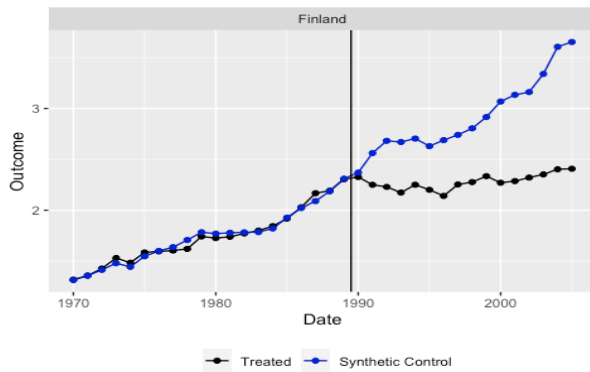


1. Selecting the predictors

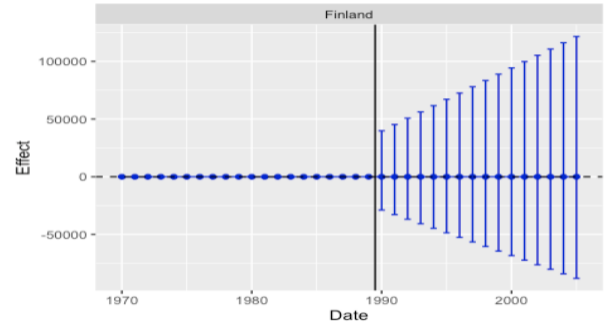
The primary goal of synthetic control approaches is to estimate the mean treatment impact on the treated (ATT). The "Treatment effect" is the difference between the treatment's actual and hypothetical consequences for a particular unit (the treated unit). The synthetic control approach builds a synthetic control group composed of a weighted mix of control units. A synthetic control group is created using pre-treatment data, and the treatment impact is calculated by comparing the treated unit's post-treatment results to the synthetic control group.

1.1. Carbon Emission and GDP

GDP per capita is used to calculate Finland's CO2 emissions treatment fit in Panel A. Panel B exhibits sub-Gaussian Bounds in and out-of-sample uncertainty. The solid vertical blue lines are 90% confidence intervals.



Panel A

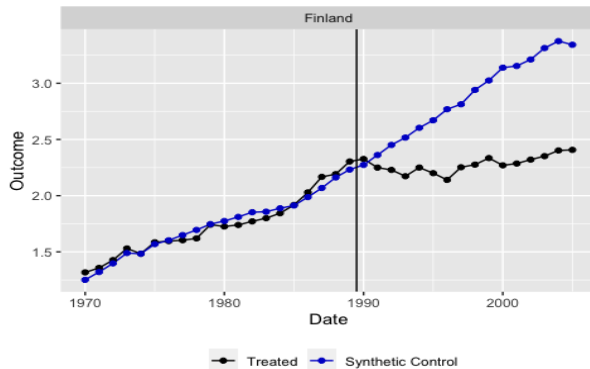


Panel B

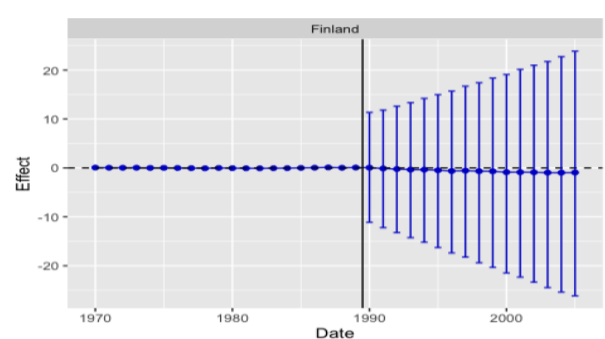
Figure A1. Unit-time treatment effect between carbon emissions in transport and GDP

In Figure A1, Panel B, the sub-Gaussian bounds "follow a zero effect" both in the pre-treatment and post-treatment periods. This suggests that the treated and control units' potential outcomes are zero when no treatment exists.

1.2. Carbon emission and Gasoline Consumption per capita



Panel A

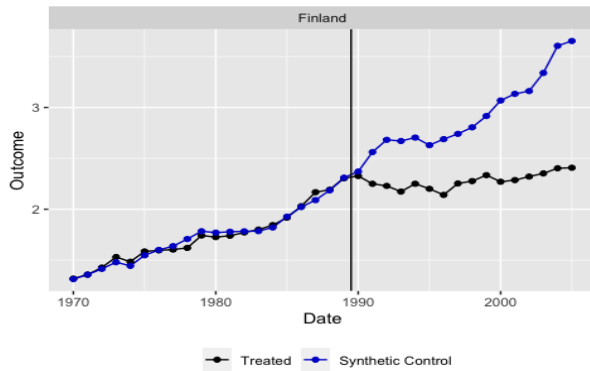


Panel B

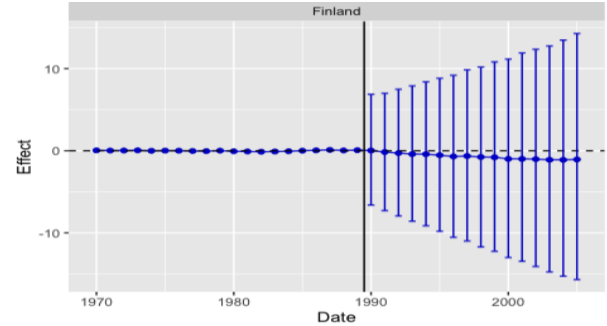
Figure A2. Unit-time treatment effect between carbon emissions and Gasoline Consumption per capita

In Figure A2, Panel A, we observe that the pre-treatment fit could be better, even though the post-treatment outcome is promising. In contrast, we see deviations in the post-treatment period in Panel B, particularly from 1995. This indicates possible differences between the control and treated groups before treatment.

1.3. Carbon Emission and Urban Population



Panel A

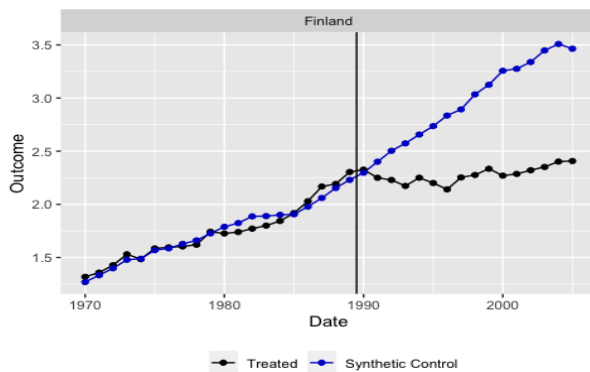


Panel B

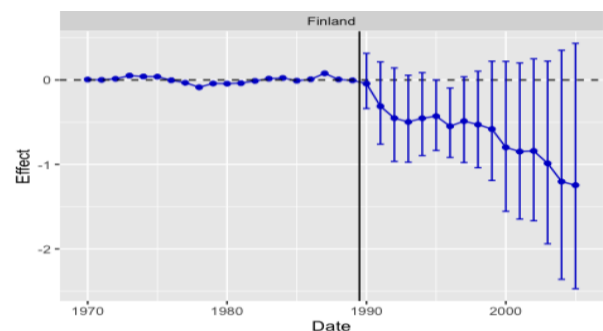
Figure A3. Unit-time treatment effect between carbon emissions in transport and Urban Population

Figure A3, Panel A, demonstrates an excellent match in the pre-treatment period and a positive outcome after treatment. On the other hand, the post-treatment is concerning due to the significant deviation from the mean. When the sub-Gaussian bounds deviate from zero, it suggests a difference in the average potential outcomes between the treated and control units when no treatment exists.

1.4. Carbon Emission and Vehicle Capita



Panel A



Panel B

Figure A4. Unit-time treatment effect between carbon emissions in transport and Vehicle capita

Figure A4 shows comparable results for vehicles per capita, both in and out of the sample sub-Gaussian bounds, similar to the findings in Figure A2 for gasoline consumption. Based on this outcome, this paper postulates that these two variables, despite their differences, have

comparable impacts on carbon emissions in the transportation sector. However, careful examination is needed to substantiate this observation, which is not the focus of this study.

2. Placebo Tests

To assess the authenticity of the findings above, a sequence of placebo tests was carried out, encompassing three distinct approaches – “in-time”, “in-space”, and “leave-one-out”.

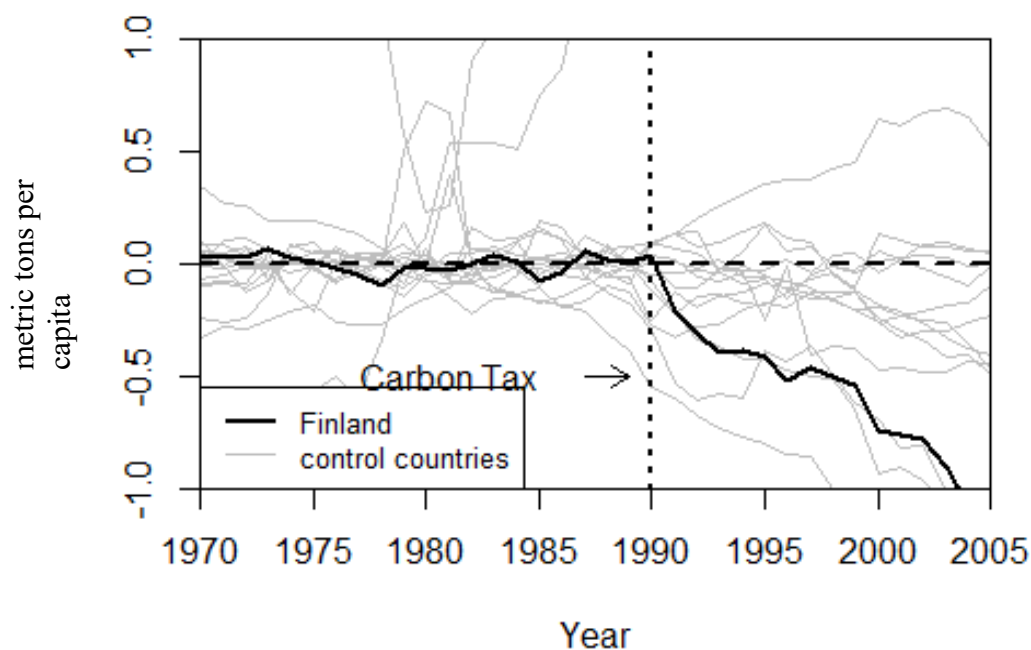
2.1. In-time test

Before the environmental tax change, the in-time tests were conducted in 1980. The synthetic control selection uses only 1970-1979 data for the two tests. To examine if a placebo therapy affects emissions following treatment in Finland and its synthetic control. Given the high placebo effect, Figures 8 and 9 may not accurately reflect the effects of the carbon tax. A trajectory similar to the synthetic control outcome is shown in Figure 12, indicating no divergence.

2.2. Permutation test

The permutation test in space creates a synthetic counterfactual for each donor nation. Compare each country's gap with its synthetic equivalent to Finland's gap in the main findings section. Suppose the disparity between many nations is as high as Finland's. In that case, it happened by coincidence rather than due to the carbon price.

Panel A



Panel B

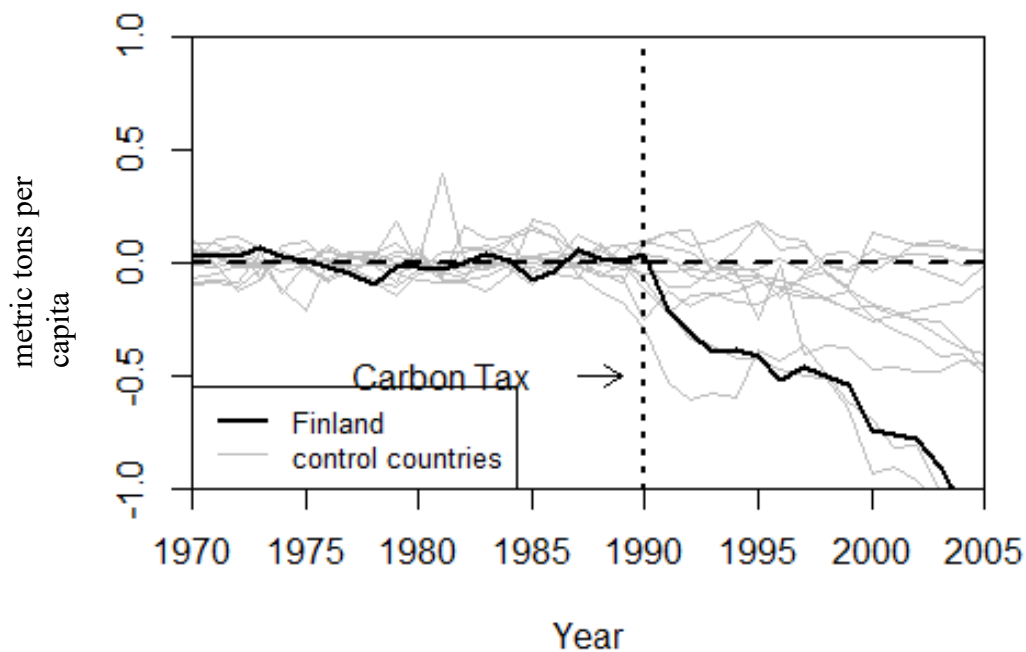


Figure A5. Permutation Test: Per Capita CO2 Emissions Gap for Finland and the Control Countries

Notes: Panel A shows Finland's per capita CO2 emissions gap and placebo gaps in all control countries. Panel B shows the per capita gap in Finland and placebo gaps for countries with a pre-treatment MSPE lower than 20.

This test determines if Finland's result is statistically unusual by comparing it to placebo outcomes from all donor nations. By calculating the fraction of nations with results that exceed or equal the intervening variable, the permutation test approach allows statistical conclusions and p-values (Abadie et al. 2015).

Figure A5 shows the in-space placebo results. Panel A shows that in certain donor countries, the synthetic control technique cannot discover a convex blend of nations that can properly recreate pre-intervention emissions. This especially applies to the US, Poland, and Portugal. This is expected because the United States had the highest carbon emissions during pre-treatment. In contrast, Poland and Portugal had the lowest. Panel B excludes nations with pre-treatment MSPEs at least 20 times Finland's, leaving 11 countries in the donor pool. Finland has the third-largest post-treatment emission gap among the remaining nations. The p-value for computing a discrepancy of such extent is 3/11, yielding a 0.27.

Nevertheless, the technique of permutation testing needs a scientific foundation when selecting a specific threshold for the MSPE value and is considered arbitrary. An enhanced inferential approach involves examining the ratio of post-treatment MSPE to pre-treatment MSPE (Abadie et al. 2010); as suggested, it was posited that a considerable ratio serves as a reliable indicator of a veritable causative influence originating from intervention. The

application of the ratio test obviates the need for implementing an arbitrary threshold criterion, mitigating the need to discard countries.

Finland has the highest ratio among all the countries in the sample, as shown in Figure A6. Randomly assigning the treatment would result in a 1/17 chance of discovering such a large ratio (0.059), the minimum p-value conceivable with my sample size.

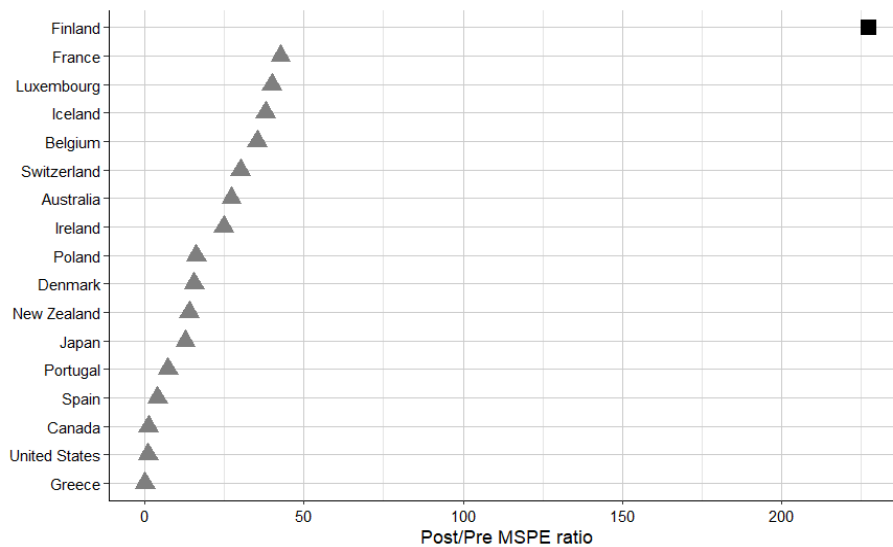


Figure A6. Ratio Test: Post-treatment MSPE to Pre-treatment MSPE for Finland and Control Countries.

Similar to (Elbaum 2021), Finland has the highest ratio. Unlike their study, this paper's result shows that Ireland's high percentage is not concerning. Despite Ireland's 1990s GDP per capita gain, which quadrupled post-treatment (Andersson 2019), emissions had the same trend. (Andersson 2019) eliminated Ireland from his sample. Donor pool selection, however, can change ratios. Abadie et al. (2015) also found many significant ratios.

Table A1: Descriptive Statistics

Variable	Mean	SD	MIN	MAX
Carbon price	0.014	0.516	−1.167	1.467
Gasoline price	0.018	0.503	−1.313	1.029
Gasoline consumption per capita	−0.002	0.551	−1.446	1.589
GDP per capita	0.005	0.393	−0.811	1.112

Note: Table A1 reports summary statistics for standardized variables used in the Synthetic Control Method (1985–2005). All series were mean-centered and scaled to unit variance to ensure comparability. Negative minimum values reflect periods when the variables fell below their sample means (e.g., economic slowdowns or lower fuel consumption)

Reference

Abadie, A., et al. (2010). "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." Journal of the American statistical Association **105**(490): 493-505.

Abadie, A., et al. (2015). "Comparative politics and the synthetic control method." American Journal of Political Science **59**(2): 495-510.

Andersson, J. J. (2019). "Carbon taxes and CO2 emissions: Sweden as a case study." American Economic Journal: Economic Policy **11**(4): 1-30.

Elbaum, J.-D. (2021). The effect of a carbon tax on per capita carbon dioxide emissions: evidence from Finland, IRENE Working Paper.