# Measuring bias in (strategically) missing EPA pollution data

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

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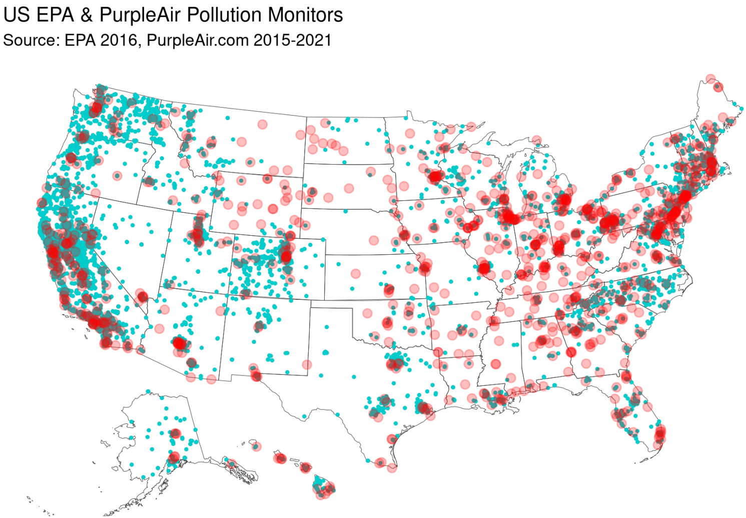
- Focus on EPA pollution data that is missing *in time*.
- Avoids using satellite estimates (has been shown to have significant error).

# PM2.5 Air Pollution Monitors





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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.

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- Purple Air monitor $j \in J_i$ at time $t$ reads PM2.5 pollution $PA_{j,t}$.
- $Winddir_{i,t,k}$ is a wind direction indicator; 1 if the prevailing wind near station $i$ at time $t$ is in the $k^{th}$ bucket (of 8 buckets).

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

**Missingness Bias:**

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

$$\text{where } \mathcal{M}_{i,h,d} = \{t : t \text{ is at hour } h \text{ and day } d \text{ and } EPA_{i,t} \text{ is Missing}\};$$
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We can also define the **algorithm bias** as the Hour-by-Day-of-week prediction error

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

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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

$$Attain_c^{annual} = 1 \text{ if } \textbf{reported} \text{ annual average PM2.5 below } 15.0\ \mu\text{g/m}^{3*}$$

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

$$\widehat{Attain}_c^{annual} = 1 \text{ if } \textbf{predicted} \text{ annual average PM2.5 below threshold}^*$$

$$\widehat{Attain}_c^{daily} = 1 \text{ if } 98^{th} \text{ percentile of } \textbf{predicted} \text{ daily average PM2.5 below threshold}^*$$

*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

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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?
- Implies an Abadie et al. 2011 style permutation inference test for each EPA monitor $i$.

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- Construct similar placebo synthetic control for PA monitor $j$ (predict $\widehat{PA}_{j,t}$).
- Calculate missingness bias and algorithm bias for the PA monitor: $Bias_{j,h,d}$
- Repeat for all PA sensors.

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- **Graphical test**: For EPA sensor $i$, compare graph of $Bias_{i,h,d}$ to placebo $Bias_{j,h,d}$ for $j \in J_i$.

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  - $\text{Ratio}_k$ = 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

- Welfare analysis based on attainment status changes and required reductions in pollution.

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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 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

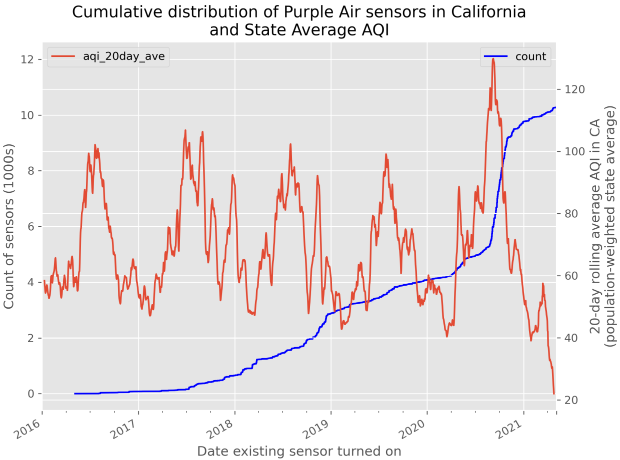


Figure 3: Valid Purple Air Monitor Locations, Contiguous United States

Source: api.purpleair.com