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

More trips and "empty miles" could drive up VMT, energy use and emissions. Car purchases enabled by TNCs

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

The net effect is unknown.

Figure source: Henao (2017)

Peer-reviewed literature

- **Rayle, Dai, Chan, Cervero, and Shaheen (2016)**
  - *Survey*: 1/3 of SF TNC users report they would have used bus or rail otherwise; probably no influence on car ownership
- **Hall, Palsson and Price (2018)**
  - *DiD*: Transit ridership increases after Uber entry, particularly in big cities. Reduces transit commute time, increases road congestion

Grey literature

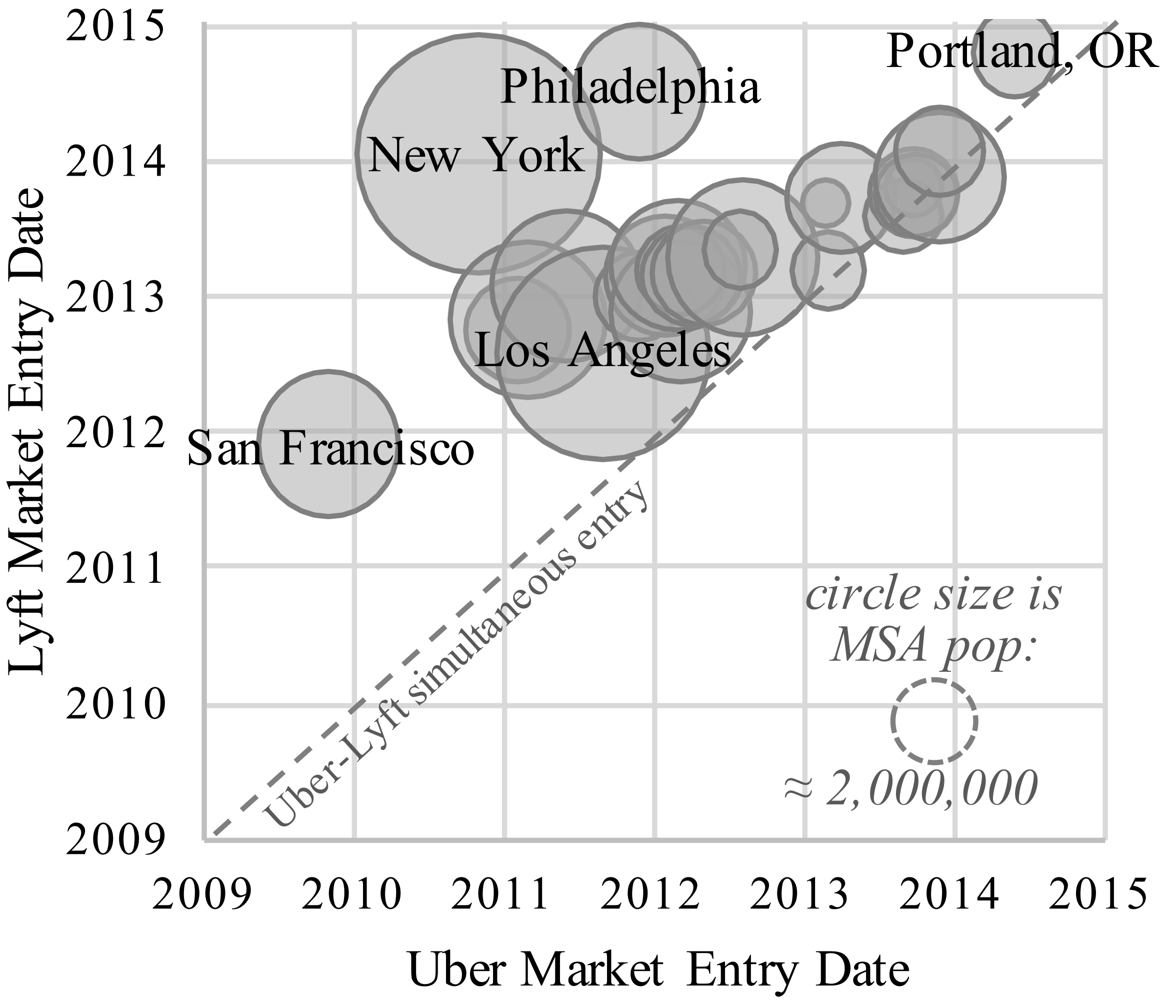
Vehicle ownership

- TNCs reduce ownership?
  - **Hampshire et al. (2017)** *survey*: former Uber users in Austin report 9% increase in ownership
  - **Clewlow and Mishra (2018)** *survey*: 9% of TNC users surveyed in 7 US metro areas report disposing of one or more vehicles
- TNCs increase ownership?
  - **Gong et al.** *DiD*: model suggests 8% increase in Chinese new vehicle registrations associated with Uber entry

Travel

- **Li et al. (2016)** *DiD*: 1.2% drop in congestion
- **Clewlow and Mishra (2018)** *survey*: 49%-61% of ridehailing trips associated with increased VMT
- **Hampshire et al. (2017)** *survey*: 23% reduction in trip likelihood after Uber left Austin
- **Henao (2017)** *survey*:
  - Less than 60% of TNC miles moving passengers
  - 85% of TNC trips in Denver shifted from modes other than personal vehicle
  - But Hall et al. (2018): Uber a complement to transit

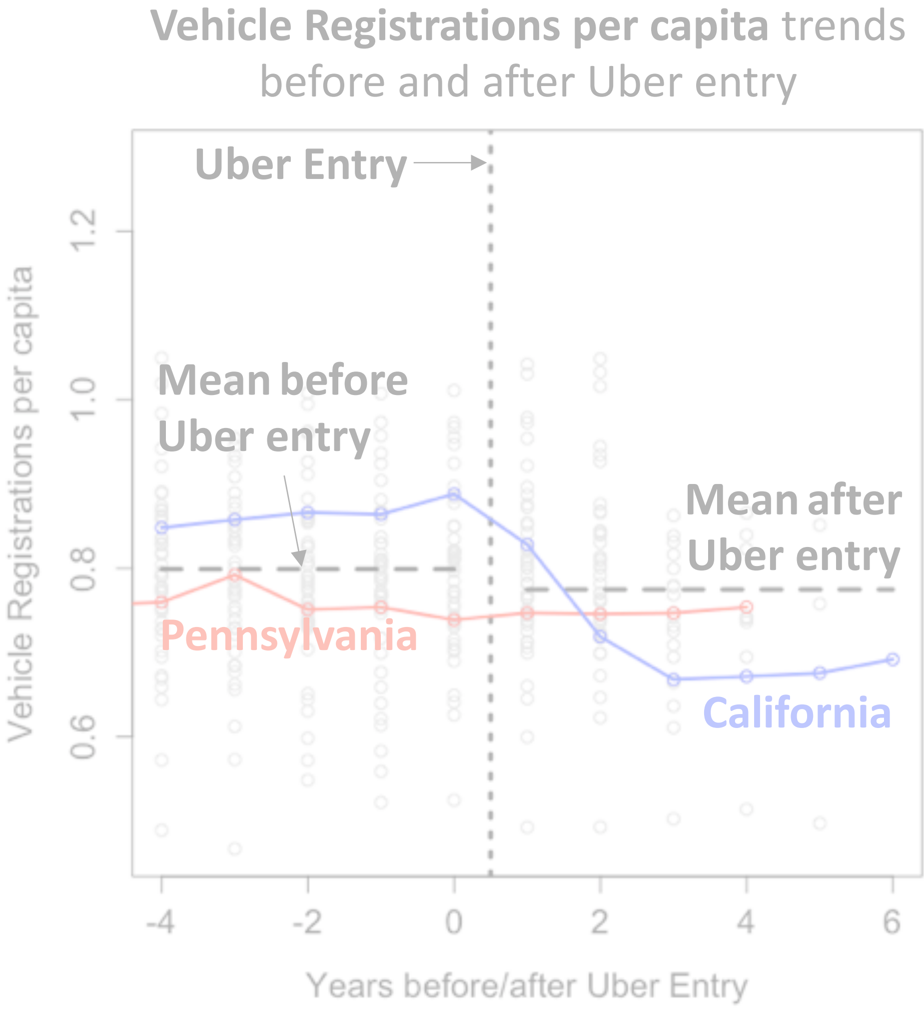
Uber & Lyft entered different cities at different times



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

- 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.

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

γ_g: fixed effect for **location** g

δ_t: fixed effect for year t

ε_{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)* • Electric vehicle registrations *(IHS/Polk)* • 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 andκ_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)*

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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?

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

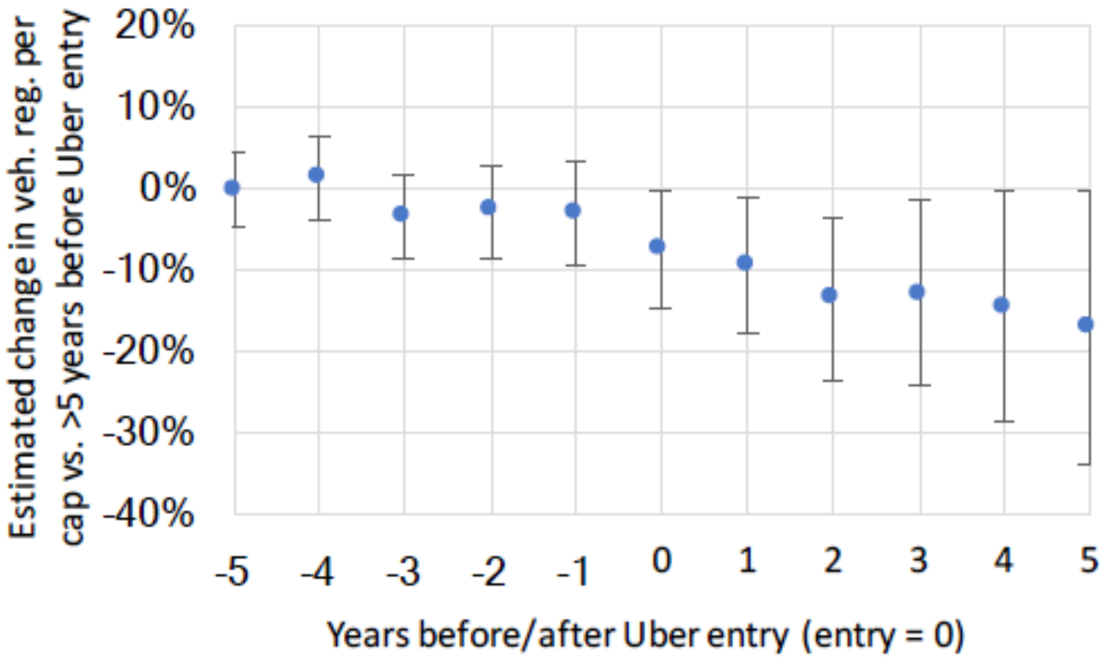
Potential concerns

- **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

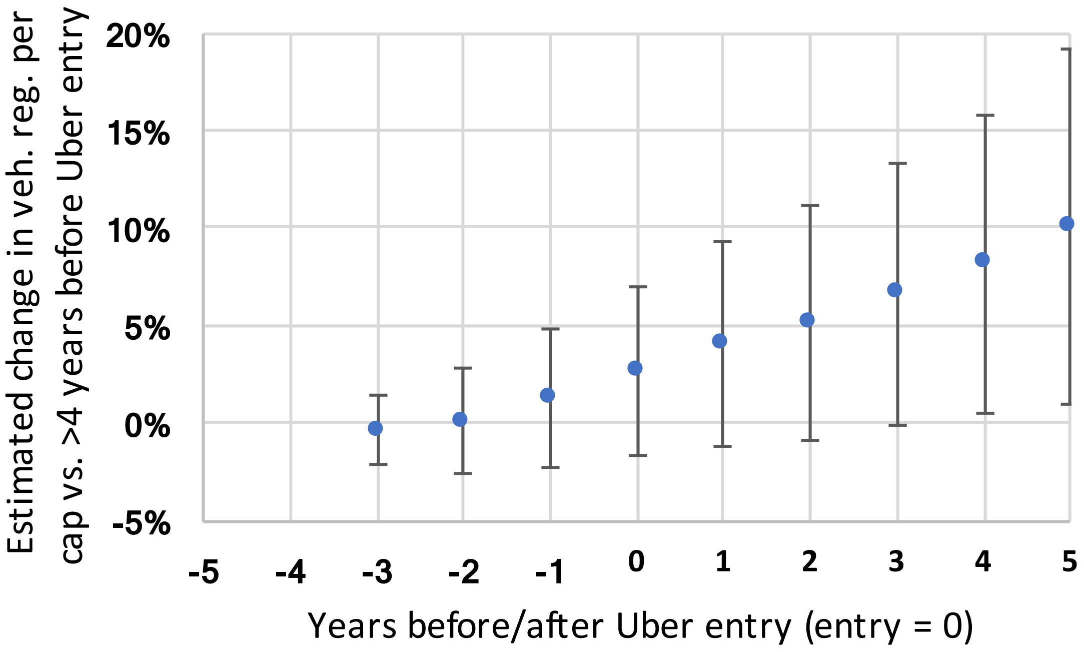
Event study identifies similar effects (without assuming parallel trends)

- 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



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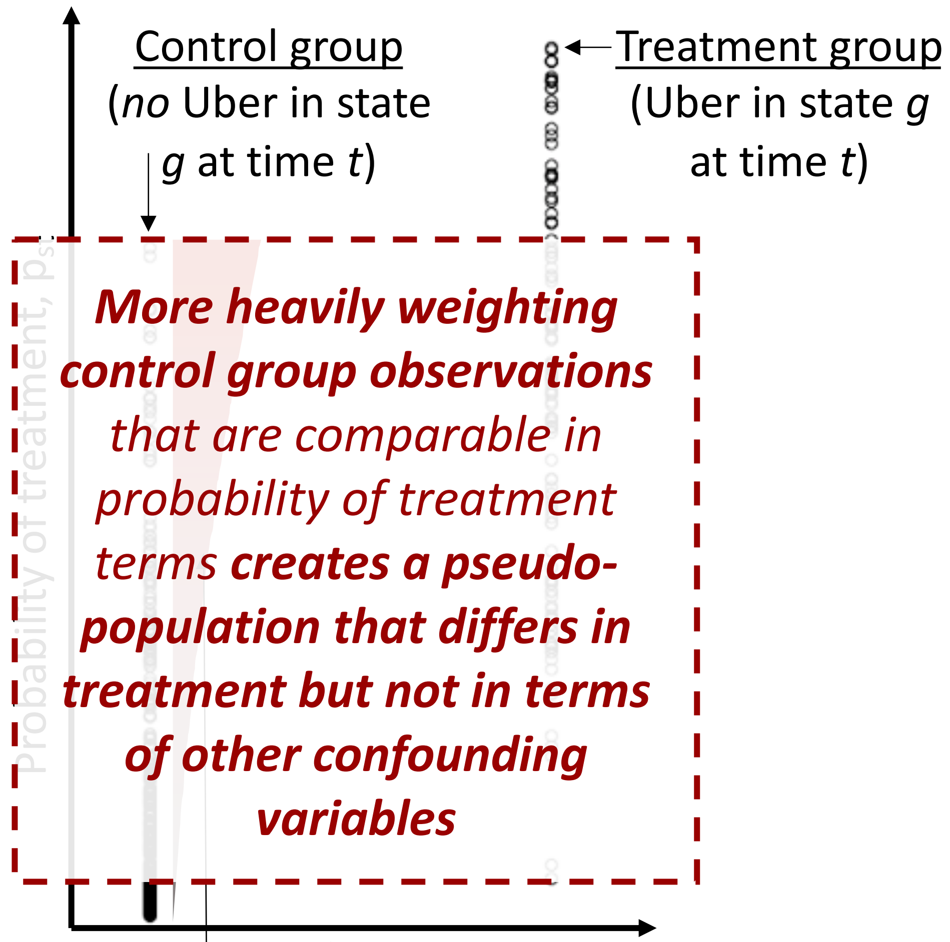
Inverse probability of treatment weighting (IPTW)

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

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

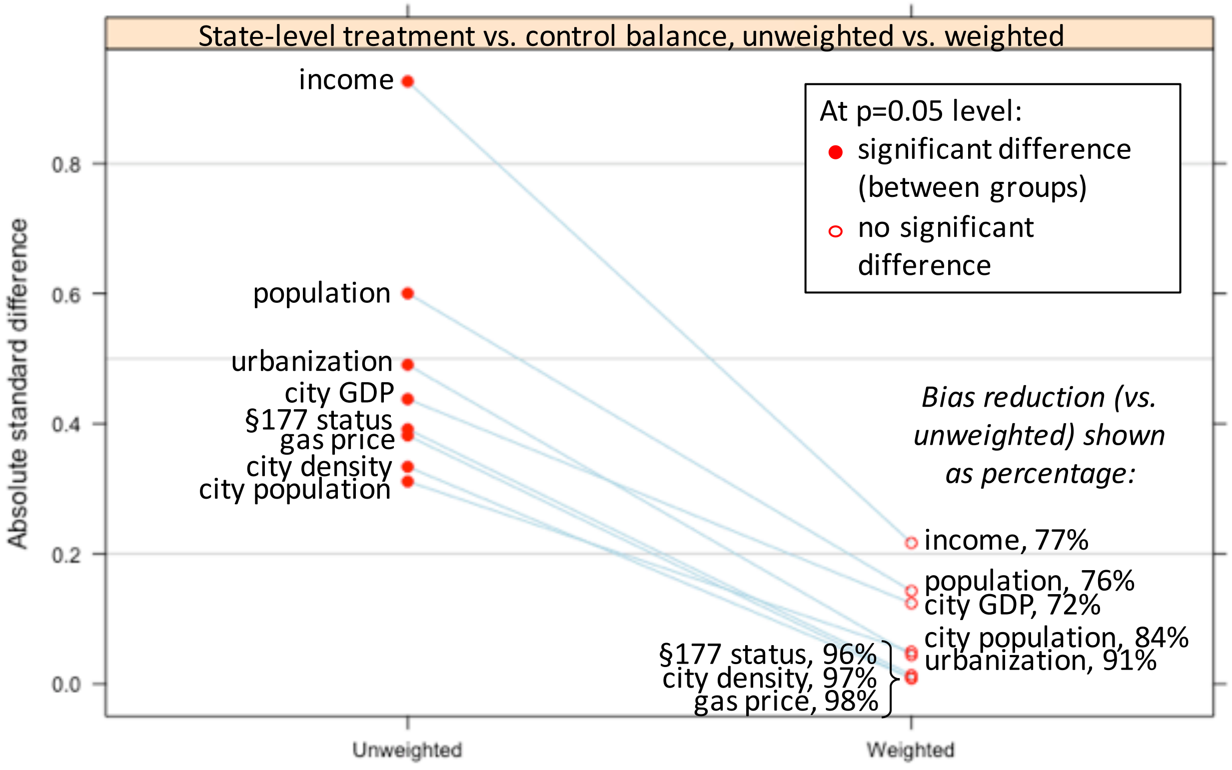
- p_{gt} is the probability of treatment for state or UA g and year t (state estimates **shown at right**)
- $\mathbf{z}_{gt}$: controls (same as primary state and UA regressions) with additive function f_m;
- ϵ_{gt}: unobserved error

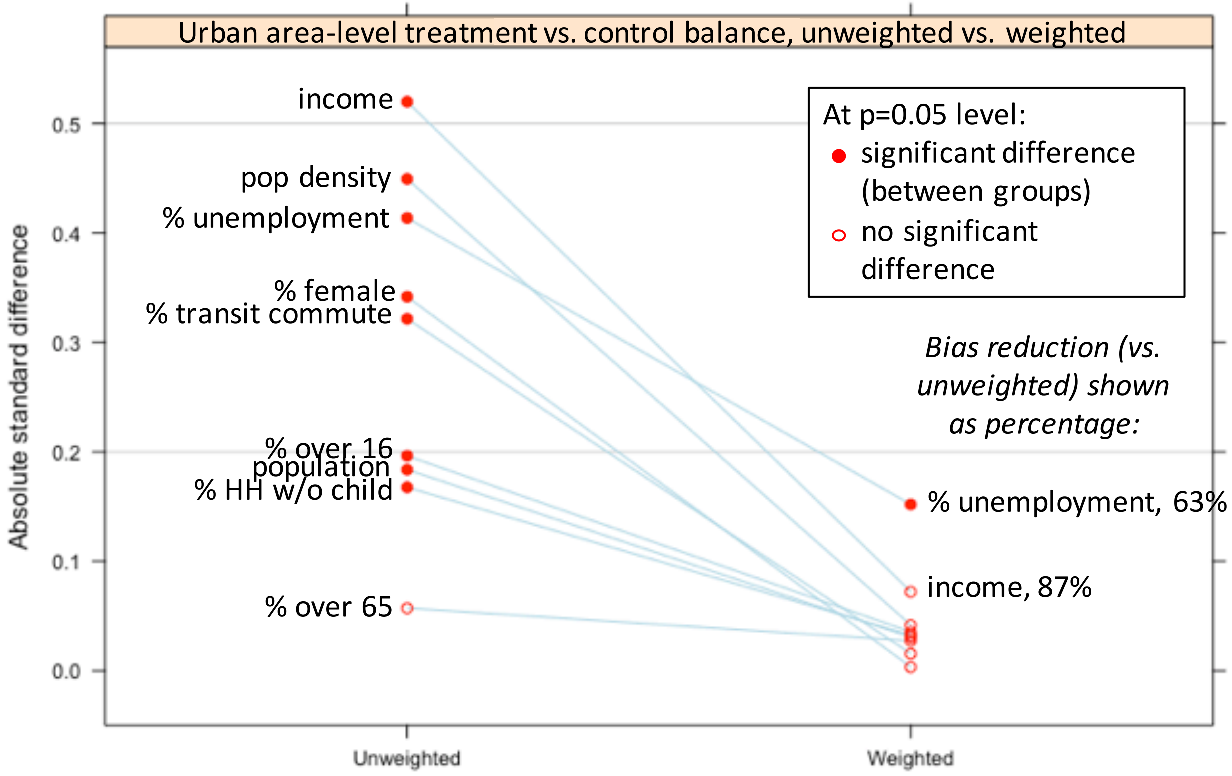


$$weight_{ctrl} = \frac{p_{st}}{1-p_{st}}$$

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?

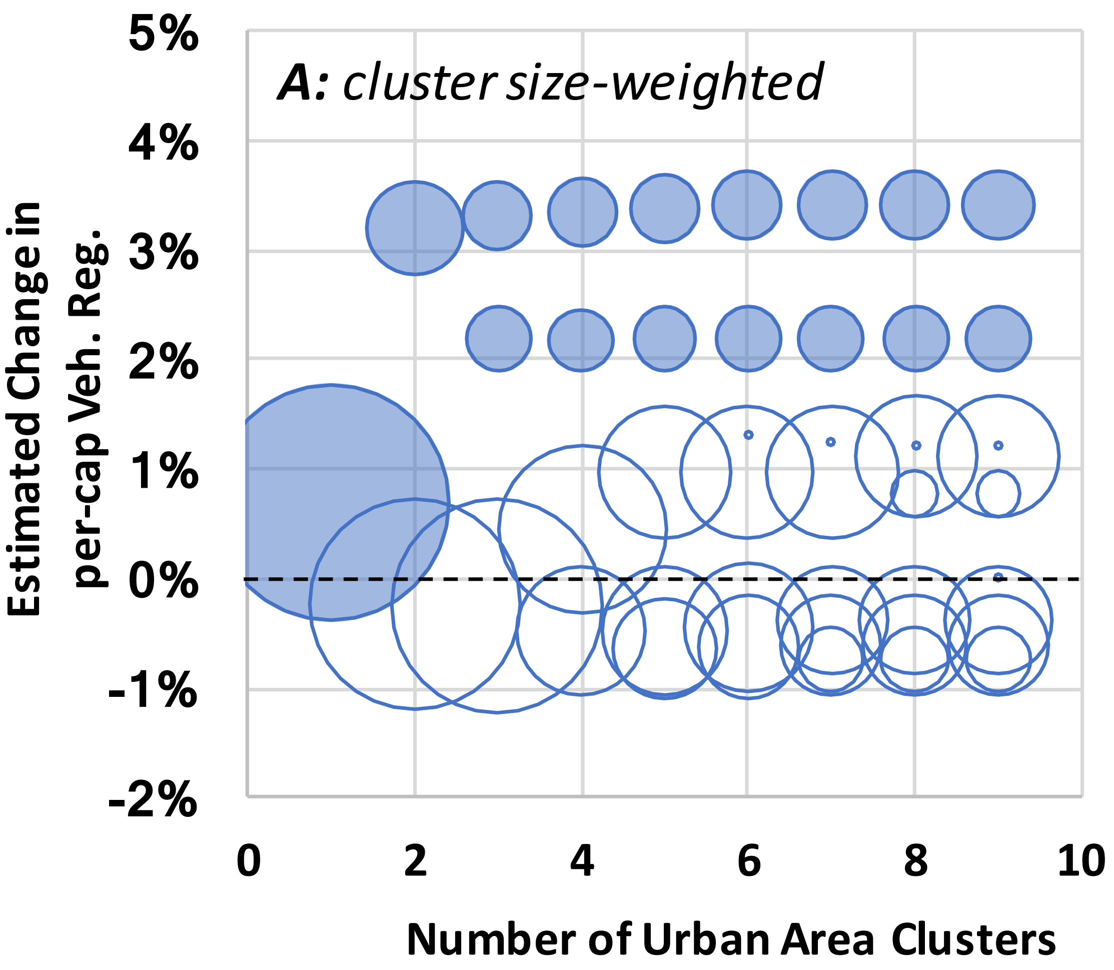
UA results consistent w/ state results when aggregated

- We aggregate urban area data by state and re-estimate 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 latent 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

Acknowledgements

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- Ward also at U.S. Department of Energy Vehicle Technologies Office

- Thanks to: Kenneth Gillingham, Albert Presto, Kate Whitefoot

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

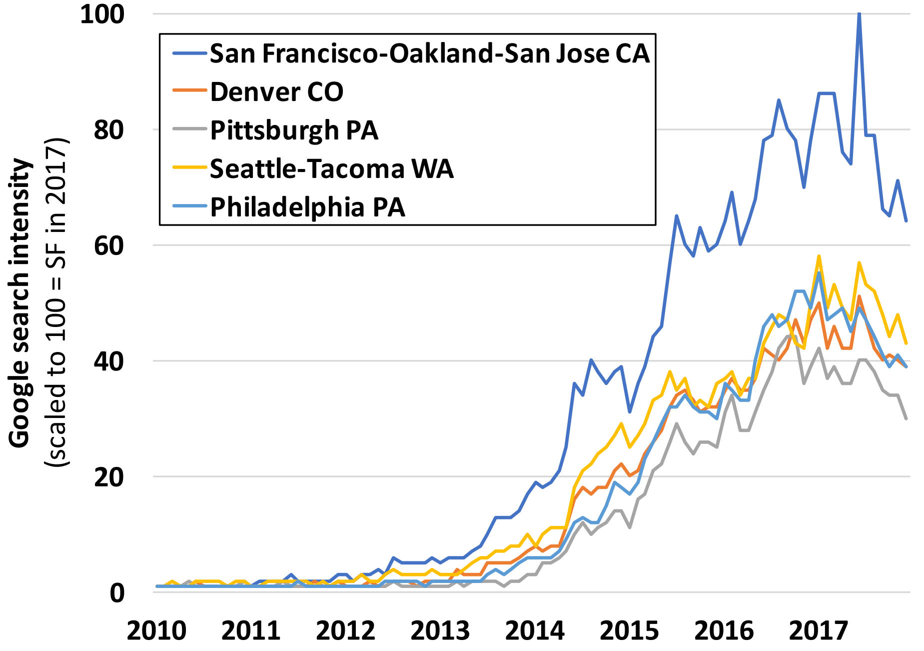
Urban-area-level analysis

	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

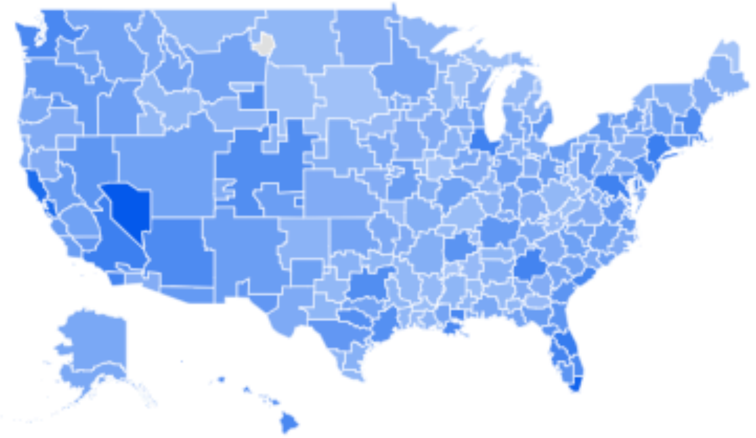
Google Trend Data

- 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:

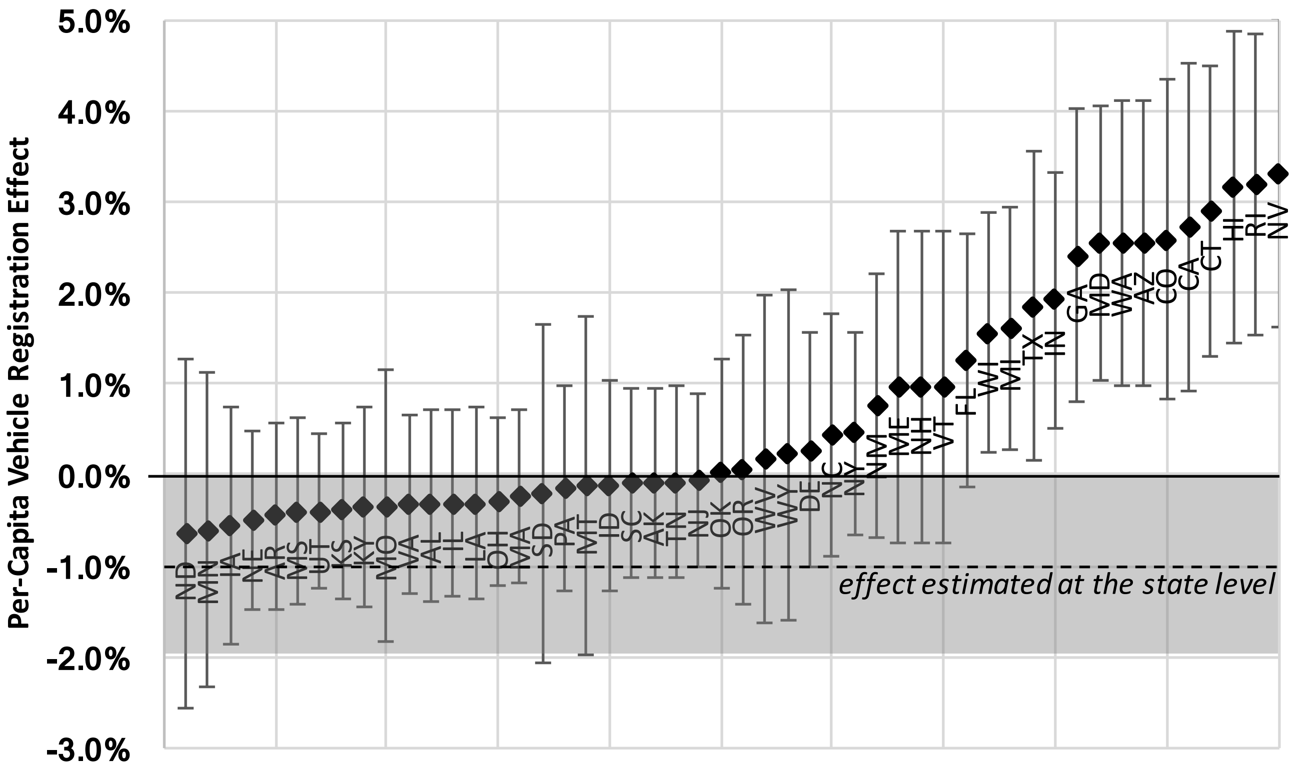


Google trend “metro areas”:



UA cluster analysis effects and state implications

- **Population-weighting UA effects within each state yields a 0.7% grand mean** (with “state effects” from –0.6% to 3.3%)
  - Roughly half the “state” estimates fall within the 95% confidence interval (–0.01% to 1.98%) of the average effect estimated at the state level



Number of Uber drivers has grown exponentially in most markets

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

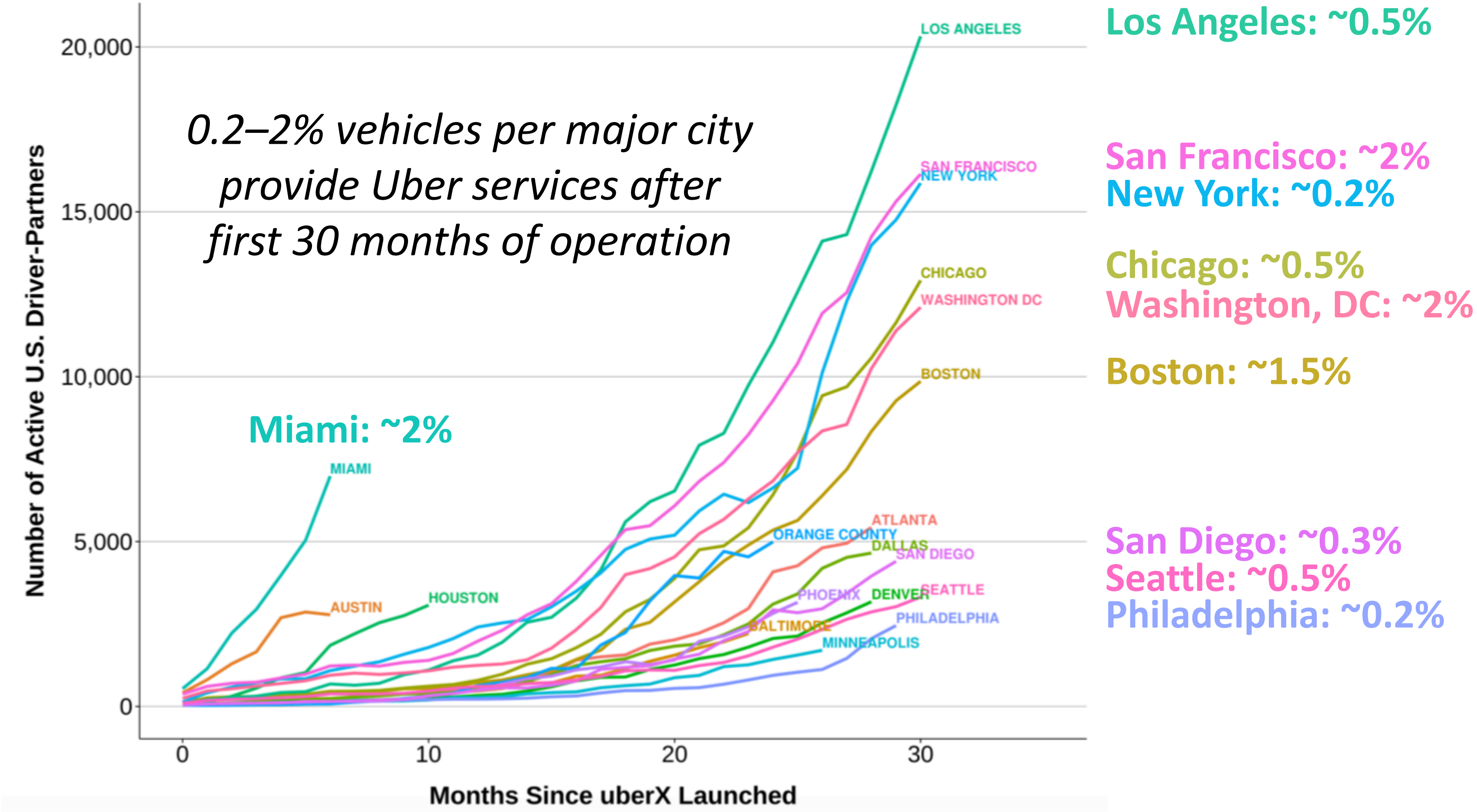
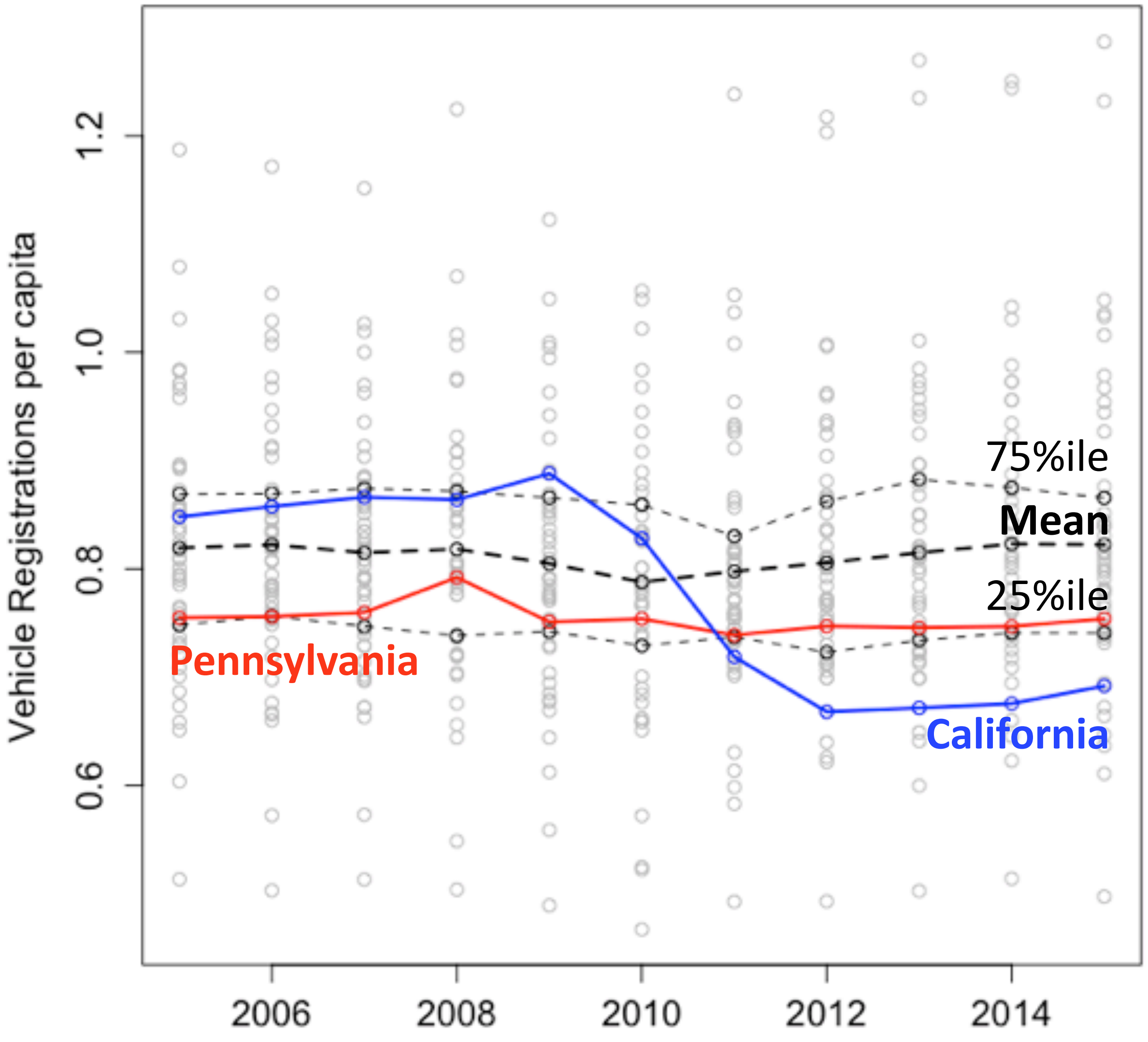


***Figure**: Hall, J. V. and Krueger, A. B. (2015). "An Analysis of the Labor Market for Uber's Driver-Partners in the United States". Princeton Working Paper #587; [1]Caron, B. (2015). "Why there's a good chance your Uber Driver is New". Business Insider. 24 Oct. http://www.businessinsider.com/uber-doubles-its-drivers-in-2015-2015-10*

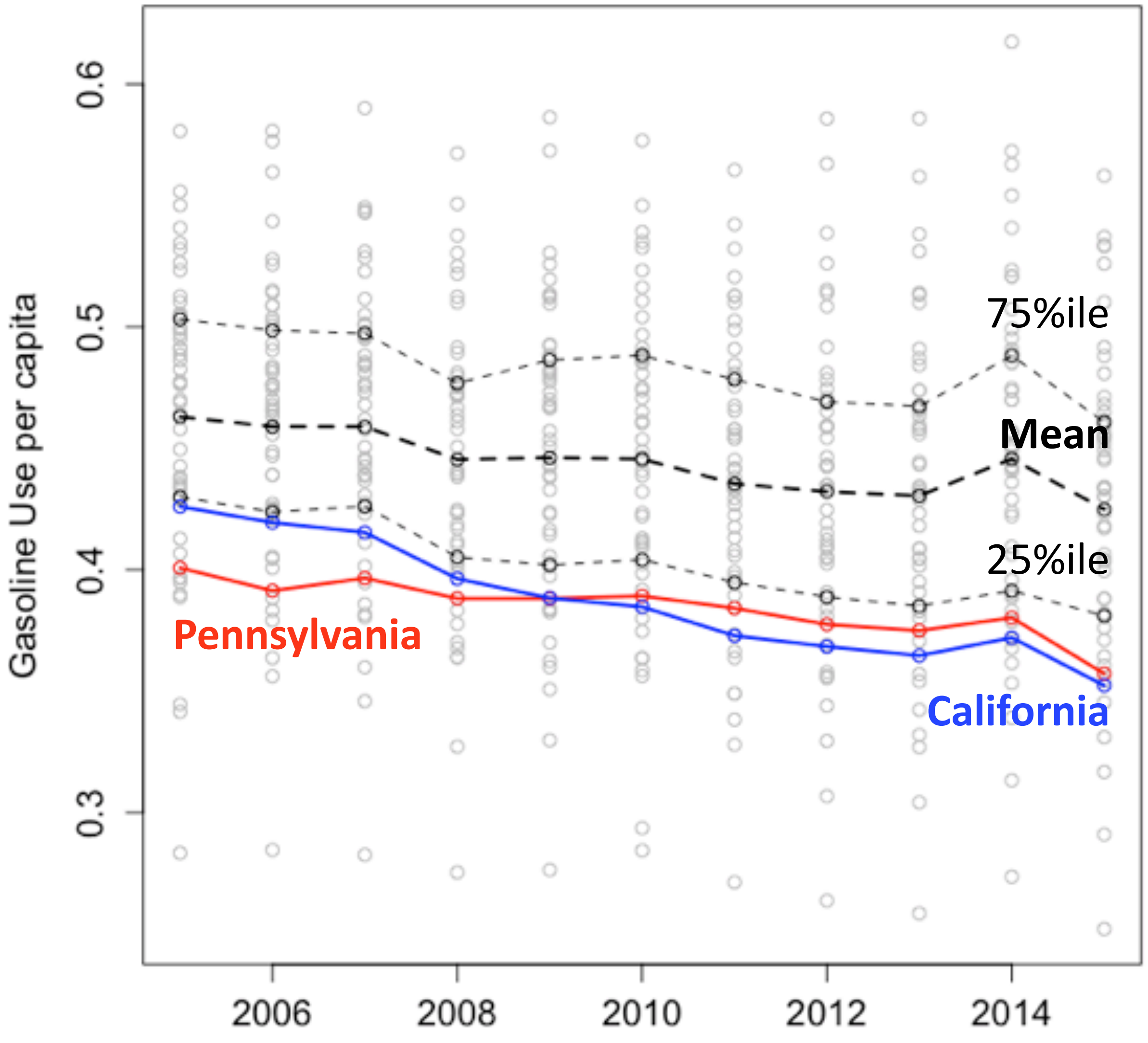
Data detail: Vehicle Registrations



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

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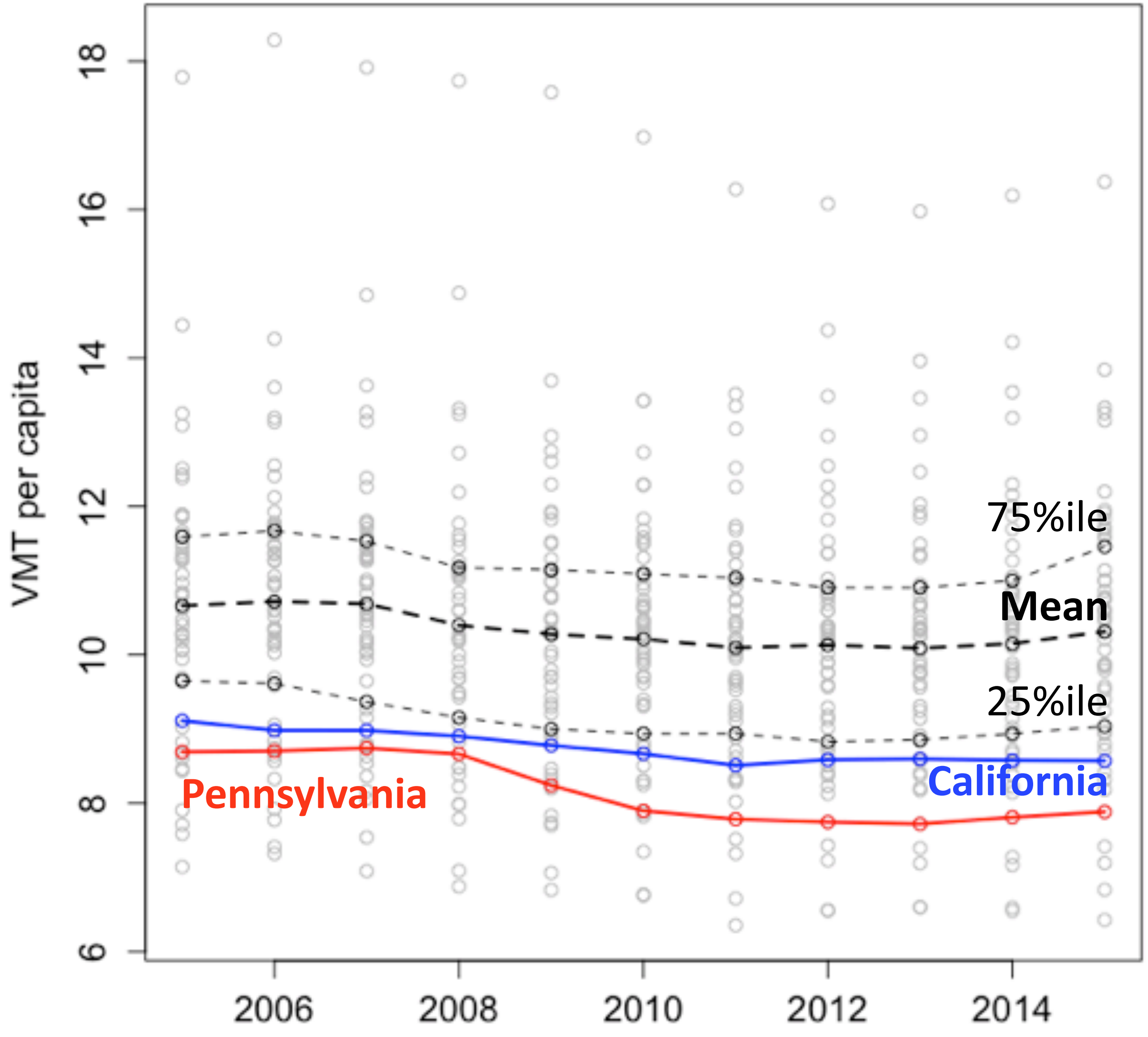
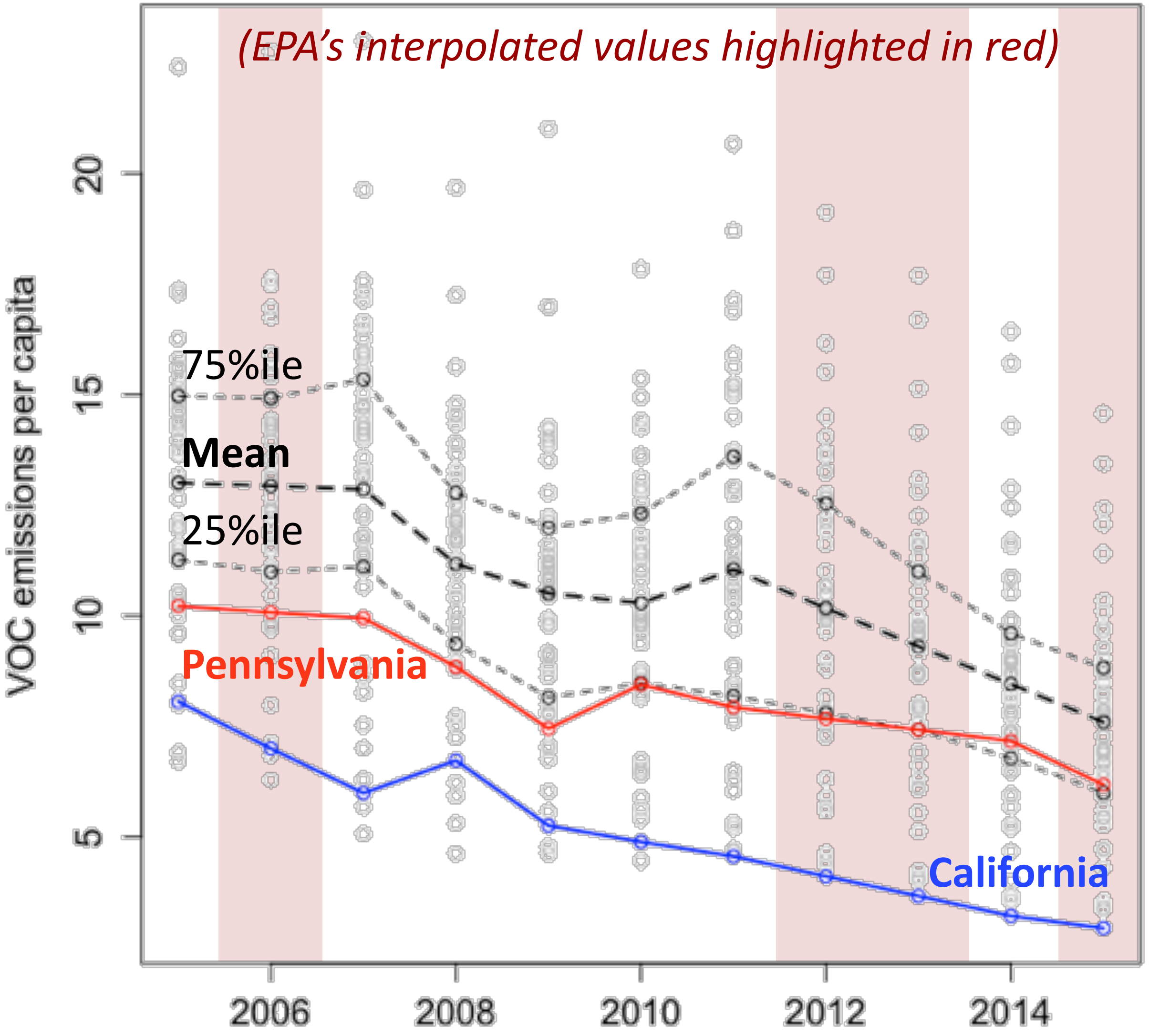
Data detail: VMT



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

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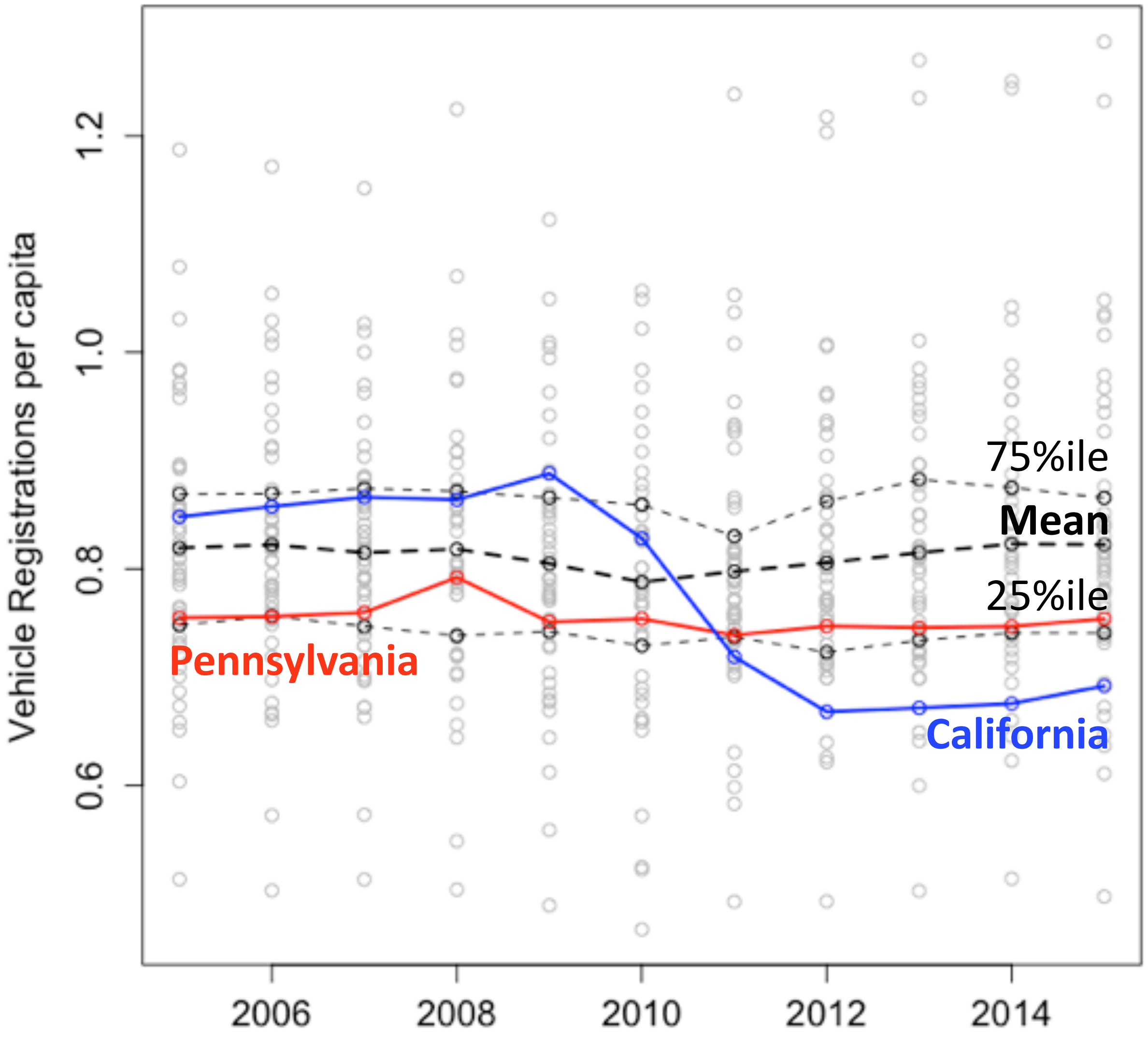
Data detail: GHG Emissions



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

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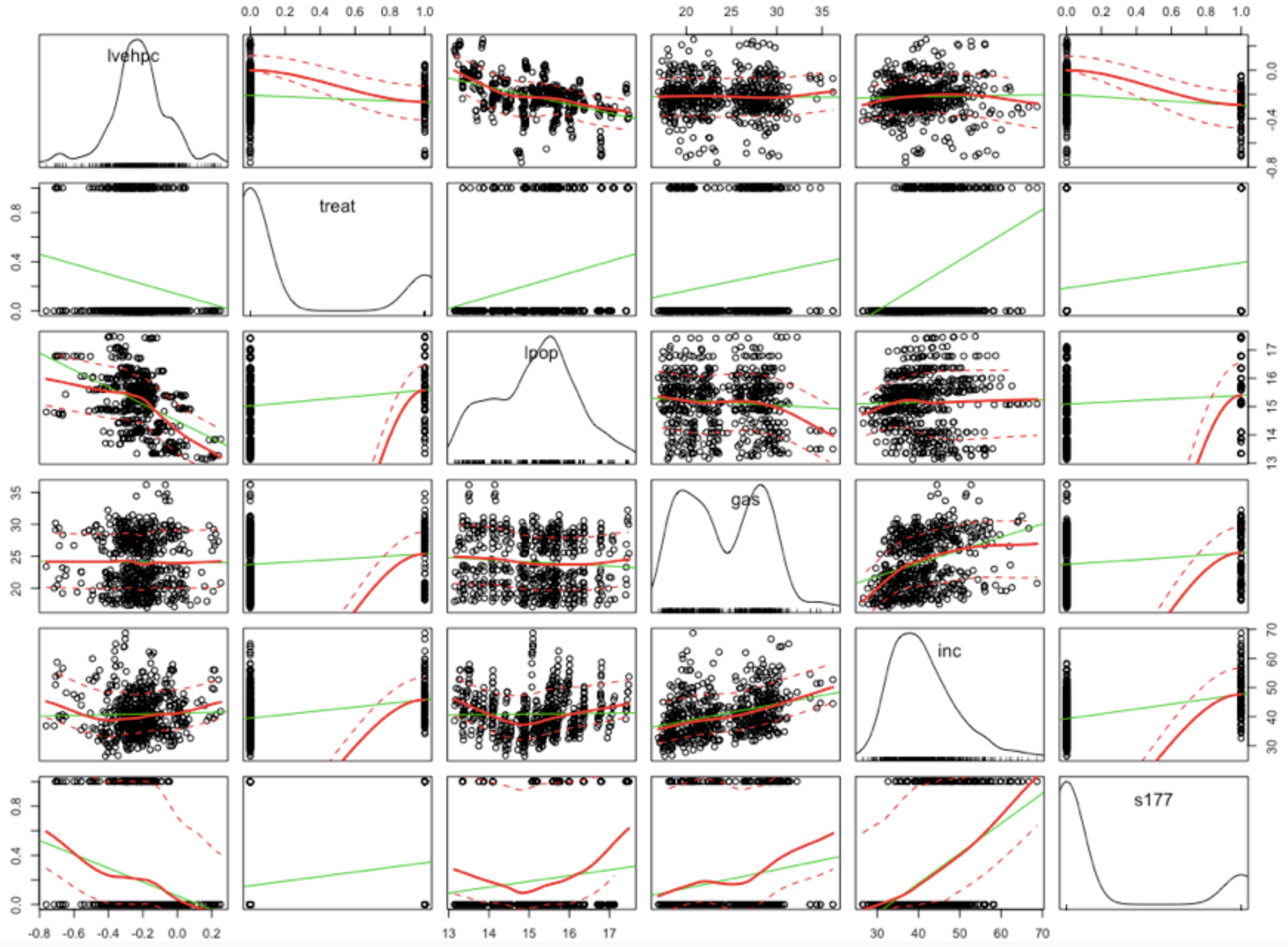
Data detail: multicollinearity



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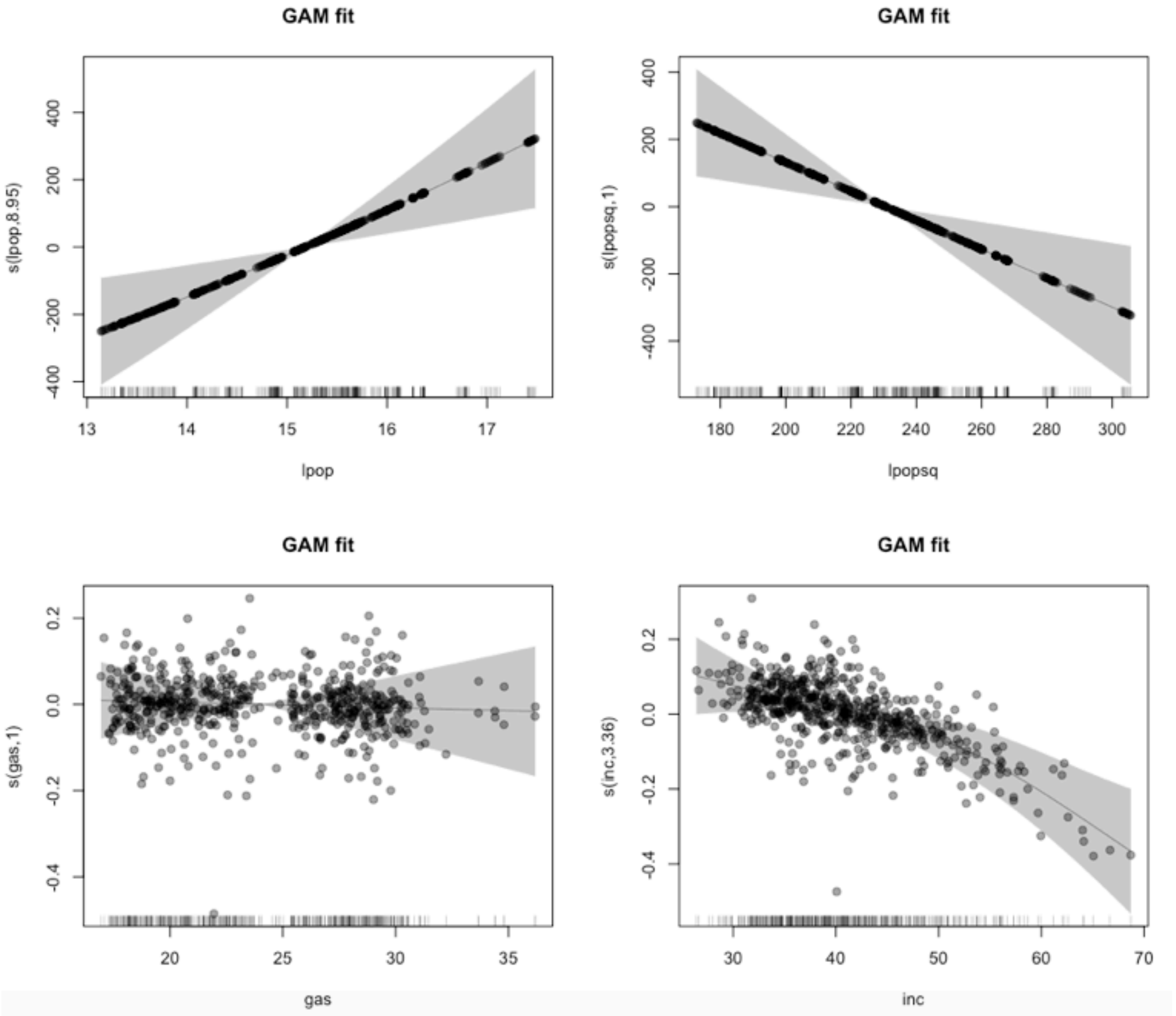
Our regression model is informed by models in relevant prior literature

		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



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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.

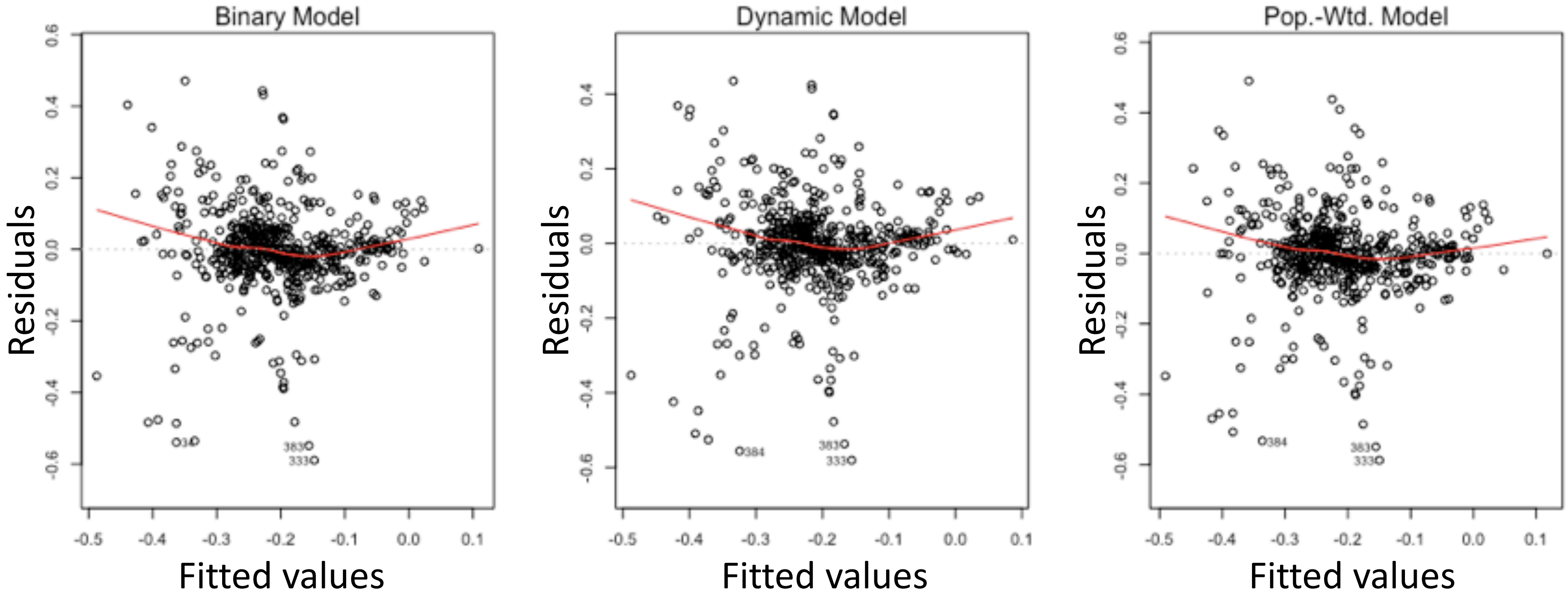
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
AK	0.078	0.030	0.035	0.085	0.113	0.140	0.085	0.085	0.085	0.085	0.188
AL	0.021	0.036	0.017	0.049	0.021	0.017	0.066	0.057	0.066	1.000	1.000
AR	0.021	0.036	0.017	0.017	0.021	0.017	0.044	0.102	0.066	1.000	1.000
AZ	0.035	0.035	0.021	0.062	0.039	0.016	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

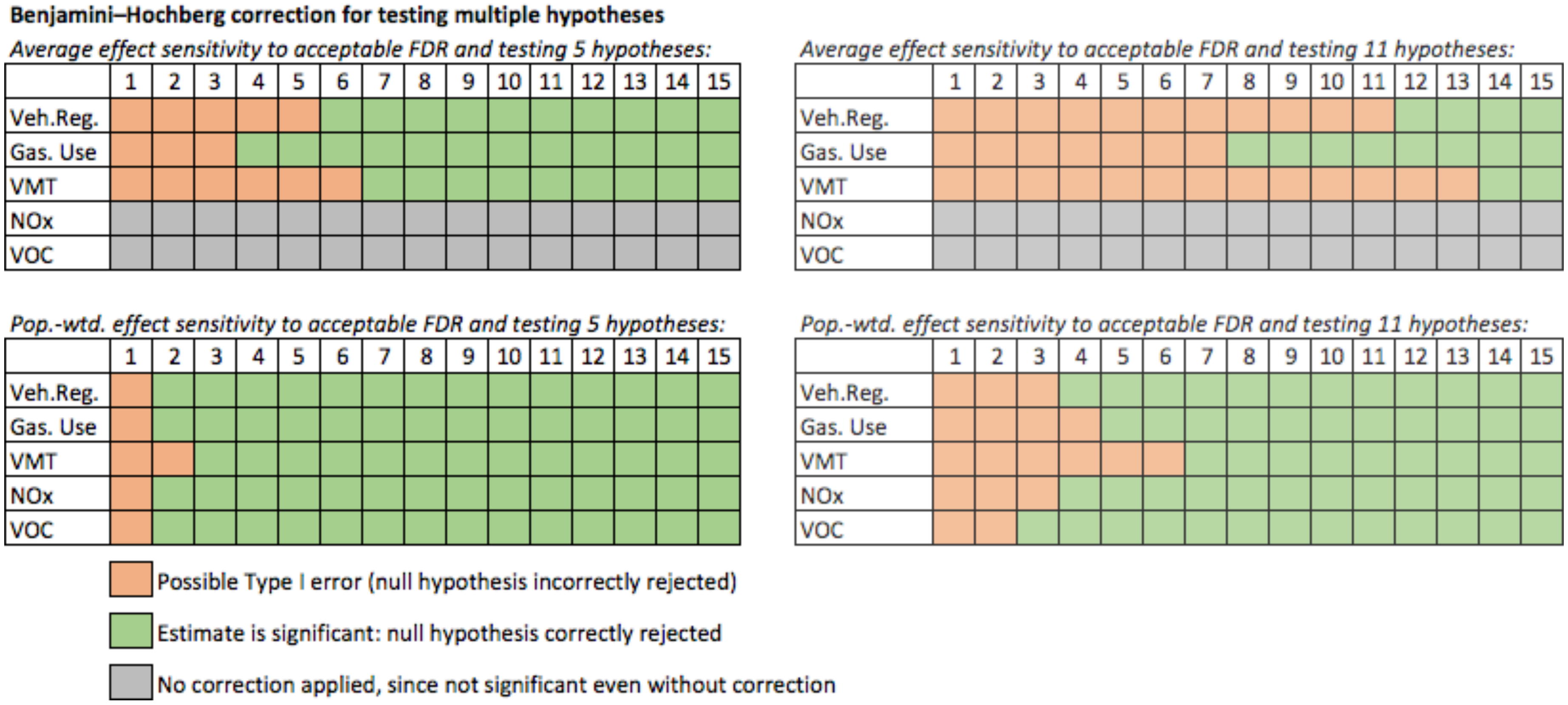
Diagnostics: residual-vs.-fitted plots



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)



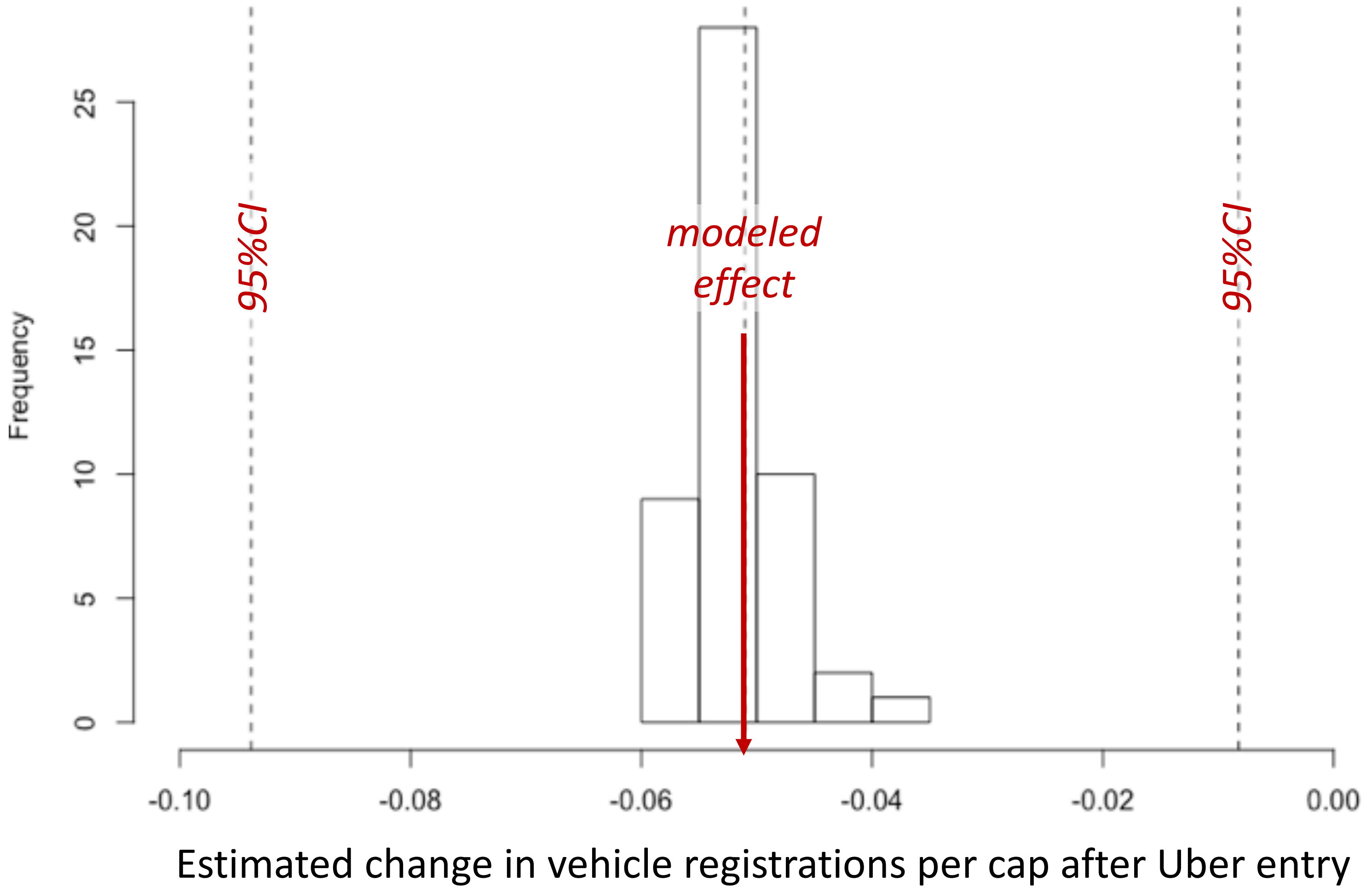
Robustness check: randomized treatment bootstrapping

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

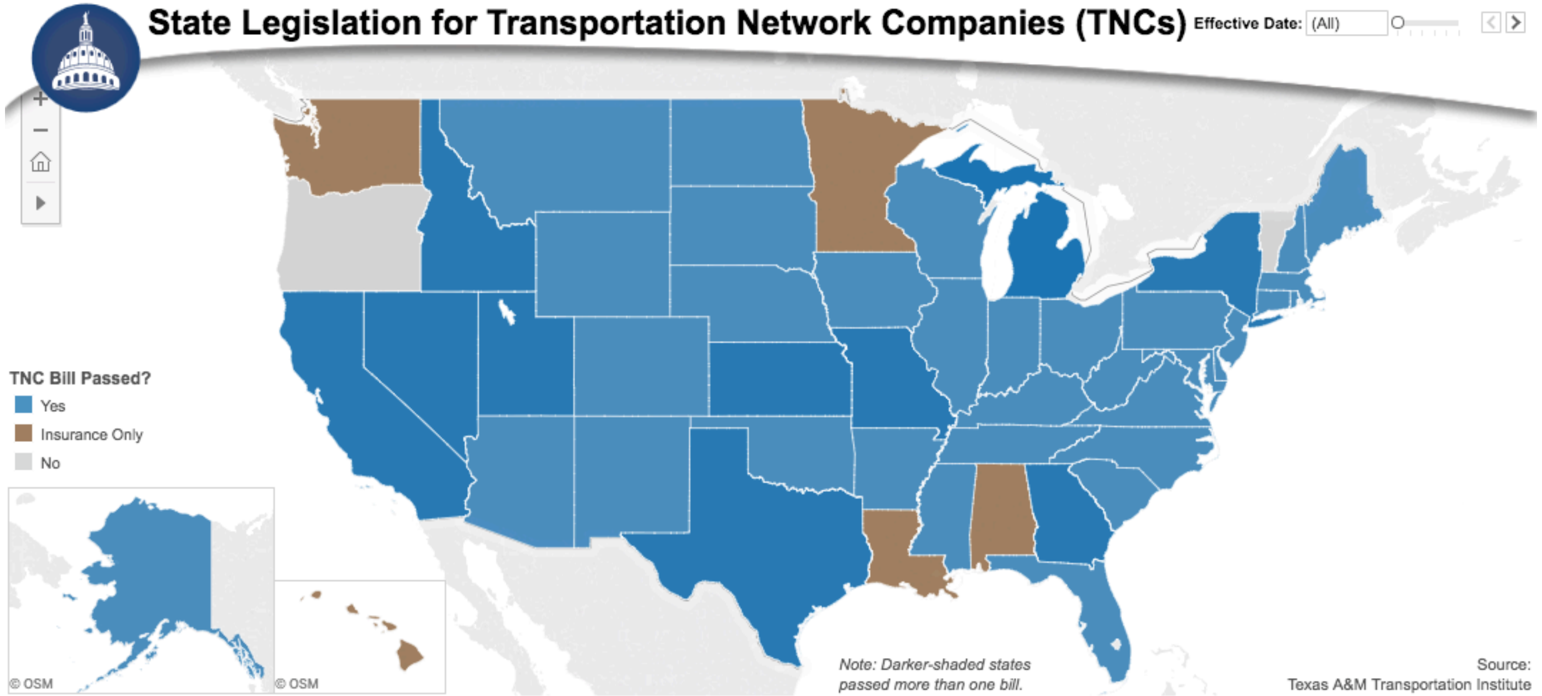
Robustness check: leave-one-out analysis

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.