Measuring bias in (strategically) missing EPA pollution data

Aaron C Watt

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- How biased is *missing* air pollution data from self-reporting US EPA monitors?

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Research Questions

- How biased is *missing* air pollution data from self-reporting US EPA monitors?
- Does this bias significantly change NAAQS attainment status?

Project Overview

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- Focus on EPA pollution data that is missing *in time*; limited to California.
- Using new consumer-based pollution monitors to understand the bias in EPA data.
- Avoids using satellite estimates (has been shown to have significant error).

Purple Air Monitors

[insert maps of California EPA and PA monitors, timelaps GIF? Timeline of adoption]

[insert pictures of PA outdoor monitors]

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3. Estimate California counties' counterfactual attainment status using included predicted missing pollution data.

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$$EPA_{i,t} = \gamma_{i,0} + \sum_{j \in J_i} \sum_{k=1}^{7} \gamma_{j,k} PA_{j,t} + u_{i,t}$$

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- Purple Air monitor $j \in J_i$ at time t reads PM2.5 pollution $PA_{j,t}$. [insert diagram of one EPA monitor and surrounding PA monitors, with wind directions]

Models: Hour-by-Day-of-week Bias of Missing EPA Monitor Pollution Data

Missingness Bias:

$$Bias_{i,h,d} = \frac{1}{|\mathcal{N}_{i,h,d}|} \sum_{t \in \mathcal{N}_{i,h,d}} EPA_{i,t} - \frac{1}{|\mathcal{M}_{h,d}|} \sum_{t \in \mathcal{M}_{h,d}} \widehat{EPA}_{i,t}$$

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We can also define the **algorithm bias** as the Hour-by-Day-of-week prediction error

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We can also define $Bias_{j,h,d}$ and $\widetilde{Bias}_{j,h,d}$ for PA monitor j (we'll come back to this).

Models: County Attainment Status

$$
\begin{aligned}
Attain_c^{annual} &= 1 \text{ if } \textbf{reported} \text{ annual average PM2.5 below threshold}^* \\
&= 1[\text{equation here}]
\end{aligned}
$$

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Attain_c^{daily} &= 1 \text{ if } 98^{th} \text{ percentile of } \textbf{reported} \text{ daily average PM2.5 below threshold}^* \\
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*averaged over 3 years in NAAQS standard. [fill in equations and thresholds]

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- Assumption: nearby PurpleAir monitors that are good predictors for EPA monitors during non-missing times will also be good predictors during missing times.
  - Specifically, reasons for EPA data missingness are not correlated with missingness or measurement error in PurpleAir data

Proposed Statistical Test

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- **The question of bias can be stated**: are the data observed during the times when the EPA monitor is turned off significantly different from the data observed when the monitor is turned on? Is it more different than by random chance?

Proposed Statistical Test

- The J_i group of PurpleAir sensors is (in a sense) a synthetic control for the EPA sensor i.
- **The question of bias can be stated**: are the data observed during the times when the EPA monitor is turned off significantly different from the data observed when the monitor is turned on? Is it more different than by random chance?
- Implies an Abadie et al. 2011 style permutation inference test for each EPA monitor i.

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  - p-value $= \frac{\text{\# of PA sensors in } i\text{'s radius with Ratio}_j \text{ larger than Ratio}_i}{\text{\# of PA sensors in } i\text{'s radius}}$

Extensions

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- Comparing county population-weighted PM2.5 pollution to EPA sensors to estimate location-based bias.

Appendix A: PurpleAir monitor correction factor

Low Concentration $PA_{cf\_1} \leq 343\ \mu g\ m^{-3}$ ~176-185 $\mu g\ m^{-3}$ as measured by the corrected sensor	$PM_{2.5} = 0.52 \times PA_{cf\_1} - 0.086 \times RH + 5.75$
High Concentration $PA_{cf\_1} > 343\ \mu g\ m^{-3}$ ~207 $\mu g\ m^{-3}$ as measured by the corrected sensor	$PM_{2.5} = 0.46 \times PA_{cf\_1} + 3.93 \times 10^{-4} \times PA_{cf\_1}^{2} + 2.97$

PA_{cf_1} = PurpleAir $PM_{2.5}$ from the higher of the 2 correction factors (cf) currently labeled as cf_1 32

Figure 1: PurpleAir correction equation for EPA monitor PM2.5 (RH = relative humidity, also measured by PA monitor)

Source: https://www.epa.gov/air-sensor-toolbox/technical-approaches-sensor-data-airnow-fire-and-smoke-map

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- Dec. 19: Data warehouse setup and transfer of existing Purple Air data

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- Depending on method of storage: $2,900 - $13,300 per month
- Only storing hourly means and SD: $4 - $15 per month