ON-DEMAND RIDESOURCING HAS REDUCED PER-CAPITA VEHICLE REGISTRATIONS AND AIR POLLUTANT EMISSIONS IN U.S. STATES

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ABSTRACT

We estimate the effect of on-demand ride-hailing service availability by Transportation Network Companies (TNCs) Uber and Lyft on per-capita vehicle ownership, energy use, travel distances, and emissions in U.S. states from 2005 to 2015 using a difference-in-difference propensity score-weighted regression model. Our results suggest that, on average during the examined period, TNC entry causes a state's per-capita vehicle registrations and volatile organic compound emissions to drop by 3% and 5%, respectively. We also find that these effects are greater in relatively urban states than in relatively rural states. Additionally, travel distances are found to decline in states with average and low urbanization by 1% and 3% respectively; no effect is detected for highly urbanized states or on average across all states. Estimated effects on gasoline consumption do not pass our robustness checks. Taken together, the externality cost implications of these TNC-induced trends represent an estimated $700 million to $7 billion in vehicular accident, congestion delay, noise, and air pollution social cost savings to the U.S. economy from 2005 to 2015.

INTRODUCTION

Transportation now contributes more carbon dioxide emissions than any other U.S. economic sector[1], and passenger vehicles comprise the majority of transportation emissions[2]. New personal transportation options, including transportation network companies (TNCs), such as Uber and Lyft, that provide on-demand mobility services, have already changed how many urban travelers move: on an average weekday in late 2016, TNCs made more than 170,000 vehicle trips in San Francisco (15% of all intra-San Francisco vehicle trips)[3]. While prior literature has examined outcomes such as drunk driving, congestion, and local entrepreneurship (summarized in SI Table STT), the net impact of these services on vehicle ownership, energy consumption, travel distances, and emissions is still unknown. Using scenario analysis, the U.S. Department of Energy's (DOE) national laboratories have suggested that energy use and emissions in a future combining shared mobility with connectivity and automation could be as much as 60% lower or 200% higher than a conventional mobility case[4]. In this wide range of possible future outcomes, a "lower-bound" scenario involves energy and emissions savings made possible by ridesharing, vehicle resizing and drivecycle smoothing; whereas, an "upper-bound" scenario involves higher energy consumption and emissions resulting from increased travel.

On-demand mobility is part of a larger ongoing transformation of shared mobility—a broader term used to describe a set of transportation modes where passengers travel using vehicles owned by another party on an as-needed basis. Transportation modes such as carpooling, bike-sharing, and shuttle services have long fit into this category. More recently, car-sharing services have allowed customers to rent a fleet-owned vehicle that is regularly available to other customers for either round-trip (e.g., Zipcar) or point-to-point (e.g., Car2Go) journeys. Furthermore, the growth and capabilities of smartphones enabled TNCs like Uber and Lyft to introduce on-demand mobility. Finally, these services opened the door for dynamic ridesharing, where algorithms efficiently route on-demand mobility services to serve several customers with different destinations in the same physical vehicle. In 2017, Uber announced the completion of 5 billion total trips[5] and Lyft announced half a billion total trips[6].

Despite rapid TNC growth in recent years, there is limited knowledge to-date on how they influence vehicle adoption, energy consumption, travel distances, and environmental outcomes. TNCs may reduce an individual's reliance on a personal vehicle, resulting in fewer vehicle registrations, or stimulate new vehicle purchases by TNC drivers, increasing the number of vehicle registrations. TNCs could reduce vehicle miles traveled (VMT) through ride pooling or by encouraging partial use of public transportation, but they may also increase VMT by requiring vehicles to travel between passenger trips ("deadheading") and by increasing travel demand. TNCs might increase or decrease energy consumption and emissions by changing VMT, by shifting VMT to vehicles with different efficiency and emissions rates, and by changing the portion of VMT traveled at hot operating temperature, when vehicles are more efficient and have lower emission rates. We aim to quantitatively estimate the net causal effects of recent TNC entry in U.S. states on vehicle adoption, energy consumption, travel distances, and environmental outcomes in those states.

PRIOR LITERATURE

On-demand mobility is a relatively recent option for passenger mobility—Uber and Lyft launched in March 2010 and June 2012, respectively, in their first market: San Francisco, California. But other types of shared mobility options were available earlier, and previous studies

have suggested that these mobility options have already affected vehicle ownership, use, and emissions. For example, a survey of a sample of Car2Go car sharing members in Calgary, San Diego, Seattle, Vancouver, and Washington, D.C. suggest that each shared vehicle in the Car2Go fleet reduces private ownership by between 1 and 11 vehicles, depending on the city and several sources of uncertainty[7]. The authors also conclude that car sharing makes possible a reduction in Car2Go member household VMT of 6–16% and vehicle travel greenhouse gas (GHG) emissions of 4–18%. For on-demand ridesharing, Hampshire et al (2017) combine survey and regression methods to conclude that the departure of Uber and Lyft from the Austin, TX market in May 2016 was associated with a 9% increase in vehicle ownership and a 23% increase in trips for individuals who transitioned from a TNC to personal vehicle mobility paradigm[8]. Clewlow and Mishra survey seven major U.S. cities and find that 9% of respondents who use ride-sharing services disposed of one or more household vehicles. However, those survey results also suggest 49% to 61% of ride-hailing trips are associated with an increase in VMT (opposite in sign of the effect identified by Hampshire et al.)[9]. Li et al. apply a difference-in-difference (DiD) regression model and find that Uber market entry decreases urban traffic congestion in the United States (3). Gong et. al also use DiD analysis to show that Uber entry is associated with an 8% increase in new vehicle ownership in China (4).

TNC services can be linked not only to the number of vehicles registered, but also to how those vehicles are used. Recent analysis suggests that fewer than 60% of miles traveled by a TNC vehicle are productive miles spent moving a passenger from an origin to a destination—the remaining 40% of TNC vehicle empty-mile travel is spent cruising in search of the next fare, driving to passenger pick-up, or driving after passenger drop-off[10]. Additionally, the travel demand induced by the convenience of on-demand ridesharing services was estimated to be as high as 85% in Denver, CO[11]. Despite potential increases in the number of trips and the total number of miles travelled to complete each trip, evidence also suggests that chaining trips in the same set of vehicles can reduce criteria air pollutant emissions.

In summary, previous survey studies have suggested respondents reported reducing vehicle ownership and either reducing or increasing VMT when TNC services are available, and prior econometric approaches have estimated the net effects of TNC entry increased vehicle ownership in China but reduced traffic congestion in the U.S. No analysis has yet examined energy and environmental outcomes, which we address below.

FINDINGS

We find that TNC entry has reduced vehicle ownership and emissions of volatile organic compounds (VOCs) in U.S. states. These results are robust to a range of model specifications and robustness checks. We also find that TNC entry has reduced VMT in less-urbanized U.S. states (using estimates reported by the U.S. Department of Transportation, DOT) in a model specification that includes degree of state urbanization interaction effects. In all cases assessed, we examine three different approaches to represent shared mobility: (1) a simple "binary" indicator that indicates whether Uber has launched in a state in a given year; (2) a "population-share" parameter indicating our estimate of the percentage of a state's population that has access to shared mobility at a given time; and (3) an "interaction" term that considers the effect of Uber entry interacted with the percent of a state's population that is urban. The binary model measures the average effect of Uber entry in the sample; while, the population-share model and the interaction model account for the fact that Uber entry in a city within a state primarily affects the urban population. We also include results from a dynamic model in the supplemental

information. For results reported, ranges provided in parenthesis represent the 95% confidence interval. In each case we subject the model to a set of robustness tests including:

(1) we conduct randomize treatment tests to ensure that the effects we estimate are unique to the particular treatment pattern observed, rather than a result of the structure of the model,
(2) we conduct leave-one-out tests to ensure that our estimates do not hinge on the data of any one state,
(3) we conduct leave-multiple-out tests to ensure that our estimates do not hinge on outliners,
(4) we conduct tests with an alternative coding of TNC entry (treating a TNC as present in a state and year if the TNC was present for at least half of that year, rather than if it was present at all during that year) to ensure that our estimates are not sensitive to coding assumptions.

We focus on findings that are statistically significant and robust.

Vehicle registrations:

Table 3 summarizes results for the effect of TNC entry on state vehicle registrations per capita. The binary model results suggest that the average effect of introducing shared mobility in (any portion of) a state is a decrease in per-capita vehicle registrations of 3.4% (95% confidence interval: 0.9% to 5.8%) over the period examined (relative to per-capita registration had the TNC not been introduced). The interaction model suggests that TNC entry yields larger reductions in per-capita vehicle registrations in states that are primarily urban than in states that are primarily rural (a 2.2% (0.3% to 4.0%) larger reduction per additional 10% of a state's population that is urban, on average). These findings are robust when subjected to our robustness tests. The population share model does not yield significant results.

In the SI, we repeat these regressions using a basic difference-in-difference model without propensity score weighting as a robustness check, and we find similar results (Table S4).

Gasoline consumption:

Table 3 also summarizes results for the effect of TNC entry on state gasoline consumption per capita. While the population-weighted model shows a significant and negative effect and the interaction model shows a significant and negative interaction effect, these estimates do not pass our robustness tests (see SI Table TTT and Figures FFF for details). Accordingly, we cannot confidently assert a non-zero TNC entry effect on gasoline consumption. Repeating these regressions using a basic (unweighted) difference-in-difference model as a robustness check yields similar results (Table S4).

Vehicle miles traveled:

Table 3 also summarizes results for the effect of TNC entry on estimated state VMT per capita, as reported by DOT[12,13]. Interaction model results suggest that TNC entry reduces per-capita VMT by 1.0% (0.3 to 1.7%) in an average-urban-population state, but that estimate increases by 0.8 percentage points (0.3 points to 1.2 points) per additional 10% of a state's population that is urban. The binary model does not yield significant results, and the population-weighted model's significant and negative result does not pass robustness checks (see SI Table TTT and Figures FFF for details). Estimated results are similar using an unweighted difference-in-difference model (Table S4).

Emissions:

Table 4 summarizes results for the effect of TNC entry on estimated per-capita emissions of GHGs, as reported by the Energy Information Administration (EIA)[14], and of the seven pollutants (CO, NH_3, NO_x, PM_{10}, $PM_{2.5}$, SO_2, and VOCs) reported in EPA's State Emissions Inventory[15]. Results for control variables are omitted in Table 5 for brevity (detailed results are reported in SI Table STT). Our binary model estimates TNC entry is estimated to reduce per-capita VOC emissions by 4.5% (1.2% to 7.9%), on average, which compares to our interaction model's estimate of a 5.4% (1.2% to 9.7%) reduction for an average-urban-population state. While, the interaction model's Uber entry-urban population interaction term is not significant, even accounting for the relatively large standard error, we estimate that VOC emissions decline in states with both average and relatively high population urban; no significant effect is observed for states with relatively rural populations. Both binary and interaction model-estimated effects are robust or near-robust (passing greater than 95% of variations for each check) to our battery of randomized treatment, leave-one-out, TNC market entry encoding, and outlier exclusion robustness checks, and similar results are produced using an unweighted difference-in-difference model (Table S5). Some regression models yield significant results for NH_3, PM_{10}, and SO_2 emissions; however, these results fail robustness checks (see SI Table STT and SI Figures SFF for details).

Controls:

For control variables, across the models we tested the coefficient for population is significant and positive, and the coefficient for population squared is significant and negative for all our models, meaning the number of per-capita vehicle registrations increases with population to a point and then decreases. The coefficient for income is significant and negative (or insignificant in the interaction specification), suggesting per-capita vehicle registrations may decrease with income, and the coefficient from Section 177 status is significant and negative, indicating per-capita vehicle registrations are lower in Section 177 states. We also find that the coefficients for gas price, biggest city population, biggest city population density, biggest city GDP, and indicators for Hurricane Katrina, Superstorm Sandy, and Cash-for-Clunkers are not statistically significant.

DISCUSSION

Our results suggest that access to TNC services has reduced per-capita vehicle registrations and emissions of volatile organic compounds in U.S. states. For the coefficients reported as significant findings, the application of several diagnostic methods—visual inspection of regression residual errors as well as randomized treatment, leave-one-out, TNC market launch encoding, or excluding-outlier robustness checks—yields no evidence of systematic error or potential misspecifications (SI Figures SFF). Our results also suggest that TNC services have likely reduced per-capita VMT in U.S. states with average or lower levels of the population urbanization.

Our analysis focuses on changes in overall state-level outcomes after TNCs enter cities within those states. We cannot identify changes to vehicle fleet mix with the available data, and there are potentially multiple alternative narratives that might explain these trends. For example, it is possible that TNCs reduce VOC emissions primarily by reducing VMT, but it is also possible that TNCs reduce VOC emissions primarily by shifting VMT away from older, less

efficient vehicles toward newer, more efficient vehicles that operate under hot steady-state conditions for a large portion of VMT. Newer vehicles are also associated with lower pollutant emissions: CO, NO_x, VOC, and PM emissions in light-duty transportation have declined 30-50% over the past ten years[16]. Although, the EPA emissions estimates we use do not account for potential changes in cold start vs. hot operation ratios induced by TNCs, so any signal captured by our linear models and data is potentially attributable to a vehicle fleet transition but not likely to drive-cycle changes. Additional study on the effect of TNC market entry on vehicle fleet composition and distribution of VMT across the fleet is needed for deeper insight about the mechanisms that produce these outcomes.

We estimate that TNC service availability in U.S. cities has reduced state per-capita vehicle ownership by 3.4% on average during the period 2005 to 2015 (relative to expected trends if the TNCs had not entered). In total, we estimate that in a counterfactual scenario where TNC services had not been available over the analysis period (and everything else would have been held constant), the vehicle fleet would have been larger by 9 million vehicles in 2015.

Further, using estimates of annual state VMT reported in DOT's State Statistical Abstracts, we estimate that TNC service availability has reduced state per-capita VMT by 1.0% in an average-urban-population state plus an increase in VMT of 0.8 percentage points per additional 10% of a state's population that is urban (or decrease of 0.8 percentage points per additional 10% of a state's population that is rural). The combined effect is a 3.7% (1.8% to 5.6%) reduction in VMT for the most rural states and a combined effect that is not statistically significant from zero for the most urban states. Using DOT's per-mile estimates of the externality costs of driving from congestion, accidents, and noise[17], this represents a social cost savings of $4 billion ($600 million to $7 billion) cumulatively over the analysis period.

Finally, using EPA estimates of passenger transportation emissions, we estimate that TNC service availability has reduced state per-capita VOC emissions by 4.5% (and as much as 5.4% and 8.0% in states with average and relatively high urbanization, respectively). Again using DOT's range of estimates for the social cost of air pollutant emissions, we estimate that these emissions reductions represent social cost savings of $400 million ($80 million to $700 million) over the analysis period.

Taken together, our estimates of TNC implications for state vehicle registrations, VMT, and VOC emissions suggest that TNC availability has reduced U.S. social costs (for health and environmental damages and congestion, accidents and noise) by $4 billion ($700 million to $7 billion) over the period 2005 to 2015.

These findings should be interpreted in context: our analysis does not identify the cause of these associations, nor does it capture the mix of trends that may lead to these net results, such as competing factors that act both to increase and to decrease VMT or changes in the fleet mix that result in fewer vehicle registrations overall but not necessarily fewer new vehicle purchases. Our effects are all estimated at the state level, and we lack the data to identify smaller-scale nuance at the city and regional levels. Furthermore, our analysis relies on datasets that use estimates of air emissions and VMT rather than observed values.

Nevertheless, the fact that recent data on TNC entry suggest relatively large, statistically significant reductions in vehicle registrations, VMT, and emissions at the state level has implications for transportation planning (e.g. road capacity, congestion), urban planning (e.g. residential and public parking), air quality attainment planning, and TNC policy. Additional study on fleet mix is needed to identify implications for automotive manufacturing; for

potentially complementary or competing transportation modes, such as mass transit and bikeshare; and for issues such as access and equity concerns.

METHODS

We use difference-in-difference (DiD) models to estimate causal effects of the intervention (i.e. TNC entry) by comparing the trends of treated and untreated groups before and after the intervention occurs. DiD methods have been used previously to evaluate the effect of TNCs on other outcomes, including traffic congestion[18], vehicle-related homicides[19], entrepreneurial activity[20], and new vehicle ownership in China[21]. The estimates of a difference-in-difference model are unbiased if trends over time would have been identical, on average, between the treatment and non-treatment groups in the absence of the intervention. A potential concern regarding bias arises if the treated and non-treated groups (e.g. states) are systematically different in other ways that might explain differences in trends among those groups. This is the case here, where, by the end of the analysis period, TNCs have entered all but five states (Alaska, Montana, South Dakota, West Virginia, Wyoming), which it is reasonable to assert are not representative of the other 45 states for direct comparison. To control for this potential bias, we apply inverse probability of treatment weights to compare post-treatment trends in treated states with weighted trends in non-treated states, probabilistically weighted to resemble the treated states along attribute dimensions that are correlated with treatment (state population, income, gasoline price, and emissions standards).

Data

We consider four dependent variables of interest (per capita vehicle registrations, gasoline consumption, VMT, and emissions of several pollutants from highway vehicles) and several independent variables (Uber and Lyft market entry dates, portion of state population served by Uber, state population, fuel prices, income, and a state's Section 177 status). We describe each in turn and identify data sources for each:

Dependent Variables (plotted by state in Supplementary Information Figure SFF):

- *Vehicle registrations (measured):* We use vehicle registration data for each state and for each year for light-duty passenger vehicles from Ward's Automotive[22]. Ward's data are based on data published in U.S. DOT's State Statistical Abstracts, which is the set of official vehicle registration data published by state DOTs.
- *Gasoline consumption (measured):* DOT's State Statistical Abstracts and Highway Statistics Series also report Federal Highway Administration estimates of annual private and commercial vehicle state level on-highway motor fuel based on reports of aggregate motor fuel sales from state motor fuel tax agencies.
- *VMT (estimated):* VMT data comes from DOT's State Statistical Abstracts, which are tracked and reported annually as a function of figures reported by state agencies. State agencies estimate aggregate VMT based on vehicle count data measured on representative roadways and distributions of roadway type within the state. VMT (table VM-2) has been published in DOT's State Statistical Abstract series since 2008; earlier data are available in DOT's Highway Statistics Series[12,13].
- *Emissions (estimated):* State-level emissions data are published annually in the EPA's State Average Emissions Trend report, which, in turn, is informed by EPA's National Emission Index. Emissions attributable to highway vehicles are estimated by the EPA

annually[15]: 2008, 2011, and 2014 estimates were developed in conjunction with the National Emissions Inventory for those years; 2005, 2007, 2009 and 2010 estimates were updated using EPA's Motor Vehicle Emission Simulator (MOVES) model; and 2006, 2012, and 2013 were interpolated. EIA estimates an annual series of State Carbon Dioxide Emissions based on energy consumption data contained in the State Energy Data System (SEDS). Transportation sector estimates are published without highway or light-duty vehicle detail after an approximately 2-year lag[14].

We divide each of the four quantities above by state population each year to compute per-capita values. Annual state-level population estimates are from DOT's State Statistical Abstract and Highway Statistics series, such that they align with VMT data and are related to Ward's Automotive vehicle registration data (the ultimate source for which is also these DOT publications). DOT population reports match U.S. Census statistics in census years and are no more than 0.6% different than Census Bureau's annual estimates of the resident population in intercensal years[23], the values for which the Census reports are calculated assuming geometric interpolation with some exceptions[24].

Independent Variables:

- *Uber and Lyft entry dates:* We adopt data from previous sources that aggregated and published a time-series of Uber market entry dates. A 2014 Forbes article first aggregated Uber launch dates from 2010–2014[25] by service area, as originally announced on Uber's official blog (on a post no longer available) and/or in local media from each new service area; the author continued to update that dataset to reflect additional Uber markets launched through December 2015. Those dates are cross-referenced against Uber market launch date data that were independently gathered and published in two later studies[18,25,26]. Burtch et al. include a table of market launch dates for UberX—Uber's lower-cost, on-demand service provided in the driver's personal vehicle, which the authors compiled directly from the Uber Blog[20]. Lyft market launch dates were requested from and provided by Lyft[27]. A comparison of Uber and Lyft market launch date time-series is depicted by combined statistical area in Figure 1. Because Lyft market entry dates are later than Uber market entry dates in all cases, we use Uber entry dates in our analysis to represent on-demand mobility availability in the state.
- *Population served by Uber in each state:* Figure 2 provides a distribution of the population share of U.S. states with TNC access over time. This information is relevant, as TNCs are introduced in specific areas or cities within a state, and the portion of a state's population with access can change over time as TNCs enter new cities. These time-series are derived for this analysis by summing within each state the population of each city where Uber is present (estimates of which are reported annually by the U.S. Census American Fact Finder) and dividing by the total state population, as published by the U.S. Department of Transportation's (DOT) annual State Statistical Abstracts[12,13]. Annual (intercensal) estimates for city populations are published in the U.S. Census' American FactFinder[23].
- *Control variables:* Our control variables include: (i) population, reported annually in DOT's State Statistical Abstract and Highway Statistics series, (ii) percentage of a state's population that is urbanized[28], (iii) state average real personal income, reported annually by the Bureau of Economic Analysis[29]; (iv) state average gasoline price data, reported

annually by the U.S. Energy Information Administration (EIA)[14], and (v) an indicator for whether each state has adopted California's more stringent vehicle emissions control requirements, pursuant to Section 177 of the Clean Air Act[30]. Additionally, recognizing that TNC market entry and use is primarily a city phenomenon, additional control variables are included for the largest city within each state, including: (vi) population[31], (vii) population density[31], and (viii) GDP[32].

The sum for each data source above across all fifty states, giving U.S. national totals, is shown for each year in Table 1. On average, population steadily increases, criteria pollutant emissions steadily decrease, and vehicle registrations and income generally increase, except for a dip in 2009–2010 corresponding to the Great Recession. Gasoline price is volatile and non-monotonic.

Propensity Score Weighted Regression Analysis

Regression

Our regression model structure is informed by models used in prior literature for our outcomes of interest (summarized in SI Table STT). Regression analysis is conducted using inverse probability of treatment weighting (described below) and the following baseline specification:

$$y_{st} = \boldsymbol{\beta}'\mathbf{x}_{st} + \boldsymbol{\alpha}'\mathbf{z}_{st} + \gamma_s + \delta_t + \varepsilon_{st} \quad (1)$$

where y_{st} is one of the four dependent variables of interest for state s and year t: 1) vehicle registrations per capita; 2) VMT per capita; 3) gasoline use per capita, or 4) one of the per capita passenger vehicle emissions estimates (CO, NH_3, NO_x, PM_{10}, $PM_{2.5}$, SO_2, and VOCs); $\mathbf{x}_{st}$ is the vector of treatment effects (i.e., an Uber indicator) for state s and year t with coefficient vector $\boldsymbol{\beta}$ (the prime indicates transpose); $\mathbf{z}_{st}$ is a vector of controls for state s and year t, including population, urban population percentage, gas price, real personal income, Section 177 status, and largest city population, density, and GDP, with corresponding coefficients $\boldsymbol{\alpha}$; γ_s is the fixed effect for state s; δ_t is the fixed effect for year t; and ε_{st} is unobserved error. Several additional statistical and diagnostic tests support the structure of the regressions (summarized in SI Figures SFF). The precision of linear regression results will be calculated using bootstrapped standard errors.

Three variations on this baseline incorporate different measures of shared mobility—(1) a simple "binary" indicator that indicates whether Uber has launched in a state in a given year; (2) a population-share parameter indicating the percentage of a state's population that has access to shared mobility at a given time; and (3) a combination of two "interaction" indicators that estimates a TNC entry effect as the effect in an "average" U.S. state in terms of portion of population that is urbanized plus the additional effect per additional degree of urbanization—as previously described in the Findings section.

We apply a battery of statistical tests to check model assumptions and test for robustness that are shown in the supplementary information, including visual inspection of residual errors (SI Figure SFF), a randomized treatment test (SI Figure SFF), leave-one-out validation (SI Figure SFF), a TNC market entry encoding check (SI Table STT), and a "leave-all-out" regression variant that excludes states with discontinuities in each of the respective dependent

variables of interest (SI Table STT), as well as two encoding checks for Uber market entry dates (SI Tables STT).

Propensity Score

Propensity scores are estimated using a logistic regression model:

$$\log\left(\frac{p_{st}}{1-p_{st}}\right) = \boldsymbol{\varphi}'\mathbf{z}_{st} + \epsilon_{st} \quad (2)$$

where p_{st} is the probability of treatment for state s and year t; $\mathbf{z}_{st}$ is a vector of controls for state s and year t, including population, urban population percentage, gas price, real personal income, Section 177 status, and largest city population, density, and GDP, with the vector of corresponding coefficients $\boldsymbol{\varphi}$; and ϵ_{st} is unobserved error. We estimate the coefficients $\hat{\boldsymbol{\varphi}}$ using generalized boosted regression, given the treatment data, and compute estimated probability of treatment $\hat{p}_{st}$ for each state and year.

Balance

After estimating the probability of treatment, we compare measures of balance to confirm that the propensity score weights succeed in matching the control group's weighted pretreatment characteristics to those of the unweighted treatment group (that is, that the weighted control and unweighted treatment group are balanced). Table 2 and Figure 3 compare for the treatment and control groups before and after weighting the set of conditional parameters used to calculate propensity scores. Weighting is shown to reduce mean differences between the treatment and unweighted control group parameters by between 70% and 100%, and while differences between treated and untreated states are statistically significant when unweighted, they are not significant in the weighted sample (even at the p=0.10 level).

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ACKNOWLEDGEMENTS

Jacob Ward is a Program Manager at the U.S. Department of Energy`s Vehicle Technologies Office, who supported him in that role while conducting this work. This study was supported in part by a grant from Carnegie Mellon University's Scott Institute for Energy Innovation, and by the Center for Climate and Energy Decision Making (SES-0949710 and SES-1463492) through a cooperative agreement between the National Science Foundation and Carnegie Mellon University. Any opinions expressed are those of the authors and not necessarily those of the sponsors.

TABLES

TABLE 1 Summary statistics for U.S. totals (gasoline price is average across states) for each year, 2005–2015. Gasoline price and income are reported in current dollars.

Parameter	Unit	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Population	million persons	296	299	302	304	307	309	312	314	316	319	321
Light-Duty Vehicles	million vehicles	234	236	237	240	239	232	231	232	234	239	241
VMT	trillion miles	2.99	3.01	3.03	2.97	2.95	2.97	2.95	2.97	2.99	3.03	3.10
CO	million tons	42.4	39.7	37.0	32.9	27.5	28.3	27.2	25.4	23.5	21.7	19.7
NH3	million tons	0.14	0.14	0.15	0.14	0.13	0.12	0.12	0.12	0.11	0.10	0.10
NOx	million tons	8.30	7.95	7.60	6.90	6.20	5.70	5.84	5.44	5.05	4.65	4.12
PM10	million tons	0.38	0.37	0.37	0.33	0.30	0.28	0.37	0.35	0.33	0.31	0.30
PM2.5	million tons	0.31	0.29	0.28	0.25	0.22	0.20	0.20	0.18	0.17	0.16	0.15
SO2	million tons	0.17	0.11	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.02
VOC	million tons	3.41	3.43	3.46	3.03	2.75	2.77	2.86	2.63	2.41	2.19	1.97
Gas Price	$/gal (current $)	2.08	2.36	2.58	3.01	2.20	2.63	3.32	3.42	3.33	3.20	2.34
Income	trillion $ (current $)	10.6	11.4	12.0	12.5	12.1	12.5	13.2	13.9	14.1	14.8	15.5
Uber Share	% states	0%	0%	0%	0%	0%	2%	8%	22%	40%	86%	90%
Uber, 1 year	% states	0%	0%	0%	0%	0%	2%	6%	14%	18%	46%	4%
Uber, 2 years	% states	0%	0%	0%	0%	0%	0%	2%	6%	14%	18%	46%
Uber, >2 years	% states	0%	0%	0%	0%	0%	0%	0%	4%	8%	22%	40%
Uber Pop. Share	% pop, state avg.	0%	0%	0%	0%	0%	0%	1%	3%	10%	19%	21%

TABLE 2 Balance table comparing the treatment and control groups before and after weighting and showing associated bias reduction in the matching parameters.

	Treatment Mean	Treatment Std Dev	Control Mean	Control Std Dev	Standard Effect	t-statistic	p-value	Bias Reduction
Unweighted Sample								
lpop	15.59	0.94	15.02	1.00	0.60	5.81	0.00	
gas	25.36	4.34	23.70	4.30	0.38	3.76	0.00	
inc	45.83	6.86	39.48	6.86	0.93	9.10	0.00	
s177	0.34	0.48	0.15	0.36	0.39	4.05	0.00	
Weighted Sample								
lpop	15.59	0.94	15.46	0.91	0.14	1.17	0.24	**77%**
gas	25.36	4.34	24.92	4.20	0.10	0.85	0.40	**74%**
inc	45.83	6.86	44.81	7.12	0.15	1.19	0.24	**84%**
s177	0.34	0.48	0.34	0.47	0.00	0.00	1.00	**100%**

TABLE 3 Regression models for per-capita vehicle registrations, per-capita gasoline use, and per-capita VMT using three measures of shared mobility: (1) binary, (2) discrete annual, and (3) population share. Coefficients for fixed effects (state and year) are not shown.

	Dependent variable:			*Dependent variable:*			*Dependent variable:*		
	log(Veh. Reg. per cap)			log(Gasoline Use per cap)			log(VMT per cap)		
	Binary	Pop. Weighted	Interaction	Binary	Pop. Weighted	Interaction	Binary	Pop. Weighted	Interaction
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
treat	−0.034***		−0.026**	0.0003		0.005	−0.004		−0.010***
	(0.013)		(0.013)	(0.004)		(0.006)	(0.003)		(0.004)
treatpop		−0.004			−0.019**			−0.015***	
		(0.027)			(0.008)			(0.005)	
I(treat-pop_u)			−0.215**			−0.096***			0.076***
			(0.092)			(0.028)			(0.024)
lpop	8.271***	8.833***	11.128***	0.521	0.504	−1.106	−0.156	−0.097	−0.502
	(2.259)	(2.334)	(3.844)	(0.734)	(0.754)	(1.116)	(0.709)	(0.710)	(0.911)
lpopsq	−0.277***	−0.294***	−0.346***	−0.018	−0.018	0.038	−0.002	−0.004	0.007
	(0.076)	(0.079)	(0.122)	(0.025)	(0.026)	(0.037)	(0.022)	(0.022)	(0.028)
gas	0.004	0.004	−0.005	−0.008***	−0.008***	−0.005**	0.001	0.002	0.001
	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
inc	−0.014***	−0.013***	0.0004	0.007***	0.007***	0.006***	0.001	0.001	0.001
	(0.004)	(0.004)	(0.007)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
s177	−0.060**	−0.059**	−0.106***	−0.005	−0.004	−0.015	0.001	0.001	−0.004
	(0.026)	(0.026)	(0.033)	(0.009)	(0.009)	(0.013)	(0.005)	(0.005)	(0.007)
citypop	−0.233	−0.195	−0.131	0.021	0.013	−0.056	−0.067	−0.067	−0.065
	(0.179)	(0.186)	(0.253)	(0.072)	(0.069)	(0.074)	(0.050)	(0.050)	(0.062)
citydensity	0.040	0.041	0.006	−0.033***	−0.032***	−0.042***	−0.002	−0.002	−0.007
	(0.032)	(0.032)	(0.046)	(0.009)	(0.009)	(0.013)	(0.010)	(0.010)	(0.013)
citygdp	0.079	0.071	0.194	−0.112*	−0.109*	−0.061	−0.092*	−0.091*	−0.126**
	(0.146)	(0.151)	(0.193)	(0.061)	(0.059)	(0.059)	(0.048)	(0.049)	(0.051)
pop_u	5.707***	5.735***	7.840***	0.300	0.145	0.148	1.179***	1.066***	1.886***
	(0.944)	(0.932)	(1.626)	(0.412)	(0.428)	(0.535)	(0.299)	(0.300)	(0.418)
katrina	−0.036	−0.048	0.017	−0.006	−0.002	−0.002	−0.063***	−0.062***	−0.059***
	(0.033)	(0.033)	(0.060)	(0.014)	(0.013)	(0.021)	(0.010)	(0.010)	(0.016)
sandy	0.076	0.077	0.050	0.007	0.002	−0.0001	−0.001	−0.004	0.003
	(0.053)	(0.060)	(0.039)	(0.007)	(0.005)	(0.006)	(0.006)	(0.004)	(0.008)
clunkers	−5.340	−7.223	−11.616	6.672	6.764	15.305	8.737	8.567	5.862
	(25.190)	(26.048)	(39.108)	(7.383)	(7.494)	(9.463)	(5.436)	(5.454)	(6.101)
Constant	−60.129***	−64.656***	−86.362***	−4.747	−4.539	6.931	−2.426	−2.845	0.532
	(16.787)	(17.307)	(30.061)	(5.406)	(5.523)	(8.454)	(5.612)	(5.609)	(7.312)
Observations	550	550	550	550	550	550	550	550	550
Log Likelihood	545.296	539.808	201.103	1,125.562	1,129.245	751.112	1,125.562	1,129.245	751.112
Akaike Inf. Crit.	-944.592	-933.617	-254.205	-2,105.124	-2,112.491	-1,354.225	-2,105.124	-2,112.491	-1,354.225
Note:									*p<0.1; **p<0.05; ***p<0.01

TABLE 4 Summary of TNC indicator coefficients from the results of the set of regression model specifications discussed (binary, discrete annual, and population share) using the logarithm of per-capita emissions of each of seven criteria pollutants (CO, NH_3, NO_x, PM_{10}, $PM_{2.5}$, SO_2, and VOCs) as the dependent variable. While only coefficients for TNC indicators are reported here, the full set of regressors shown in and discussed in conjunction with equation (1) are used.

	Dependent variable: log emissions per capita							
	VOC	NOx	CO	NH3	PM10	PM2.5	SO2	GHG
treat	−0.045***	−0.010	−0.024	−0.023**	0.037*	0.011	0.046***	0.006
	(0.017)	(0.013)	(0.019)	(0.011)	(0.020)	(0.015)	(0.017)	(0.007)
treatpop	−0.018	0.014	−0.015	−0.059***	0.139**	0.052	0.027	0.010
	(0.029)	(0.041)	(0.028)	(0.017)	(0.057)	(0.052)	(0.027)	(0.013)
treat	−0.054**	−0.009	−0.044*	−0.030**	0.038**	0.026	0.026*	0.021***
	(0.022)	(0.016)	(0.024)	(0.013)	(0.018)	(0.019)	(0.014)	(0.008)
I(treat-pop_u)	−0.119	−0.107	−0.002	0.006	−0.015	−0.1	0.048	−0.130***
	(0.095)	(0.108)	(0.098)	(0.055)	(0.144)	(0.143)	(0.082)	(0.046)
Note:								*p<0.1; **p<0.05; ***p<0.01

FIGURES



FIGURE 1 Comparison of Uber and Lyft market launch dates by combined statistical area (CSA) (left).

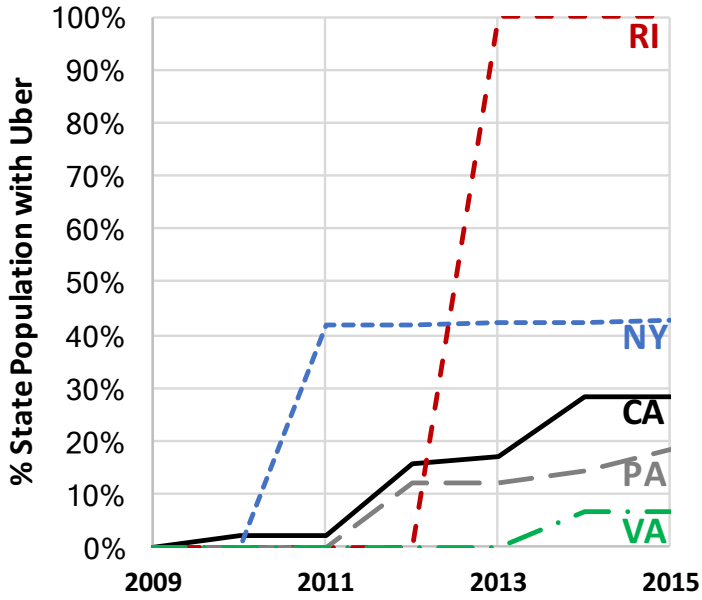


FIGURE 2 The population share of states with Uber access for five illustrative states from 2009–2015. Uber enters California (CA) first in 2010 and launches in other cities in the state over time. This "gradual expansion" trend is as is also shown by Pennsylvania (PA) and for most other states not shown (FL, IA, ID, IN, KS, LA, MA, MI, NC, NM, NV, OH, OK, OR, TX, WA, and WI). In New York (NY), Uber's entry into a single city (New York City) accounts for most of the state population share with Uber access, which is also the case for some other states where populations with Uber access are either entirely or mostly concentrated in a single metropolitan area (AZ, CO, HI, IL, KY, MO, ND, NE, OR, TN, and WI). In Rhode Island (RI), Uber declares entry for the whole state at once, which also occurs in CT and NJ. Virginia (VA) is shown to underscore that in some states Uber was available to a small part of the population (<10%) by the end of 2015 (AL, AR, GA, MD, ME, MN, SC, UT, VA, and VT). And, not shown are the five states Uber still had not entered by the end of this analysis period: AK, MT, SD, WV, and WY.

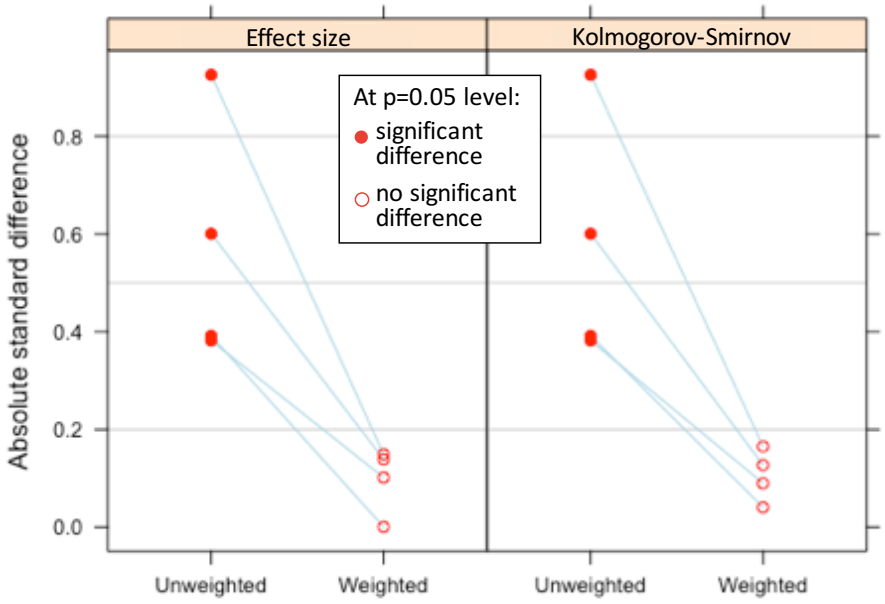


FIGURE 3 Effect size plot comparing the treatment and control groups before and after weighting (using propensity scores calculated both using effect size (left) and Kolmogorov-Smirnov (right) stopping criteria and showing associated bias reduction in the matching parameters. Closed red circles indicate a statistically significant difference before weighting; open circles reflect no significant difference after weighting.

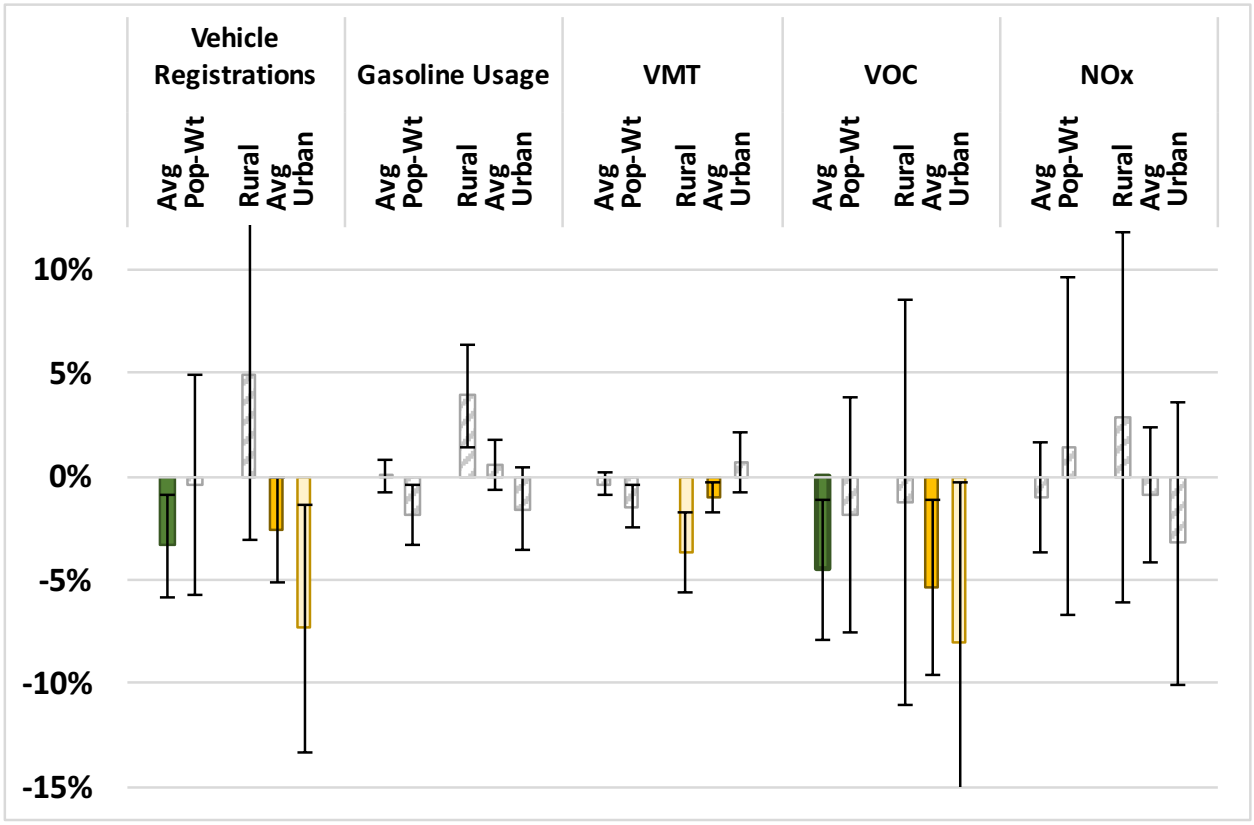


FIGURE 4 Summary depiction of the estimated effect of TNC entry effects associated with vehicle registration, gasoline use, VMT, and emissions (NO_x and VOCs shown) for each of a binary (average effect), discrete annual (dynamic effect) and population-share regression model.

PRELIMINARY SUPPLEMENTAL INFORMATION

TABLE S1 Variable coding (will eventually be combined with Table 1).

Variable	Description
treat	Uber indicator – binary
treatpop	Uber indicator – weighted by % of state population with Uber access
lpop	log of state population
lpopsq	(log of state population)^2
gas	average retail gas price in a state
inc	real personal income per capita
s177	indicator for state Section 177 status (those states using California's more stringent emissions standards)
citypop	population of the city at the center of the largest MSA in a state
citydensity	density of the city at the center of the largest MSA in a state
citygdp	GDP of the city at the center of the largest MSA in a state
pop_u	% of state population that is considered urban by the Census (measured compared to the "average" state = 74% urban; positive values are more urban and negative values less so)
katrina	indicator for Louisiana in 2005 (when Katrina scrapped thousands of vehicles)
sandy	indicator for New York and New Jersey in 2010 (when Sandy scrapped thousands of vehicles)
clunkers	Number of vehicles scrapped in a state via Federal "cash-for-clunkers" program in 2009

TABLE S2 Summary of robustness checks.

	Coefficient	RT	LOO	Enc	LMO
Vehicle Registrations					
Avg	-3.4% ***	●	◒	●	●
Pop-Wt	-0.4%	○	○	○	○
Rural	4.9%	○	○	○	○
Avg	-2.6% **	●	◒	●	◒
Urban	-7.4% **	●	◒	○	●
Gasoline Usage					
Avg	0.0%	○	○	○	●
Pop-Wt	-1.9% **	○	◒	●	○
Rural	3.9% ***	○	◒	○	●
Avg	0.5%	○	○	○	○
Urban	-1.6%	○	◒	○	○
VMT					
Avg	-0.4%	○	○	○	○
Pop-Wt	-1.5% ***	○	◒	●	●
Rural	-3.7% ***	●	●	●	●
Avg	-1.0% ***	◒	◒	●	◒
Urban	0.6%	○	○	○	○
VOC					
Avg	-4.5% ***	●	◒	●	●
Pop-Wt	-1.8%	○	○	○	○
Rural	-1.2%	○	○	○	●
Avg	-5.4% **	●	◒	○	●
Urban	-8.0% **	●	◒	○	○

	Coefficient	RT	LOO	Enc	LMO
NH3					
Avg	-2.3% **	●	◒	○	○
Pop-Wt	-5.9% ***	○	●	●	●
Rural	-3.2%	○	○	○	●
Avg	-3.0% **	●	◒	○	●
Urban	-2.8%	○	○	○	○
PM10					
Avg	3.7% *	◒	○	●	○
Pop-Wt	13.9% **	○	◒	●	◒
Rural	4.3%	◒	○	○	○
Avg	3.8% **	●	○	●	●
Urban	3.5%	○	○	○	●
SO2					
Avg	4.6% ***	●	●	●	○
Pop-Wt	2.7%	○	●	○	○
Rural	0.9%	○	○	○	○
Avg	2.6% *	◒	○	○	○
Urban	3.6%	●	○	●	○

TABLE S3 Ordinary least-squares (OLS) regression results for vehicle registration, gasoline use, and VMT outcomes.

	Dependent variable:								
	log(Veh. Reg. per cap)			log(Gasoline Use per cap)			log(VMT per cap)		
	Binary	Pop. Weighted	Interaction	Binary	Pop. Weighted	Interaction	Binary	Pop. Weighted	Interaction
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
treat	−0.032**		−0.029**	−0.003		0.007*	0.001		−0.008**
	(0.015)		(0.012)	(0.005)		(0.004)	(0.005)		(0.003)
treatpop		0.005			−0.023**			−0.007	
		(0.031)			(0.011)			(0.011)	
I(treat-pop_u)			−0.073			−0.101***			0.054***
			(0.056)			(0.019)			(0.017)
lpop	7.242***	8.074***	8.148***	1.900***	1.911***	0.349	0.816	0.760	−0.065
	(1.767)	(1.734)	(1.841)	(0.631)	(0.614)	(0.624)	(0.621)	(0.607)	(0.553)
lpopsq	−0.254***	−0.281***	−0.270***	−0.070***	−0.071***	−0.008	−0.036*	−0.034*	−0.008
	(0.059)	(0.058)	(0.060)	(0.021)	(0.021)	(0.020)	(0.021)	(0.020)	(0.018)
gas	0.008	0.008	0.005	−0.013***	−0.012***	−0.007***	−0.007***	−0.006***	0.0003
	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
inc	−0.012***	−0.012***	−0.014***	0.010***	0.010***	0.007***	0.005***	0.005***	0.001
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
s177	−0.009	−0.010	−0.058***	−0.007	−0.006	−0.001	0.001	0.002	−0.001
	(0.020)	(0.020)	(0.021)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
citypop	−0.021	−0.003	−0.276	−0.059	−0.059	−0.039	0.033	0.032	−0.035
	(0.171)	(0.172)	(0.185)	(0.061)	(0.061)	(0.063)	(0.060)	(0.060)	(0.055)
citydensity	0.014	0.013	0.046	−0.011	−0.010	−0.025***	−0.013	−0.013	−0.007
	(0.024)	(0.024)	(0.028)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
citygdp	−0.190	−0.234	0.128	−0.075	−0.072	−0.044	−0.140**	−0.136**	−0.128***
	(0.189)	(0.189)	(0.149)	(0.067)	(0.067)	(0.051)	(0.066)	(0.066)	(0.045)
pop_u	2.841***	2.943***	5.396***	1.208***	1.115***	−0.132	1.190***	1.157***	1.409***
	(0.783)	(0.798)	(0.994)	(0.280)	(0.282)	(0.337)	(0.275)	(0.279)	(0.299)
katrina	−0.053	−0.057	−0.038	0.005	0.006	−0.009	−0.045	−0.044	−0.062
	(0.081)	(0.081)	(0.188)	(0.029)	(0.029)	(0.064)	(0.028)	(0.028)	(0.056)
sandy	0.071	0.069	0.070**	−0.004	−0.005	−0.001	0.003	0.003	0.003
	(0.057)	(0.057)	(0.029)	(0.020)	(0.020)	(0.010)	(0.020)	(0.020)	(0.009)
clunkers	−5.858	−5.318	−3.805	2.616	2.421	8.806	5.989	5.898	7.602
	(13.569)	(13.633)	(18.338)	(4.844)	(4.825)	(6.214)	(4.771)	(4.770)	(5.511)
Constant	−50.937***	−57.162***	−59.881***	−13.876***	−13.927***	−4.402	−9.450**	−9.027**	−2.609
	(13.094)	(12.850)	(14.084)	(4.675)	(4.548)	(4.772)	(4.604)	(4.496)	(4.232)
Observations	550	550	550	550	550	550	550	550	550
R^2	0.806	0.804	0.865	0.973	0.973	0.986	0.981	0.981	0.990
Adjusted R^2	0.776	0.774	0.844	0.968	0.969	0.984	0.979	0.979	0.989
Residual Std. Error	0.074 (df = 477)	0.075 (df = 477)	0.035 (df = 476)	0.026 (df = 477)	0.026 (df = 477)	0.012 (df = 476)	0.026 (df = 477)	0.026 (df = 477)	0.011 (df = 476)
Note:									*p<0.1; **p<0.05; ***p<0.01

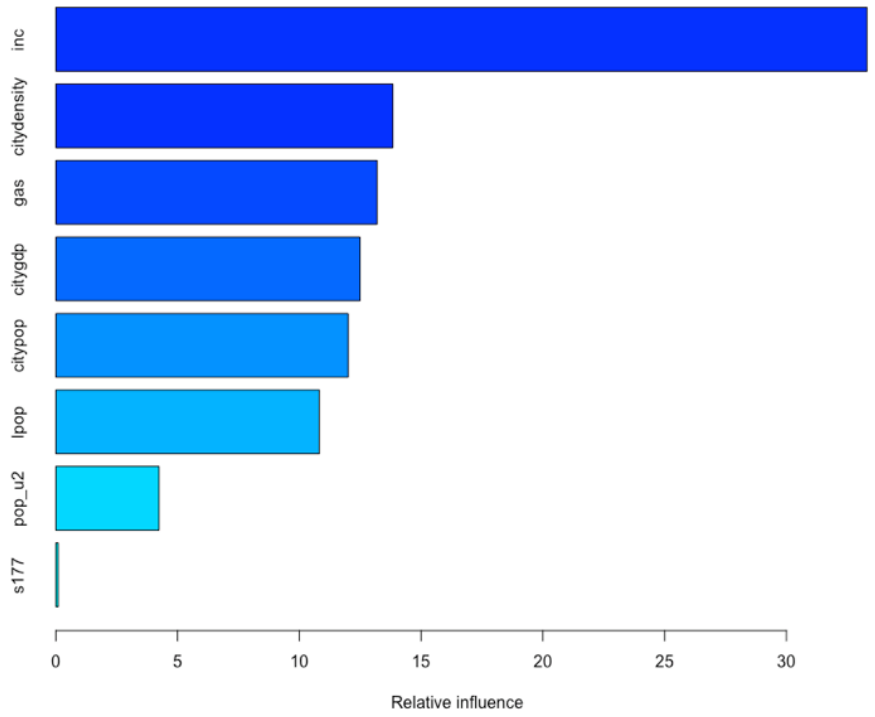
TABLE S4 Ordinary least-squares (OLS) regression results for emissions (CO, NH_3, NO_x, PM_{10}, $PM_{2.5}$, SO_2, and VOCs) outcomes.

	Dependent variable: log emissions per capita							
	VOC	NOx	CO	NH3	PM10	PM2.5	SO2	GHG
treat	−0.050**	−0.013	0.004	−0.01	0.010	−0.014	0.051	−0.003
	(0.023)	(0.024)	(0.020)	(0.027)	(0.032)	(0.035)	(0.041)	(0.010)
treatpop	−0.006	0.080*	0.072*	−0.081	0.185***	0.095	0.098	0.016
	(0.046)	(0.048)	(0.041)	(0.054)	(0.063)	(0.070)	(0.083)	(0.021)
treat	−0.050**	−0.018	−0.003	−0.006	−0.001	−0.018	0.051	0.000
	(0.023)	(0.024)	(0.021)	(0.027)	(0.032)	(0.036)	(0.042)	(0.010)
I(treat-pop_u)	0.000	0.116	0.165*	−0.097	0.239*	0.091	0.008	−0.061
	(0.102)	(0.107)	(0.091)	(0.121)	(0.142)	(0.157)	(0.186)	(0.049)
Note:								*p<0.1; **p<0.05; ***p<0.01

TABLE S5 Inverse probability of treatment weights.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
AK	0.011	0.006	0.010	0.077	0.032	0.074	0.072	0.072	0.072	0.072	0.076
AL	0.055	0.062	0.058	0.080	0.055	0.058	0.093	0.096	0.106	1.000	1.000
AR	0.020	0.087	0.078	0.078	0.083	0.078	0.098	0.170	0.093	1.000	1.000
AZ	0.035	0.035	0.042	0.062	0.072	0.033	0.072	1.000	1.000	1.000	1.000
CA	0.115	0.118	0.161	1.079	0.902	1.000	1.000	1.000	1.000	1.000	1.000
CO	0.242	0.327	0.240	0.449	0.333	0.177	1.145	1.000	1.000	1.000	1.000
CT	0.501	0.231	0.236	0.327	0.672	0.246	0.461	0.461	0.654	1.000	1.000
DE	0.050	0.066	0.038	0.047	0.071	0.034	0.059	0.038	0.059	0.103	1.000
FL	0.011	0.065	0.035	0.035	0.072	0.036	0.137	0.194	0.194	1.000	1.000
GA	0.031	0.031	0.044	0.037	0.024	0.037	0.445	1.000	1.000	1.000	1.000
HI	0.049	0.033	0.045	0.195	0.072	0.191	0.203	0.396	1.000	1.000	1.000
IA	0.028	0.040	0.220	0.252	0.350	0.252	0.317	0.451	0.554	1.000	1.000
ID	0.008	0.009	0.010	0.012	0.009	0.010	0.011	0.009	0.014	1.000	1.000
IL	0.119	0.085	0.087	0.273	0.085	0.164	1.000	1.000	1.000	1.000	1.000
IN	0.035	0.035	0.033	0.042	0.046	0.039	0.616	0.616	1.000	1.000	1.000
KS	0.008	0.015	0.181	0.194	0.134	0.181	0.427	0.607	0.519	1.000	1.000
KY	0.055	0.055	0.052	0.071	0.055	0.052	0.086	0.086	0.086	1.000	1.000
LA	0.037	0.005	0.010	0.056	0.093	0.324	0.406	0.406	0.448	1.000	1.000
MA	0.298	0.658	0.324	0.517	1.625	0.324	3.733	1.000	1.000	1.000	1.000
MD	0.165	0.313	0.312	0.432	0.677	0.273	1.032	0.767	1.000	1.000	1.000
ME	0.014	0.017	0.014	0.098	0.110	0.115	0.086	0.086	0.086	1.000	1.000
MI	0.014	0.014	0.017	0.017	0.008	0.029	0.452	0.452	1.000	1.000	1.000
MN	0.078	0.063	0.078	0.129	0.063	0.061	0.313	1.000	1.000	1.000	1.000
MO	0.017	0.012	0.010	0.053	0.017	0.098	0.142	0.142	0.258	1.000	1.000
MS	0.015	0.015	0.014	0.024	0.015	0.024	0.027	0.030	0.033	1.000	1.000
MT	0.008	0.008	0.009	0.011	0.011	0.009	0.039	0.025	0.039	0.039	0.060
NC	0.028	0.056	0.086	0.733	0.103	0.047	0.159	0.853	1.000	1.000	1.000
ND	0.008	0.008	0.037	0.048	0.072	0.052	0.121	0.121	0.121	0.212	1.000
NE	0.035	0.035	0.225	0.225	0.328	0.225	0.619	0.557	0.854	1.000	1.000
NH	0.065	0.127	0.058	0.098	0.189	0.247	0.208	0.135	0.135	1.000	1.000
NJ	0.057	0.152	0.057	0.081	0.149	0.081	0.239	1.050	1.000	1.000	1.000
NM	0.025	0.024	0.023	0.032	0.025	0.023	0.037	0.037	0.037	1.000	1.000
NV	0.277	0.147	0.147	0.204	0.217	0.162	0.197	0.201	0.216	1.000	1.000
NY	0.093	0.261	0.738	1.015	0.816	0.555	1.000	1.000	1.000	1.000	1.000
OH	0.030	0.043	0.036	0.259	0.032	0.049	0.294	0.191	0.294	1.000	1.000
OK	0.005	0.007	0.006	0.039	0.025	0.034	0.327	0.436	1.000	1.000	1.000
OR	0.020	0.024	0.024	0.240	0.028	0.024	0.150	0.147	0.147	1.000	1.000
PA	0.018	0.119	0.073	0.372	0.138	0.201	1.430	1.000	1.000	1.000	1.000
RI	0.037	0.033	0.033	0.081	0.062	0.073	0.175	0.245	1.000	1.000	1.000
SC	0.011	0.011	0.051	0.051	0.057	0.051	0.070	0.081	0.090	1.000	1.000
SD	0.008	0.011	0.035	0.043	0.065	0.035	0.063	0.041	0.063	0.081	0.449
TN	0.035	0.035	0.044	0.061	0.053	0.044	0.388	0.889	1.000	1.000	1.000
TX	0.040	0.057	0.087	0.458	0.504	0.458	0.974	1.000	1.000	1.000	1.000
UT	0.039	0.039	0.038	0.052	0.040	0.038	0.049	0.041	0.115	1.000	1.000
VA	0.085	0.163	0.071	0.083	0.170	0.083	0.170	0.170	0.170	1.000	1.000
VT	0.014	0.055	0.039	0.049	0.073	0.043	0.056	0.052	0.083	1.000	1.000
WA	0.042	0.030	0.059	0.243	0.120	0.109	1.000	1.000	1.000	1.000	1.000
WI	0.012	0.014	0.053	0.074	0.059	0.053	0.079	0.144	0.179	1.000	1.000
WV	0.010	0.010	0.010	0.012	0.010	0.010	0.009	0.009	0.009	0.010	0.058
WY	0.045	0.082	0.047	0.128	0.088	0.047	0.128	0.116	0.116	0.131	0.303

FIGURE S1 Propensity score generalized boosted modeling (GBM) regression results.


inc
citydensity
gas
citygdp
citypop
lpop
pop_u2
s177
0
5
10
15
20
25
30
Relative influence

532