Estimation and Implications of Bias in EPA Pollution Measurement

Aaron C Watt

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Research Questions

- How biased are EPA monitor-based measures of local air quality?
- Does this bias significantly change NAAQS attainment status?

Context

Previous Works in EPA Pollution Monitors

Satellite Data:

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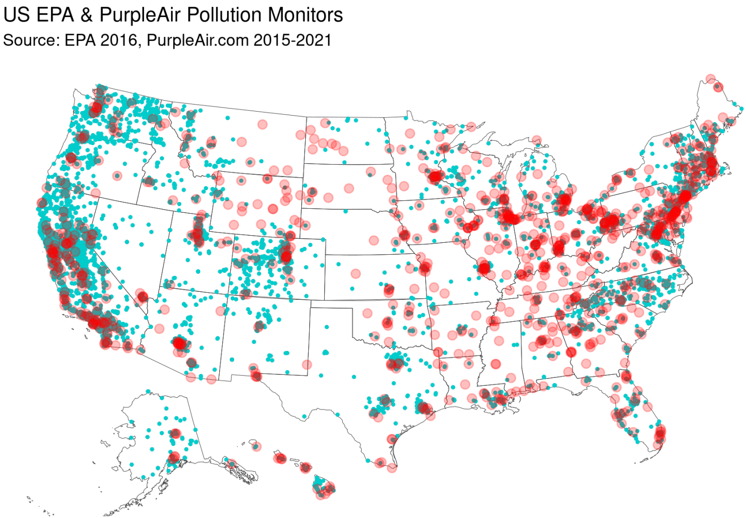
This project

- Using new consumer-based pollution monitors (PurpleAir).
- Avoids using satellite estimates (has been shown to have significant error).
- Focus on EPA pollution data that is missing *in time*, specifically PM2.5

Use PM2.5 Air Pollution Monitors to Predict Missing EPA Data



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- **Estimate bias of reported EPA pollution:** difference between predicted pollution at missing times and reported pollution at nonmissing times.
- **Estimate counties' counterfactual attainment status:** Include estimated missing pollution data.

Models: Predictive model of each EPA monitor PM2.5 pollution

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

- Analysis done at the month and quarter level; suppressing that subscript.
- t is a unique hour within a given month or quarter.
- EPA monitor i at time t reads PM2.5 pollution $EPA_{i,t}$.
- For each EPA monitor i, there are J_i Purple Air monitors within a 10-mile radius.
- Purple Air monitor $j \in J_i$ at time t reads PM2.5 pollution $PA_{j,t}$.
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Models: Hour-by-Day-of-week Bias of Missing EPA Monitor Pollution Data

Missingness Bias:

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where $\mathcal{M}_{i,h,d} = \{t : t \text{ is at hour } h \text{ and day } d \text{ and } EPA_{i,t} \text{ is Missing}\};$

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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

$Attain_c^{annual} = 1$ if **reported** annual average PM2.5 below 15.0 μg/m^{3*}

$Attain_c^{daily} = 1$ if 98^{th} percentile of **reported** daily average PM2.5 below 35 μg/m^{3*}

*averaged over 3 years in NAAQS standard. [fill in equations and thresholds]

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- Yes: simple rule based on pollution concentrations.

Proposed Statistical Test

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- Implies an permutation inference test for each EPA monitor i.

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- Calculate missingness bias and algorithm bias for the i^{th} EPA monitor using J_i PA monitors with n_i missing hour observations.

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- Calculate missingness bias and algorithm bias for PA monitor j: $Bias_{j,h,d}$
- Repeat for all PA sensors.

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  - Ratio_k = sum of squared missingness bias / sum of squared algorithm bias
  - 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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- Welfare analysis based on attainment status changes and required reductions in pollution.
- 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 2: 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. 12: Proof of concept for 2 EPA sensors (Fresno, and [need to pick another low on Mu's list])
- 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

Appendix C: PurpleAir Takeup

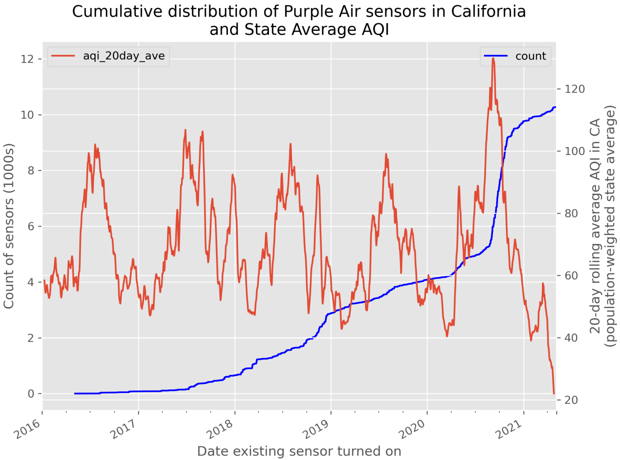

Figure 3: Valid Purple Air Monitor Locations, Contiguous United States