Quantifying the impact of Clean Air Policy Interventions

For Air Quality Management

Rising environmental concerns require the implementation of appropriate policies to manage environmental risk. One such risk arises from air pollution. As part of the process of air quality management it is important to understand how effective different policies are to determine whether a policy should be, for example, scrapped, changed, or rolled out across different sectors or regions. However, evaluating clean air policies is a challenge because of the complex physical and chemical processes in the atmosphere and other socioeconomic factors that may also be impacting pollution levels. This briefing document outlines a methodological approach that can be used to provide evidence of the success or otherwise of different clean air policies for different geographical areas and time periods.

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- Short-term changes in air quality are dominated by meteorological variations so changes in emissions may be masked by variations in the weather.
- The impact of policy interventions on air quality is difficult to isolate from other causes of air pollution, such as natural changes in emissions, atmospheric chemistry and socio-economic factors.
- Previous studies fail to fully account for the effects of weather and natural seasonal or year-by-year trends in air quality.
- Working with environmental scientists, data scientists and economists we develop a novel approach to quantifying the impact of clean air policy interventions based on observational data.
- We use machine learning techniques to strip out the effects of weather (**Fig. 1**), followed by a synthetic control method to account for natural variability or trends in the data (**Fig. 2**).

Machine Learning (ML)

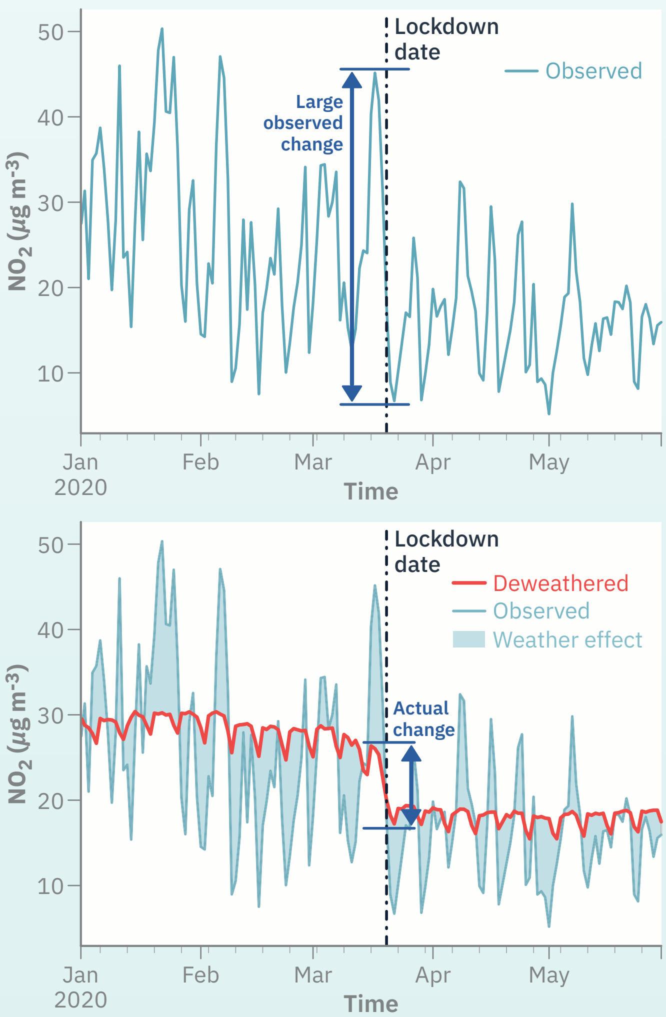

Fig. 1 An example showing the deweathering technique. (top) Observed air pollutant concentrations; (bottom) Deweathered air pollutant concentrations. In this example, de-weathering helps to quantify the impact on air quality of the COVID-19 lockdown (as an intervention) in the UK.

Deweathering techniques remove the impact of weather conditions from the observed pollutant concentrations (Grange and Carslaw, 2019; Shi et al., 2021).

Synthetic Control Method (SCM)

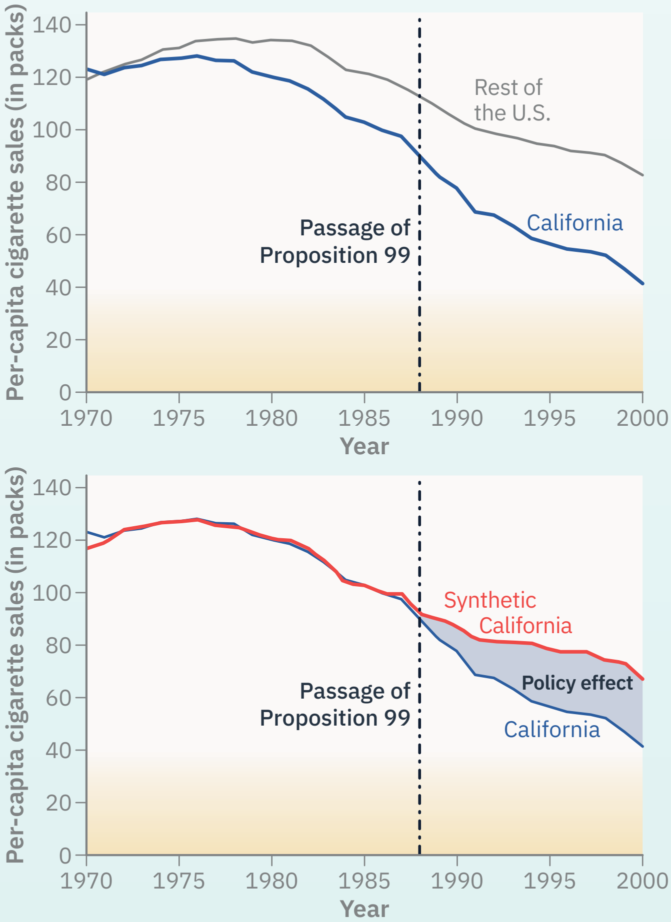

Fig. 2 An example showing the synthetic control method. (top) Trends in per-capita cigarette sales: California vs. the rest of the United States; (bottom) Effect of the policy: California vs. Synthetic California. In this example, the synthetic control method helps to quantify the impact of cigarette policy in California on per-capita sales.

The SCM provides a way to evaluate policy by creating a suitable comparison group for the treated unit that is directly exposed to the policy.

To evaluate the impact of the California tobacco control program in 1989, Abadie et al. (2010) proposed a SCM that uses a weighted average of a set of control groups (38 US states - unexposed to the policy) to construct a counterfactual trend (a synthetic California).

The observed differences after the intervention can be regarded as the impact of the policy (the causal effect).

Application to the Birmingham Clean Air Zone (CAZ)

STEP 1:
ML-based meteorological normalisation to “deweather”

- Collect surface-based meteorological observations, pollutant concentrations and time variables for over 40 monitoring stations across a number of UK cities.
- For each pollutant and for each station, build a random forest machine learning model to predict the pollutant concentrations (70% for training the model, 30% for testing the model)
- Replace meteorological variables randomly within the study period for each time point.
- Repeat the steps above (300 times for example) and average the predicted concentrations to generate a “deweathered” concentration for each hour (Grange et al., 2018; Shi et al., 2021).

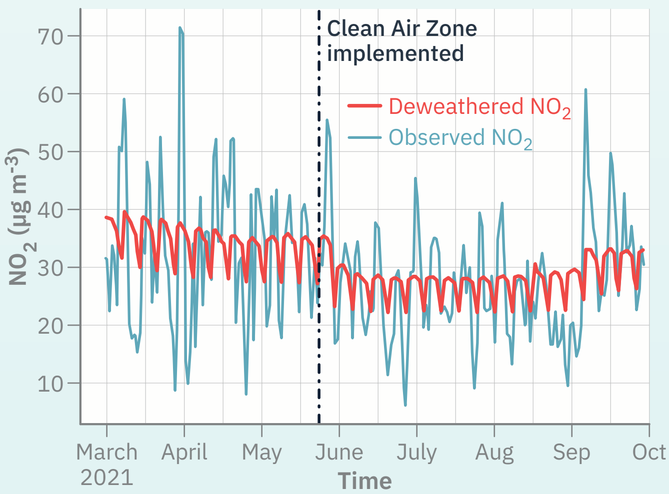

Fig. 3 Daily observed vs. deweathered NO_2 concentrations at an air quality monitoring site within Birmingham Clean Air Zone before and after the implementation of the policy.

For a tutorial on the method and to access the codes we used in our data analysis see clean-air-research.org.uk/resources/ or email Professor Zongbo Shi (z.shi@bham.ac.uk)

STEP 2:
Augmented SCM (ASCM) for causal inference

- Assign air quality stations (15-20) from other UK cities to act as a control group (not exposed to the clean air zone or similar interventions during the study period), with similar socio-economic characteristics during the pre-intervention period (6 months) and post-intervention period (6 months).
- Use ASCM (Ben-Michael et al., 2021) to mimic the synthetic outcome (“de-weathered” pollution levels) of the treatment unit (stations exposed to Birmingham CAZ) as if they were not exposed to the CAZ.
- Calculate the differences between the treatment unit and the synthetic control group.
- The difference is the true (causal) effect of the policy intervention and will tell us whether the CAZ helped to reduce emissions in an area compared to different synthetically constructed control groups that were not subject to a CAZ type policy.

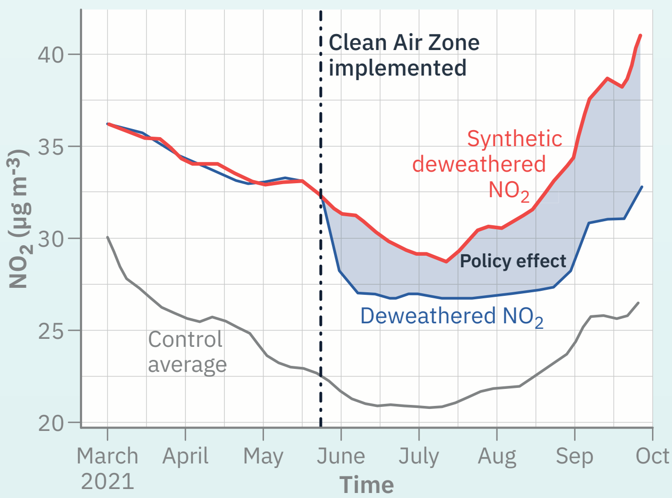

Fig. 4 Weekly deweathered vs. synthetic deweathered NO_2 at an air quality monitoring site in Birmingham, showing the causal effects of Birmingham CAZ on NO_2 concentrations.

Previous Approaches for Air Policy Evaluation

- Air quality models have been widely used to predict the impact of a policy on air quality. They contain large uncertainties (which simulate the dynamics of the atmospheric pollutant concentrations based on simplified mathematical representation of physical and chemical processes, and emission inventories), compromising the robustness of the model predictions.
- Econometric models used to identify the causality of air policy impacts include the Difference-in-Difference (DID) method, Regression Discontinuity Design (RD or RDD) and the Synthetic Control Method (SCM).
  - DID compares a control group (not subject to any policy intervention) and a treatment group (with the policy implemented) before and after the implementation but could be inaccurate when the two groups show no similar trends before the policy is implemented (the parallel pre-trend assumption).
  - SCM generates the weighted average of the control group to construct a counterfactual series, which is more accurate.

Data-driven ML-ACSM offers an alternative approach to the commonly used air quality modelling.

Advantages of ML-ASCM over other data-driven techniques

ML-ASCM Approach		**Previous Approaches**
• Capable of accurate evaluation of any air pollution control policy. • Requires temporally/spatially resolved observations before and after the implementation of policies. • Requires data from a number of control stations/ cities that are not subject to similar policies.		**Simple before-after comparison** • May bias the impact of the policy interventions as other explanatory factors (confounding factors), such as weather conditions, economic fluctuations, Covid lock-down/recovery, and other random events are not properly controlled for.
ML-based RF model		**Statistical Model**
• More accurate predictions. • Better at handling correlations between other explanatory variables (multicollinearity and interaction effects).		• Limited ability to control for multicollinearity and interaction effects between different explanatory variables.
ASCM	**vs**	**DID and RD**
• Does not require a parallel pre-trends assumption. • Generates dynamic outcomes. • Can be used for single treatment unit. • Employs Ridge regression on the outcome to adjust the weight matrix from a simple SCM approach. • Can be employed without predictors (only use outcomes). • Can be extended to more general cases.		• The parallel pre-trend assumption is usually violated in practice. • Only compares causal impact between the treatment group (more than one unit) and the control group. **SCM** • Selection for the control group in the real world that is able to pass the strict theoretical assumptions is difficult. • Limited use in a few special cases.

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