Assumption-Lean Causal Inference for Mobile Source Air Pollution

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Motivation

Pollutionwatch Pollution

'Autobesity' on course to worsen air pollution caused by motoring

Trend for bigger, heavier cars means more particles get released from brakes, tyres and road surfaces

The Washington Post
Democracy Dies in Darkness

CLIMATE Environment Weather Climate Solutions Climate Lab Green Living Business of Climate

HIDDEN PLANET

Why tires — not tailpipes — are spewing more pollution from your cars

Wear and tear on vehicles' tires and brakes emit fine particles into the air, linked to heart and lung disease

Car tyres produce vastly more particle pollution than exhausts, tests show

Toxic particles from tyre wear almost 2,000 times worse than from exhausts as weight of cars increases

Emissions from tailpipes in developed countries are much lower in new cars, with those in Europe far below the legal limit. Photograph: Jacob King/PA

Statistical Issues

Causal Inference - Modified Treatment Policy

- Estimate **counterfactual** outcome under treatment A

$$E(Y_{A\,=\,\text{new policy}}) - E(Y_{A\,=\,\text{observed}})$$

- i.e. What if we increased EVs by 10%?

Assumption-Lean - Nonlinear Model / ML

- Avoid parametric assumptions (i.e. linear model)

↓

- Use arbitrary machine learning
  - random forest, gradient boosting, etc.

Interference / Spillover

Unit treatment

Effect of treatment

Statistical Issues

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- Estimate **counterfactual** outcome under treatment A

[illegible]

- i.e. What if we increased EVs by 10%?

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Solved in IID Data

Interference / Spillover

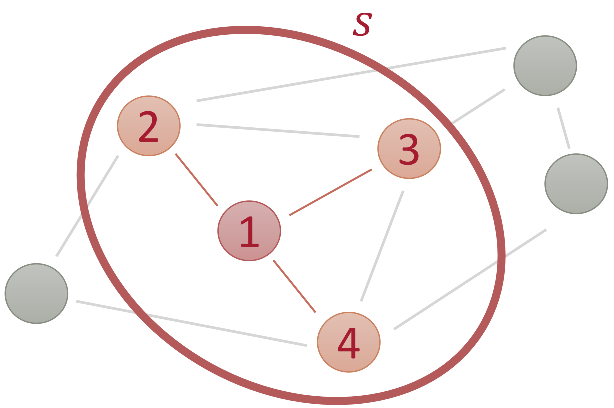
Unit treatment

Effect of treatment

Causal Inference and Spillover

Spillover Effect

Treatment now also a **summary function** of neighbors in network



Combine into summary

$$A_s = s(A_{i_1}, \dots A_{i_m})$$

(weighted sum, mean, max, etc.)

Modified Treatment Policy (MTP)

What happens if we replace A with $A^* = d(A)$?

MTP on a Summary

Combining summary and intervention yields **induced intervention**

$$A_s^* = s(d(A_{i_1}), \dots d(A_{i_m}))$$

Estimate joint effect of

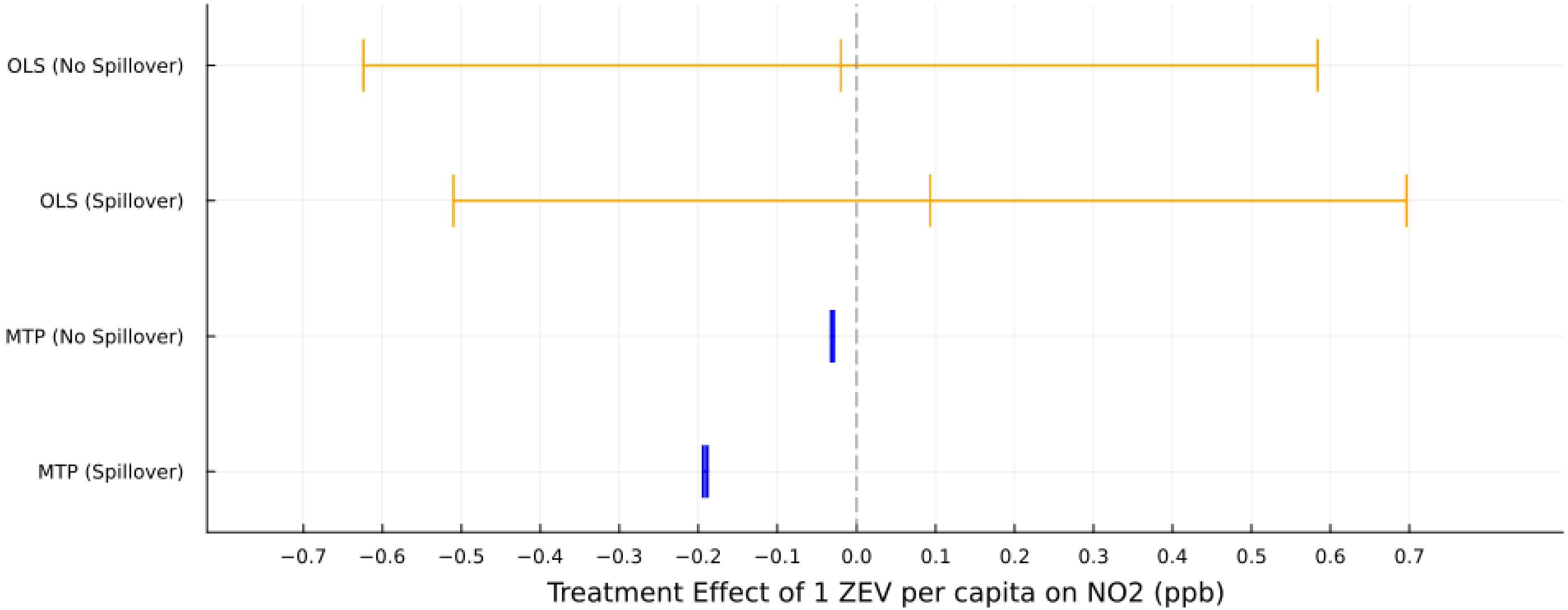
$$(A^*, A_s^*)$$

via machine-learning-based causal estimators [Ogburn *et al.* 2022]

- Propensity Score $g(A, A_s | X)$
- Outcome Regression $E(Y | A^*, A_s^*, X)$

Results

- OLS vs MTP (*Propensity-augmented Plug-In with LightGBM and KLIEP*)



- *Interpretation*: Had everyone started driving an electric vehicle from 2013-2019, we would expect average NO2 to decrease by ~5%

Thank you!
Questions?

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