.000	Missouri	0.000	Wyoming
0.000	Montana		

Figure B.8: Electricity emissions (2013) state weights in synthetic control

Predictor	Weight
Real GDP p.c.	0
Employment manufacturing p.c.	0
Industry turnover p.c.	0
Electricity Emissions p.c. 2012	0.231
Electricity Emissions p.c. 2010	0.161
Electricity Emissions p.c. 2005	0.608

Figure B.9: Electricity emissions (2013) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Real GDP p.c.	54.134	40.753	47.156
Employment manufacturing p.c.	0.044	0.046	0.053
Industry turnover p.c.	9402.515	9402.849	10428.374
Emissions p.c. 2008	1.391	1.290	14.446
Emissions p.c. 2005	1.171	1.306	14.878
Emissions p.c. 2003	1.211	1.229	14.729

Figure B.10: Electricity emissions (2009) predictor means

Weight	State	Weight	State
0.001	Alabama	0.002	Nebraska
0.060	Alaska	0.001	New Mexico
0.002	Arkansas	0.002	North Carolina
0.002	Colorado	0.001	North Dakota
0.002	Florida	0.002	Ohio
0.002	Georgia	0.002	Oklahoma
0.880	Idaho	0.002	Pennsylvania
0.003	Illinois	0.002	South Carolina
0.001	Indiana	0.004	South Dakota
0.002	Iowa	0.002	Tennessee
0.001	Kansas	0.002	Texas
0.001	Kentucky	0.001	Utah
0.002	Louisiana	0.002	Virginia
0.002	Michigan	0.004	Washington
0.002	Minnesota	0.001	West Virginia
0.002	Mississippi	0.002	Wisconsin
0.001	Missouri	0.000	Wyoming
0.001	Montana		

Figure B.11: Electricity emissions (2009) state weights in synthetic control

Predictor	Weight
Real GDP p.c.	0
Employment manufacturing p.c.	0
Industry turnover p.c.	0.061
Emissions p.c. 2008	0.3
Emissions p.c. 2005	0.211
Emissions p.c. 2003	0.428

Figure B.12: Electricity emissions (2009) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Real GDP p.c.	54.387	54.223	47.408
Employment manufacturing p.c.	0.041	0.041	0.049
Industry turnover p.c.	9303.591	9396.845	10730.077
Residential Emissions p.c. 2012	0.721	0.706	0.973
Residential Emissions p.c. 2010	0.776	0.746	1.179
Residential Emissions p.c. 2005	0.788	0.798	1.272

Figure B.13: Residential emissions (2013) predictor means

Weight	State	Weight	State
0.000	Alabama	0.000	Nebraska
0.014	Alaska	0.000	New Mexico
0.000	Arkansas	0.000	North Carolina
0.046	Colorado	0.000	North Dakota
0.116	Florida	0.000	Ohio
0.000	Georgia	0.000	Oklahoma
0.000	Idaho	0.000	Pennsylvania
0.000	Illinois	0.000	South Carolina
0.000	Indiana	0.000	South Dakota
0.000	Iowa	0.000	Tennessee
0.000	Kansas	0.000	Texas
0.000	Kentucky	0.000	Utah
0.000	Louisiana	0.038	Virginia
0.000	Michigan	0.785	Washington
0.000	Minnesota	0.000	West Virginia
0.000	Mississippi	0.000	Wisconsin
0.000	Missouri	0.000	Wyoming
0.000	Montana		

Figure B.14: Residential emissions (2013) state weights in synthetic control

Predictor	Weight
Real GDP p.c.	0.215
Employment manufacturing p.c.	0.191
Industry turnover p.c.	0.16
Residential Emissions p.c. 2012	0.139
Residential Emissions p.c. 2010	0.01
Residential Emissions p.c. 2005	0.286

Figure B.15: Residential emissions (2013) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Real GDP p.c.	54.134	54.066	47.156
Employment manufacturing p.c.	0.044	0.044	0.053
Industry turnover p.c.	9402.515	9414.288	10428.374
Residential Emissions p.c. 2008	0.786	0.807	1.286
Residential Emissions p.c. 2005	0.788	0.794	1.272
Residential Emissions p.c. 2003	0.804	0.804	1.366

Figure B.16: Residential emissions (2009) predictor means

Weight	State	Weight	State
0.000	Alabama	0.000	Nebraska
0.000	Alaska	0.000	New Mexico
0.000	Arkansas	0.000	North Carolina
0.000	Colorado	0.000	North Dakota
0.060	Florida	0.000	Ohio
0.000	Georgia	0.000	Oklahoma
0.000	Idaho	0.000	Pennsylvania
0.000	Illinois	0.000	South Carolina
0.000	Indiana	0.000	South Dakota
0.000	Iowa	0.000	Tennessee
0.000	Kansas	0.001	Texas
0.000	Kentucky	0.000	Utah
0.038	Louisiana	0.101	Virginia
0.000	Michigan	0.785	Washington
0.000	Minnesota	0.000	West Virginia
0.000	Mississippi	0.000	Wisconsin
0.000	Missouri	0.008	Wyoming
0.000	Montana		

Figure B.17: Residential emissions (2009) state weights in synthetic control

Predictor	Weight
Real GDP p.c.	0.223
Employment manufacturing p.c.	0.149
Industry turnover p.c.	0.162
Residential Emissions p.c. 2008	0.038
Residential Emissions p.c. 2005	0
Residential Emissions p.c. 2003	0.427

Figure B.18: Residential emissions (2009) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Employment manufacturing p.c.	0.041	0.041	0.049
Industry turnover p.c.	9303.591	9303.681	10730.077
Real GDP p.c. 2012	55.689	55.685	48.756
Real GDP p.c. 2010	54.556	54.698	47.429
Real GDP p.c. 2005	53.780	53.780	47.190

Figure B.19: Real GDP (2013) predictor means

Weight	State	Weight	State
0.003	Alabama	0.009	Nebraska
0.052	Alaska	0.000	New Mexico
0.003	Arkansas	0.004	North Carolina
0.012	Colorado	0.027	North Dakota
0.026	Florida	0.005	Ohio
0.006	Georgia	0.003	Oklahoma
0.003	Idaho	0.007	Pennsylvania
0.220	Illinois	0.003	South Carolina
0.003	Indiana	0.006	South Dakota
0.005	Iowa	0.005	Tennessee
0.005	Kansas	0.005	Texas
0.003	Kentucky	0.004	Utah
0.004	Louisiana	0.509	Virginia
0.004	Michigan	0.043	Washington
0.000	Minnesota	0.002	West Virginia
0.003	Mississippi	0.004	Wisconsin
0.005	Missouri	0.004	Wyoming
0.001	Montana		

Figure B.20: Real GDP (2013) state weights in synthetic control

Predictor	Weight
Employment manufacturing p.c.	0.483
Industry turnover p.c.	0.433
Real GDP p.c. 2012	0.022
Real GDP p.c. 2010	0
Real GDP p.c. 2005	0.062

Figure B.21: Real GDP (2013) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Employment manufacturing p.c.	0.044	0.044	0.053
Industry turnover p.c.	9402.515	12586.607	10428.374
Real GDP p.c. 2008	56.322	56.320	48.429
Real GDP p.c. 2005	53.780	53.774	47.190
Real GDP p.c. 2003	50.776	50.791	44.610

Figure B.22: Real GDP (2009) predictor means

Weight	State	Weight	State
0.011	Alabama	0.020	Nebraska
0.179	Alaska	0.012	New Mexico
0.009	Arkansas	0.014	North Carolina
0.024	Colorado	0.018	North Dakota
0.021	Florida	0.012	Ohio
0.014	Georgia	0.012	Oklahoma
0.012	Idaho	0.017	Pennsylvania
0.025	Illinois	0.010	South Carolina
0.010	Indiana	0.019	South Dakota
0.023	Iowa	0.012	Tennessee
0.015	Kansas	0.014	Texas
0.010	Kentucky	0.020	Utah
0.039	Louisiana	0.134	Virginia
0.010	Michigan	0.156	Washington
0.034	Minnesota	0.010	West Virginia
0.008	Mississippi	0.012	Wisconsin
0.014	Missouri	0.035	Wyoming
0.014	Montana		

Figure B.23: Real GDP (2009) state weights in synthetic control

Predictor	Weight
Employment manufacturing p.c.	0
Industry turnover p.c.	0
Real GDP p.c. 2008	0.415
Real GDP p.c. 2005	0.42
Real GDP p.c. 2003	0.164

Figure B.24: Real GDP (2009) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Employment manufacturing p.c.	0.041	0.041	0.049
Real GDP p.c.	54.387	54.341	47.408
Industry turnover p.c. 2012	9421.909	9499.849	11964.037
Industry turnover p.c. 2010	8996.727	9330.738	10778.956
Industry turnover p.c. 2005	9458.010	9406.785	10205.327

Figure B.25: Industry turnover (2013) predictor means

Weight	State	Weight	State
0.000	Alabama	0.000	Nebraska
0.000	Alaska	0.000	New Mexico
0.000	Arkansas	0.001	North Carolina
0.001	Colorado	0.000	North Dakota
0.000	Florida	0.001	Ohio
0.123	Georgia	0.000	Oklahoma
0.000	Idaho	0.001	Pennsylvania
0.000	Illinois	0.000	South Carolina
0.000	Indiana	0.000	South Dakota
0.000	Iowa	0.001	Tennessee
0.000	Kansas	0.000	Texas
0.000	Kentucky	0.000	Utah
0.006	Louisiana	0.632	Virginia
0.000	Michigan	0.000	Washington
0.164	Minnesota	0.000	West Virginia
0.000	Mississippi	0.000	Wisconsin
0.001	Missouri	0.069	Wyoming
0.000	Montana		

Figure B.26: Industry turnover (2013) state weights in synthetic control

Predictor	Weight
Employment manufacturing p.c.	0.186
Real GDP p.c.	0.26
Industry turnover p.c. 2012	0.334
Industry turnover p.c. 2010	0
Industry turnover p.c. 2005	0.221

Figure B.27: Industry turnover (2013) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Employment manufacturing p.c.	0.044	0.044	0.053
Real GDP p.c.	54.134	52.063	47.156
Industry turnover p.c. 2008	10337.280	10337.587	11927.069
Industry turnover p.c. 2005	9458.010	9457.245	10205.327
Industry turnover p.c. 2003	7712 .134	7713.718	8527.372

Figure B.28: Industry turnover (2009) predictor means

Weight	State	Weight	State
0.011	Alabama	0.011	Nebraska
0.035	Alaska	0.002	New Mexico
0.008	Arkansas	0.007	North Carolina
0.160	Colorado	0.004	North Dakota
0.064	Florida	0.010	Ohio
0.015	Georgia	0.006	Oklahoma
0.007	Idaho	0.009	Pennsylvania
0.035	Illinois	0.006	South Carolina
0.006	Indiana	0.008	South Dakota
0.009	Iowa	0.010	Tennessee
0.010	Kansas	0.006	Texas
0.007	Kentucky	0.013	Utah
0.046	Louisiana	0.257	Virginia
0.007	Michigan	0.168	Washington
0.026	Minnesota	0.006	West Virginia
0.007	Mississippi	0.011	Wisconsin
0.009	Missouri	0.000	Wyoming
0.006	Montana		

Figure B.29: Industry turnover (2009) state weights in synthetic control

Predictor	Weight
Employment manufacturing p.c.	0.001
Real GDP p.c.	0
Industry turnover p.c. 2008	0.621
Industry turnover p.c. 2005	0.288
Industry turnover p.c. 2003	0.09

Figure B.30: Industry turnover (2009) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Employment manufacturing p.c.	0.041	0.041	0.049
Real GDP p.c.	54.387	45.319	47.408
Total employment p.c. 2012	0.545	0.544	0.587
Total employment p.c. 2010	0.526	0.532	0.577
Total employment p.c. 2005	0.562	0.562	0.598

Figure B.31: Total employment (2013) predictor means

Weight	State	Weight	State
0.003	Alabama	0.004	Nebraska
0.034	Alaska	0.059	New Mexico
0.003	Arkansas	0.005	North Carolina
0.009	Colorado	0.005	North Dakota
0.274	Florida	0.009	Ohio
0.009	Georgia	0.012	Oklahoma
0.003	Idaho	0.013	Pennsylvania
0.021	Illinois	0.000	South Carolina
0.003	Indiana	0.003	South Dakota
0.003	Iowa	0.005	Tennessee
0.004	Kansas	0.026	Texas
0.006	Kentucky	0.009	Utah
0.022	Louisiana	0.010	Virginia
0.315	Michigan	0.020	Washington
0.004	Minnesota	0.073	West Virginia
0.006	Mississippi	0.002	Wisconsin
0.007	Missouri	0.011	Wyoming
0.008	Montana		

Figure B.32: Total employment (2013) state weights in synthetic control

Predictor	Weight
Employment manufacturing p.c.	0.543
Real GDP p.c.	0
Total employment p.c. 2012	0.255
Total employment p.c. 2010	0.024
Total employment p.c. 2005	0.178

Figure B.33: Total employment (2013) predictor weights in synthetic control

	Treated	Synthetic	Sample Mean
Employment manufacturing p.c.	0.044	0.044	0.053
Real GDP p.c.	54.134	45.518	47.156
Total employment p.c. 2008	0.564	0.566	0.607
Total employment p.c. 2005	0.562	0.562	0.598
Total employment p.c. 2003	0.553	0.552	0.588

Figure B.34: Total employment (2009) predictor means

Weight	State	Weight	State
0.018	Alabama	0.007	Nebraska
0.083	Alaska	0.123	New Mexico
0.024	Arkansas	0.023	North Carolina
0.008	Colorado	0.002	North Dakota
0.104	Florida	0.022	Ohio
0.028	Georgia	0.014	Oklahoma
0.017	Idaho	0.019	Pennsylvania
0.018	Illinois	0.041	South Carolina
0.019	Indiana	0.004	South Dakota
0.006	Iowa	0.023	Tennessee
0.008	Kansas	0.017	Texas
0.027	Kentucky	0.009	Utah
0.024	Louisiana	0.016	Virginia
0.054	Michigan	0.015	Washington
0.006	Minnesota	0.162	West Virginia
0.027	Mississippi	0.008	Wisconsin
0.022	Missouri	0.000	Wyoming
0.004	Montana		

Figure B.35: Total employment (2009) state weights in synthetic control

Predictor	Weight
Employment manufacturing p.c.	0.174
Real GDP p.c.	0
Total employment p.c. 2008	0.032
Total employment p.c. 2005	0.462
Total employment p.c. 2003	0.331

Figure B.36: Total employment (2009) predictor weights in synthetic control

C Additional Results

C.1 Results for Alternative Treatment year 2009

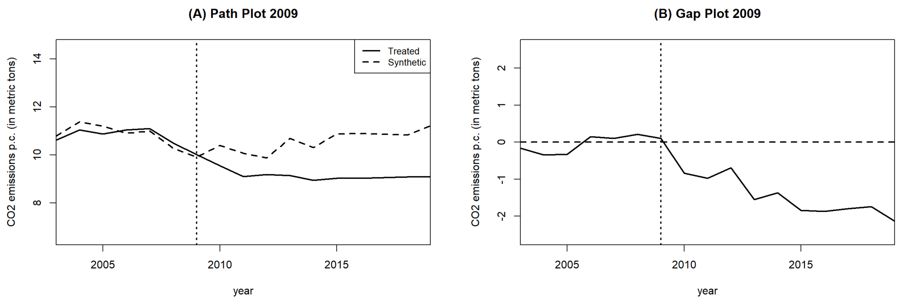

Figure C.1: Trends in total CO2 emissions p.c. 2003-2019: California versus synthetic California (treatment year 2009)

Figure C.2: Trends in CO2 emissions p.c. in electricity sector: California versus synthetic California (treatment year 2009)

Figure C.3: Trends in CO2 emissions p.c. in buildings sector: California versus synthetic California (treatment year 2009)

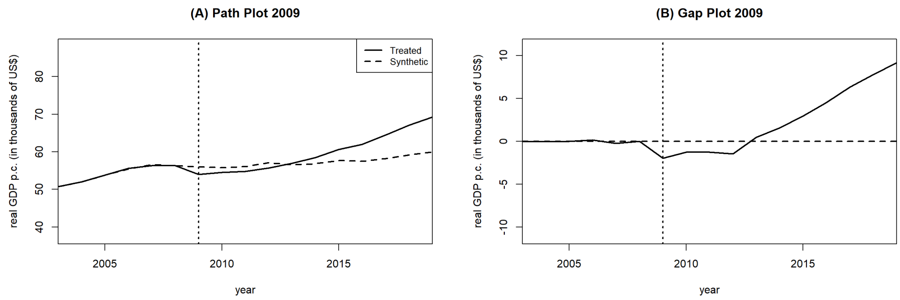

Figure C.4: Trends in real GDP p.c. 2003-2019: California versus synthetic California (treatment year 2009)

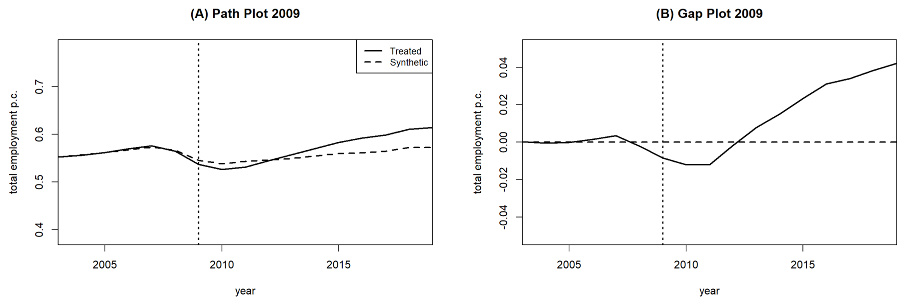

Figure C.5: Trends in total employment p.c. 2003-2019: California versus synthetic California (treatment year 2009)

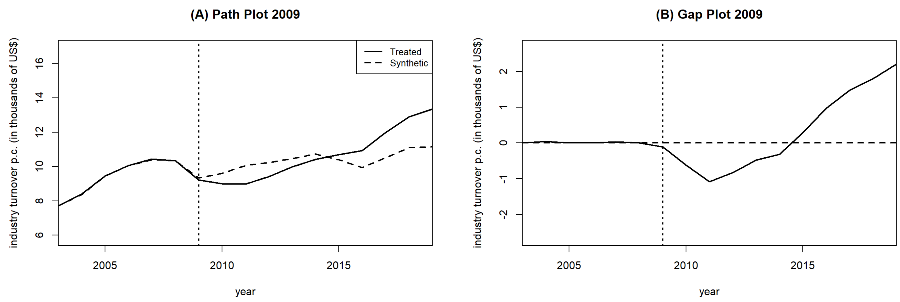

Figure C.6: Trends in industry turnovers p.c. 2003-2019: California versus synthetic California (treatment year 2009)

C.2 Placebo Tests and post/pre-MSPE rankings

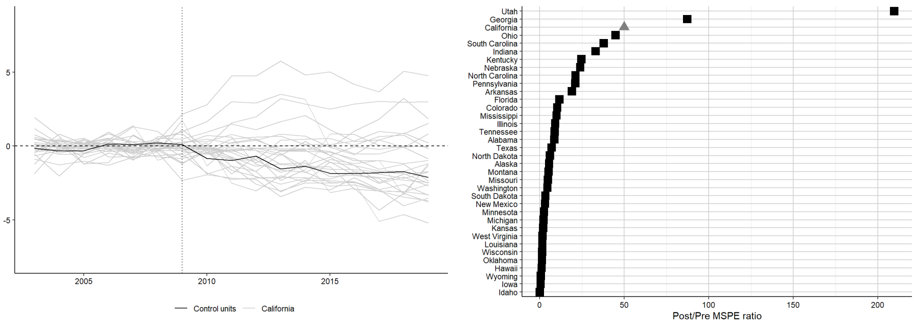

Figure C.7: Placebo test and post/pre-MSPE rankings for total CO2 emissions p.c. (treatment year 2009)

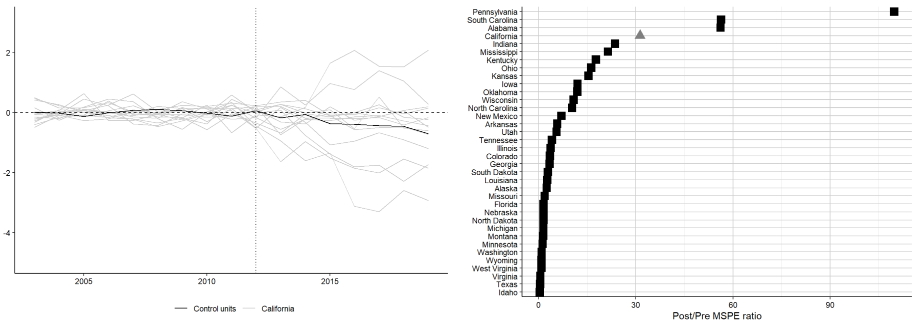

Figure C.8: Placebo test and post/pre-MSPE rankings for CO2 emissions p.c. in electricity sector (treatment year 2013)

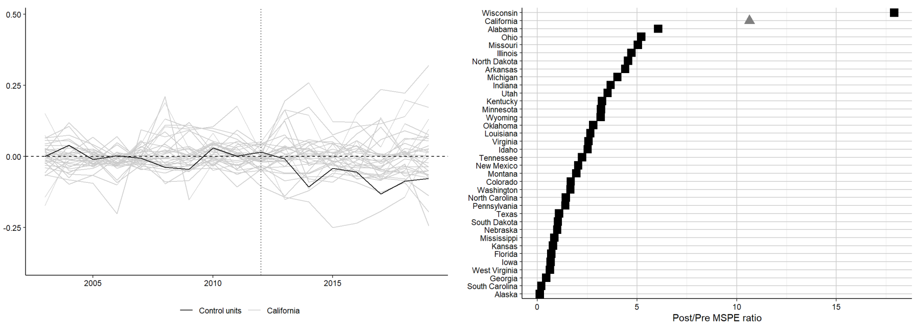

Figure C.9: Placebo test and post/pre-MSPE rankings for CO2 emissions p.c. in buildings sector (treatment year 2013)