Contents

1 Introduction

Since the industrial revolution, the amount of greenhouse gases in the atmosphere has increased tremendously. This has made the greenhouse effect, which would normally make Earth a liveable planet by raising its temperatures, much more severe, a phenomenon which is usually referred to as climate change. (IPCC, 2013) [13]

While governments have long relied on prescriptive regulation to tackle this issue, economists have always favoured market-based tools that range from emission trading schemes to carbon taxes. As many countries transition to these kind of policies (more than 40 countries already have carbon pricing in place according to the World Bank (2021) [5]) it is more important than ever to analyze the effects their implementation had on both emissions and the economy. This will allow countries to choose the most appropriate and effective tools depending on the different circumstances they face while making it possible to reach the environmental targets they've set at the least possible cost.

Interestingly, while manufacturing accounts for around 30% of the emissions around the world (Our World In Data) [9] very few carbon taxes (and ETSs) currently in place target its emissions. This usually happens because of various policymakers' fears ranging from loss of competitiveness to carbon leakage.

More importantly, there have been even fewer analyses of these policies and of their potential or actual impact on the sector's energy efficiency or emissions. (Floros & Vlachou, 2005 and Martin, de Preux, & Wagner, 2014) [11] [16] To expand this field we, thus, try to answer the question of whether carbon taxes were able to reduce the carbon intensity of British Columbia's manufacturing sector.

We choose specifically BC's application of the tax because it is almost unique in two key features: it doesn't have particular exemptions targeted at manufacturers and it is revenue-neutral. Furthermore, the region enacted no other policy targeting emissions or fuels during the period we will consider, thus, making it possible to analyze the carbon tax's effects in isolation. BC also has 10 post-intervention years, something that gives us the opportunity to evaluate the long-term effects of this policy (Government of British Columbia) [8].

To do so, we will implement the Synthetic Control Approach, an extension of the Difference-in-Difference Estimator (Abadie and Gardeazabal 2003 and Abadie, Diamond, and Hainmueller, 2010, 2015) [3] [2] [1] that allows us to relax the parallel trend assumption, which wouldn't be satisfied by our data.

This analysis will be carried out in the following way. In Section 2 we will discuss carbon taxes from a theoretical standpoint, the current literature on their effects on manufacturers, the BC's implementation, and the current literature discussing it. In Section 3, we will present the Difference-in-Difference Estimator, discuss why we can't use it in this case, the theory behind the synthetic control method, the variables we will use, and the sources of our data. Section 4, covers the result of our model while in Section 5 we perform some Placebo Tests to assess its robustness. Finally, Section 6 concludes.

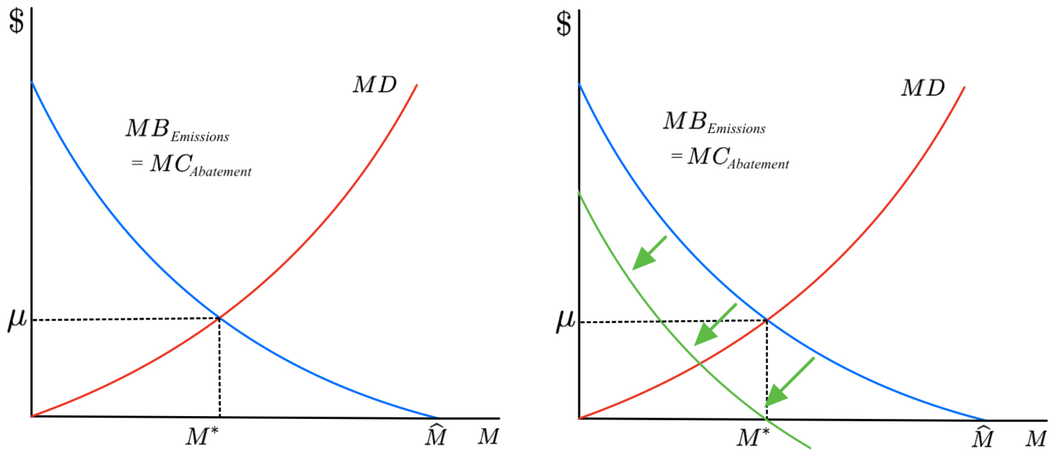
2 Carbon Tax

Earth receives energy from the sun. To balance the incoming energy that is absorbed by the surface, thus, roughly the same amount must be radiated by Earth back to space. As Earth radiates at much longer wavelengths than the sun a big portion of what is radiated back is absorbed by the atmosphere and reradiated back to Earth. The extent of energy the atmosphere absorbs is determined by gases, called greenhouse gases, such as water vapour and CO_2. This is what we call the greenhouse effect, as described by the IPCC, the intergovernmental panel on climate change (2013) [13].

At natural levels, the greenhouse effect makes Earth a liveable planet by raising temperatures above the freezing point of water. However, many greenhouse gases are produced by human industrial activities and, in particular, by the combustion of fossil fuels, and thus, their concentration in the atmosphere has increased tremendously since the Industrial Revolution. This has made the greenhouse effect much more severe, a phenomenon which is usually referred to as climate change.

To avoid the tremendous consequences the continuation of this process would lead to, economists have proposed various tools and approaches. One of the most debated and used ones is the carbon tax.

Figure 1: Carbon tax's introduction, graphical representation



2.1 Theory

A carbon tax is a tax applied to each unit of CO_2 emissions. To show how such a policy works, by following an approach similar to Nordhaus (1994) [18], we start by looking at Figure 1.

The economy initially (see the left-hand part of Figure 1) produces $\hat{M}$ emissions, a level at which the Marginal Benefit (i.e., the benefit of an additional unit of emissions) will be 0, thus, making it irrational for the firms in the economy to emit both more or less, on aggregate. When making this choice, though, companies don't take into account the damages these emissions cause to the environment, damages that we aim to address with the introduction of a carbon tax. Considering the damage emissions inflict to the environment (as represented by MD, the marginal damage, in the Figure), the socially optimal level of emissions would, therefore, be given by M^*, a level at which $MB_{Emissions}$ intersects MD. Socially, no additional unit of emissions should be released into the atmosphere as the benefit brought by it would be lower than the damage it would cause. Similarly, no further abatement should be carried out as its cost would be higher than the benefit it would bring to the environment.

The introduction of a carbon tax (shown in the right-hand part of Figure 1) causes the

$MB_{Emissions}$ to shift down by the amount of the tax itself as firms now pay the tax rate on each unit of emissions they produce. If $t = \mu$, at the new equilibrium the amount of emissions that are released is M^*, the socially efficient equilibrium. We can show this mathematically too. After the introduction of the tax, a rational firm will face the following optimization problem:

$$\min_{M_i} \ CT_i = C_i + tM_i$$

i.e., firm i will minimize, with its choice of M_i, its total costs made up of the abatement cost and the total tax paid.

Note that $C_{Abatement}$=-$B_{Emissions}$ because foregoing a unit of emissions (i.e., abating) means losing the benefits that unit would bring, a loss that we can interpret as the cost of the abatement.

By using the traditional minimization technique we get:

$$\frac{\delta CT_i}{\delta M_i} = 0$$
$$\frac{\delta C_i}{\delta M_i} + t = 0$$
$$MC_i + t = 0$$

And thus:

$$MC_i = -t \text{ or } MB_i = t$$

We can see how M^*, the socially efficient level of emissions, is what will be emitted if the tax rate is $t = \mu$.

In addition, this also shows us that the level of emissions that is reached, which depends on the tax level, is reached at the lowest possible cost as all the firms' marginal costs of abatement are equal. Indeed, if two firms had two different MC transferring abatement from the firm with the highest marginal cost to the one with the lowest cost would yield a cost-saving. This is because a unit of abatement costs MC_H for the highest cost firm while it only costs MC_L for the lowest cost one (at a fixed level of emissions M) where $MC_H > MC_L$. The difference between the two marginal costs is, thus, the cost reduction that can be achieved by performing the transfer. More in general, as long as $MC_i > MC_j$ for some firm i and j, such a transfer generates a reduction in the overall cost of abatement of the economy. Only when all the marginal costs are equal no transfer is cost-saving and, therefore, the least cost of abatement is reached. We have, thus, shown how carbon taxes can achieve the socially optimal level of emissions at the least cost possible.

Another very important property carbon taxes have is that they don't require the institutions who are setting them up to know anything but the aggregate level of marginal damage and marginal benefit of emissions. In addition, even in the case in which these two curves are unknown, a trial-and-error approach can be followed. Indeed, environmental agencies can set a level for the tax, see whether the reduction in emissions is higher, lower, or equal to their target, and then adjust the tax accordingly (i.e., increasing the rate if emissions are too high or decreasing it if emissions are too low) always knowing that each level of emissions that is being reached, is being reached at the least cost possible. Importantly, carbon taxes also have dynamic effects, as they incentivize firms to seek technologies capable of reducing their emissions. This stimulates green technological development, thus, making it more and more possible to do away with polluting industrial processes. The last benefit of a correctly applied carbon tax is that it yields a double dividend. Besides achieving its environmental target, it is a tax and, as such, it produces revenue for the government, revenue that can be used to decrease other distortionary taxes (Pearce, 1991) [20].

Of course, carbon taxes also have some limitations. The biggest one is that they require governments to continuously update tax rates for targets to be reached. For instance, a carbon tax will have to be adjusted according to inflation (as it is in terms of current currency value) and because of new technologies. Another issue of carbon taxes is that since they are applied to consumers products' prices and since lower-income consumers tend to spend a bigger portion of their income on carbon-intensive goods, they can have regressive effects. In practice, though, this effect can be mitigated by correct uses of the tax's revenues.

Table 1: Manufacturing GDP (percentage of total GDP in 2018)

	%
World	15.39
East Asia & Pacific	22.79
Europe & Central Asia	13.96
Latin America & Caribbean	12.86
Middle East & North Africa	13.13
North America	11.25
South Asia	14.44
Sub-Saharan Africa	10.68

2.2 Carbon Taxes and Manufacturing

The manufacturing sector makes up more than 15% of the World's GDP as can be seen in Table 1 (sourced from the World Bank's World Development Indicators data set) and is, thus, a very important part of many countries economies. It is also, though, one of the biggest producers of Greenhouse Gases emissions because of the carbon intensity of its activities. Indeed, Table 2 (constructed using an Our World In Data elaboration [9]) shows that it accounts for around 30% of the worldwide emissions, a figure that makes it the biggest emitter in 2016.

In order to truly tackle climate change, thus, it is fundamental to implement policies that are able to incentivize its shift to carbon neutrality. Unfortunately, though, not many of the environmental policies currently in place address this sector directly, especially if we refer to carbon taxes.

Governments and their constituents tend to believe that the introduction of such policies would reduce the competitiveness of the firms that are subjected to them, competitiveness that is fundamental in the global marketplaces in which most manufacturers sell their products. In addition, it is a common belief that enacting environmental policies will simply push polluters to relocate where such constraints are not present, a phenomenon commonly known as carbon leakage. Very often, thus, governments stick to

Table 2: Global GHG emissions by sector (percentage of total emissions in 2016)

	%
Manufacturing	29.4
Agriculture, Forestry, & Land Use	20.1
Transport	16.2
Energy Use in Buildings	17.5
Unallocated Fuel Combustion	7.8
Fugitive Emissions from Energy Production	5.8
Waste	3.2

and expand currently in place command-and-control approaches that, while being inefficient and inadequate, are preferred both by themselves, for the electoral reasons we explained, and by firms, for the greater certainty they bring about. (Keohane, Revesz, & Stavins, 1998) [14]

Even more surprisingly, the topic of carbon taxes for the manufacturing sector has been explored by very few academic articles. Among these the most relevant ones were Floros & Vlachou (2005) [11] and Martin, de Preux, & Wagner (2014) [16].

Floros & Vlachou (2005) [11] applied a two-stage translog model using data of the period in order to analyze interfuel and interfactor substitution in the Greek manufacturing's cost function and, subsequently, used the estimated elasticities to try and investigate the impact a carbon tax would have on the energy-related CO_2 emissions of the manufacturing sub-sectors. The authors found that a tax of $50 per ton of CO_2 would result in an overall reduction in emissions, from their 1998 level, of 17.6% if no electricity restructuring is allowed or 30.5% if it is. This result is found to be achieved because of both improved energy efficiency and energy conservation. They, thus, concluded that there are considerable possibilities to reduce both direct and indirect CO_2 emissions of the manufacturing sector with the implementation of a carbon tax.

Martin, de Preux, & Wagner (2014) [16] instead, analyzed the effects of the Climate Change Levy (CCL) a comprehensive environmental policy introduced by the UK's government. This consists of a carbon tax and a scheme of voluntary agreements available to plants that operate in energy-intensive industries under which plants adopt specific targets for carbon emissions in exchange for a high discount on the carbon tax. The authors compared changes in outcome between the two regimes and found that the carbon tax had a strong negative impact on energy intensity (in particular at more energy-intensive plans). They found that the carbon tax reduced energy intensity by 18.1% and electricity use by 22.6%. They also didn't find any impact of the tax on employment, gross output, and total factor productivity. Lastly, they found no evidence of plant closures or relocations.

To further the exploration of this topic with a more recent and long-term analysis we focus on the case of British Columbia.

2.3 BC's Carbon Tax

BC's carbon tax was announced by the incumbent BC's Liberal Premier Gordon Campbell as a core part of his platform's comprehensive approach to tackling climate change for the 2005 General Elections. Also because of this attention to environmental problems in the May 17 2005 election, Campbell and the BC Liberals won a second majority government. (Elections BC) [6] The carbon tax, though, was later introduced in July 2008, with a rate of C$10/t CO_2 and was applied to all fossil fuels used in the province. (Government of British Columbia) [8]

The introduction of such a broadly applied carbon tax was, according to Harrison (2013) [12], possible for 5 key reasons that are unique to BC:

1. The prevalent role hydroelectric plants played in the generation of energy in the province
2. The strong voters' interest in the issue of climate change
3. The wide support the right-center majority government enjoyed in the business community
4. The strong personal commitment of the Premier

5. The British Columbian institutional structure that gives great power to the leader of the party that holds the majority

The tax rate was, subsequently, increased up to C$30/t CO_2 by 2012 (rising by C$5/ton CO_2 per year). This rate is then converted into C$ per unit of fuel (e.g., litres of gasoline) and applied directly to their sales.

An important feature for our analysis is that the tax only exempts few emissions that include: fuels exported from BC, fuel used by planes and ships travelling to or from BC, any non-combustion CO_2 emission, and all non-fossil fuel emissions. While additional exemptions were added over time such as those for the agricultural sector none affected manufacturers specifically. Because of this limited number of exemptions, the tax covers around 70-75% of the greenhouse emissions of the province. The fact that there are no particular exemptions for the manufacturing sector or some of its sub-sectors allows us to evaluate the true impact such a policy would have when fully targeted to industries.

Critically, this tax was also designed to be revenue-neutral. This means, that any revenue generated by it is used only to reduce other taxes or for direct transfers, and not to increase government expenditure, thus, only causing a tax shift. In practice, a bit more than half of the transfers have been targeted at businesses, with the rest being directed to households. Interestingly, these transfers were mostly in the form of general tax cuts up to 2012 (directed particularly at low-income households for what concerns personal tax rates) but have since started being used for some specific initiatives, such as the “Interactive digital media tax credit”. Overall, the tax ended up being revenue negative, costing BC’s government around C$1 billion from its inception to 2015 (out of a revenue of C$6.1 billions). This was caused mostly by the revenues being lower than expected, a sign that the tax was indeed successful in curbing emissions. Although revenue neutrality is a feature economists have always suggested carbon taxes should have, (because of the double dividend property) BC’s tax is quite unique in being designed around it, something that makes it a particularly interesting case to analyze.

Lastly, while BC also applies a motor fuel tax on applicable fuel sales it hasn’t changed its rate, nor introduced other environmental policies, from the inception of the carbon tax, thus, making it possible to attribute any effect only to the carbon tax.

British Columbia is, thus, a perfect choice for the analysis we want to carry out as it provides a long post-intervention period and is one of the purest examples of carbon taxes in practice.

2.3.1 Current Literature

We now take a look at the current literature on the province's carbon tax.

While no analysis of the effect on manufacturing emissions was conducted many studies tried to assess what the effect of this policy on emissions was. By analyzing these papers together Murray, Rivers (2015) [17] concluded that the tax reduced greenhouse emissions by a value between 5% and 15%. Indeed, even though different methodologies for estimating the counterfactual scenarios were used, the results of the studies they analyzed are all quite close.

The economic implications of the tax were also widely analyzed. The studies analyzed by Murray, Rivers (2015) [17] suggest that there is little net impact of the tax on economic performance. This is true even if we see negative effects in some sectors (such as the agricultural one), as these are likely compensated by positive impacts in other sectors. Interestingly, Beck M. et al. (2015) [7] found out how this was only possible because of the double dividend effect. Indeed, had the tax revenues not been recycled by offsetting other taxes the slightly negative effect on welfare that they witnessed would have been much bigger (-0.13% instead of -0.08%), thus, pointing at the importance of how revenues are used.

As we discussed, one of the potential drawbacks of a carbon tax is that it can be regressive if its revenues are not distributed properly. The studies on the actual distributional impact of the tax, though, provided some different results. Lee, Sanger (2008) [15] found that, while initially the tax wasn't regressive, the increases in its rate were not coupled by significantly enough redistributive measures, a fact that led to it becoming slightly regressive over time. Conversely, Beck et al. (2015) [7] found that the tax was progressive even before the revenue redistributions took place. This is attributed to part of the tax affecting wages, a change that doesn't impact low-income households as they derive most of their income from government transfers. Overall, it is reasonable to conclude that the correctives applied to the tax have succeeded in not making it regressive or at least extensively so.

Lastly, Murray, Rivers (2015) [17] analyzed the political support the tax enjoys. They found out the tax is supported by an average of 50.5% of the BC population, with higher percentages as time went on (even if with some exceptions). Nevertheless, regressions performed by the authors show that opposition to the policy is high in some key demographics. Middle-aged males, with low or middle income, living in a small community are the group with the highest likelihood of opposing the measure. Conversely, young females with high income living in a large urban area are the least likely opposers.

3 Methodology

We now turn our attention to the methodology we will use for the analysis.

The outcome variable on which we will assess the effect of the policy will be the carbon intensity of the manufacturing sector. This variable will be expressed in kilotons of CO_2e (CO_2 equivalents) emissions over millions of 2015 US dollars. This measure was chosen because it allows us to truly determine whether the tax was able to improve, in environmental terms, the technology and the processes used by manufacturers or whether any decrease in emissions happened because of a shrinkage of the sector.

Our analysis will cover the period that goes from 1990 to 2018 (the last year for which data is available).

3.1 The Difference-in-Difference Estimator

A proper methodology for this type of studies that has also been used by various articles on the BC's carbon tax effectiveness such as Elgie, McClay (2013) [10] and Rivers, Schaufele (2012) [21] would be the difference-in-difference estimator. It consists of comparing the changes in outcomes between an intervention group (i.e., a population that is subjected to a treatment) and a control group (which is not subject to the treatment).

To the typical assumption of the OLS model, the difference-in-difference estimator adds the parallel trend one. This assumption requires that the difference between the treatment and control group would have to be constant over time if no treatment was to happen. If the assumption is violated, the results of the effect's estimation will be biased, thus, invalidating the analysis. This assumption is usually verified via visual inspection for the pre-intervention period. For it to be satisfied, though, we also have to be careful in choosing a control group in which everything that changes, but the treatment, changes in the intervention group too in the period that goes from the intervention to our evaluation of its effects.

Once a control group that satisfies the property is found the treatment effect is estimated to be:

$$(y_{c1} - y_{i1}) - (y_{c2} - y_{i2})$$

Where c and i identify the control and intervention group, respectively, and the number identifies a pre-intervention observation (when it is 1) or a post-intervention observation (when it is 2).

This is exemplified in Figure 2.

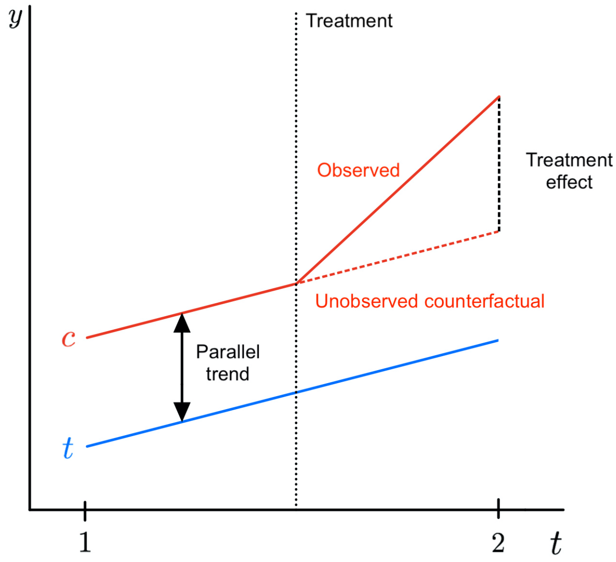
We construct a set of potential control groups we might choose to see if some satisfy the parallel trend assumption. The set is made up of Algeria, Brazil, Egypt, Indonesia, Iran, Japan, Mexico, New Zealand, the Philippines, Saudi Arabia, South Africa, Turkey, and the United States. All of these countries never had policies that target manufacturing emissions directly as of 2018, the last year of our analysis. (OECD, 2019) [19]

Unfortunately, simply by visual inspection, neither any of them singularly nor their unweighted average satisfies the parallel trend assumption. We, thus, have to rely on a different technique that relaxes this requirement.

3.2 The Synthetic Control Method

A different approach that overcomes this assumption and is particularly suited for this case is the synthetic control method proposed in Abadie and Gardeazabal (2003) [3] and Abadie, Diamond, and Hainmueller (2010, 2015) [2] [1]. We call this the synthetic

Figure 2: Difference-in-Difference estimation, graphical explanation



control method because it involves the creation of a synthetic control unit that is a convex, weighted combination of the potential control units we described before. The idea on which this approach is based is that, when we have few available comparison units, it is often the case that a combination of them will do a better job of closely tracking the unit of interest than any of them alone would do.

To go through this procedure in a more formal way we introduce some notation. Say we have units $j = 1, ..., J+1$, of which $j = 1$ is the treated one and the others are untreated, that we observe for the periods $t = 1, ..., T_0, ..., T$. Say also that the intervention occurs at $t = T_0$. Further, we define Y^I_{jt} as the outcome of unit j at time t if subjected to the treatment and Y^N_{jt} as the outcome of unit j at time t if not subjected to the treatment.

What we want to estimate is:

$$\alpha_{1t} = Y^I_{1t} - Y^N_{1t}$$

for $t = T_0 + 1, ...T$ (i.e., the difference between the outcome when unit 1 is subject to the treatment and when it is not in the post-treatment period).

Crucially, Y^N_{1t} is not observed and is what we want to estimate with our model.

To try and perform this reproduction using a synthetic control group we introduce some observed covariates on which to base our comparison of the two on. We define U_j as a $(r \times 1)$ matrix containing the r covariates' values for unit j. To account for unobserved factors we will also consider up to M, with $M \leq T_0$, linear combinations of the outcome variable $Y_j^K = \sum_{s=1}^{T_0} k_s Y_{js}$ with K being a $(T_0 \times 1)$ vector $K = (k_1, ..., k_{T_0})'$ of weights. We, thus, define a synthetic control unit as a vector $(J \times 1)$ of weights $W = (w_2, ..., w_{J+1})$ where $w_j \geq 0$ for any $j \in [2, ..., J+1]$ and $\sum_{j=2}^{J+1} w_j = 1$. What we want to choose, therefore, is a W^* such that the resulting synthetic control best approximates the outcome predictors U_1 and the M linear combinations of pre-intervention outcomes $Y_1^{K_1}, ..., Y_1^{K_M}$ of the treated unit.

Formally, we choose a W^* such that:

$$\sum_{j=2}^{J+1} w_j^* Y_j^{K_l} = Y_1^{K_l} \quad \forall l \in [1, M]$$

and

$$\sum_{j=2}^{J+1} w_j^* U_j = U_1$$

In such a case, our estimator of the treatment effect in period t (for $t \in [T_0 + 1, ..., T]$), thus, becomes:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

In empirical applications, though, an exact solution to these equations doesn't often exist. We, thus, have to turn this into an optimization problem through which we will find the closest possible solution to these equations. To do so, we introduce a distance between the treated unit and the synthetic control predictors we defined before, which we will then minimize with our choice of W^*.

We define $X_1 = (U_1', Y_1^{K_1}, ..., Y_1^{K_{T_0}})'$, a $(k \times 1)$ vector that contains all of the characteristics on which we want the synthetic control and the treated unit to be similar (note that $k = r + M$). Similarly, we introduce a $(k \times J)$ matrix X_0 with $(U_j', Y_j^{K_1}, ..., Y_j^{K_{T_0}})'$ as its $j^{th} - 1$ row.

The distance that we will then minimize is:

$$\|X_1 - X_0W\|V = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{1}$$

We can see how V, a $(k \times k)$ symmetric and positive definite matrix, comes into play here. For computational reasons, V is usually restricted to being a diagonal matrix in practical applications of the method. As such, V is to be considered as another set of weights, weights that are, though, assigned to the different characteristics (predictors) present in X_1 and X_0 and on which we based the optimization problem. V should be chosen so as to give high weights to the most predictive factors. This can be done either manually, if there are strong assessments of the variables' importance, or in a data-driven fashion.

In the second case (which is the approach we will follow), we choose V^* so as minimize the pre-intervention MSPE (the mean squared prediction error) of the outcome variable. To do this rigorously, we define $T_P \leq T_0$ as the pre-intervention period up to which we will minimize the MSPE, Y_I as a $(T_P \times 1)$ vector containing the outcome values for the treated unit up to $t = T_P$, and Y_N as a $(T_p \times J)$ matrix containing the outcome values for the control units up to $t = T_P$. Then $V^* \in \nu$, the set of all positive definite diagonal matrices, is chosen so as to minimize:

$$(Y_I - Y_N W^*(V))'(Y_I - Y_N W^*(V)) \tag{2}$$

where $W^*(V)$ is the optimal W, in equation (1), for a given V.

The `synth()` package in `R`, which is the tool we will use to fit our model, solves this nested optimization problem minimizing equation (2) based on $W^*(V)$ given by equation (1).

3.3 Variables

The variables that we will use as predictors in our analysis are the following:

- `SectorGDPPerCapita`: The manufacturing GDP per capita measured in millions of 2015 USD per thousands of people.

- `ShareOfSectorGDP`: The share of manufacturing GDP over the total GDP of the region in question measured in percentage
- `ShareOfLowCarbonEnergy`: The share of low carbon energy over the total produced by the region in question measured in percentage
- `ShareOfResearchOverGDP`: The share of GDP spent on R&D over the total GDP of the region in question measured in percentage

These variables were then all averaged over the 1990-2007 period (except for the share of R&D which was averaged from 1997 to 2007) to create a single metric on which to fit the model for each.

The first predictor was chosen because it gives us an idea of the maturity and development of the sector, something that should have an impact on its carbon intensity. The second, instead, tells us how important manufacturing is for the economy of the region in question, another factor that should influence its carbon intensity.
`ShareOfLowCarbonEnergy` directly affects the emissions produced in the region and should, thus, also impact how carbon-intensive manufacturers are. Lastly, the importance of research can be used as a proxy of the level of innovation in a certain region, a characteristic that was found to be a key determinant of manufacturing emissions. (Agnolucci, Arvanitopoulos 2019) [4]

We also add three years of lagged `CarbonIntensity` to the pool of predictors: 1995, 2001, and 2003

3.4 Data Sources

In order to create these variables, many datasets were combined and elaborated.

For BC the following datasets were used:

- Canada's Official Greenhouse Gas Inventory 2020 dataset (available on the Open Government portal and licensed under the Open Government Licence – Canada) for manufacturing CO_2 emissions equivalents

- Statistics Canada Table 36-10-0402-01 and 36-10-0396-01 (for pre-1997 data) for GDP (total, manufacturing, and expenditure in R&D)
- Statistics Canada Table 18-10-0005-01 for the CPI
- Statistics Canada Table 17-10-0009-01 for the population
- Statistics Canada Table 25-10-0029-01 and 25-10-0004-01 (for pre-1995 data) for the energy production broken up into sources

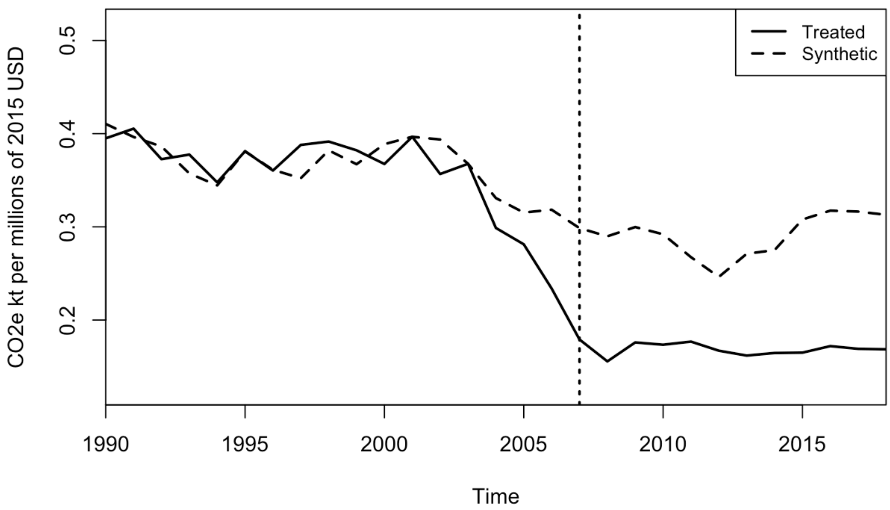
For the rest of the world, the data sources are the following:

- Climate Watch Historical GHG Emissions 2021 for manufacturing CO_2 equivalents emissions
- EuroMonitor's Economies and Consumers Quarterly Data for GDP (total, manufacturing, and expenditure in R&D) and the population
- An Our World in Data elaboration of the BP Statistical Review of World Energy present on the website's Energy Mix page for the share of low carbon energy produced
- OECD National Accounts GDP table for the US's CPI

This data was then elaborated in the following way.

As BC 2018's GDP was only available in 2012 dollars, it was converted to current dollars using the ratio between 2018 and 2012 CPI. All of BC's GDP values were then translated into 2015 Canadian Dollars using the ratio between the 2015 CPI and the CPI of the year to which that observation referred to. These values were then transformed in 2015 US dollars using an exchange rate obtained from the OECD National Accounts GDP table. For the rest of the world GDP was converted to 2015 US dollars via y-o-y exchange rates directly by EuroMonitor.

Figure 3: BC and synthetic BC's carbon intensities with 2008 as the treatment year

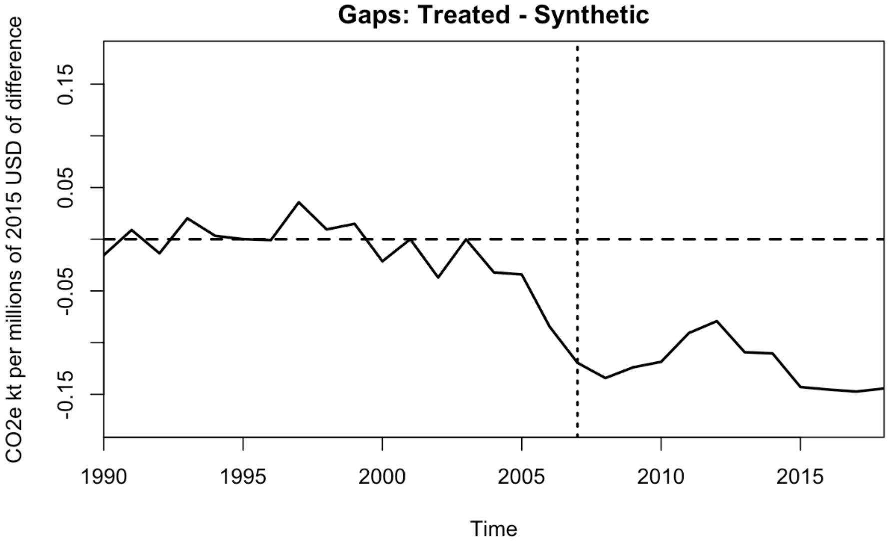


4 Results

Running the model we see, first of all, that the carbon tax has decreased manufacturers' carbon intensity but that, interestingly, it has started to do so in 2006. Up to the previous year the synthetic British Columbia and the real one track each other fairly well considering the numerous up and downs of the dependent variable's curve. After that year, though, a gap between the two starts, a gap that is then consistently present and expands in the next few years (see Figure 3 and 4). This could be explained by the fact that British Columbia's carbon tax was proposed in its platform by the winner of the 2005 elections. His win likely led manufacturers to improve the energy efficiency of their plants and operations before the tax was formally implemented in July 2008. We call this the anticipation effect.

By rerunning the model setting 2006 as the treatment year, the year in which the two curves started to diverge before, as Abadie, Diamond, and Hainmueller (2010) [2] suggest in cases in which an anticipation effect is present, we see that the results are almost identical. As Figure 5 and 6 show, the effect of the carbon tax is still present, is

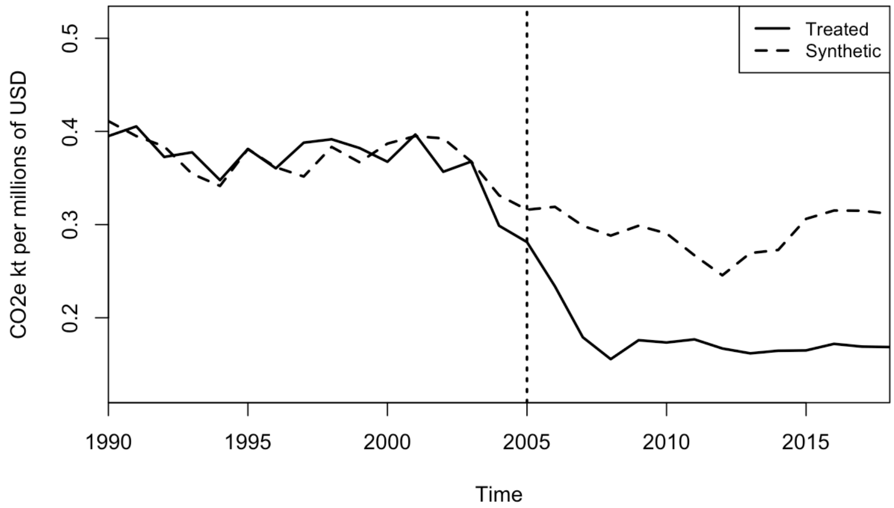
Figure 4: The gap between BC and synthetic BC's carbon intensities with 2008 as the treatment year



of a similar entity, and starts in 2006 as we saw before. We will, thus, base our analysis on this case (Note that the predictors are now averaged on periods that end in 2005).

Firstly, looking at the two paths we can pick up a few key trends. Interestingly, the difference between them starts getting smaller in the period 2008-2012 and then comes back to the initial value around 2015. This is due to a decrease, and subsequent increase, in the carbon intensity of the synthetic control. This could be caused by the 2008's economic crisis which hit countries around the world in that period. In the regions that make up the synthetic control, the economic crisis could have pushed less innovative and less cost-efficient manufacturers out of the market leaving space only for the most competitive players. The manufacturers that were pushed out, though, are very likely the most carbon-intensive ones, a fact that could have led to this trend. This push was also likely not present in BC because of the tax and the fact that it had already driven manufacturers toward more efficient and modern productions. Another interesting piece of information we can draw from the two paths is that the subsequent increases in the tax rate don't seem to have had any effect on the sector's carbon intensity which has remained flat from the introduction of the tax onward. This could be

Figure 5: BC and synthetic BC's carbon intensities with 2006 as the treatment year



due to two factors. First, firms knew the schedule the rates increases would have and have, thus, planned the efficiency improvements well in advance even though the full tax rate would have been reached only later on. Secondly, it might be possible that firms in this sector only had access to a limited set of sufficiently efficient technologies both from a cost and an environmental standpoint, a set that didn't expand much over the tax's implementation period and that, thus, led to them not being able to improve their efficiency after a certain level was reached.

Turning to weights, we see that most of the predictors' ones (Table 4) are assigned to the lagged variables but that `SectorGDPPerCapita` and `ShareOfResearchOverGDP` have values that are very close to the British Columbian ones. Indeed, the former has a value of 4.801 in the synthetic control unit against the BC's one of 4.852 while the latter has 0.971 for both BC and the synthetic control. Both `ShareOfSectorGDP` and `ShareOfLowCarbonEnergy` have values that are more distant from the BC's ones than the control unit set's means, see Table 5, and were assigned no weights at all.

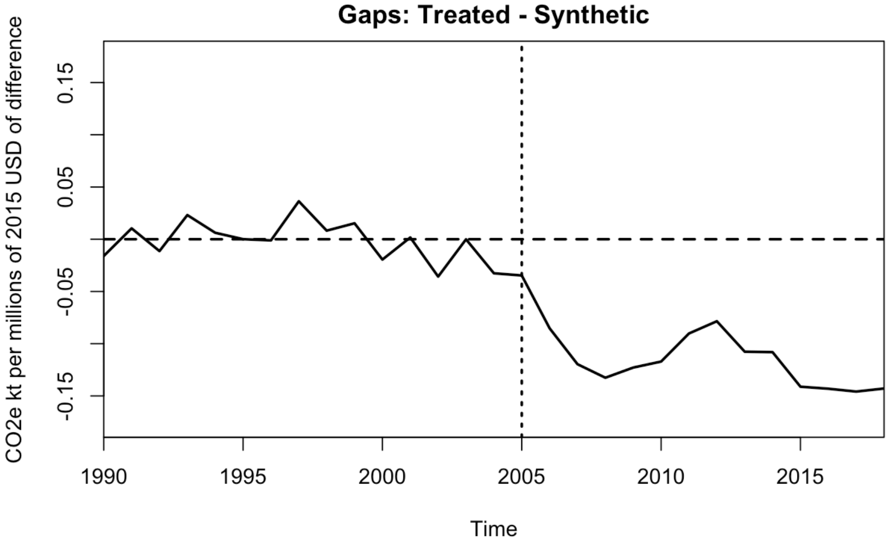
Table 3: Weights assigned to the countries

	Treatment Year	
	2008	2006
Mexico	0.374	0.392
New Zealand	0.275	0.267
Japan	0.164	0.163
Iran	0.055	0.053
Saudi Arabia	0.027	0.025
Algeria	0.024	0.024
United States	0.018	0.000
South Africa	0.013	0.014
Turkey	0.011	0.014
Egypt	0.010	0.010
Indonesia	0.010	0.016
Philippines	0.09	0.013
Brazil	0.09	0.010

Table 4: Weights assigned to the predictors

	Treatment Year	
	2008	2006
`SectorGDPPerCapita`	0.060	0.005
`ShareOfSectorGDP`	0.000	0.000
`ShareOfLowCarbonEnergy`	0.000	0.000
`ShareOfResearchOverGDP`	0.007	0.083
`CarbonIntensity` in 1995	0.174	0.375
`CarbonIntensity` in 2001	0.373	0.010
`CarbonIntensity` in 2003	0.386	0.528

Figure 6: The gap between BC and synthetic BC's carbon intensities with 2006 as the treatment year



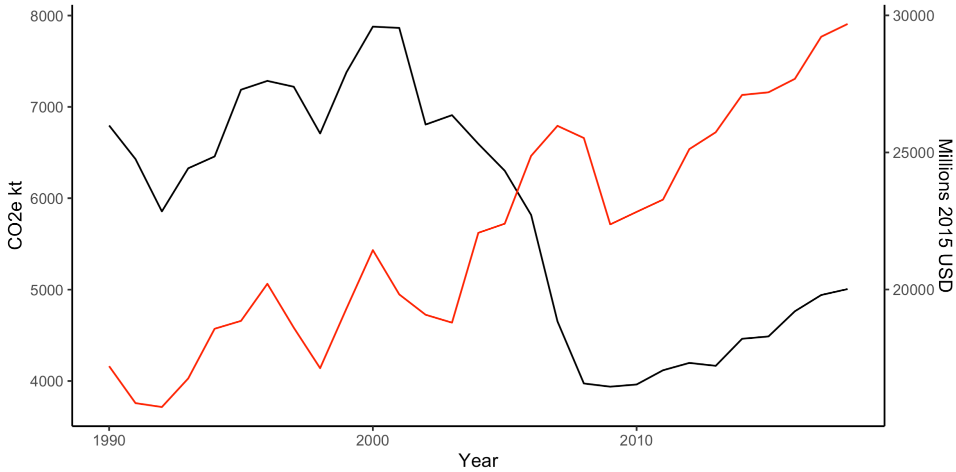
This tells us one of two things: either that the introduction of the lagged measurements takes up too much weight and leads to those two variables being ignored during the fit or that those two variables don't have the predictive power on carbon intensity we expected. To verify which of the two is correct we will undertake a placebo test in which all but one of the lagged variables will be removed and we will see whether in that case the shares of manufacturing GDP and low carbon energy are assigned some weights or not. Looking at Table 3, instead, the countries to which the most weight was assigned are, in order of importance, Mexico, New Zealand, and Japan (followed by some of the others with weights close to 0). It is important to note that both the predictors and the countries' weights are very similar in the initial case in which we set 2008 as the treatment year (Table 4 and 3). This confirms us that we're witnessing an anticipation effect and that it is correct to set 2006 as the intervention year.

Numerically, the introduction of the tax is found to have reduced, on average, BC's carbon intensity by around 0.118 CO_2e kt per millions of 2015 US dollars each year. In the last year we analyzed, this reduction was of 0.143 CO_2e kt per millions of 2015 US dollars, a decrease of more than 45%.

Table 5: Treated, synthetic, and control group's values of predictors with 2006 as the treatment year

	Treated	Synthetic	Sample Mean
`SectorGDPPerCapita`	4.852	4.801	3.052
`ShareOfSectorGDP`	17.166	23.663	22.897
`ShareOfLowCarbonEnergy`	10.551	16.435	12.208
`ShareOfResearchOverGDP`	0.971	0.971	0.794
`CarbonIntensity` in 1995	0.381	0.381	0.525
`CarbonIntensity` in 2001	0.397	0.395	0.688
`CarbonIntensity` in 2003	0.368	0.368	0.673

Figure 7: BC's manufacturing emissions (black) against BC's manufacturing GDP (red)



Over the period from 2006 to 2018, the total difference between BC's `CarbonIntensity` and the synthetic control's one was around 1.53 CO_2e kt over millions of 2015 US dollars. In percentage, this was a staggering 40.4% decrease over the 12 years.

It is, lastly, interesting to analyze what is happening to manufacturing emissions and GDP in a disaggregated way. Looking at Figure 7, we see that up to 2005 BC's emissions and manufacturing GDP tend to move mostly in the same direction. In particular, we can observe how the GDP's curve tends to anticipate the trend of the emissions curve. From that date and until 2008, however, emissions start to quickly decrease while GDP continues to go up uninterruptedly: this is what is causing the effect we witnessed in our model. In 2008, GDP decreases sharply too but that is likely due to the, at that time, ongoing economic crisis. Shortly after, GDP starts going up again and, while emissions track its trend, the distance between the two remains at the 2007 level where it was maximum.

5 Placebo Tests

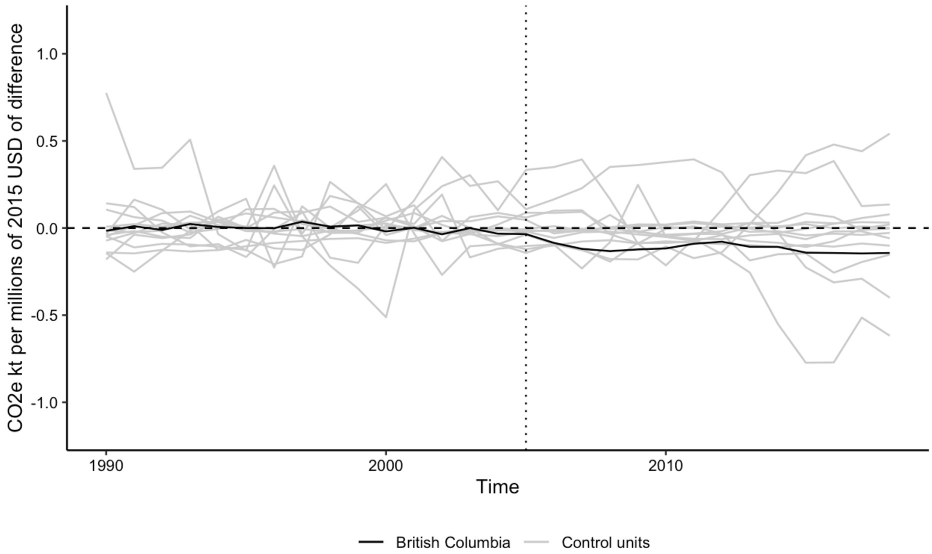
We perform three types of checks to confirm the robustness of our model: a location placebo, a leave-one-out test, and a re-run of the model with only one lagged variable.

Overall, the three tests help us in verifying the solidity and reproducibility of our results. In addition, the first allows for inference and the calculation of our result's p value. (Abadie, Diamond, & Hainmueller, 2015) [1]

5.1 Location Placebo

This first test (as in Abadie, Diamond, & Hainmueller, 2010 [2]) consists in setting other countries as the treated ones, fitting a synthetic control to them, and verifying whether the effects we find are larger than the one we found in BC's case. If this was true then we could conclude that our analysis doesn't provide significant evidence of an effect of the carbon tax on manufacturing carbon intensity. If, on the other hand, the placebo test showed that the gap estimated for BC is unusually large relative to the gaps for

Figure 8: The gaps between countries and their synthetic counterparts' carbon intensities when no countries are filtered

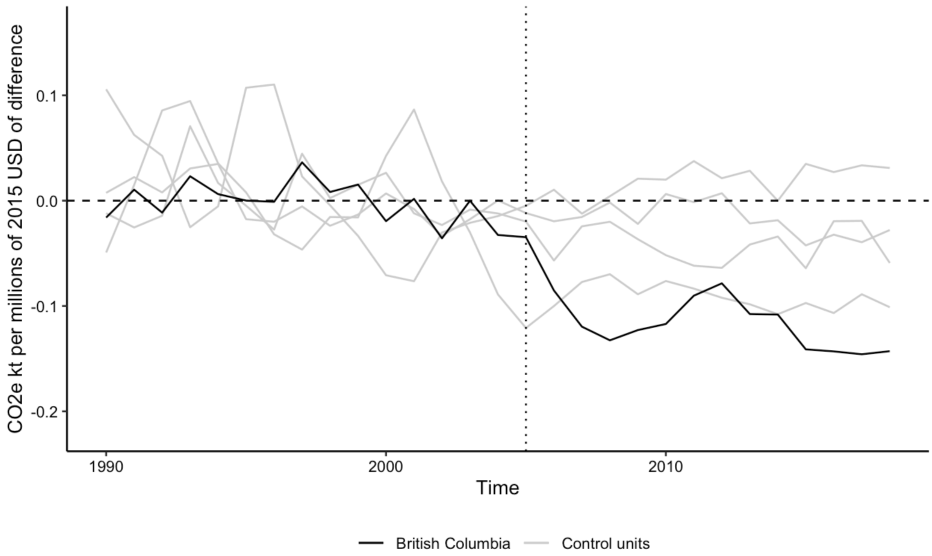


the other countries (that did not implement environmental control policies targeting the manufacturing sector), then we could conclude that our analysis provides significant evidence of an effect of the carbon tax on manufacturing carbon intensity. This procedure was ran and the accompanying graphs were created using the `SCTools() R` package.

Looking graphically at the size of the effects (Figure 8) we see that BC only has one of the biggest effects but we also see that the countries which have a larger one, when the treatment is assigned to them, all have significant variability in the pre-intervention period. Indeed, if we look at the same graph but we remove all of the countries for which the pre-intervention MSPE was 10 times greater than in BC's case (Figure 9) we see that BC is definitely unique in the size and consistency of its effect.

Lastly, we analyze the ratio between post-treatment MSPE and the pre-treatment one. This is a more precise and less arbitrary evaluation as it measures by how many times the post-intervention MSPE (or, in other terms, the difference between the BC and the synthetic control's post-intervention paths) is bigger than the pre-intervention one. The first, is an estimation of the effect of the treatment while the second is indicator of the

Figure 9: The gaps between countries and their synthetic counterparts' carbon intensities when countries with a pre-intevention MSPE greater than 10 times the BC's one are excluded



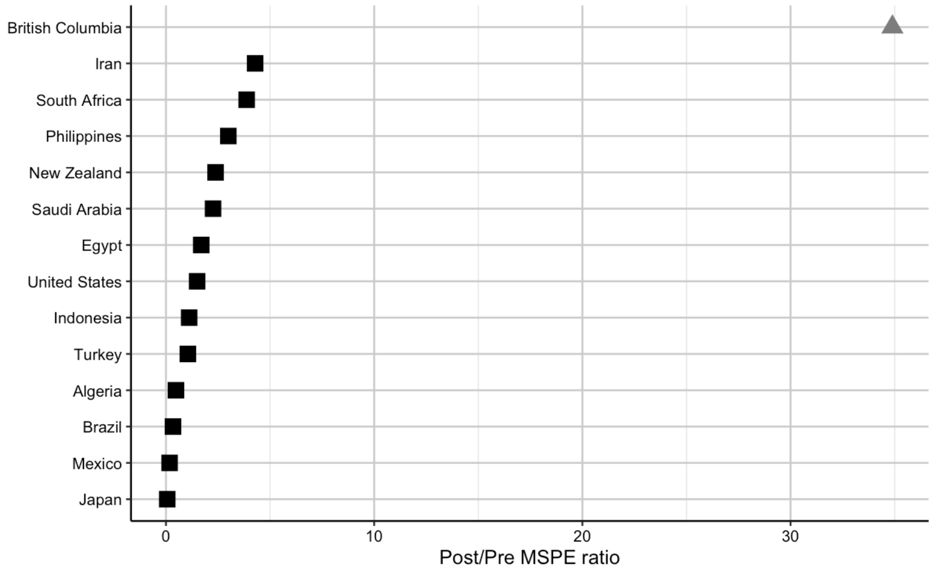
pre-treatment fit limitations. We see how the BC's ratio is clearly the biggest (Figure 10). As such, we conclude the probability of finding such a big effect is $p = \frac{1}{14} = 0.0714$, the smallest possible p-value in our control group's set and a value that makes the result significant.

5.2 LOO

In the leave-one-out test we remove one country at a time from the controls' set and fit a synthetic control for BC using the remaining control units. If the effect of the tax that we found in Section 4 is particularly big or small compared to the one we get in these other cases it could be the case that one, very influential country is responsible for most of the result. This would, in turn, cast doubts on the reproducibility and validity of our conclusions.

We see, though, in Figure 11 that the estimated effect in the case in which we remove no country (i.e., the result we obtained in Section 4) is approximately in the middle of

Figure 10: The post/pre-intervention MSPE ratios

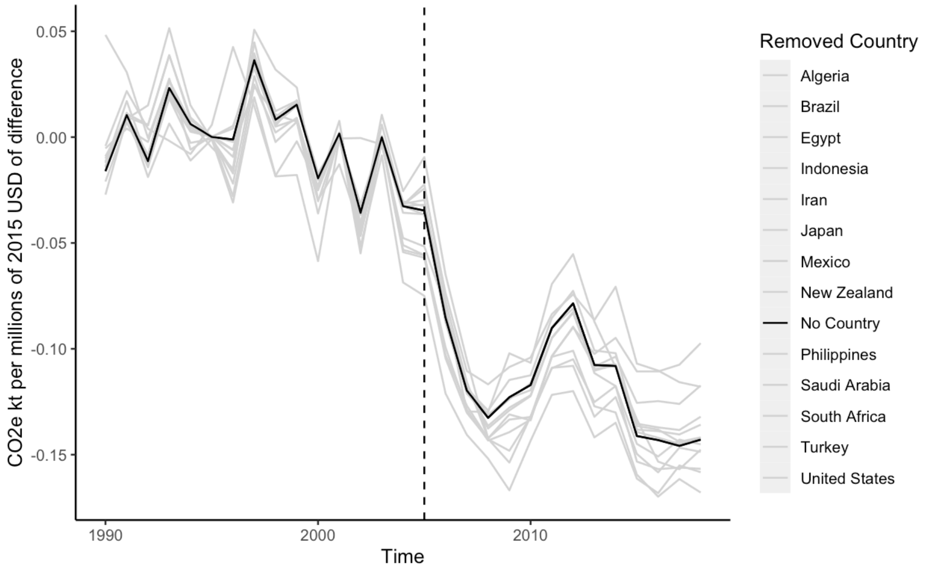


the range of the possible ones when we remove a country. Even though in a few cases the estimated effect is smaller, it is always positive and significantly so. Indeed, we can see how in all cases the estimated effect belongs to a fairly contained range of which no value would change our conclusions. These findings, thus, give us confidence that our result is robust.

5.3 Model with one lagged variable

Lastly, we re-fit the synthetic control by introducing only one lagged variable, instead of three, as predictor and we verify whether the results we obtain are different from the ones found in Section 4. In particular, this allows us to evaluate if `ShareOfSectorGDP` and `ShareOfLowCarbonEnergy` were assigned zero weight because of the lagged variables' presence or simply because they don't have the predictive power on manufacturing carbon intensity we expected. It is important to point out that we leave one lagged variable (2003) in the predictors' set as it creates a baseline level for our variable of interest's fit. This is fundamental particularly in a case like ours in which the outcome

Figure 11: The gap between BC and synthetic BC's carbon intensities in the LOO tests



variable has values that vary significantly from a control unit to another.

We see that (Figure 12 and 13) while the fit is slightly worse, the results are substantially unchanged with the estimated effect being almost the same.

Turning to our object of interest, we find that, once again, no weight was assigned to `ShareOfSectorGDP` and `ShareOfLowCarbonEnergy` while the other three predictors were all assigned positive ones (Table 6).
Such a result, confirms us that the share of manufacturing GDP over the total isn't

Table 6: Weights assigned to the predictors with only one lagged variable

`SectorGDPPerCapita`	0.007
`ShareOfSectorGDP`	0.000
`ShareOfLowCarbonEnergy`	0.000
`ShareOfResearchOverGDP`	0.118
`CarbonIntensity` in 2003	0.875

Figure 12: BC and synthetic BC's carbon intensities with only one lagged variable

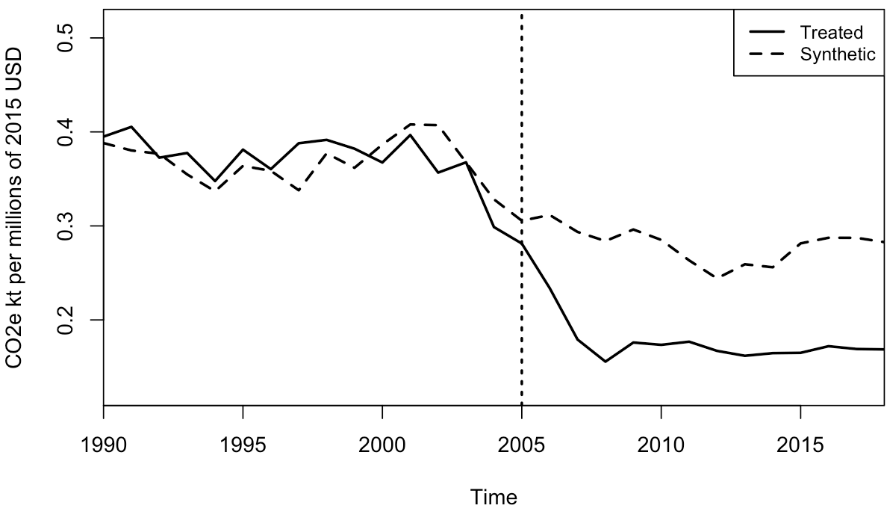
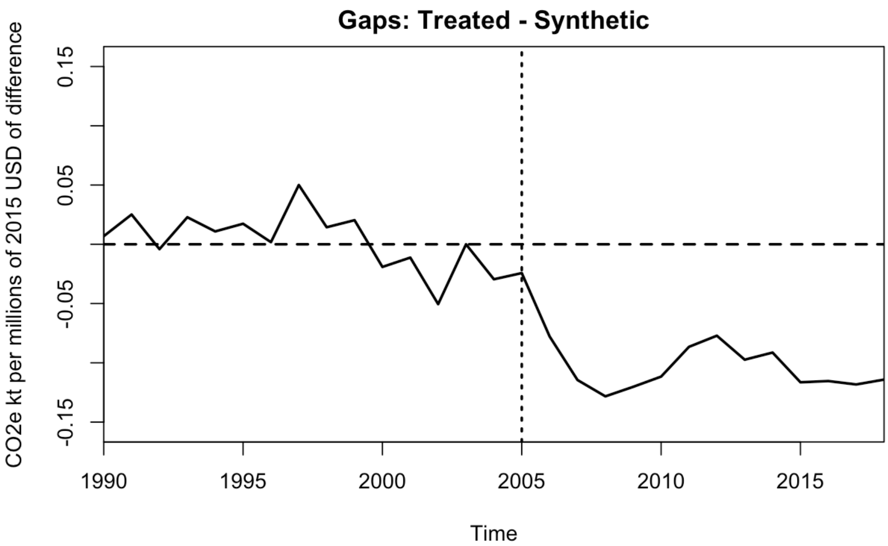


Figure 13: The gap between BC and synthetic BC's carbon intensities with only one lagged variable



correlated with the carbon intensity of the manufacturing sector, thus, pointing out that how important manufacturing is for a country's economy has no effect on its carbon intensity. This finding also supports the conclusion that the share of low carbon energy produced in an economy isn't correlated with the carbon intensity of the manufacturing sector. We have to note, though, that our variable considered the energy produced for the use of the whole economy and not just of manufacturers. If we had access to the same metric but limited to the manufacturing sector, thus, we might find a different result.

6 Conclusion

To succeed in the fight against climate change, it is important to rely on environmentally and economically efficient measures such as carbon taxes or emissions trading schemes.

This analysis shows how a carbon tax can be an effective tool in reducing the carbon intensity of one of the most significant emitters in the world's economy, the manufacturing sector.

With the implementation of a carbon tax, BC, was able to reduce manufacturers' carbon intensity by approximately 40% over the period from 2006 to 2018 or around 1.53 CO_2e kt per millions of 2015 US dollars. This effect is similar in direction to the ones found in the UK's case by Martin, de Preux, & Wagner (2014) [16] but is around double in size.

To estimate this, we constructed a control unit made up of various countries that didn't implement a carbon tax or a similar policy but had a similar pre-intervention trajectory of CO_2 emissions, level of manufacturing GDP per capita, and share of GDP spent on R&D. Interestingly, we also found that the manufacturing sector's share of GDP and the share of low carbon energy over the total produced in a region are not correlated with the carbon intensity of manufacturers.

The results were also found to be robust under a series of placebo tests. Furthermore, the reassignment of the treatment at random in the sample showed that the probability of obtaining a post-treatment result as large as that for BC is just $p = 0.0714$.

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