# Effects of On-Demand Ridesourcing on U.S. Vehicle Ownership, Travel, Energy, and Environmental Outcomes

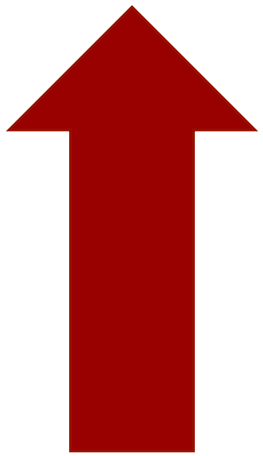
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# Transportation Network Companies (TNCs) move people differently

*The net effect is unknown.*



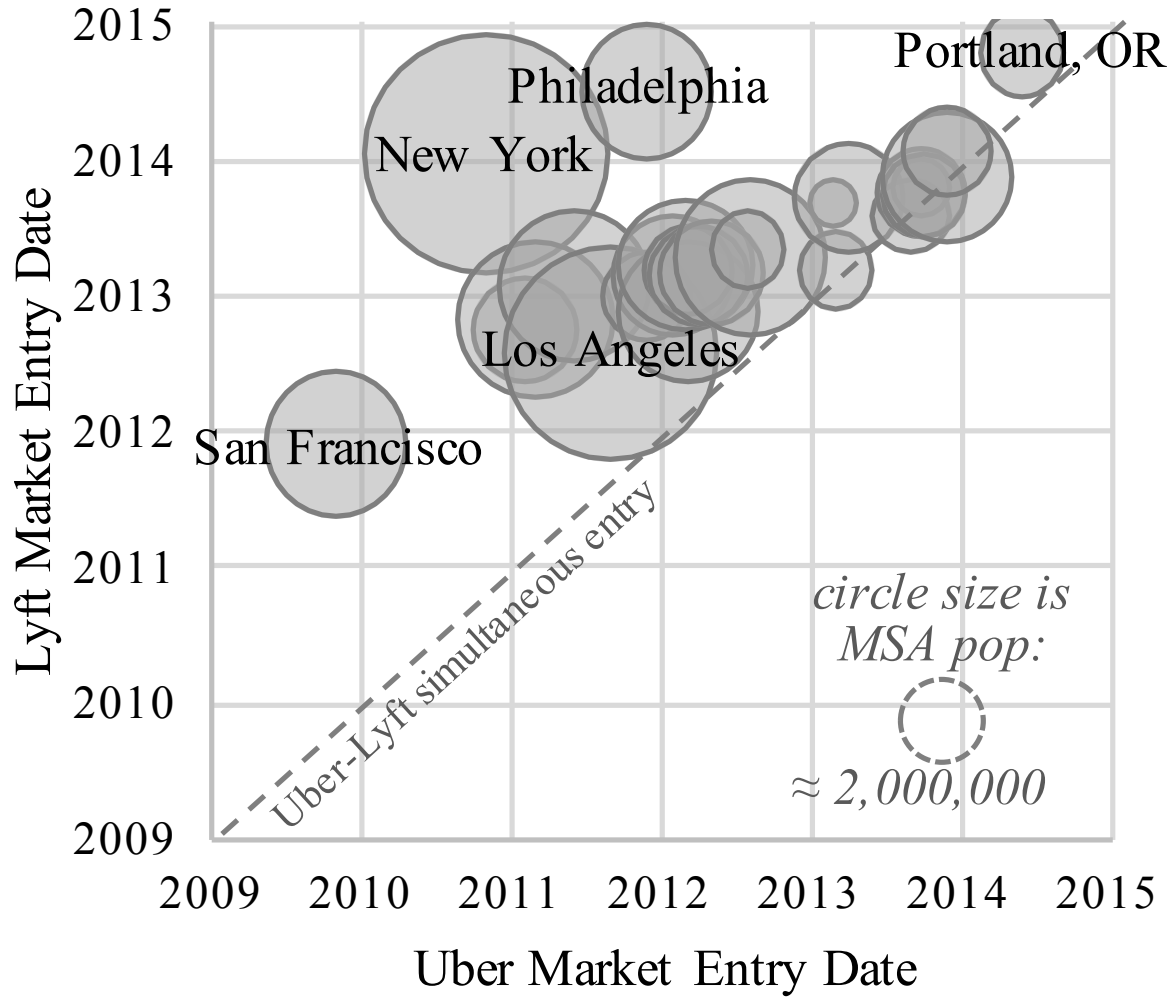
*More trips and "empty miles" could drive up VMT, energy use and emissions…*



*…but newer, more efficient TNC vehicles (running hot) could reduce energy use & emissions; higher marginal cost of travel could reduce travel*

*Figure source: Henao (2017)*

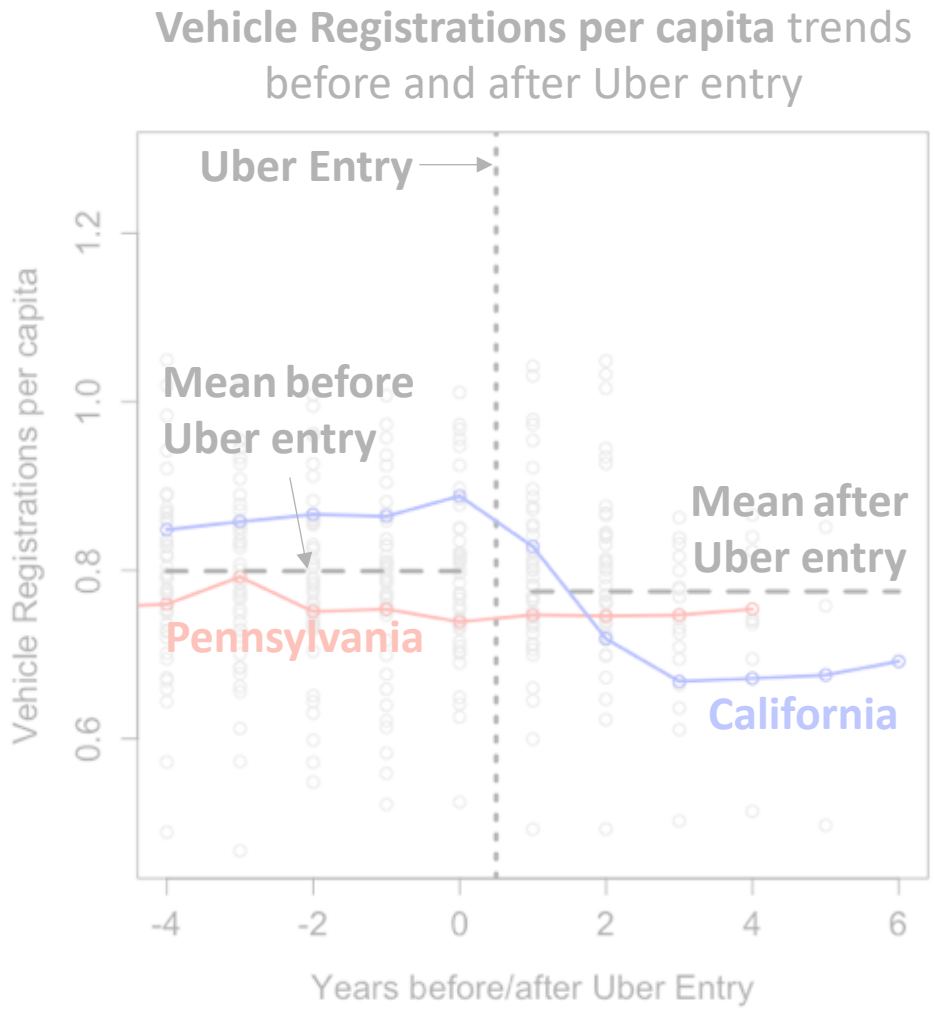
# Uber & Lyft entered different cities at different times




- Through 2017, Uber entered 212 metro areas (~46% of all metro areas).
- TNCs accounted for >170,000 trips in San Francisco (15% of intra-city trips) in 2016 and >90,000 trips in Seattle in 2018.

*Data: Bi (2014), Li (2016), Brazil and Kirk (2016), and Lyft (2016)*

# What changes do Uber/Lyft cause?



# Difference-in-difference model

$$y_{gt} = \boldsymbol{\beta}^{\top}\mathbf{x}_{gt} + \boldsymbol{\alpha}^{\top}\mathbf{z}_{gt} + \gamma_g + \delta_t + \varepsilon_{gt}$$

$y_{gt}$: one of several dependent variables for **location** $g$ and year $t$

$\mathbf{x}_{gt}$: vector of treatment effects (i.e., an Uber indicator)

$\mathbf{z}_{gt}$: vector of controls

$\gamma_g$: fixed effect for **location** $g$

$\delta_t$: fixed effect for year $t$

$\varepsilon_{gt}$: unobserved error.

**Location** modeled at two levels of resolution: state and at urban-area

# Comparison of State and Urban Area models

| | | State | Urban Area (UA) |
|---|---|---|---|
| **Dependent Variables** *(per capita)* | **Vehicle Ownership** | • **Vehicle registrations** *(U.S. DOT/Ward's)* | • **Vehicle registrations** *(IHS/Polk)*<br>• **Electric vehicle registrations** *(IHS/Polk)*<br>• **New vehicle purchases** *(IHS/Polk)* |
| | **Travel** | • **VMT** *(DOT)** | • **Transit ridership** *(DOT/FTA)* |
| | **Energy** | • **Gasoline purchased** *(DOT)* | • **N/A** |
| | **Environment** | • **Emissions** *(EPA)*** | • **Pollutant concentrations** |
| **Treatment** | **Uber/Lyft Entry** | • **Uber/Lyft, news coverage & lit.** | • **Uber/Lyft, news coverage & lit.** |
| **Control Variables** | | • State population, urban population percentage, gas price, real personal income, Section 177 status, and largest city controls (population, density, and GDP) *(all from BEA)* | • UA population, portion of population over age 16 and over 65, population density, unemployment rate, income, and transit commute percentage *(all from U.S. Census)* |

** Estimated by DOT using traffic sensors on select roadways ** Estimated by EPA using the MOVES model*

*Data source differences highlighted in red italics*

# Treatment encodings (Uber market entry)

| | State level | Urban Area (UA) level |
|---|---|---|
| 1) **Average effect**: *Does Uber entry associated with a change in vehicle registrations*?* | $\mathbf{x}_{gt} \in \{0,1\}$ Uber present anywhere in state | $\mathbf{x}_{gt} \in \{0,1\}$ Uber present anywhere in UA |
| 2) **Interaction effect:** *Is Uber's entry effect heterogeneous as a function of observable UA variables*?* | | $\mathbf{x}_{gt} * z_{gt}^{V}$ , where $\mathbf{x}_{gt} \in \{0,1\}$ Uber present anywhere in UA and $z_{gt}^{V}$ is variable of interest for UA $g$ and year $t$ |
| 3) **Cluster effect:** *Is Uber's entry effect heterogeneous as a function of a collection of similar UA variables*?* | | $\mathbf{x}_{gt} * \kappa_g$ , where $\mathbf{x}_{gt} \in \{0,1\}$ Uber present anywhere in UA and$\kappa_g$ is an cluster indicator for UA $g$ and year $t$ |

**at the state or UA level over the analysis periods considered (2005–2015 and 2011–2017, respectively)*

# Results: Estimated effect on vehicle registrations different at state and urban level

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Veh. Reg. | VOCs | EV Reg. | Gas. Use | VMT | Transit Trips |
| *State-Level Model* | | | | | | |
| Treatment Effect | −0.031** | −0.042** | | 0.001 | −0.003 | |
| | (0.012) | (0.016) | | (0.004) | (0.003) | |
| Observations | 550 | 550 | | 550 | 550 | |
| Deg. Freedom | 474 | 474 | | 474 | 474 | |
| Adjusted R-Sq. | 0.844 | 0.962 | | 0.840 | 0.834 | |
| *Urban Area-Level Model* | | | | | | |
| Treatment Effect | 0.007** | | −0.0001 | | | −0.001 |
| | (0.003) | | (0.0002) | | | (0.012) |
| Observations | 3,402 | | 3,402 | | | 1,848 |
| Deg. Freedom | 2,903 | | 2,903 | | | 1,570 |
| Adjusted R-Sq. | 0.913 | | 0.705 | | | 0.998 |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

*VOC result based on EPA estimates modeled using MOVES

PRELIMINARY RESULTS

# Should we believe these results?


9

# Results are robust to robustness checks

1. **Randomized treatment bootstrapping:** confirms our model predicts no effect when there is none
2. **Leave-one-out analysis:** shows no one individual state has disproportionate influence on the estimated effect
3. **Leave-multiple-out analysis:** replicates results even without states with data discontinuities
4. **Time-varying group fixed effects:** allows for different time-linear trends in different groups

| | Coefficient | RT | LOO | Enc | LMO |
|---|---|---|---|---|---|
| **Vehicle Registrations** | -3.1% ** | ● | ◒ | ● | ● |
| **VOC** | -4.2% ** | ● | ◒ | ● | ● |

*Notes:* ***RT*** *- Randomized Treatment;* ***LOO*** *- Leave-one-out;* ***Enc*** *- Uber treatment alternative encodings;* ***LMO*** *- Leave-multiple-out; ● robust, ◒ "near-robust", ○ not robust*

* Urban area results still pending

# Results are robust to sensitivity analysis

1. **Alternative dependent variable normalization:** i.e., per licensed driver or per urban population,
2. **Alternative period of analysis:** i.e., 2009–2015,
3. **Alternative treatment encoding:** annualizing between June and July instead of December and January,
4. **Additional control variables:** indicators for Uber leasing/incentive programs, Lyft market entry, and transit, and
5. **Alternative specifications with lagged treatment:** by one and two years

* Some results still pending

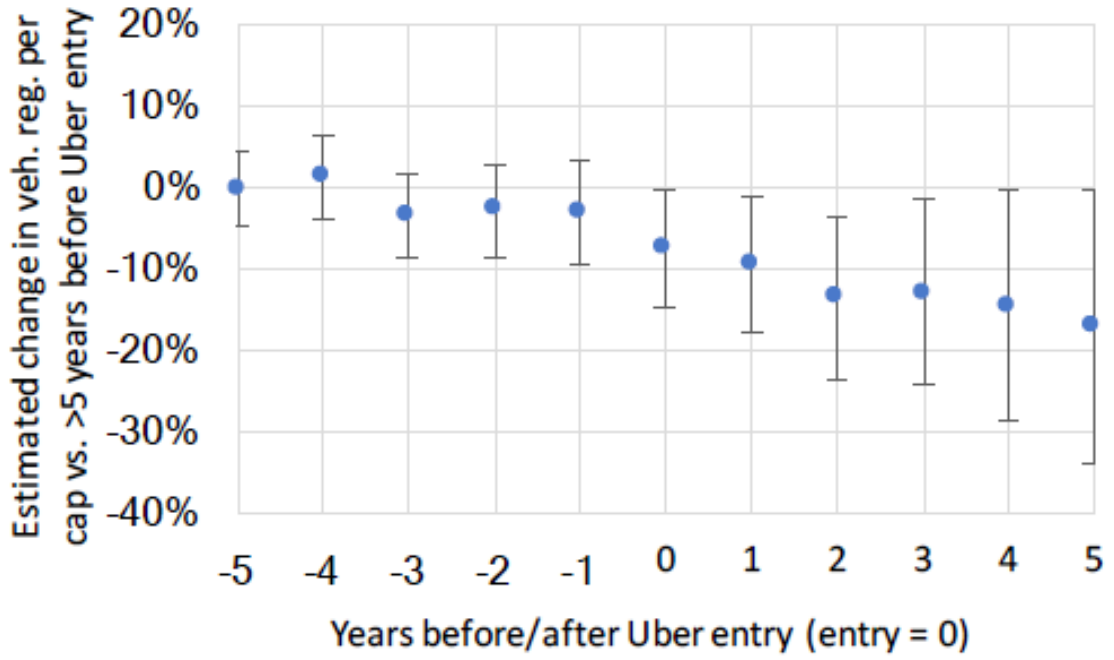
# Potential concerns

- **Exogeneous intervention**
  - Uber says decision to enter was
    - opportunistic, rather than strategic (e.g.: not in anticipation to changes in vehicle ownership)
    - informed by google searches for Uber/Lyft in cities - we are investigating whether data support this
  - Event study tests whether changes appear to precede or follow entry
- **Parallel trends**
  - Event study tests whether effects can be observed without assuming parallel trends
- **Conflation**
  - IPTW creates balanced pseudo-populations to address conflation of treatment with properties of treated vs. untreated groups
- **Spillover**
  - We assume negligible any possible effects of experience with Uber/Lyft in other cities on vehicle ownership, etc. in home city

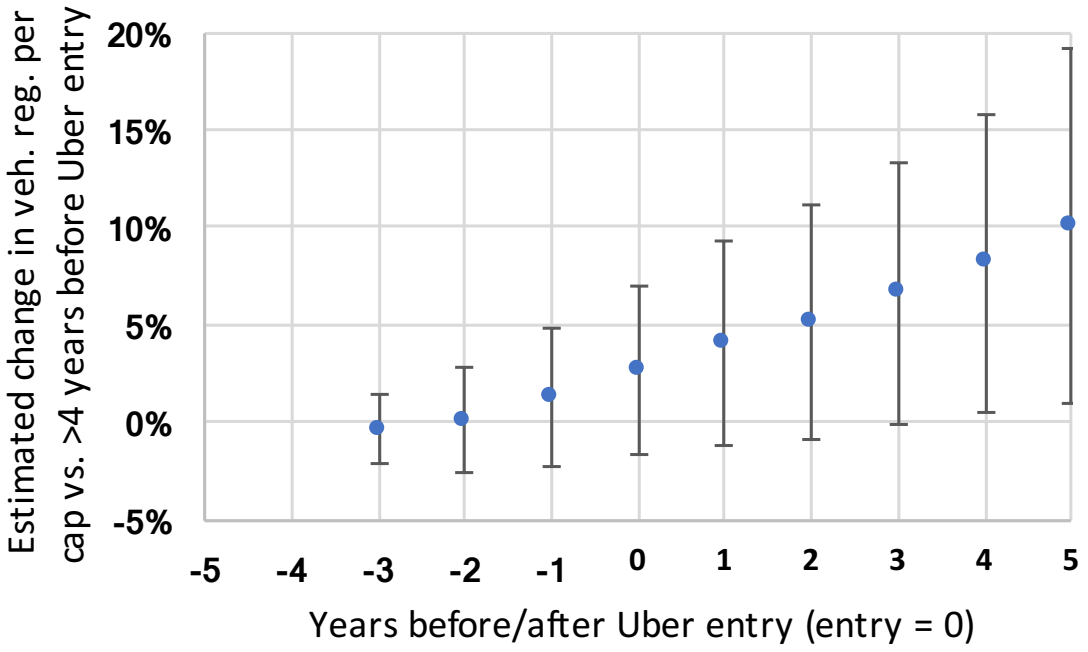
# Event study identifies similar effects (without assuming parallel trends)

- No evidence of significant pre-treatment changes in per-capita vehicle registrations
- Significant evidence of changes at some point in time after treatment

**State level**




**Urban Area (UA) level**

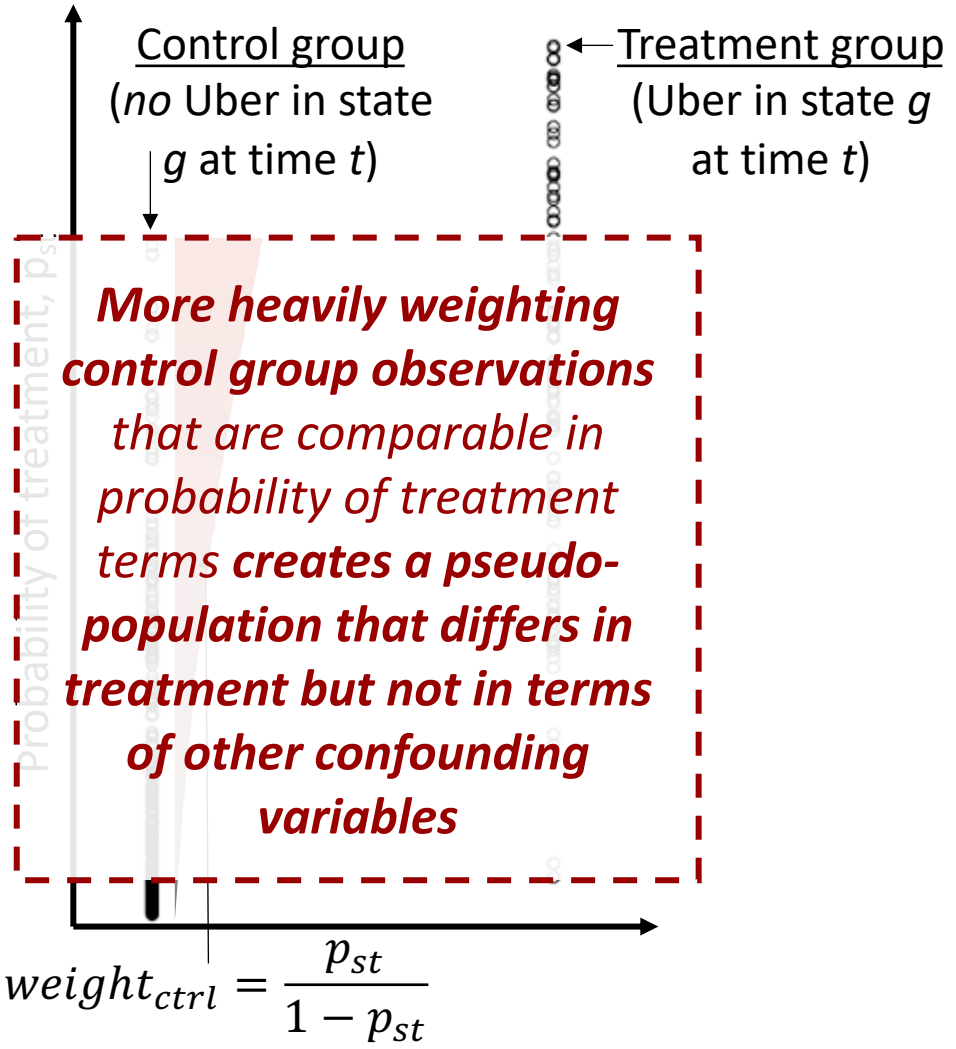


# Inverse probability of treatment weighting (IPTW)

- To control for conflation of treatment with other factors, we estimate probability of treatment based on observables:

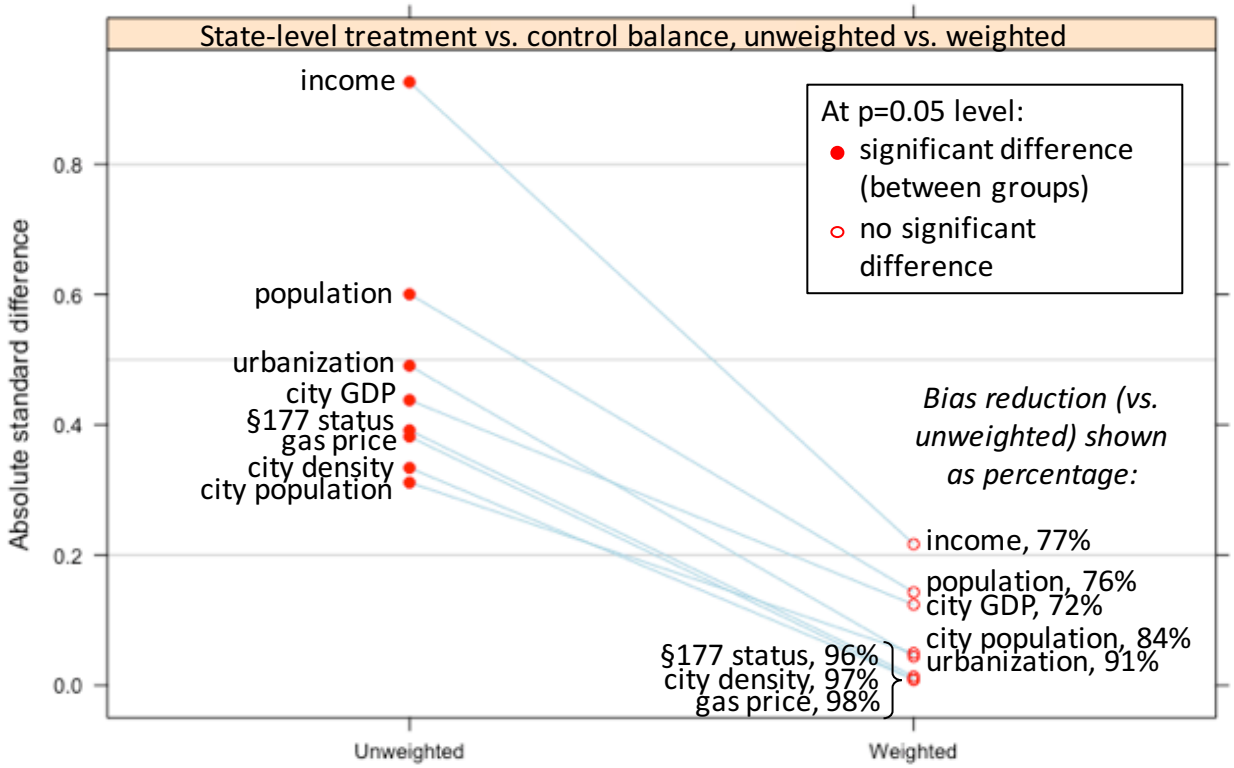
$$\log\left(\frac{p_{gt}(\mathbf{z}_{gt})}{1-p_{gt}(\mathbf{z}_{gt})}\right) = \sum_m f_m(\mathbf{z}_{gt}) + \epsilon_{gt}$$

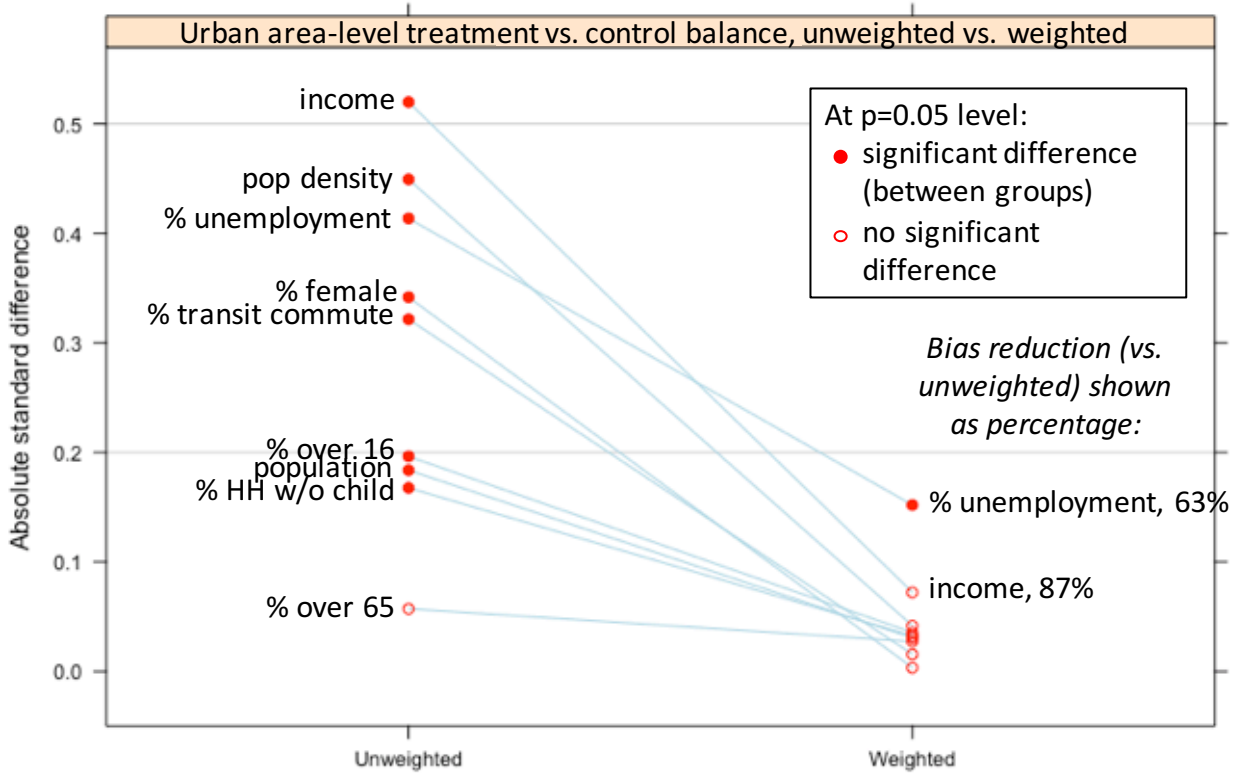
- $p_{gt}$ is the probability of treatment for state or UA $g$ and year $t$ (state estimates **shown at right**)
- $\mathbf{z}_{gt}$: controls (same as primary state and UA regressions) with additive function $f_m$;
- $\epsilon_{gt}$: unobserved error



# IPTW offers superior balance for DiD control

- State-level weighting improves balance* by by 70% to 100%, to the point of no significant difference.
- UA-level weighting also achieves indistinguishability except for unemployment rate (where the 8.1% vs. 7.9% for the weighted control vs. treatment groups are practically comparable).




** Referring to no statistically significant mean differences between treatment and unweighted control group parameters*

# OLS & LTT models: similar estimates, lower significance

- **OLS**
  - *State level:* same sign, smaller magnitude, loss of significance
  - *UA level:* similar in magnitude and significance
- **Time trends**
  - *State level:* same sign, smaller magnitude, loss of significance
  - *UA level:* similar in magnitude and significance

| | *Dependent variable: log(Veh. Reg. per cap)* | | |
|---|---|---|---|
| | IPTW | OLS | IPTW w/ time trends |
| *State-Level Model* | | | |
| Treatment Effect | −0.031** | −0.025 | −0.021 |
| | (0.012) | (0.015) | (0.017) |
| Observations | 550 | 550 | 550 |
| Deg. Freedom | 474 | 474 | 425 |
| Adjusted R-Sq. | 0.844 | 0.782 | 0.894 |
| *Urban Area-Level Model* | | | |
| Treatment Effect | 0.007** | 0.007* | 0.006* |
| | (0.003) | (0.004) | (0.003) |
| Observations | 3,402 | 3,402 | 3,402 |
| Deg. Freedom | 2,903 | 2,903 | 2,412 |
| Adjusted R-Sq. | 0.913 | 0.913 | 0.954 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

# How should we interpret these results?


17

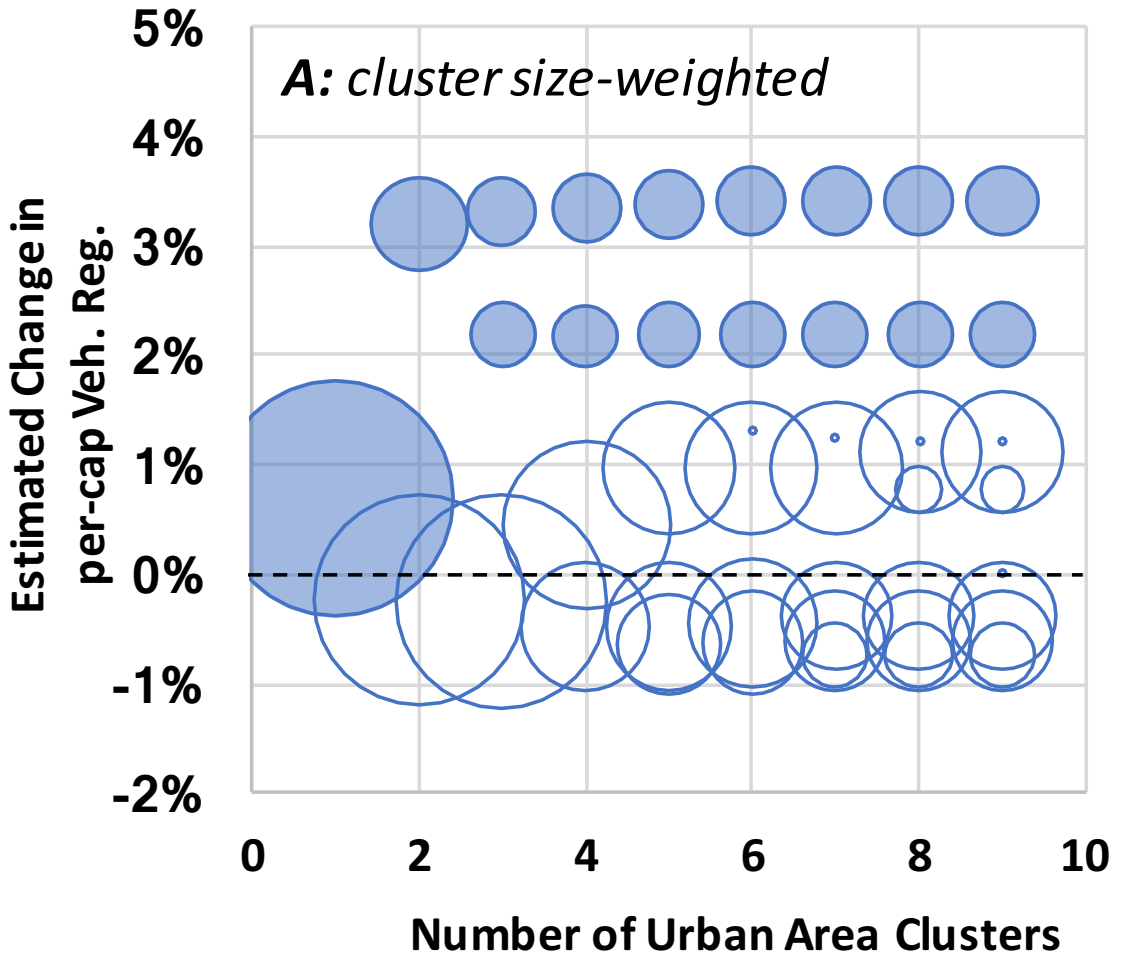
# UA results consistent w/ state results when aggregated

- We aggregate urban area data by state and re-specifying the state-level model
- Aggregated UA data consistent with state-level analysis (with smaller magnitude)
- Same effects can look different when averaged across states vs. urban areas due to heterogeneity

| | *log(Veh. Reg. per cap)* | | |
|---|---|---|---|
| | State data at state level | UA data at UA level | UA data at state level |
| Treatment Effect | −0.031** | 0.007** | −0.010** |
| | (0.012) | (0.003) | (0.005) |
| Observations | 550 | 3,402 | 287 |
| Deg. Freedom | 474 | 2,903 | 229 |
| Adjusted R-Sq. | 0.844 | 0.913 | 0.963 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

# Uber entry affects cities heterogeneously

- Hierarchical clustering identifies groups of urban areas that are similar in covariates
- Clustering pattern stabilizes at 5 clusters
- In two of these clusters, Uber entry has statistically significant positive effects (blue)
  - Effect not significant in other clusters



# Uber appears to increase ownership in large dense cities & small family-focused cities w/ low vehicle ownership

| cluster | center city | TNC effect estimate | number of urban areas in cluster | vehicle registrations per capita | population | population density | % of commutes by transit | % unemployment | income per capita | % households w/o children | electric vehicle percentage | rail trips per capita | bus trips per capita | paratransit trips per capita |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | **New York, NY** | **3.4% ***** | **45** | **-0.76** | **1.53** | **1.48** | **1.70** | **-0.21** | **1.46** | **-0.07** | **1.98** | **0.30** | **0.91** | **0.07** |
| 2 | Tampa, FL | -0.5% | 150 | 0.10 | 0.01 | 0.14 | 0.02 | -0.16 | 0.25 | -0.10 | -0.19 | -0.39 | -0.26 | -0.08 |
| **3** | **Riverside, CA** | **2.2% **** | **39** | **-0.94** | **-0.14** | **0.14** | **-0.20** | **1.30** | **-0.06** | **-2.05** | **0.22** | **-0.47** | **-0.37** | **-0.25** |
| 4 | San Antonio, TX | -0.6% | 94 | -0.20 | -0.26 | -0.30 | -0.12 | -0.66 | -0.40 | 0.23 | -0.32 | N/A | 0.70 | 0.17 |
| 5 | Tulsa, OK | 1.0% | 157 | 0.48 | -0.26 | -0.41 | -0.39 | 0.29 | -0.40 | 0.49 | -0.25 | -0.50 | -0.45 | 0.09 |

*Note: *p<0.1; **p<0.05; ***p<0.01*

PRELIMINARY RESULTS

# Concluding observations

- **TNC entry appears to**
  - reduce vehicle registrations when averaged across states
  - increase vehicle registrations when averaged across urban areas
- **Why? Effect of TNC entry is heterogeneous**
  - Appears to increase vehicle registrations in large, dense cities and in small, family-focused cities with low per-capita vehicle registrations
  - Effect in other classes of cities not significant in our current clusters
  - Further characterization of heterogeneity in process
- **Evidence supports causal interpretation (but is not definitive)**
- **Some evidence that TNC entry may reduce VOC emissions**
  - …but caveat that these are estimated with EPA MOVES modeling structure and inputs
- **Net effects on travel, energy, transit, EVs not statistically significant**
  - Could have heterogeneous effects or effects we can't identify with this model

# Future work

- **Continue heterogeneity assessment**
  - Examine robustness of our heterogeneity characterization to alternative clustering approaches and patent profile analysis
  - Leverage clustering and latent class results to inform our selection of urban area covariates for models with interactions (continuous and categorical)
- **Air quality**
  - Investigate approaches to account for non-random sensor placement

# Appendix

# Data

**State-level analysis**

| | Variable | Source |
|---|---|---|
| **Dependent Variables** | Energy use | US-DOT (measured) |
| | Vehicle ownership | US-DOT/Ward's (measured) |
| | Vehicle miles traveled | US-DOT (estimated) |
| | Emissions | US-EPA (estimated) |
| **Treatment** | TNC market entry | Uber/Lyft, news coverage, prior lit. |
| **Control Variables and Inter-actions** | Population | US-DOT |
| | Portion of state urbanized | US-Census |
| | State avg. real personal income | US-BEA |
| | State avg. gas price | US-BEA |
| | CAA section 177 status | US-EPA |
| | Largest city pop | US Census |
| | Largest city density | US Census |
| | Largest city GDP | US-BEA |

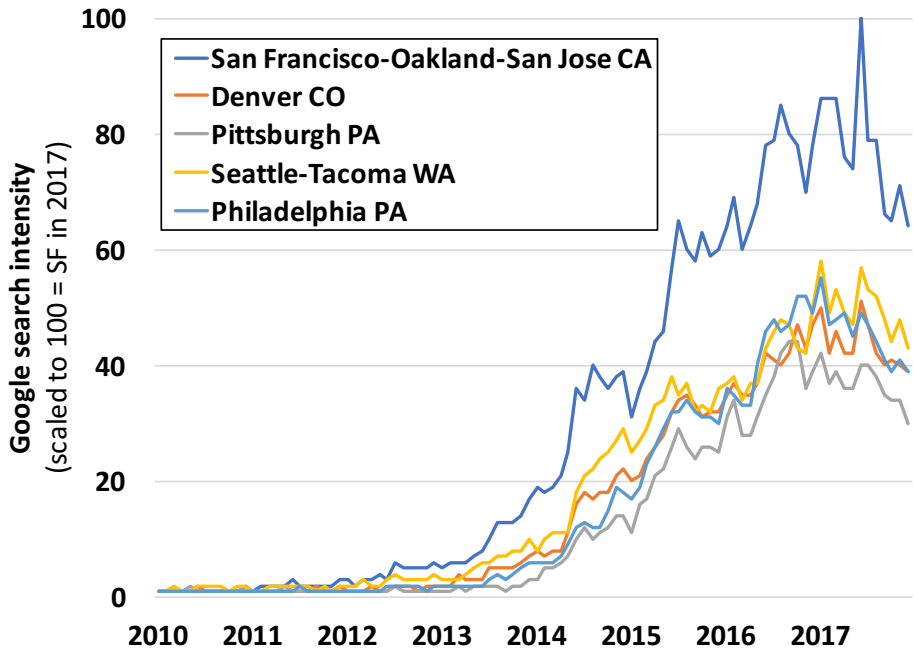
**Urban-area-level analysis**

| | Variable | Source |
|---|---|---|
| **Dependent Variables** | Vehicle ownership | IHS/Polk (measured) |
| | Electric vehicle registration percentage | IHS/Polk (measured) |
| | Air pollutant concentrations | US-EPA (measured) |
| | Transit ridership | US-DOT/FTA (measured, when reported) |
| **Treatment** | TNC market entry | Uber/Lyft, news coverage, prior lit. |
| **Control Variables and Inter-actions** | Population | US-Census |
| | Portion of population over age 16 | US-Census |
| | Portion of population over age 65 | US-Census |
| | Population density | US-Census |
| | Unemployment rate | US-Census |
| | Income | US-Census |
| | Percent commuting by transit | US-Census |

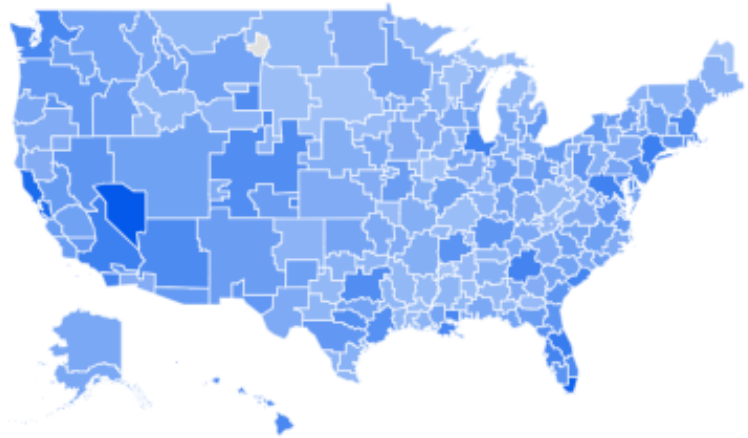
# Google Trend Data

- We know from Uber that trends in Google searches for “Uber” and related terms influenced market entry
- Data could control for one factor that influenced market entry
- Limitations:
  - Available as integers 1–100 scaled to a peak search intensity (for a given geography and time)
  - Available for 209 metro areas (vs. our 485)
  - Potential misalignment between Google and our Census UA definitions (e.g. Google’s “West Palm Beach, FL”, which the Census groups with Miami)

**Example of Google trends for “Uber” in 5 cities:**

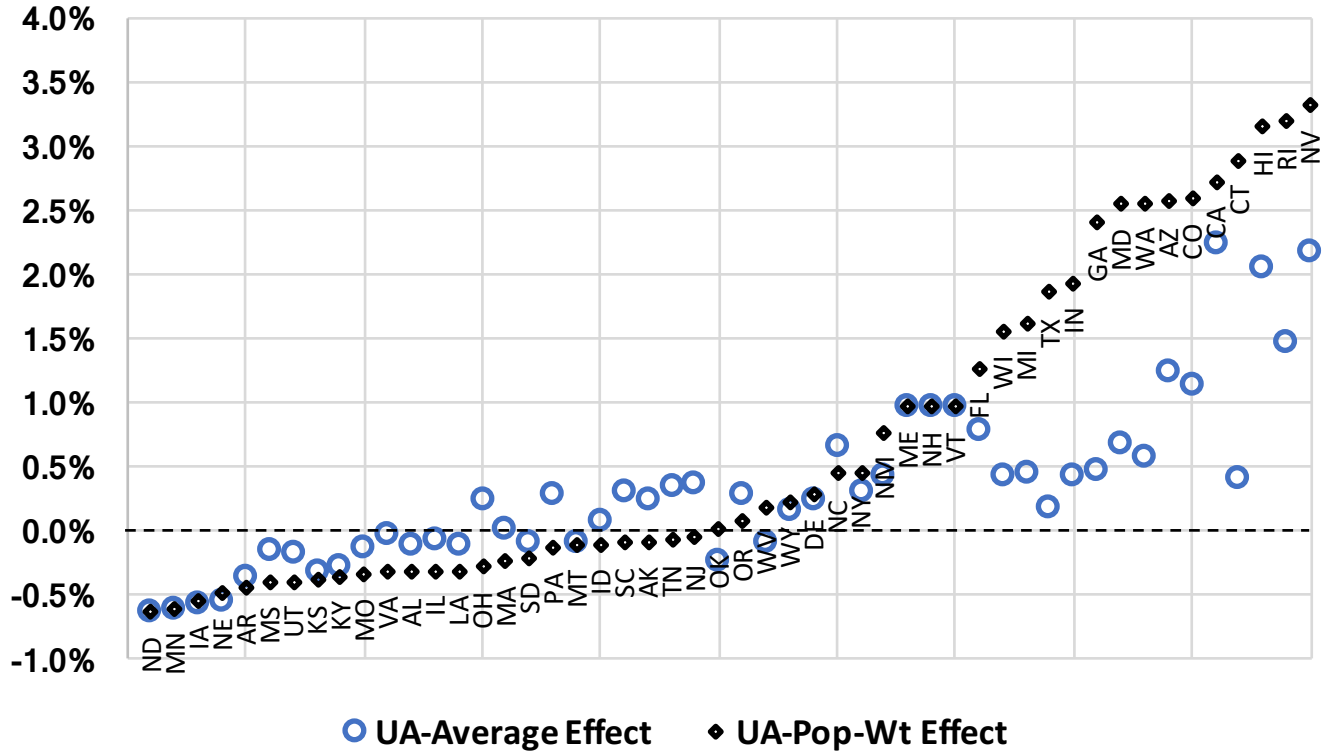



**Google trend “metro areas”:**



# UA cluster analysis effects and state implications

- **Averaging UA effects within each state yields a 0.3% grand mean** (with state "average effects" from –0.7% to 3.4%)
- **Population-weighting UA effects within each state yields a 0.7% grand mean** (with state "state effects" from –0.6% to 3.3%)
- Differences in average and population-weighted state effects suggest **heterogeneity even within states**



# Clustering robustness

- [Still in progress]

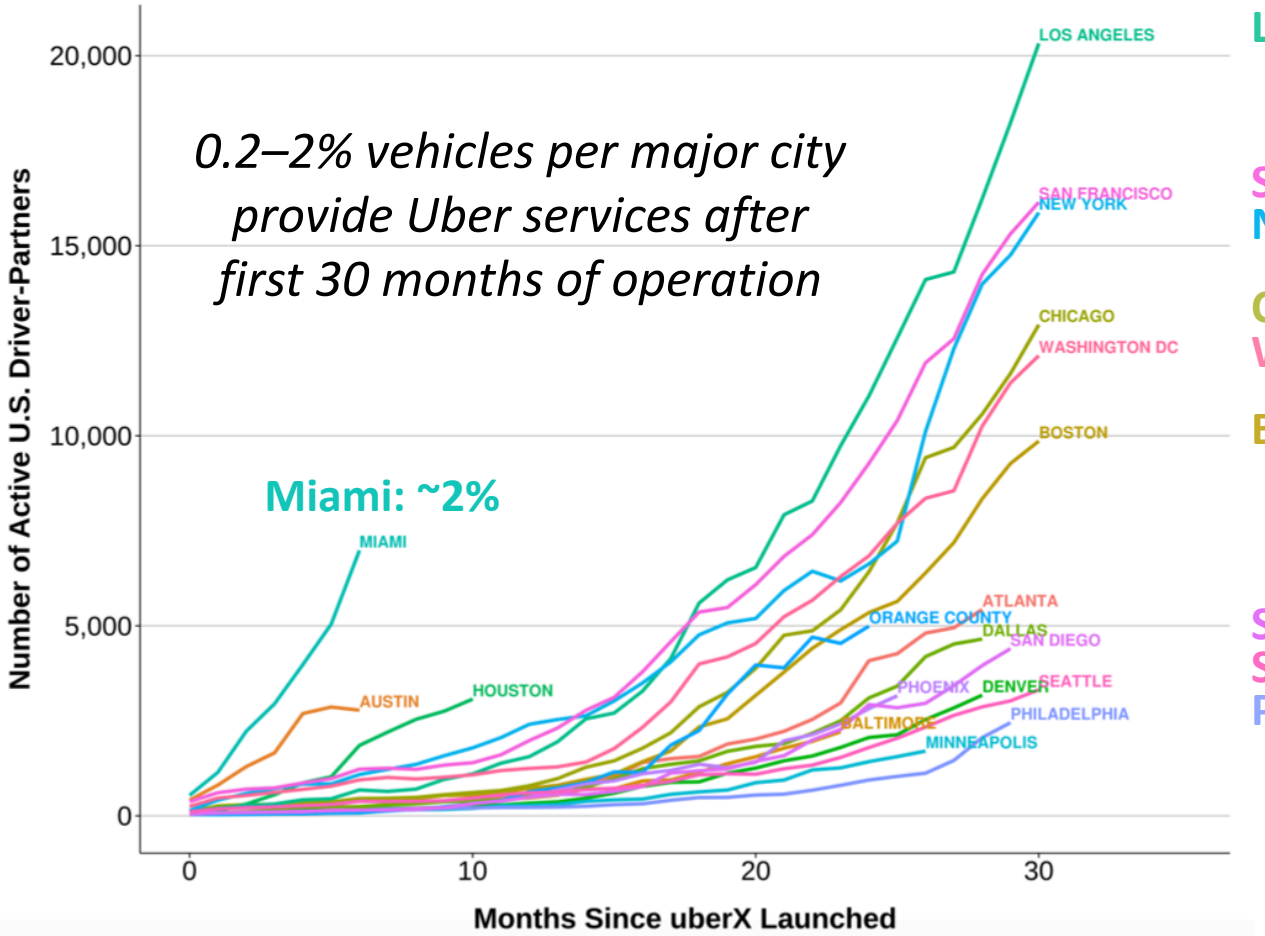
# Literature

| *Outcome:* | ***Inferences based on:*** |
|---|---|
| | **Survey of Car2Go users[1]** |
| **Vehicle ownership** | ↓1 – 11 vehicles (per Car2Go veh.) |
| **"Travel"** | ↓6–16% VMT (Car2Go users) |

*[1]Martin & Shaheen, 2016; [2]Hampshire et al, 2017; [3]Clewlow & Mishra, 2017; [4]Li et al, 2016; [5]Gong et al, 2017*

# Number of Uber drivers has grown exponentially in most markets

**Estimated number of Uber drivers nationally: 160k in 2014 and 320k in 2015[1].**




Los Angeles: ~0.5%

San Francisco: ~2%
New York: ~0.2%

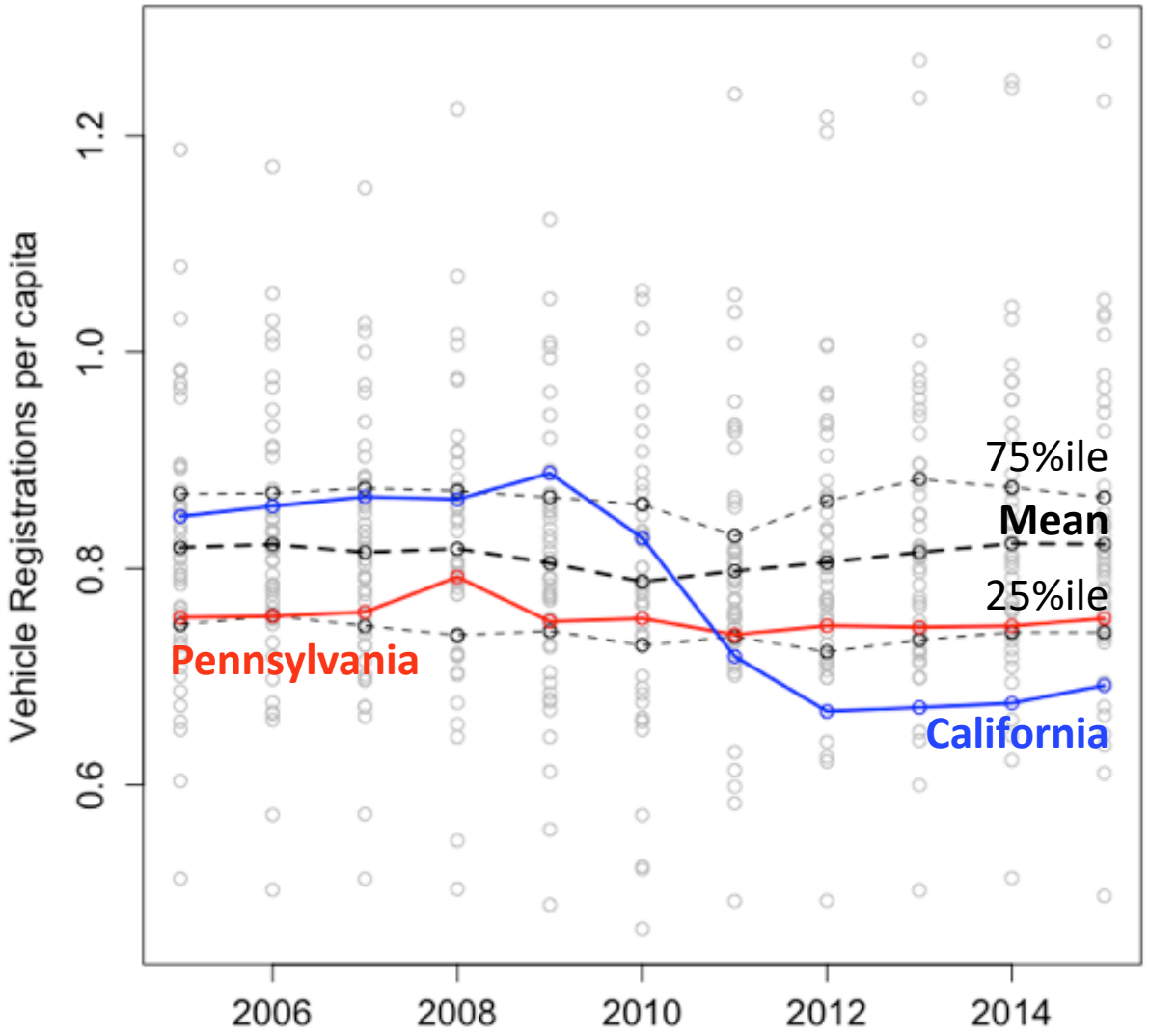
Chicago: ~0.5%
Washington, DC: ~2%

Boston: ~1.5%

San Diego: ~0.3%
Seattle: ~0.5%
Philadelphia: ~0.2%

***Figure**: Hall, J. V. and Krueger, A. B. (2015). "An Analysis of the Labor Market for Uber's Driver-Partners in the United States". Princeton Working Paper #587; [1]Caron, B. (2015). "Why there's a good chance your Uber Driver is New". Business Insider. 24 Oct. http://www.businessinsider.com/uber-doubles-its-drivers-in-2015-2015-10*

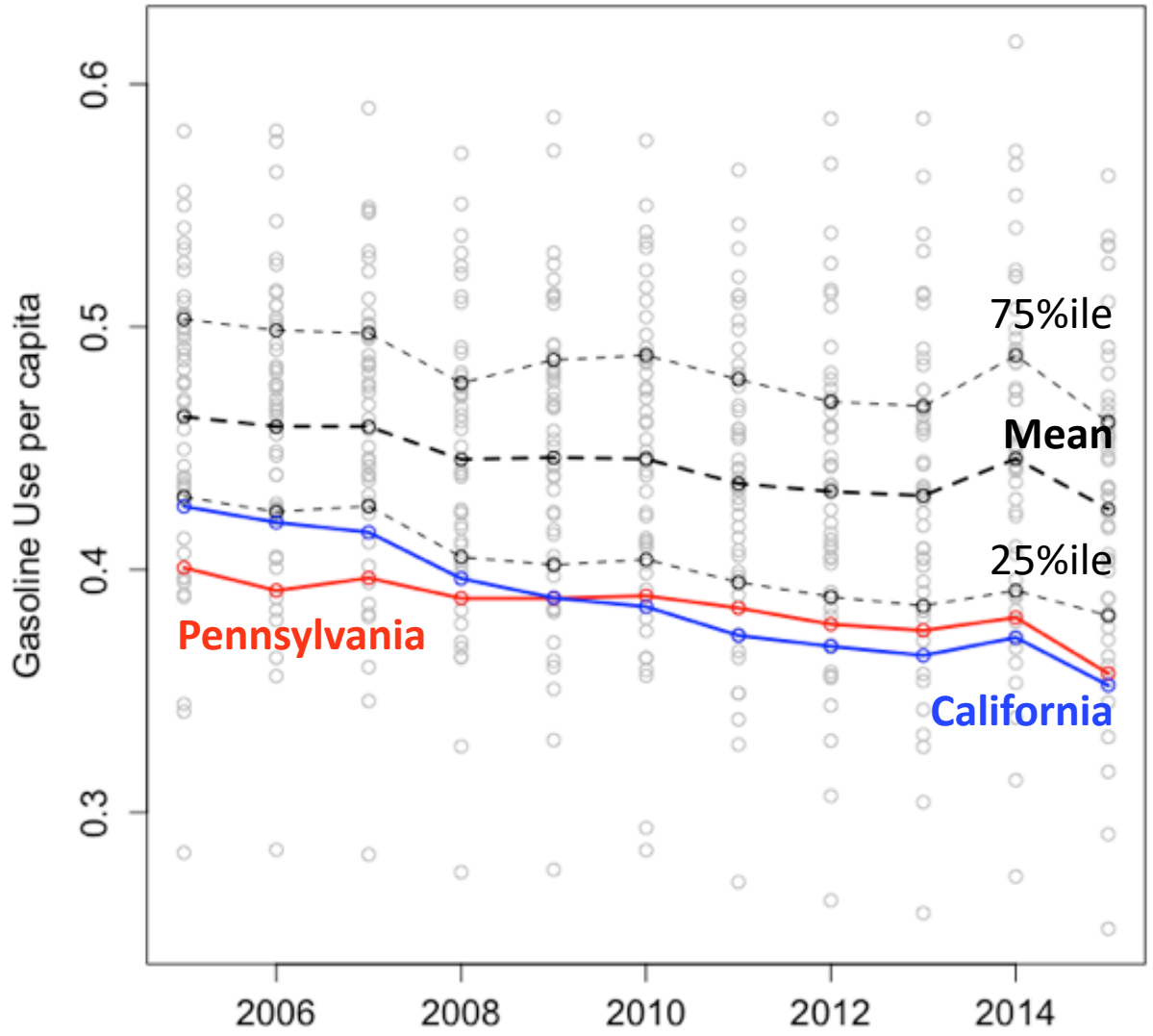
# Data detail: Vehicle Registrations




*Data source: U.S. DOT, https://www.fhwa.dot.gov/policyinformation/*

- **Source**: U.S. DOT's *Highway Statistics* and *State Statistical Abstract* Series
- **Method**: State motor vehicles agencies report to U.S. DOT number of legally registered vehicles

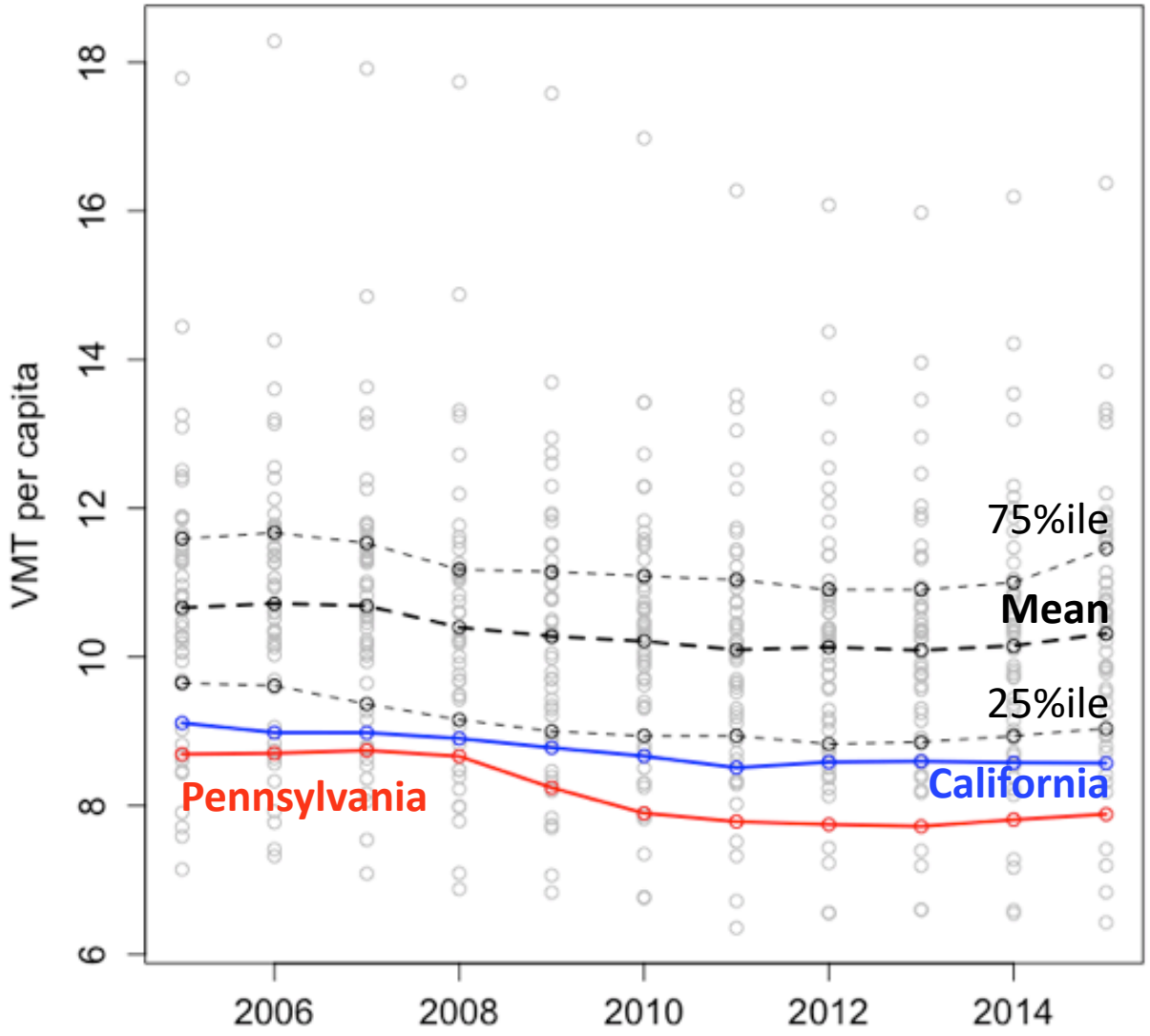
# Data detail: Gasoline Use




*Data source: U.S. DOT, https://www.fhwa.dot.gov/policyinformation/*

- **Source**: U.S. DOT's *Highway Statistics* and *State Statistical Abstract* Series
- **Method**: each State's respective motor fuel tax receipts, as reported to DOT

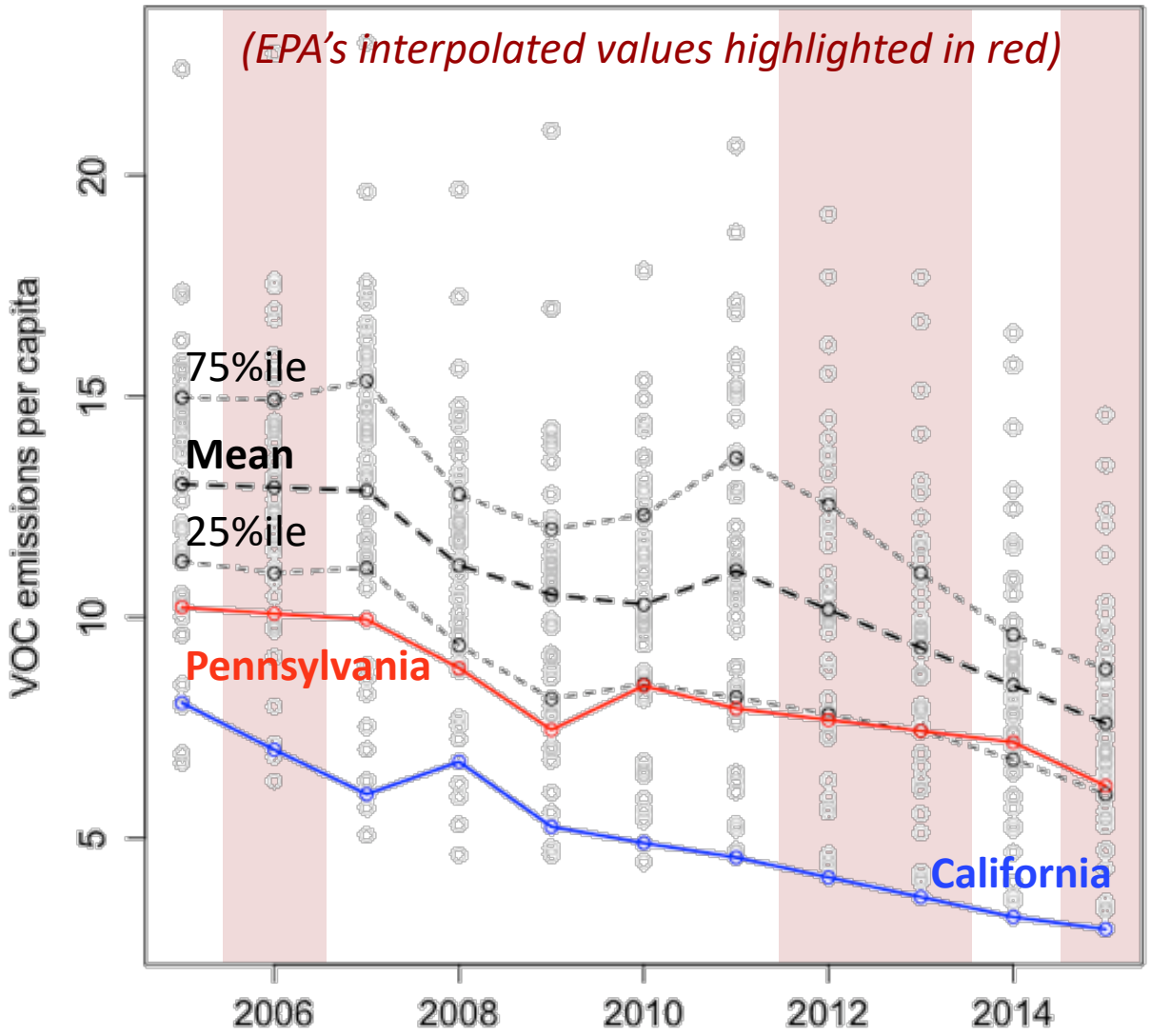
# Data detail: VMT




*Data source: U.S. DOT, https://www.fhwa.dot.gov/policyinformation/*

- **Source**: U.S. DOT's *Highway Statistics* and *State Statistical Abstract* Series
- **Method**: DOT estimates based on weighted aggregation of in-road "loop" detector-collected data

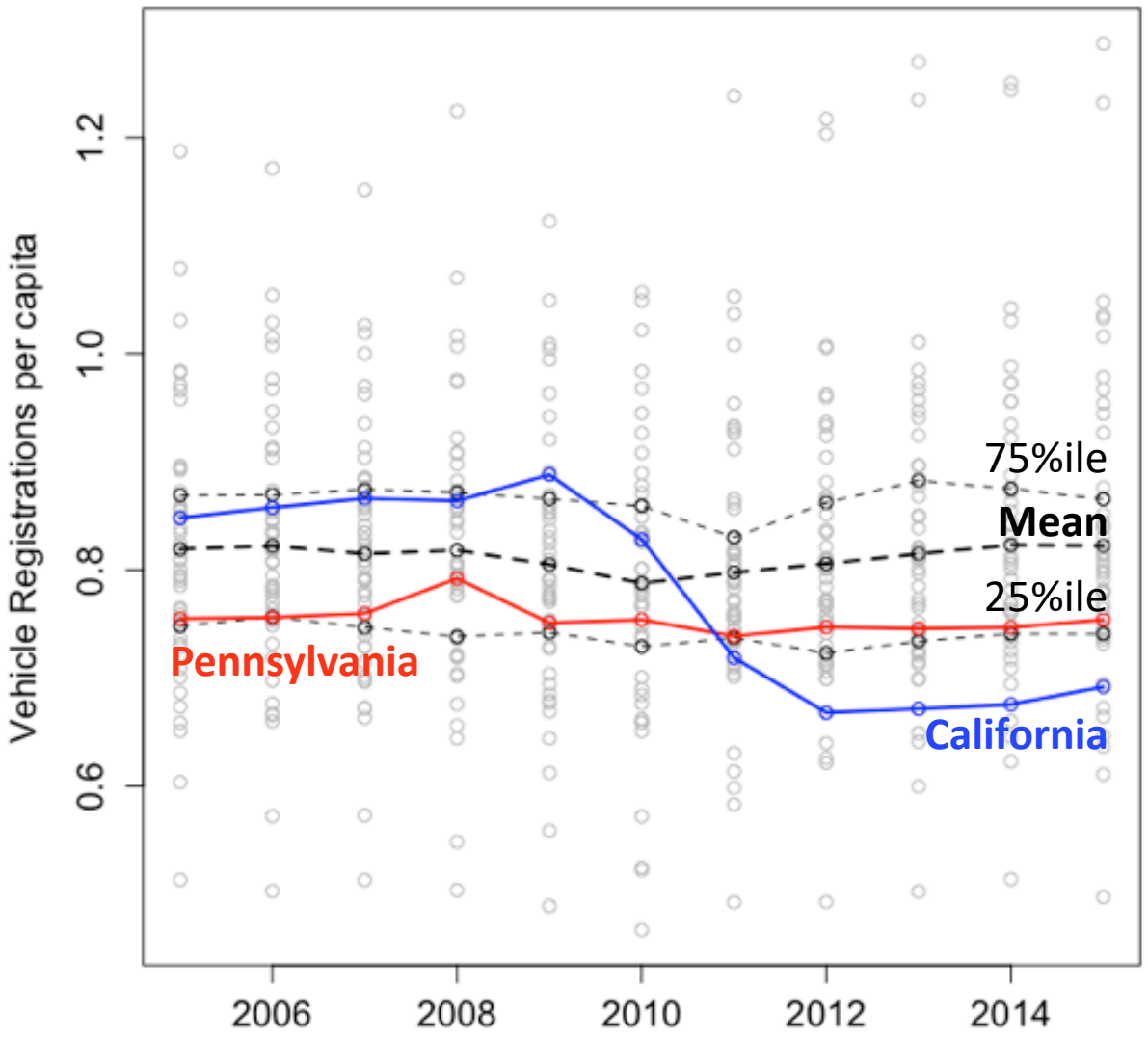
# Data detail: Pollutant Emissions




- **Source**: U.S. EPA's *Air Pollutant Emissions Trends*
- **Method**: *National Emissions Inventory* modeling in 2008, 2011, 2014, and additional MOVES modeling in 2005, 2007, 2009, and 2010

*Data source: U.S. EPA, https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data*

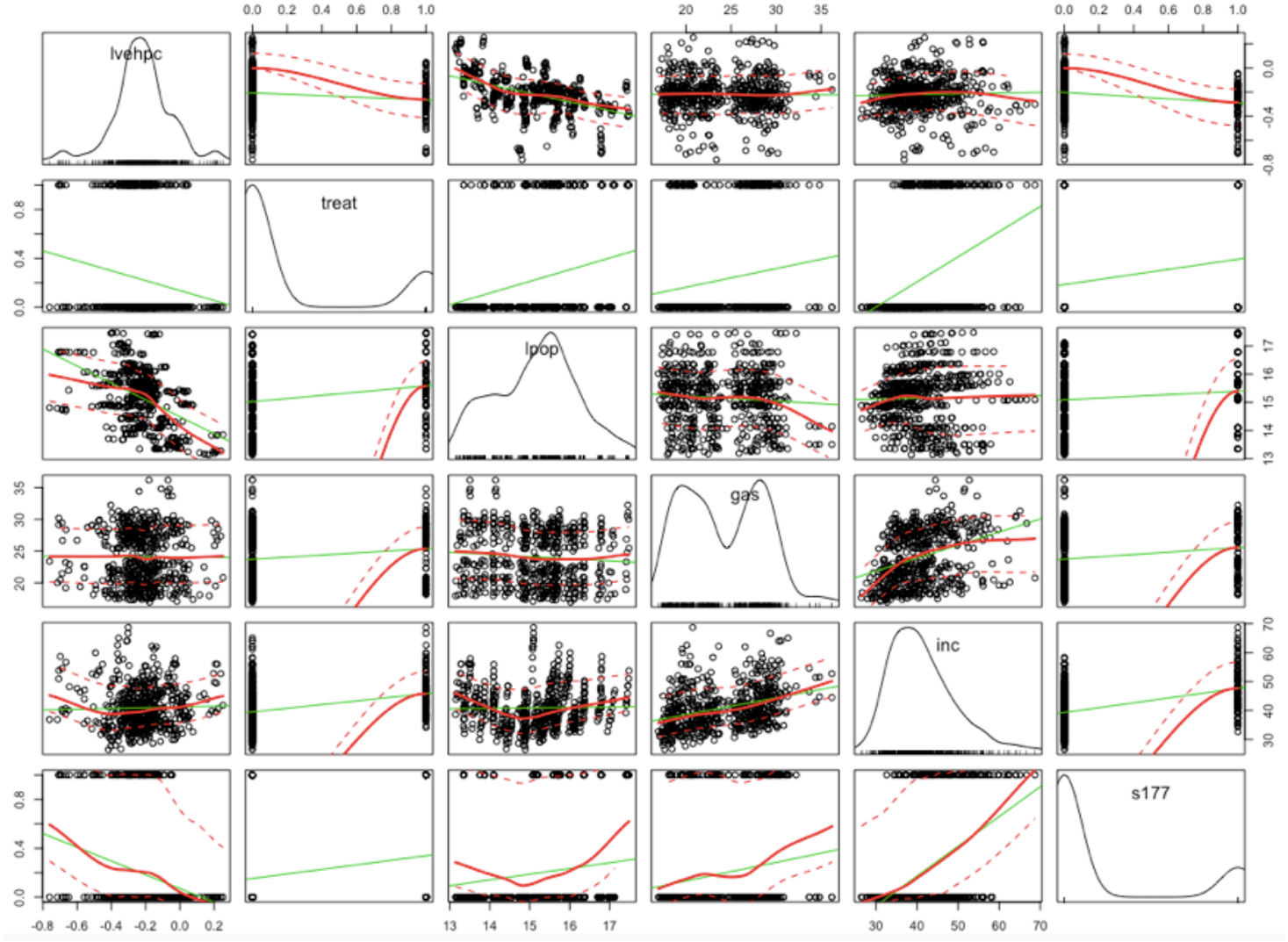
# Data detail: GHG Emissions




*Data source: U.S. DOT, https://www.fhwa.dot.gov/policyinformation/*

- **Source**: U.S. DOT's *Highway Statistics* and *State Statistical Abstract* Series
- **Method**: each State's respective motor vehicles agency reports number of legally registered vehicles to DOT

# Data detail: multicollinearity



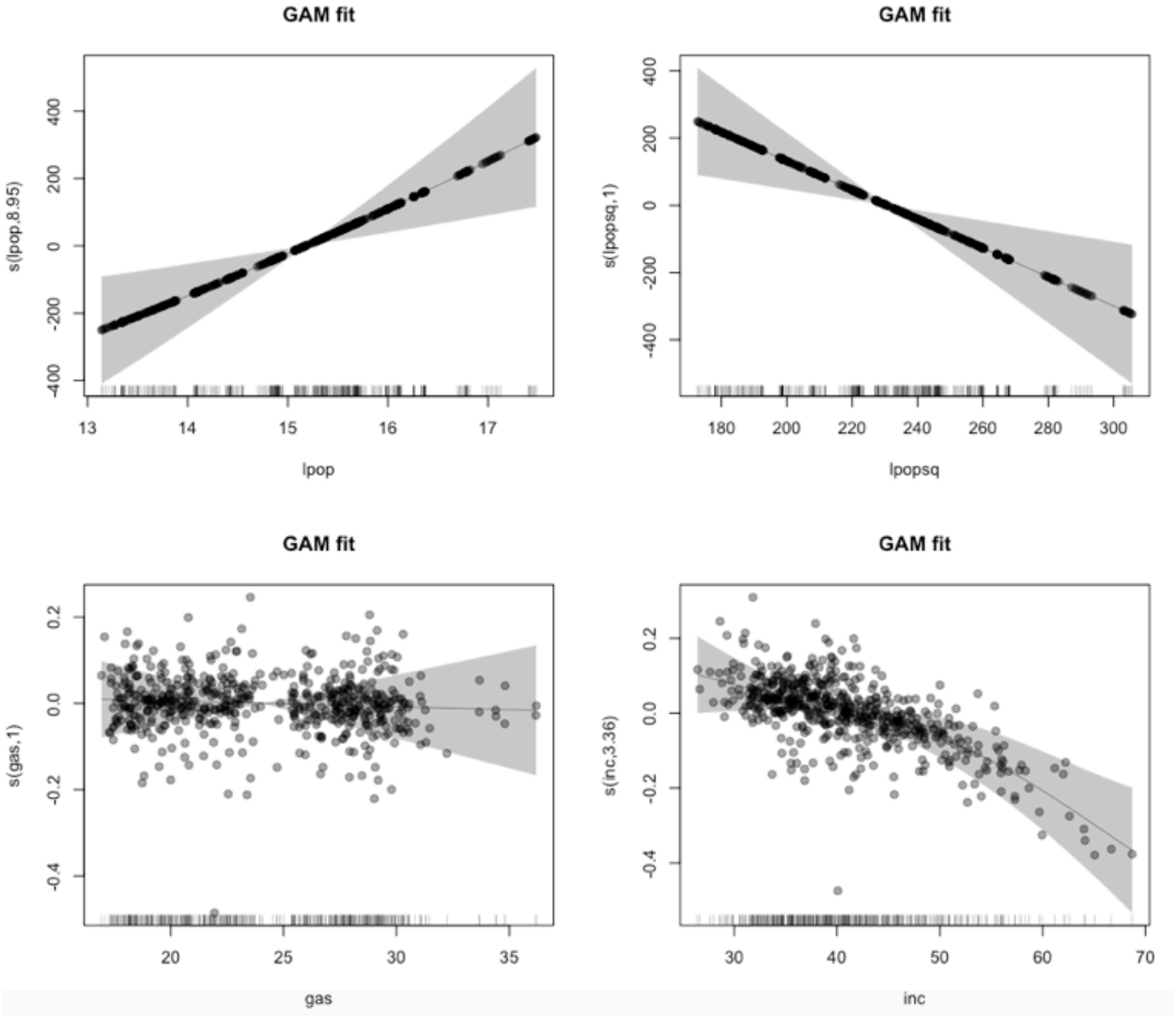
# Our regression model is informed by models in relevant prior literature

| | | Gillingham, Jenn, and Azevedo (2015) | Gillingham (2014) | Greene (2012) | Schimek (2014) | Small and Van Dender (2007) | this model |
|---|---|---|---|---|---|---|---|
| **Dependent Variable** | | log(VMT) | log(VMT) | log(VMT) | number of household vehicles | Vehicle stock | per-capita vehicle regs., gasoline use, VMT, and emissions |
| Independent Variables | **Population** | | | | Household size | Lagged (t-1) stock | log |
| | **Gas Price** | log | log | log | | log | X |
| | **Income** | log(GDP) | index | X | log | log | X |
| | **Vehicle Characteristics** | X | X | X | | X | |
| | **Time FX** | X | X | X | | X | X |
| | **Geographic FX** | X | | | | | X |
| | **Density** | | | | X | | |
| | **Demographics** | | | | X | | |
| | **Transit** | | | | X | | |
| **Sample Size** | | 30 M | 3 - 5 M | 41 | 15,916 | 1,734 | 550 |
| **Geography** | | PA | CA | US | US | US | US |

# Generalized additive models (GAMs) inform controls variable functional form

- Top: log(*pop*), *at right*, and (log(*pop*))$^2$, *far right*, both linear when both included

- Bottom: both *gas*, *at right*, and *inc*, *far right*, are linear (or near-linear) without transformation



# Probability, $p_{st}$, of Uber treatment

- Estimates modeled using logistic regression (see slide 10)
- Predicted treatment 83% accurate
- Estimates (numerical values) compared to actual treatment (in black boxes) at right:

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AK | 0.072 | 0.029 | 0.033 | 0.078 | 0.101 | 0.123 | 0.078 | 0.078 | 0.078 | 0.078 | 0.159 |
| AL | 0.021 | 0.035 | 0.017 | 0.047 | 0.021 | 0.017 | 0.062 | 0.054 | 0.062 | **0.326** | **0.259** |
| AR | 0.021 | 0.035 | 0.017 | 0.017 | 0.021 | 0.017 | 0.042 | 0.092 | 0.062 | **0.293** | **0.274** |
| AZ | 0.034 | 0.034 | 0.021 | 0.058 | 0.038 | 0.016 | 0.060 | **0.166** | **0.527** | **0.589** | **0.230** |
| CA | 0.187 | 0.110 | 0.297 | 0.675 | 0.348 | **0.302** | **0.859** | **0.881** | **0.881** | **0.881** | **0.593** |
| CO | 0.258 | 0.274 | 0.129 | 0.387 | 0.274 | 0.122 | 0.365 | **0.456** | **0.646** | **0.538** | **0.614** |
| CT | 0.588 | 0.307 | 0.341 | 0.504 | 0.581 | 0.278 | 0.350 | 0.350 | 0.350 | **0.498** | **0.581** |
| DE | 0.041 | 0.074 | 0.031 | 0.077 | 0.076 | 0.029 | 0.074 | 0.037 | 0.080 | 0.146 | **0.320** |
| FL | 0.020 | 0.126 | 0.051 | 0.051 | 0.110 | 0.051 | 0.203 | 0.219 | 0.203 | **0.670** | **0.593** |
| GA | 0.019 | 0.032 | 0.045 | 0.020 | 0.019 | 0.020 | 0.354 | **0.578** | **0.578** | **0.494** | **0.393** |
| HI | 0.113 | 0.041 | 0.043 | 0.135 | 0.050 | 0.315 | 0.220 | 0.271 | **0.271** | **0.541** | **0.555** |
| IA | 0.021 | 0.048 | 0.110 | 0.122 | 0.258 | 0.122 | 0.266 | 0.356 | 0.365 | **0.404** | **0.522** |
| ID | 0.036 | 0.036 | 0.017 | 0.050 | 0.036 | 0.017 | 0.049 | 0.027 | 0.062 | **0.311** | **0.226** |
| IL | 0.124 | 0.221 | 0.132 | 0.319 | 0.126 | 0.132 | **0.490** | **0.711** | **0.828** | **0.755** | **0.701** |
| IN | 0.020 | 0.034 | 0.016 | 0.021 | 0.047 | 0.021 | 0.287 | 0.260 | **0.421** | **0.589** | **0.606** |
| KS | 0.021 | 0.048 | 0.122 | 0.129 | 0.274 | 0.122 | 0.355 | 0.372 | 0.455 | **0.683** | **0.725** |
| KY | 0.021 | 0.035 | 0.017 | 0.047 | 0.035 | 0.017 | 0.054 | 0.060 | 0.054 | **0.333** | **0.274** |
| LA | 0.021 | 0.035 | 0.038 | 0.293 | 0.089 | 0.122 | 0.293 | 0.266 | 0.293 | **0.337** | **0.428** |
| MA | 0.287 | 0.580 | 0.283 | 0.531 | 0.609 | 0.300 | 0.666 | **0.850** | **0.850** | **0.805** | **0.750** |
| MD | 0.336 | 0.324 | 0.230 | 0.460 | 0.511 | 0.283 | 0.497 | 0.374 | **0.524** | **0.497** | **0.643** |
| ME | 0.041 | 0.026 | 0.026 | 0.156 | 0.134 | 0.086 | 0.104 | 0.104 | 0.104 | **0.308** | **0.437** |
| MI | 0.035 | 0.058 | 0.036 | 0.036 | 0.058 | 0.020 | 0.348 | 0.349 | **0.498** | **0.548** | **0.592** |
| MN | 0.158 | 0.274 | 0.129 | 0.182 | 0.274 | 0.175 | 0.398 | **0.671** | **0.664** | **0.538** | **0.614** |
| MO | 0.020 | 0.047 | 0.021 | 0.119 | 0.049 | 0.108 | 0.287 | 0.259 | 0.287 | **0.299** | **0.409** |
| MS | 0.021 | 0.035 | 0.017 | 0.017 | 0.035 | 0.017 | 0.048 | 0.042 | 0.048 | **0.062** | **0.048** |
| MT | 0.024 | 0.024 | 0.013 | 0.048 | 0.039 | 0.017 | 0.095 | 0.044 | 0.097 | 0.088 | 0.082 |
| NC | 0.023 | 0.032 | 0.035 | 0.380 | 0.082 | 0.020 | 0.130 | 0.374 | **0.349** | **0.533** | **0.393** |
| ND | 0.024 | 0.024 | 0.033 | 0.079 | 0.076 | 0.033 | 0.078 | 0.091 | 0.091 | 0.141 | **0.226** |
| NE | 0.029 | 0.048 | 0.122 | 0.122 | 0.274 | 0.122 | 0.391 | 0.336 | 0.456 | **0.546** | **0.595** |
| NH | 0.059 | 0.153 | 0.051 | 0.185 | 0.205 | 0.151 | 0.217 | 0.131 | 0.131 | **0.415** | **0.665** |
| NJ | 0.215 | 0.484 | 0.212 | 0.226 | 0.465 | 0.226 | 0.517 | 0.518 | **0.764** | **0.788** | **0.702** |
| NM | 0.035 | 0.030 | 0.017 | 0.048 | 0.035 | 0.017 | 0.054 | 0.060 | 0.054 | **0.270** | **0.274** |
| NV | 0.274 | 0.122 | 0.122 | 0.293 | 0.294 | 0.143 | 0.266 | 0.146 | 0.288 | **0.266** | **0.175** |
| NY | 0.092 | 0.241 | 0.379 | 0.611 | 0.478 | 0.254 | **0.605** | **0.881** | **0.857** | **0.863** | **0.860** |
| OH | 0.018 | 0.043 | 0.019 | 0.276 | 0.037 | 0.028 | 0.304 | 0.319 | 0.304 | **0.483** | **0.436** |
| OK | 0.021 | 0.048 | 0.022 | 0.122 | 0.029 | 0.022 | 0.293 | 0.277 | **0.398** | **0.489** | **0.522** |
| OR | 0.035 | 0.022 | 0.022 | 0.333 | 0.048 | 0.022 | 0.146 | 0.146 | 0.146 | **0.325** | **0.185** |
| PA | 0.063 | 0.174 | 0.095 | 0.483 | 0.221 | 0.163 | 0.507 | **0.752** | **0.752** | **0.729** | **0.653** |
| RI | 0.087 | 0.041 | 0.041 | 0.164 | 0.144 | 0.071 | 0.100 | 0.136 | **0.281** | **0.287** | **0.336** |
| SC | 0.021 | 0.035 | 0.017 | 0.017 | 0.021 | 0.017 | 0.048 | 0.062 | 0.062 | **0.333** | **0.274** |
| SD | 0.014 | 0.034 | 0.028 | 0.071 | 0.072 | 0.029 | 0.082 | 0.046 | 0.082 | 0.102 | 0.183 |
| TN | 0.020 | 0.034 | 0.021 | 0.058 | 0.047 | 0.021 | 0.259 | 0.260 | **0.287** | **0.421** | **0.606** |
| TX | 0.013 | 0.030 | 0.023 | 0.078 | 0.149 | 0.078 | 0.289 | **0.639** | **0.675** | **0.835** | **0.894** |
| UT | 0.021 | 0.035 | 0.017 | 0.048 | 0.035 | 0.017 | 0.046 | 0.026 | 0.102 | **0.266** | **0.274** |
| VA | 0.119 | 0.330 | 0.130 | 0.176 | 0.335 | 0.176 | 0.517 | 0.518 | 0.517 | **0.552** | **0.511** |
| VT | 0.038 | 0.066 | 0.031 | 0.079 | 0.079 | 0.032 | 0.054 | 0.051 | 0.093 | **0.298** | **0.249** |
| WA | 0.252 | 0.119 | 0.177 | 0.364 | 0.269 | 0.313 | **0.738** | **0.897** | **0.829** | **0.797** | **0.488** |
| WI | 0.036 | 0.028 | 0.092 | 0.233 | 0.216 | 0.092 | 0.111 | 0.160 | 0.166 | **0.365** | **0.514** |
| WV | 0.035 | 0.035 | 0.017 | 0.048 | 0.035 | 0.017 | 0.020 | 0.026 | 0.026 | 0.058 | 0.237 |
| WY | 0.030 | 0.076 | 0.033 | 0.098 | 0.043 | 0.033 | 0.100 | 0.088 | 0.100 | 0.116 | 0.166 |

# Inverse prob. of treatment weights:

$$weight_{ctrl} = \frac{p_{st}}{1 - p_{st}}$$

- Control state-years that "look similar" to treatment state-years get higher weights: CA, CT, MA, MD, NJ, NY, PA, VA, etc.
- Control state-years that "look different" get lower weights: AK, ID, KY, MS, MT, NM, SC, WV, etc.

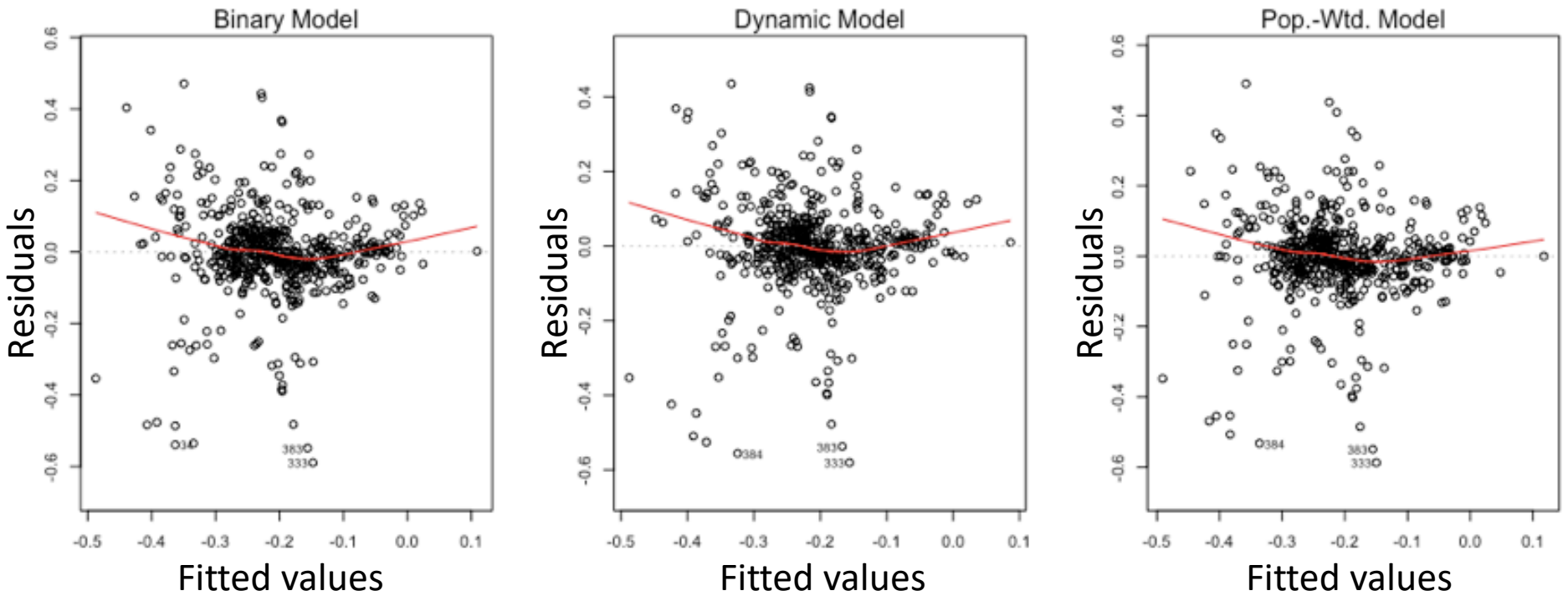
| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AK | 0.078 | 0.030 | 0.035 | 0.085 | 0.113 | 0.140 | 0.085 | 0.085 | 0.085 | 0.085 | 0.188 |
| AL | 0.021 | 0.036 | 0.017 | 0.049 | 0.021 | 0.017 | 0.066 | 0.057 | 0.066 | 1.000 | 1.000 |
| AR | 0.021 | 0.036 | 0.017 | 0.017 | 0.021 | 0.017 | 0.044 | 0.102 | 0.066 | 1.000 | 1.000 |
| AZ | 0.035 | 0.035 | 0.021 | 0.062 | 0.039 | 0.016 | 0.064 | 1.000 | 1.000 | 1.000 | 1.000 |
| CA | 0.230 | 0.124 | 0.423 | 2.074 | 0.535 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| CO | 0.347 | 0.377 | 0.148 | 0.632 | 0.377 | 0.139 | 0.576 | 1.000 | 1.000 | 1.000 | 1.000 |
| CT | 1.426 | 0.442 | 0.518 | 1.016 | 1.384 | 0.386 | 0.537 | 0.537 | 0.537 | 1.000 | 1.000 |
| DE | 0.042 | 0.080 | 0.032 | 0.083 | 0.082 | 0.030 | 0.080 | 0.038 | 0.087 | 0.171 | 1.000 |
| FL | 0.020 | 0.144 | 0.053 | 0.053 | 0.123 | 0.053 | 0.255 | 0.280 | 0.255 | 1.000 | 1.000 |
| GA | 0.019 | 0.033 | 0.047 | 0.020 | 0.019 | 0.020 | 0.547 | 1.000 | 1.000 | 1.000 | 1.000 |
| HI | 0.128 | 0.043 | 0.045 | 0.156 | 0.053 | 0.459 | 0.283 | 0.372 | 1.000 | 1.000 | 1.000 |
| IA | 0.021 | 0.051 | 0.124 | 0.139 | 0.347 | 0.139 | 0.362 | 0.552 | 0.576 | 1.000 | 1.000 |
| ID | 0.037 | 0.037 | 0.018 | 0.053 | 0.037 | 0.018 | 0.051 | 0.028 | 0.066 | 1.000 | 1.000 |
| IL | 0.141 | 0.283 | 0.152 | 0.468 | 0.144 | 0.152 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| IN | 0.020 | 0.035 | 0.016 | 0.021 | 0.049 | 0.021 | 0.403 | 0.352 | 1.000 | 1.000 | 1.000 |
| KS | 0.021 | 0.051 | 0.139 | 0.148 | 0.377 | 0.139 | 0.550 | 0.592 | 0.833 | 1.000 | 1.000 |
| KY | 0.021 | 0.036 | 0.017 | 0.049 | 0.036 | 0.017 | 0.057 | 0.064 | 0.057 | 1.000 | 1.000 |
| LA | 0.021 | 0.036 | 0.039 | 0.415 | 0.097 | 0.139 | 0.415 | 0.362 | 0.415 | 1.000 | 1.000 |
| MA | 0.402 | 1.384 | 0.395 | 1.130 | 1.556 | 0.429 | 1.991 | 1.000 | 1.000 | 1.000 | 1.000 |
| MD | 0.507 | 0.479 | 0.298 | 0.853 | 1.044 | 0.395 | 0.987 | 0.598 | 1.000 | 1.000 | 1.000 |
| ME | 0.043 | 0.026 | 0.026 | 0.185 | 0.155 | 0.094 | 0.116 | 0.116 | 0.116 | 1.000 | 1.000 |
| MI | 0.036 | 0.062 | 0.038 | 0.038 | 0.062 | 0.020 | 0.533 | 0.535 | 1.000 | 1.000 | 1.000 |
| MN | 0.188 | 0.377 | 0.148 | 0.222 | 0.377 | 0.212 | 0.660 | 1.000 | 1.000 | 1.000 | 1.000 |
| MO | 0.020 | 0.049 | 0.021 | 0.135 | 0.051 | 0.120 | 0.403 | 0.350 | 0.403 | 1.000 | 1.000 |
| MS | 0.021 | 0.036 | 0.017 | 0.017 | 0.036 | 0.017 | 0.051 | 0.044 | 0.051 | 1.000 | 1.000 |
| MT | 0.025 | 0.025 | 0.013 | 0.050 | 0.040 | 0.017 | 0.105 | 0.046 | 0.108 | 0.097 | 0.089 |
| NC | 0.024 | 0.034 | 0.036 | 0.613 | 0.089 | 0.020 | 0.150 | 0.598 | 1.000 | 1.000 | 1.000 |
| ND | 0.025 | 0.025 | 0.035 | 0.086 | 0.082 | 0.035 | 0.085 | 0.100 | 0.100 | 0.165 | 1.000 |
| NE | 0.030 | 0.051 | 0.139 | 0.139 | 0.377 | 0.139 | 0.641 | 0.507 | 0.837 | 1.000 | 1.000 |
| NH | 0.063 | 0.181 | 0.054 | 0.227 | 0.258 | 0.178 | 0.277 | 0.150 | 0.150 | 1.000 | 1.000 |
| NJ | 0.273 | 0.940 | 0.268 | 0.291 | 0.870 | 0.291 | 1.072 | 1.077 | 1.000 | 1.000 | 1.000 |
| NM | 0.036 | 0.031 | 0.017 | 0.051 | 0.036 | 0.017 | 0.057 | 0.064 | 0.057 | 1.000 | 1.000 |
| NV | 0.377 | 0.139 | 0.139 | 0.415 | 0.417 | 0.167 | 0.362 | 0.171 | 0.405 | 1.000 | 1.000 |
| NY | 0.101 | 0.317 | 0.611 | 1.568 | 0.915 | 0.341 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| OH | 0.019 | 0.045 | 0.020 | 0.382 | 0.038 | 0.029 | 0.437 | 0.468 | 0.437 | 1.000 | 1.000 |
| OK | 0.021 | 0.051 | 0.022 | 0.139 | 0.030 | 0.022 | 0.415 | 0.383 | 1.000 | 1.000 | 1.000 |
| OR | 0.036 | 0.022 | 0.022 | 0.498 | 0.051 | 0.022 | 0.171 | 0.171 | 0.171 | 1.000 | 1.000 |
| PA | 0.068 | 0.211 | 0.104 | 0.936 | 0.283 | 0.195 | 1.027 | 1.000 | 1.000 | 1.000 | 1.000 |
| RI | 0.095 | 0.043 | 0.043 | 0.196 | 0.168 | 0.076 | 0.111 | 0.157 | 1.000 | 1.000 | 1.000 |
| SC | 0.021 | 0.036 | 0.017 | 0.017 | 0.021 | 0.017 | 0.051 | 0.066 | 0.066 | 1.000 | 1.000 |
| SD | 0.014 | 0.035 | 0.029 | 0.076 | 0.078 | 0.030 | 0.090 | 0.049 | 0.090 | 0.113 | 0.224 |
| TN | 0.020 | 0.035 | 0.021 | 0.062 | 0.049 | 0.021 | 0.350 | 0.352 | 1.000 | 1.000 | 1.000 |
| TX | 0.013 | 0.031 | 0.024 | 0.085 | 0.175 | 0.085 | 0.407 | 1.000 | 1.000 | 1.000 | 1.000 |
| UT | 0.021 | 0.036 | 0.017 | 0.051 | 0.036 | 0.017 | 0.048 | 0.027 | 0.113 | 1.000 | 1.000 |
| VA | 0.135 | 0.493 | 0.150 | 0.213 | 0.504 | 0.213 | 1.072 | 1.077 | 1.072 | 1.000 | 1.000 |
| VT | 0.040 | 0.071 | 0.032 | 0.086 | 0.086 | 0.033 | 0.057 | 0.054 | 0.102 | 1.000 | 1.000 |
| WA | 0.337 | 0.135 | 0.215 | 0.572 | 0.367 | 0.456 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| WI | 0.037 | 0.029 | 0.102 | 0.304 | 0.276 | 0.102 | 0.125 | 0.191 | 0.200 | 1.000 | 1.000 |
| WV | 0.036 | 0.036 | 0.017 | 0.051 | 0.036 | 0.017 | 0.021 | 0.027 | 0.027 | 0.062 | 0.310 |
| WY | 0.031 | 0.082 | 0.034 | 0.108 | 0.045 | 0.034 | 0.112 | 0.097 | 0.112 | 0.131 | 0.199 |

# Emissions outcomes overview

| Pollutant | Concern | Highway vehicle % of 2015 U.S. emissions | LDV change from MY2005–2015 |
|---|---|---|---|
| **CO** | Displaces oxygen in the blood and deprives vital organs of oxygen | **30%** | **–30%** |
| **NOx** | Irritant gas that can cause inflammation of the airways; precursor to smog and acid rain | **34%** | **–40%** |
| **VOC** | Eye, nose and throat irritation, and potential nervous system damage | **11%** | **–20%** |
| PM10 | Particles evade respiratory defenses and lodge deep in the lungs | 1% | 0% |
| PM2.5 | Haze; particles evade respiratory defenses and lodge deep in the lungs | 2% | 0% |
| SO2 | Severe (potentially life-threatening) irritation of the nose and throat; particulate precursor | 1% | –50% |
| **GHG** | Climate change | **27%** | **–10% to –25%** |

*Sources: highway emissions from http://cta.ornl.gov/data/tedb36/Edition_36_Full_Doc.pdf; MY2005–2015 comparison from https://greet.es.anl.gov/publication-vehicles-13*

# Diagnostics: residual-vs.-fitted plots




*Note: plots shown using log(vehicle registrations per capita) as dependent variable.*

# Diagnostics: sensitivity to false detection rate (FDR)

- Estimated effects testing 5 hypotheses are robust to FDRs as low as 2–3% (population-weighted models) and 4–7% (average effect models).
- Also shown (at right) is sensitivity for testing 11 hypotheses (for 6 other pollutant series tested)

**Benjamini–Hochberg correction for testing multiple hypotheses**

*Average effect sensitivity to acceptable FDR and testing 5 hypotheses:*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Veh.Reg. | | | | | | | | | | | | | | | |
| Gas. Use | | | | | | | | | | | | | | | |
| VMT | | | | | | | | | | | | | | | |
| NOx | | | | | | | | | | | | | | | |
| VOC | | | | | | | | | | | | | | | |

*Average effect sensitivity to acceptable FDR and testing 11 hypotheses:*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Veh.Reg. | | | | | | | | | | | | | | | |
| Gas. Use | | | | | | | | | | | | | | | |
| VMT | | | | | | | | | | | | | | | |
| NOx | | | | | | | | | | | | | | | |
| VOC | | | | | | | | | | | | | | | |

*Pop.-wtd. effect sensitivity to acceptable FDR and testing 5 hypotheses:*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Veh.Reg. | | | | | | | | | | | | | | | |
| Gas. Use | | | | | | | | | | | | | | | |
| VMT | | | | | | | | | | | | | | | |
| NOx | | | | | | | | | | | | | | | |
| VOC | | | | | | | | | | | | | | | |

*Pop.-wtd. effect sensitivity to acceptable FDR and testing 11 hypotheses:*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Veh.Reg. | | | | | | | | | | | | | | | |
| Gas. Use | | | | | | | | | | | | | | | |
| VMT | | | | | | | | | | | | | | | |
| NOx | | | | | | | | | | | | | | | |
| VOC | | | | | | | | | | | | | | | |

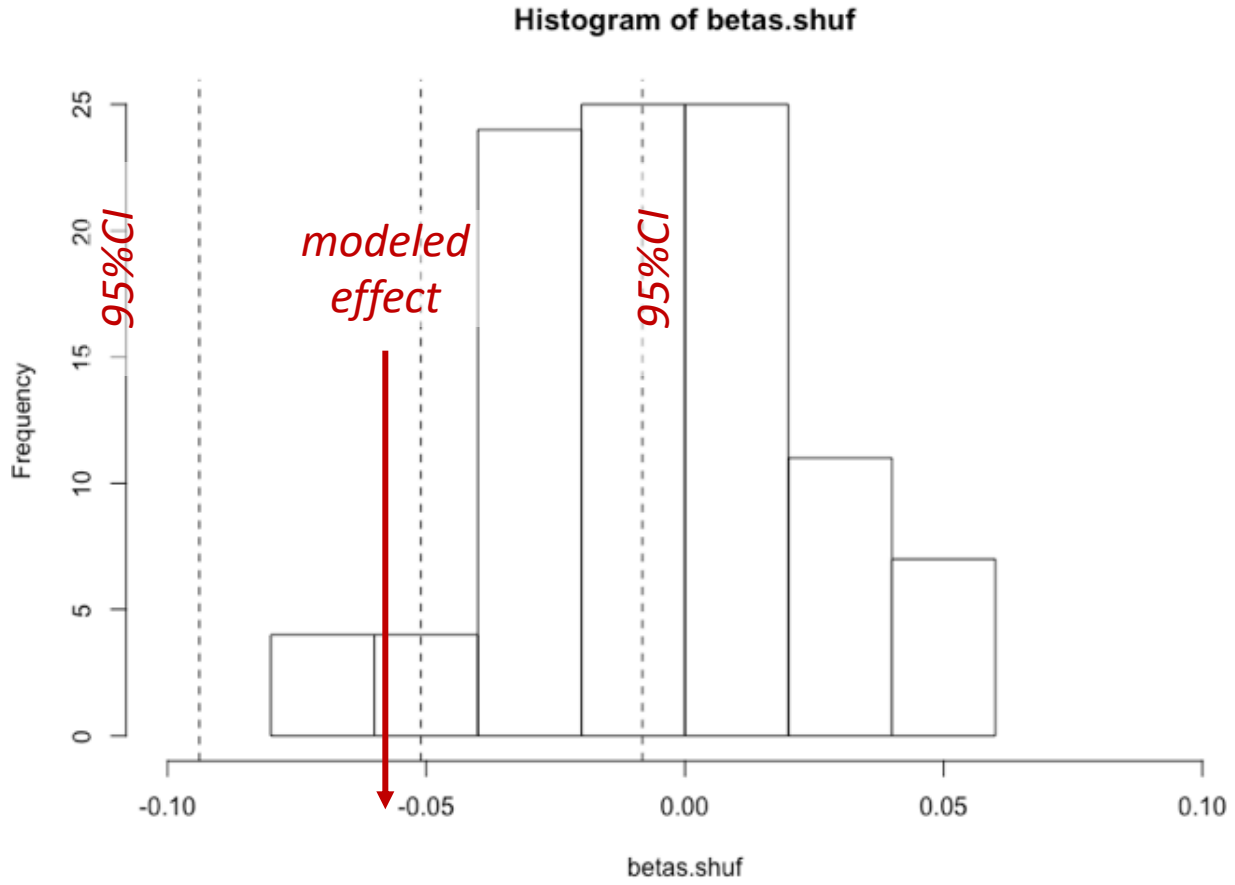
Possible Type I error (null hypothesis incorrectly rejected)

Estimate is significant: null hypothesis correctly rejected

No correction applied, since not significant even without correction

# Robustness check: randomized treatment bootstrapping

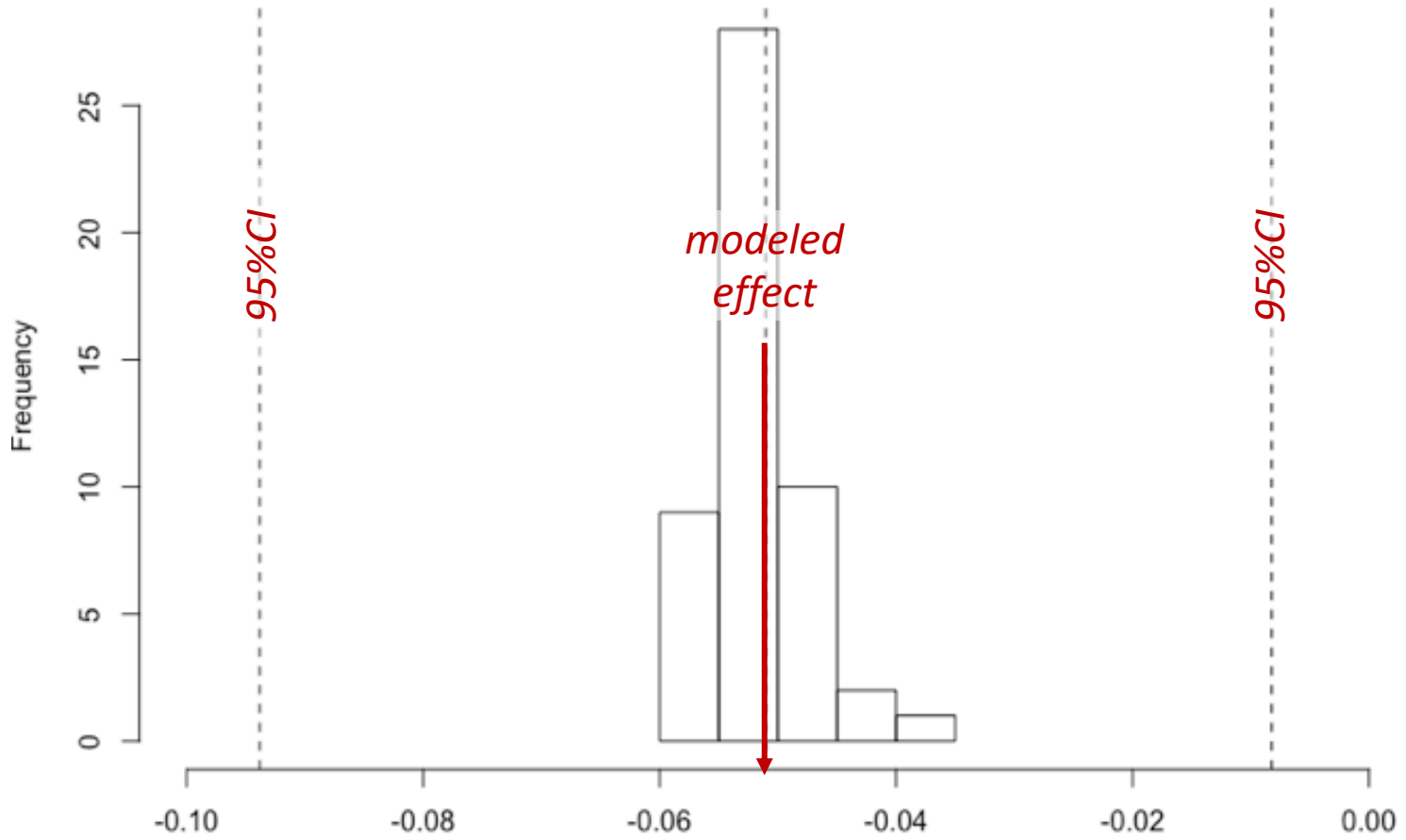
*Our regression model-estimated effect (in red) compared to results applying that model to randomized treatment (histogram distribution):*




Estimated change in vehicle registrations per cap after Uber entry

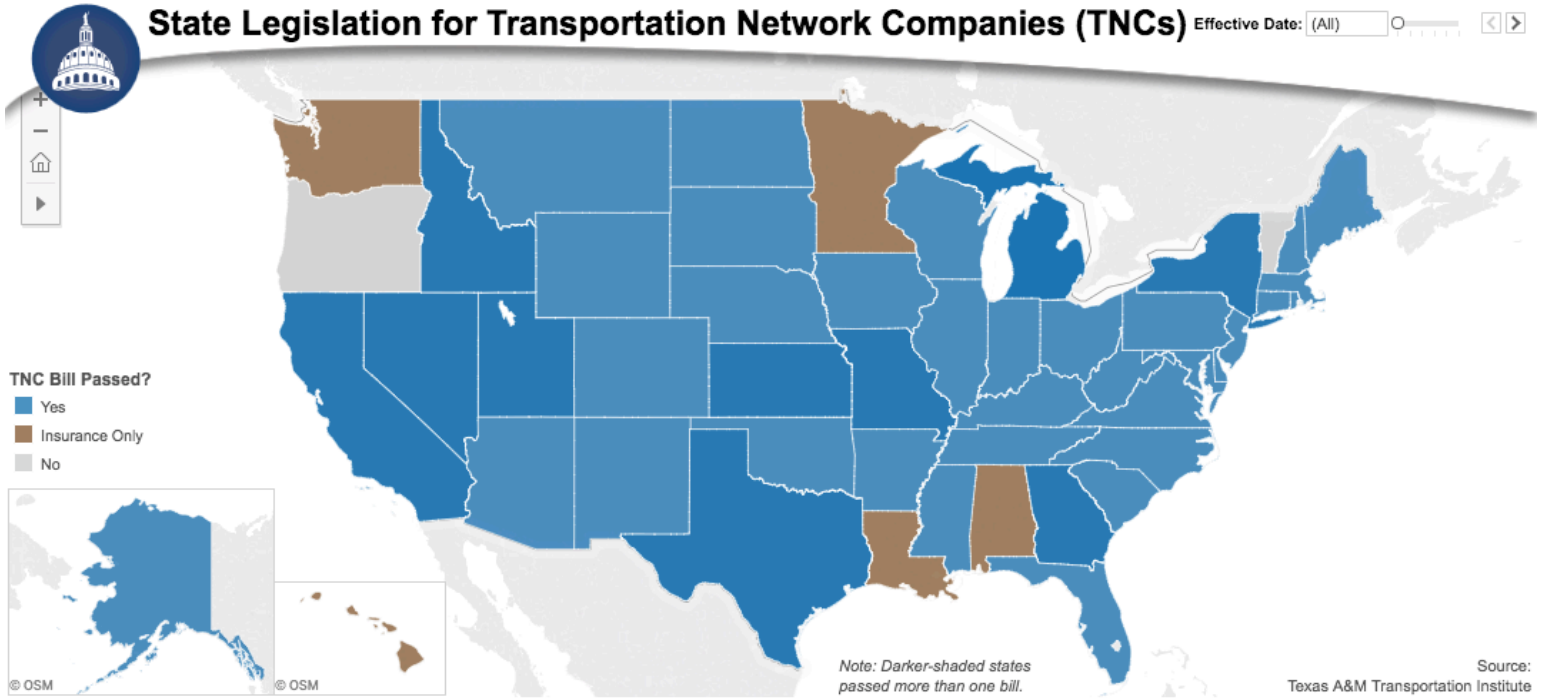
# Robustness check: leave-one-out analysis

*Our regression model-estimated effect (in red) compared to results leaving one state out at a time (histogram distribution):*



# Context: State TNC Policies

- **State suspensions—cease and desist orders previously issued in (at least) 4 states:** California (2010), Virginia, (2014), Pennsylvania (2014), South Carolina (2014),
- **As of 2017, 43 states regulated TNCs:**




*Source: Goodin, G. and Moran, M. (2017). Testimony to the Texas Senate Committee on Business and Commerce. https://policy.tti.tamu.edu/wp-content/uploads/2017/03/TTI-PRC-TNCs-SBC-031417.pdf.*