Effectiveness of Emissions Trading Systems on Reducing CO_2

Jared Able, Joshua Jackson, Zachary Brennan, Alexandria Wheeler, Nicholas Geiser

GitHub Repository

Introduction

CO_2 emissions from energy production and industry drive global warming. To limit warming to 1.5°C, the IPCC calls for a drastic 40% reduction in CO_2 emissions from 2019 levels by 2030 and a 70% reduction by 2040. Despite this warning, emissions rose annually by 2.1% during 2000-2009 and 1.3% annually during 2010-2019.

Public policy is essential to reducing emissions, with emissions trading systems (ETS) — or "cap-and-trade" — as one tool. Rooted in the work of Coase (1960) and Dales (1968), ETS set a cap on emissions and allow trading of emission credits among emitters. ETS have already been applied to reduce pollutants like sulfur dioxide under the Clean Air Act Amendments of 1990. More recently, the Regional Greenhouse Gas Initiative (RGGI) limits CO_2 emissions from power plants in 11 eastern US states. Our goal is to evaluate the impact of RGGI on CO_2 emissions in 7 of these states over the initial implementation period.

Stakeholders and KPIs

Our stakeholders consist of the EPA, state governments, and power companies. We estimate the effectiveness of cap and trade programs and the significance of our estimations by calculating:

- **% change in power plant CO_2 emissions** between actual and synthetic groups
- **placebo tests** in control states.

Methods and Model

Our dataset combines EPA emissions data (1995-2020) with economic, demographic, and meteorological data—such as GDP, population size, electricity usage, and temperature—as some key covariates of emissions. To place states on even footing in the modeling process, features are computed as per capita quantities where reasonable by dividing by the US Census population estimates. Population itself is used as a feature by computing a population density with state area information. Further processing includes the application of twelve-month moving averages on all features to smooth data and reduce seasonal oscillation. A winsorization technique for clipping extreme values is applied to eliminate outliers in messy spectra, and Box-Cox and log transforms are applied to reduce skew.

Our analysis employs synthetic control techniques, which allow one to estimate the effect of an intervention when a direct control group isn't available. Specifically, a synthetic control is constructed by assigning optimized weights to a set of control states. These weights are chosen to minimize the differences between the synthetic and treated state before the intervention.

We employ an augmented synthetic control, allowing for both positive and negative weights in order to increase model accuracy, as described in Ben-Michael, Feller, and Rothstein (2021). With an intervention date of January 1, 2009, the final model was trained on data from 1999 to 2009 and evaluated from 2009 to 2014. The model uses 10 transformed features and a donor pool of 33 non-RGGI control states. Model tuning prioritized the alignment of covariates of the real and synthetic across model features and included efforts to reduce skewness of the data. Finally, the 7 selected RGGI states offer robust data for validation and testing.

Results

Our initial estimates found that 3 out of 7 RGGI members show statistically significant reduction in power plant carbon dioxide emissions. In particular, Massachusetts exhibited an estimated 79% reduction in total CO_2. The validity of our results was tested using the placebo method, in which we performed a synthetic control fit for each state in the donor pool while using the treated state as a control unit. These tests evaluate whether the observed post-treatment divergence in a RGGI state is more extreme than what is typically seen in control states. We find a p-value of 0.03 for Massachusetts, which is within the traditional 0.10 threshold for significance.

Afterward, an r^2 calculation is performed to evaluate the pre-treatment fit for each treated state. The r^2 values from our initial model were poor. For Massachusetts, $r^2 = 0.26$. To improve the pre-treatment fit, an alternative model was developed. The second model dramatically improved our r^2 values—in Massachusetts, $r^2 = 0.91$—but this second model appears to overfit the data, even as it decreases our significance with $p = 0.18$. Further efforts are required to achieve a balanced fit model and thus establish more reliable significances.

Future Goals

In addition to further model refinements for improved pre-treatment fits, increased fit stability across treated units, we identify several avenues for future study:

- **Anticipation effects from RGGI:** RGGI was signed by seven of its constituent states in 2005, and over the following years, additional states joined the initiative. It was not until 2008 that the first auction was held, and only in 2009—which we have taken as our nominal treatment start year—was compliance enforced. It is possible that treatment effects may have occurred in anticipation of this first auction.
- **Interaction effects from electricity markets:** Electricity markets extend beyond state borders. While our energy production and energy use features provide a low-order picture of the total energy flowing into or out of a state, the interaction between electricity markets in RGGI and non-RGGI states may bias our findings.
- **Cost-effectiveness of RGGI:** Our project evaluates the statistical significance of the implementation of RGGI on member states. Next steps include quantifying the cost-effectiveness of RGGI in comparison to alternative emissions reduction policies.
- **Alternative outcome measures:** We hope to provide a more comprehensive assessment of RGGI's impact by exploring other outcomes besides CO_2 emissions such as particulate emissions, NOX, ozone, and other factors in air pollution.