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HIGHLIGHTS

We estimate effects of Uber/Lyft market entry on U.S. urban areas

Vehicle registrations per capita increase by 0.7% on average

Effect on registrations is larger in car-dependent and slow-growth cities

Transit displacement is larger in cities with high income or fewer children

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The impact of Uber and Lyft on vehicle ownership, fuel economy, and transit across U.S. cities

Jacob W. Ward,[1] Jeremy J. Michalek,[1,6,*] Constantine Samaras,[2] Inês L. Azevedo,[3] Alejandro Henao,[4] Clement Rames,[4] and Tom Wenzel[5]

SUMMARY

We estimate the effects of transportation network companies (TNCs) Uber and Lyft on vehicle ownership, fleet average fuel economy, and transit use in U.S. urban areas using a set of difference-in-difference propensity score-weighted regression models that exploit staggered market entry across the U.S. from 2011 to 2017. We find evidence that TNC entry into urban areas causes an average 0.7% increase in vehicle registrations with significant heterogeneity in these effects across urban areas: TNC entry produces larger vehicle ownership increases in urban areas with higher initial ownership (car-dependent cities) and in urban areas with lower population growth (where TNC-induced vehicle adoption outpaces population growth). We also find no statistically significant average effect of TNC entry on fuel economy or transit use but find evidence of heterogeneity in these effects across urban areas, including larger transit ridership reductions after TNC entry in areas with higher income and more childless households.

INTRODUCTION

The past decade saw the advent and growth of ridesourcing, a travel mode in which a passenger uses a mobile device to request a ride with a nearby driver at a transaction price determined in real time by a transportation network company (TNC), such as Uber or Lyft. During this period, the daily number of Americans traveling in for-hire vehicles more than doubled (Federal Highway Administration, 2019; Conway, 2018). Uber, which launched its basic level of service (UberX), in 2012, had entered 224 U.S. urban areas (approximately half of those identified by the U.S. Census) by the end of 2017, as Figure 1 and Table S2 show. In absolute terms, the 0.5% of total passenger trips now served by TNCs is still relatively small, but in urban areas, the effects can be substantial—by 2016, TNCs accounted for 15% of all intra-San Francisco vehicle trips on an average weekday (San Francisco County Transportation Authority, 2017).

While a growing body of research finds that TNCs lead to significant changes in transportation-related outcomes such as new vehicle purchases in China (Gong et al., 2017), traffic congestion (Li et al., 2016), motor vehicle homicide (Greenwood and Wattal, 2015; Lagos et al., 2019; Barrios et al., 2019), and passenger safety (Chaudhry et al., 2018), as well as other outcomes as varied as AirBnB demand (Zhang et al., 2018), entrepreneurial activity (Burtch et al., 2018), and urban crime (Weber, 2019), few studies have yet reached conclusions about effects of TNCs on energy and climate change-relevant outcomes like petroleum consumption and greenhouse gas (GHG) emissions. Both outcomes are particularly important for the transportation sector, which has long consumed the bulk of petroleum products produced and recently became a greater GHG emitter than any other sector in the U.S (Davis et al., 2019). These outcomes are a function of total vehicle travel and fuel efficiency and are related to the size of the vehicle fleet and availability of transportation alternatives. Higher vehicle ownership rates have historically been associated with both higher transportation energy consumption per capita (Newman and Kenworthy, 2006) and greater emissions from vehicle production: there were nearly 17 million new vehicles sold in the U.S. in 2018, each generating nearly 8 metric tons of GHGs from the manufacturing process (Davis et al., 2019) (Figure S1).

The introduction of TNC services could disrupt the relationship between vehicle ownership and transportation energy consumption and emissions not only in the U.S. but also globally, including in countries like China and India, where vehicle registration numbers are climbing more than 10% each year (Davis et al.,

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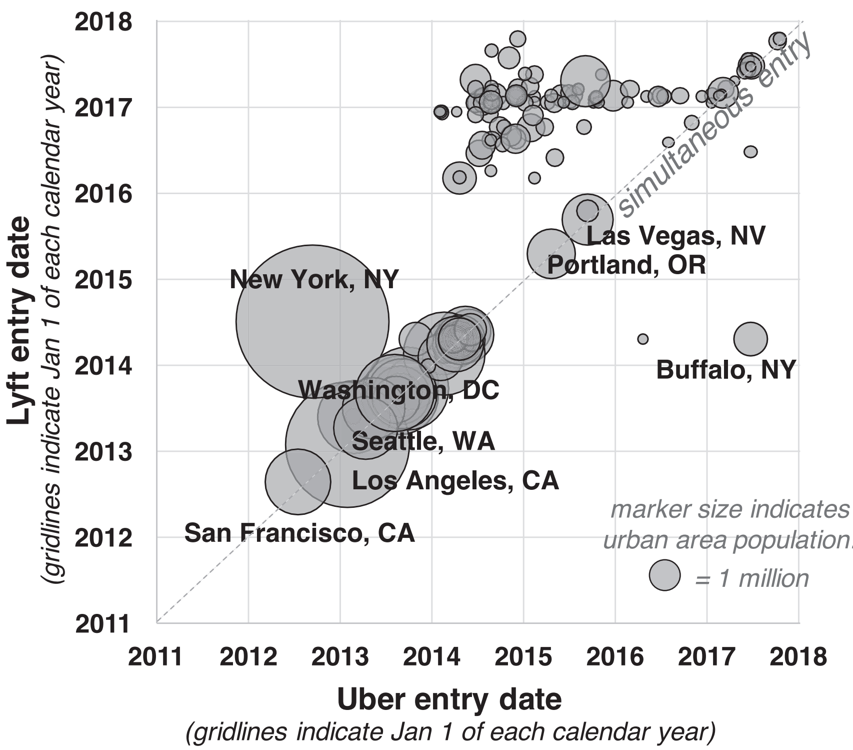

Figure 1. Uber and Lyft entry over time by urban area

Uber entry date (x axis) is compared to Lyft entry date (y axis) for each of the 224 urban areas with TNC access by the end of 2017. Urban areas are depicted by bubbles proportional to population size.

2019). There are reasons to believe, *a priori*, that TNC market entry could increase vehicle ownership, as aspiring TNC drivers purchase new vehicles, or decrease vehicle ownership, as passengers with access to TNC services shed or delay the purchase of a private vehicle. Similarly, TNC market entry could potentially increase average vehicle fuel economy, as TNC drivers anticipating high-mileage invest in relatively efficient vehicles, or decrease vehicle fuel economy, if TNC drivers are attracted to larger—and less fuel-efficient—vehicles to accommodate more riders and associated price premiums (through "Uber XL" and "Lyft XL" services). TNC entry could also increase transit ridership, by improving access, or decrease transit ridership, if acting as a replacement. And the relative impact of each of these (and other) effects may vary across urban areas. As TNCs continue to diffuse across global cities, understanding the impact on total vehicles, energy, and emissions becomes increasingly important.

The few published articles that do examine TNC impacts on energy and the environment are constrained to survey methods or limited geographies, and, when taken together, reach inferences and conclusions that initially may appear inconsistent with one another. Previous analyses of TNC effects on vehicle ownership, for example, have found either a decrease in vehicle ownership (Ward et al., 2019) or that "ridesourcing probably did not influence car ownership behavior" (Rayle et al., 2016). Considered with appropriate context and constraints, these findings are not necessarily inconsistent (the decline in vehicle ownership was modeled at the U.S. state level, while the no-effect finding was based on a survey specific to San Francisco, CA), but their differences point to the need for a coherent framework within which to interpret such findings and their associated implications.

As described above, plausible underlying narratives can explain either an increase or a decrease in vehicle ownership after TNC market entry (or a net-zero effect, as a result of the simultaneous presence of pressures in both directions): new economic opportunity afforded by TNC entry could motivate would-be TNC vehicle drivers to increase vehicle registrations; whereas, private vehicle-free mobility newly afforded to would-be passengers could prompt vehicle shedding and/or new vehicle purchase delays. Several working papers use surveys to understand these vehicle ownership relationships: a positive correlation for TNC drivers (Berliner and Tal, n.d.) and a negative correlation for TNC passengers (Clewlow and Mishra, 2017; Alemi et al., 2018a, 2018b; Feigon and Murphy, 2016). Other working papers use empirical panel data to observe or model a net effect, finding both increases (Gong et al., 2017; Schaller Consulting, 2018) or decreases (Hampshire et al., 2017) in vehicle ownership.

Effects of TNCs on fleet fuel economy are also ambiguous *a priori*, as drivers motivated by lower operating costs could plausibly migrate to newer, more efficient vehicles (Uber and Lyft require newer vehicles in some cities (Uber, 2020)), just as drivers motivated by the potential for large-party-trip price premiums may shift to larger, less efficient vehicles. Only one peer-reviewed article to date reports a TNC-fuel economy relationship, finding that ridesourcing vehicles are more efficient compared to non-ridesourcing vehicles (Wenzel et al., 2019). Two working papers agree (Gong et al., 2017; Kitchel and Wise, 2017); while another suggests that TNC vehicle fuel economies are lower than those of taxis (Wagner, 2017).

The effects of TNCs on public transit ridership are similarly equivocal, with several survey-based studies finding ridesourcing can either replace transit (Rayle et al., 2016) or complement it (Yan et al., 2018; Zhang and Zhang, 2018; Hall et al., 2018) as an effective extension of an otherwise fixed network (several working papers also suggest replacement (Alemi et al., 2018b; Norris and Xiong, 2019; Manville et al., 2018) or complementarity (Feigon and Murphy, 2016; Schweiterman and Livingston, 2018)). Importantly, two of these previous studies report heterogeneous effects—a more positive transit correlation is found either (1) in bigger cities as well as cities with smaller transit agencies (Hall et al., 2018) or (2) as a function of high population density and households with fewer vehicles (Zhang and Zhang, 2018)—and a working paper finds commuter rail usage increases while city bus usage declines, on average, with variation in effects across cities (Babar and Burtch, 2017).

We propose that heterogeneity of the effects of TNC entry in different types of cities may be responsible for some of the apparent discrepancies in reported effects, since average effects can look different depending on what subset of locations are included in the study scope and how they are aggregated. To quantify and systematically organize the potentially fundamental changes to personal travel across U.S. urban areas and associated energy and environmental outcomes, we estimate effects of Uber and Lyft entry on vehicle ownership, fleet average fuel economy, and transit ridership outcomes using a set of difference-in-difference propensity score-weighted regression models that exploit staggered TNC market entry into urban areas across the U.S. from 2010 to 2017. We combine annual individual vehicle registration data from Polk/IHS Markit with annual ZIP code-level sociodemographic data from the U.S. Census Bureau and aggregate to the urban area to estimate effects. We find that estimated vehicle ownership, fuel economy, and transit ridership effects of TNC entry vary across urban areas. Accordingly, we characterize this heterogeneity across urban areas and estimate that (1) TNC entry increases vehicle ownership on average, and this increase is larger in urban areas with higher initial vehicle ownership ("car-dependent cities") and in urban areas with lower growth rates; (2) the effect of TNC entry on fleet fuel economy is not statistically significant on average, but it is more positive in urban areas with lower rates of childless households than in urban areas with higher rates of childless households; and (3) the effect of TNC entry on transit ridership is not statistically significant on average, but it is more negative (larger reduction) in urban areas with higher rates of childless households or higher income than in urban areas with lower rates of childless households or lower income. These results offer a novel framework for informing future energy, transportation, and urban planning decision-making.

RESULTS

Analyses are conducted using a series of difference-in-difference models with inverse probability of treatment weighting (IPTW). The difference-in-difference method is a quasi-experimental technique that compares trends before and after a treatment—i.e., TNC market entry in this study—against counterfactual trends in an untreated control group, and IPTW weights help ensure the control group is appropriately comparable to the treatment group (see Transparent Methods in the SI for details and Table S10 for a comparison with unweighted results). We specify models to estimate average TNC entry effects on vehicle ownership, fuel economy, and transit ridership and then characterize heterogeneity in this effect by (1) leveraging two exploratory methods (heterogeneous treatment effect [HTE] and cluster analysis) to identify explanatory variables associated with differences in treatment effects and (2) estimating interaction effects of these identified variables in our primary specification (testing the null hypothesis that these variables do not influence treatment effects). Specifically, in our first exploratory method, we conduct HTE analysis to

Table 1. Results for average effects

	Dependent variable, log:		
	Vehicle registration, per capita	Average fuel economy	Transit trips, per capita
Treatment	0.007**	3.00×10^{-4}	5.19×10^{-4}
	(0.004)	(8.76×10^{-4})	(0.0116)
Covariate controls	Y	Y	Y
Time fixed effects	Y	Y	Y
Group fixed effects	Y	Y	Y
Group time trends	Y	Y	Y
Observations	3395	3395	1848
Deg. freedom	2894	2894	1569
Adjusted R-Sq.	0.948	0.979	0.998

Covariate, time fixed effects, group fixed effects, and group time trend coefficient estimates not shown. *p<0.1; **p<0.05; ***p< 0.01.

Average treatment effects of TNC entry on urban areas in the U.S. from three regression models estimating (1) vehicle registrations per capita, (2) average fuel economy, and (3) transit ridership (coefficients for control variables, fixed effects, and linear time trends are excluded for brevity). Expanded results and a comparison with OLS results are presented in Table S10.

estimate urban area-specific TNC effects and identify factors that differ between urban areas with positive versus negative estimated effects. In a second, complementary exploratory method, we cluster similar urban areas, calculate cluster-specific TNC effects, and identify factors that differ between clusters with statistically significant versus non-significant estimated effects. Finally, in our primary specification, we add targeted treatment interaction terms identified by the HTE and cluster analysis to our regression model to confirm whether these urban area characteristics explain the heterogeneity in TNC entry effects across urban areas. We present average effect results first (Table 1), followed by HTE (Figure 2, Table 2), cluster analysis (Figure 3, Table 3), and results of our primary specification (Table 4, Figure 4).

Average effect

On average, we find TNC entry in an urban area increases per capita vehicle registrations by 0.7% (95% confidence interval: 0.1–1.3%), and we find no significant average effect on fleet average fuel economy or per capita transit trips (Table 1). Each estimate can be interpreted as a weighted average across urban areas (Table S2, Figure S4). The estimated average effect on registrations is also robust to a battery of robustness checks and sensitivity analyses (Table S9), including randomized treatment (Figure S7), leave-one-out analysis (Figures S8 and S9), leave-multiple-out analysis (Figure S10), alternative treatment encoding (Table S12), disaggregation of transit ridership data (Table S13), and an event study (Figure S6). When data are aggregated to the state level of resolution, rather than the urban area level, estimated average effects are negative (Table S11), consistent with a study by Ward et al. (2019) using state-level data. This suggests heterogeneous effects: When effects of TNC entry differ across urban areas, averaging across states, rather than urban areas, can produce different estimates – in this case changing sign. In the following sections, we use HTE and cluster analysis to identify features of urban areas that are important for determining the type of response urban areas have to TNC entry, and we use these results to inform our primary specification, testing for interaction effects with these urban area features.

Heterogeneous treatment effects

In a first approach to exploring heterogeneity, we estimate urban area-specific TNC entry effects and find estimates ranging from an 11.0% decrease in per capita vehicle registrations in Redding, CA to a 15.7% increase in Gainesville, FL, and from a 1.9% decrease in fleet average fuel economy in Greely, CO to a 2.6% increase in Thousand Oaks, CA. Transit ridership data are unavailable for nearly half of urban areas and so are not reported in this approach. Figure 2 shows the distribution of those estimated effects in urban areas that are statistically significant, and Table S5 provides the full results.

TNC entry is associated with a significant decline in vehicle registrations per capita in 38 urban areas (17% of 224 treated urban areas) and an increase in 58 (26%) urban areas. Conducting a linear regression using a

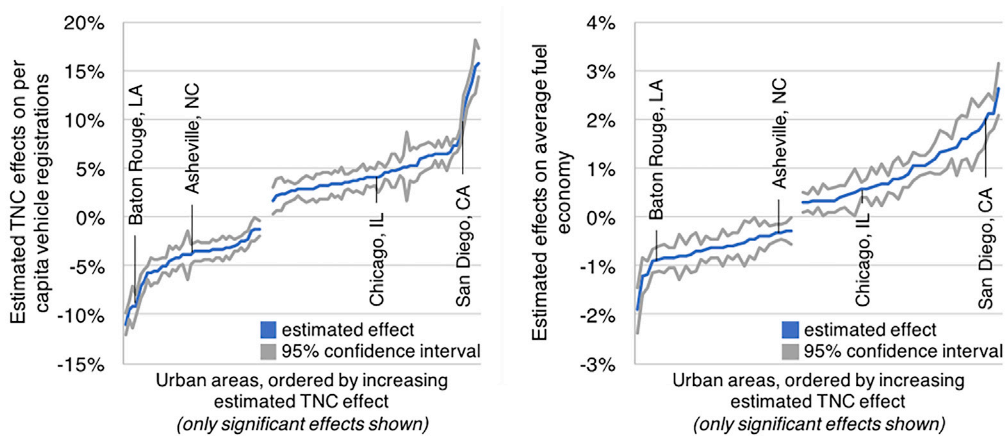

Figure 2. Heterogeneous treatment effect results

Effects on TNC entry on per capita vehicle registrations (left) and fleet average fuel economy (right), ranked by urban area from lowest to highest; only statistically significant effects are shown. The center blue line illustrates treatment effects, and the gray bands indicate 95% confidence intervals. Detailed results are presented in Table S5.

binary variable equal to 1 if an urban area has a statistically significant positive estimated HTE effect and 0 if it has a statistically significant negative estimated HTE effect (other urban areas are excluded) (Table 2), we find that urban areas with positive estimated effects on vehicle registrations tend to be smaller, lower income, and have more vehicle registrations per capita, transit commuters, and childless households than urban areas with negative estimated effects. TNC entry is also associated with a significant decline in fleet average fuel economy in 30 (13%) urban areas and increase in 38 (17%) urban areas; urban areas with positive effects on fleet average fuel economy also tend to be smaller, lower income (at the 90% confidence level), and have more vehicle registrations per capita and transit commuters but fewer households without children than urban areas with negative effects. Estimated effects on per capita vehicle registrations and average fuel economy are not significant in 57% and 70% of urban areas, respectively (not shown). Because each treated urban area observes only one TNC entry event, our ability to confidently identify effects for specific urban areas is limited, and we use this analysis primarily to identify candidate hypotheses for which urban area attributes are important in determining the type of response an urban area will have to TNC entry.

Cluster effects

As a complementary approach to characterizing heterogeneity, we use hierarchical clustering to identify and group similar urban areas and then estimate TNC entry effects for each cluster. In Figure 3 we show for alternative exogeneous specifications for the number of clusters the resulting effect in each cluster of TNC entry on per capita vehicle registrations (detailed results for the 3- and 4-cluster cases are presented in Table S6, and results for alternative clustering methods and clustering features are presented in Figures S12 and S13). Significant estimates range from a 1%–3% increase (excluding the single-urban-area cluster containing New York City, which contains only one treatment observation), and all estimates range from a 1.8% decrease to a 3.0% increase. Conducting a linear regression for the case of 3 clusters using a binary variable equal to 1 if an urban area is in a cluster with a statistically significant positive estimated effect and 0 otherwise, we find that the significant-and-positive-effect clusters include urban areas that are, on average, smaller with lower incomes and population growth rates, higher vehicle ownership rates, and more households without children compared to the clusters with estimated effects that are not statistically significant (Table 3). Results for 4 clusters are presented in Figure S11.

Figure 3 also shows for each cluster the effect of TNC entry on average fuel economy, significant estimates of which range from a 0.4%–0.5% increase and all estimates of which range from a 0.07% decrease to a 0.4% increase. As was the case for heterogeneity in estimated vehicle registration effects, the cluster with significant-and-positive-effects includes urban areas that are, on average, smaller with lower incomes and population growth rates and higher vehicle ownership rates and more households without children compared to the clusters with insignificant-effects, as Table 3 again shows.

Table 2. Urban-area attributes influencing treatment effects: HTE results

	Dependent variable:	
	Indicator: TNC entry has a statistically significant [1 = positive, 0 = negative] HTE-estimated effect for per capita registrations	Indicator: TNC entry has a statistically significant [1 = positive, 0 = negative] HTE-estimated effect for fleet fuel economy
Vehicle registrations per capita	0.284**	0.628**
	(0.141)	(0.141)
Population, log	−0.040**	−0.033**
	(0.017)	(0.017)
Δ population, log	−0.448	0.533
	(0.765)	(1.051)
Income	−0.282***	−0.161*
	(0.095)	(0.095)
Transit commuters, log +1	1.396**	2.528***
	(0.662)	(0.637)
Unemployment rate	−1.133	0.936
	(0.822)	(0.834)
Childless household rate	0.818***	−2.238***
	(0.294)	(0.305)
Gasoline price	−0.003	−0.002
	(0.003)	(0.003)
Observations	3395	3395
Degrees of freedom	2895	2895
Adjusted R-squared	0.042	0.057

*p < 0.1; **p < 0.05; ***p < 0.01.

Coefficients of a linear model estimating whether the HTE-estimated urban area effect for vehicle registrations or fuel economy is statistically significant ($p < 0.05$) and positive (dependent variable indicator = 1) versus negative (dependent variable indicator = 0) as a function of other covariates used in the primary regression. Results are used to identify candidate urban area characteristics that may be important in determining response to TNC entry.

Estimates are overall robust to the battery of robustness checks already described as well as to additional checks for alternative clustering methods (with further detail the SI). New York City appears as a "cluster" of just one urban area in each figure and is not explicitly explored further in this analysis because the intent is to identify trends across cities, and single-city estimates based on a single TNC entry event may not be reliable. For the effect of TNC entry on transit ridership, none of our clusters had significant effects. Like the HTE analysis, we use the results of this analysis primarily to identify candidate hypotheses for which urban area attributes are important in determining the type of response an urban area will have to TNC entry.

Primary model specification

In our primary specification for characterizing differences across urban areas, we introduce treatment interaction regressions that include the six dimensions of urban area attributes suggested by either the HTE results or the clustering analysis results as being important to determining the direction of TNC entry effects: vehicle registrations per capita (in a pre-treatment reference year, 2010, to avoid endogeneity in modeling vehicle registrations in 2011–2017), population, population growth, income, the percentage of commuters who travel by transit, and the percentage of households without children (all also measured in a pre-treatment reference year, 2011) (Table S8). As Table 4 and Figure 4 show, we find evidence of heterogeneity in TNC effects across all outcomes studied: larger increases on vehicle ownership in urban areas with higher initial vehicle ownership and lower growth rates; larger increases on average fuel economy in urban areas with lower childless households rates; and

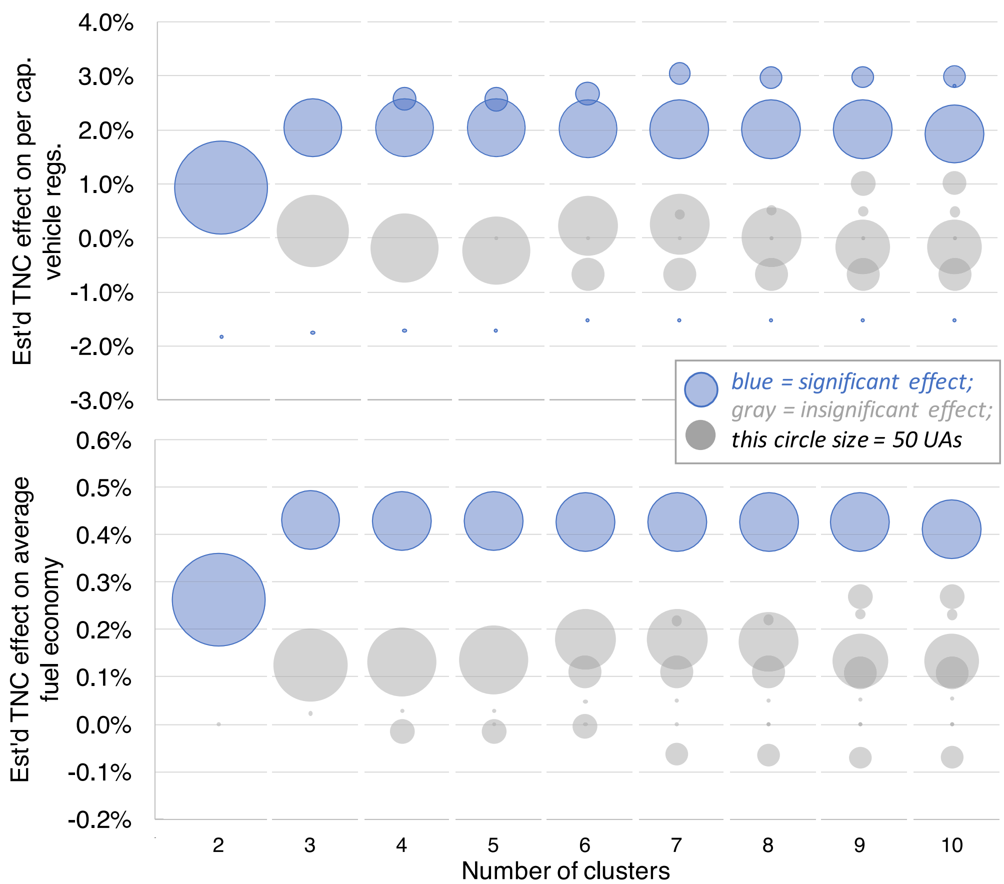

Figure 3. Cluster analysis results

TNC treatment effect on the change in per capita vehicle registrations (top) and average fuel economy (bottom) varies by urban area typology and is consistently significant and positive (indicated in blue) for one-to-two clusters of urban areas across a sweep of exogenously specified cluster numbers (excluding the single-urban-area cluster containing New York City). Statistically significant effects are highlighted in blue, and estimates that are not significant are gray. The size of each circle reflects the number of urban areas in each cluster; note that the weighted average (by number of urban areas per cluster) of cluster effects is consistent across the number of clusters and with the average estimates in Table 1. Detailed results are presented in Table S6.

larger decreases in transit ridership in urban areas with higher incomes and higher childless households rates. Estimates are generally robust to a battery of robustness checks (Table S9), including randomized treatment (Figure S7), leave-one-out analysis (Figures S8 and S9), leave-multiple-out analysis (Figure S10), alternative quantile resolution (Table S15), continuous interactions (Table S16), and corrections for multiple hypothesis tests (Table S14).

DISCUSSION

We apply HTE analysis, cluster analysis, and a regression analysis with interaction effects as three different ways to characterize the heterogeneity of vehicle ownership, fuel economy, and transit ridership impacts as Uber and Lyft enter into urban areas. Our results suggest that access to these TNC services has significant and heterogeneous effects on vehicle ownership (per capita vehicle registrations). All three methods agree that TNC entry tends to produce larger increases in vehicle ownership for those urban areas with higher initial vehicle ownership (Table S8). So, "car-dependent cities" (urban areas in the top 50% of vehicle registrations per capita) remain or become even more so after the introduction of TNCs, whereas car ownership is not necessarily increased when TNCs enter less car-dependent areas. And our primary specification suggests that while TNC-stimulated new vehicle acquisitions tend to outpace new residents in slower-population-growth areas, in

Table 3. Urban-area attributes influencing treatment effects: cluster analysis results

	Dependent variable:	
	Indicator: TNC entry [1 = has, 0 = does not have] a statistically significant positive cluster-estimated effect for per capita registrations	Indicator: TNC entry [1 = has, 0 = does not have] a statistically significant positive cluster-estimated effect for fleet fuel economy
Vehicle registrations per capita	1.023***	1.023***
	(0.083)	(0.083)
Population, log	−0.032***	−0.032***
	(0.009)	(0.009)
Δ population, log	−5.663***	−5.663***
	(0.439)	(0.439)
Income	−0.243***	−0.243***
	(0.052)	(0.052)
Transit commuters, log +1	0.695	0.695
	(0.516)	(0.516)
Unemployment rate	−0.080	−0.080
	(0.386)	(0.386)
Childless household rate	1.155***	1.155***
	(0.146)	(0.146)
Gasoline price	0.004*	0.004*
	(0.002)	(0.002)
Observations	3395	3395
Degrees of freedom	2895	2895
Adjusted R-squared	0.1892	0.1892

*p < 0.1; **p < 0.05; ***p < 0.01.

Coefficients of a linear model estimating whether the cluster containing each urban area has or does not have a significant ($p < 0.05$) positive estimated TNC effect on vehicle registrations or fuel economy as a function of other covariates used in the primary regression. Results are identical for both dependent variables because the set of clusters with positive effects are identical for the 3-cluster case. Results for the 4-cluster case are presented in Figure S11. Results are used to identify candidate urban area characteristics that may be important in determining response to TNC entry.

faster-population-growth areas, more new residents afforded the flexibility of being potential TNC passengers depresses overall per capita private vehicle registrations.

Our interaction effects model and our HTE model also agree that TNC entry tends to produce larger increases in fleet average fuel economy in urban areas with fewer childless households, but our cluster analysis results suggest the opposite. One possible interpretation for the importance of childless households is that the purchase of efficient new vehicles by new TNC drivers results in a smaller relative efficiency increase in urban areas with a higher concentration of smaller cars than in urban areas with a higher concentration of family cars. Increases in average fuel economy can reduce fuel consumption and associated emissions, although the net effect also depends on potential changes in travel behavior, which was not studied here due to lack of annual vehicle travel distance data at the urban area level.

Finally, the interaction effects model suggests that TNC entry tends to produce larger decreases in transit ridership for urban areas with higher incomes and childless household rates, (we did not identify statistically significant results for transit in our HTE and cluster analysis models). A potential interpretation is that TNCs have a greater tendency to displace transit in cities where potential passengers possess a greater ability to pay for more expensive, more convenient travel modes and where potential passengers are childless and may have fewer family constraints, such as car seats, and different

Table 4. Results for primary model specification

	Dependent variable, log: Vehicle registration, per capita	Average fuel economy	Transit trips, per capita
Treatment	0.006	0.002**	0.003
	(0.008)	(0.001)	(0.027)
Treatment × $1_{Top50\%\_VehicleRegistrations}$	0.009**	-2.2×10^{-5}	−0.002
	(0.004)	(4.2×10^{-4})	(0.013)
Treatment × $1_{Top50\%\_Population}$	−0.006	8.5×10^{-5}	0.024
	(0.008)	(6.9×10^{-4})	(0.021)
Treatment × $1_{Top50\%\_PopulationGrowth}$	−0.009**	-5.2×10^{-4}	−0.002
	(0.004)	(3.8×10^{-4})	(0.013)
Treatment × $1_{Top50\%\_ChildlessHHRate}$	0.003	−0.001**	−0.026**
	(0.004)	(0.000)	(0.013)
Treatment × $1_{Top50\%\_Income}$	0.000	-4.6×10^{-4}	−0.051***
	(0.005)	(4.4×10^{-4})	(0.017)
Treatment × $1_{Top50\%\_TransitRidership}$	0.004	-5.5×10^{-4}	0.027
	(0.005)	(4.2×10^{-4})	(0.020)
Covariate controls	Y	Y	Y
Time fixed effects	Y	Y	Y
Group fixed effects	Y	Y	Y
Group time trends	Y	Y	Y
Observations	3395	3395	1584
Deg. freedom	2407	2407	1034
Adjusted R-sq.	0.972	0.996	0.998

Covariate, time fixed effects, group fixed effects, and group time trend coefficient estimates not shown. [†]computed post-hoc and not directly estimated; *p < 0.1; **p < 0.05; ***p < 0.01.

Treatment effects of TNC entry in US urban areas from three regression models for (1) vehicle registrations per capita, (2) fleet average fuel economy, and (3) transit trips per capita, each including interactions with categorical measures of vehicle ownership, population, population growth, childless household rate, income, and transit commuters. $\mathbf{1}_{Top50\%\_X}$ is an indicator function that is 1 for urban areas with values of characteristic X in the top 50% of all urban areas in the data set (0 otherwise). Coefficients for controls, fixed effects, and linear time trends are omitted for brevity. Alternative specifications and robustness checks are presented in Tables S9–S16.

travel behavior, such as frequenting bars and restaurants. Declines in transit ridership affect transit revenues and potentially affect service availability and access. Additionally, diversion of trips from transit to TNC travel has implications for energy use, emissions, and road congestion.

Limitations of the study

Our analysis controls for all described urban area covariates using an approach "doubly robust" to model specification by including these controls in the regression specification as well as in determining propensity score weights using a flexible functional form via gradient boosting. The difference-in-difference model specification also controls for unobserved effects, to the extent that they are time-invariant in each urban area (captured by group fixed effects) or consistent across urban areas (captured by time fixed effects). The addition of linear time trends provides further flexibility to control for different trends across urban areas. Remaining factors for which we (and similar econometric models) cannot control are any unobserved nonlinear changes in trends of unobserved variables that differ across urban areas. We are not aware of additional factors that changed nonlinearly and heterogeneously across urban areas during the analysis period that are correlated with treatment and substantially influence our dependent variables enough to bias our estimates, and our robustness checks protect against some potential effects of this form (e.g.: via leave-one-out tests).

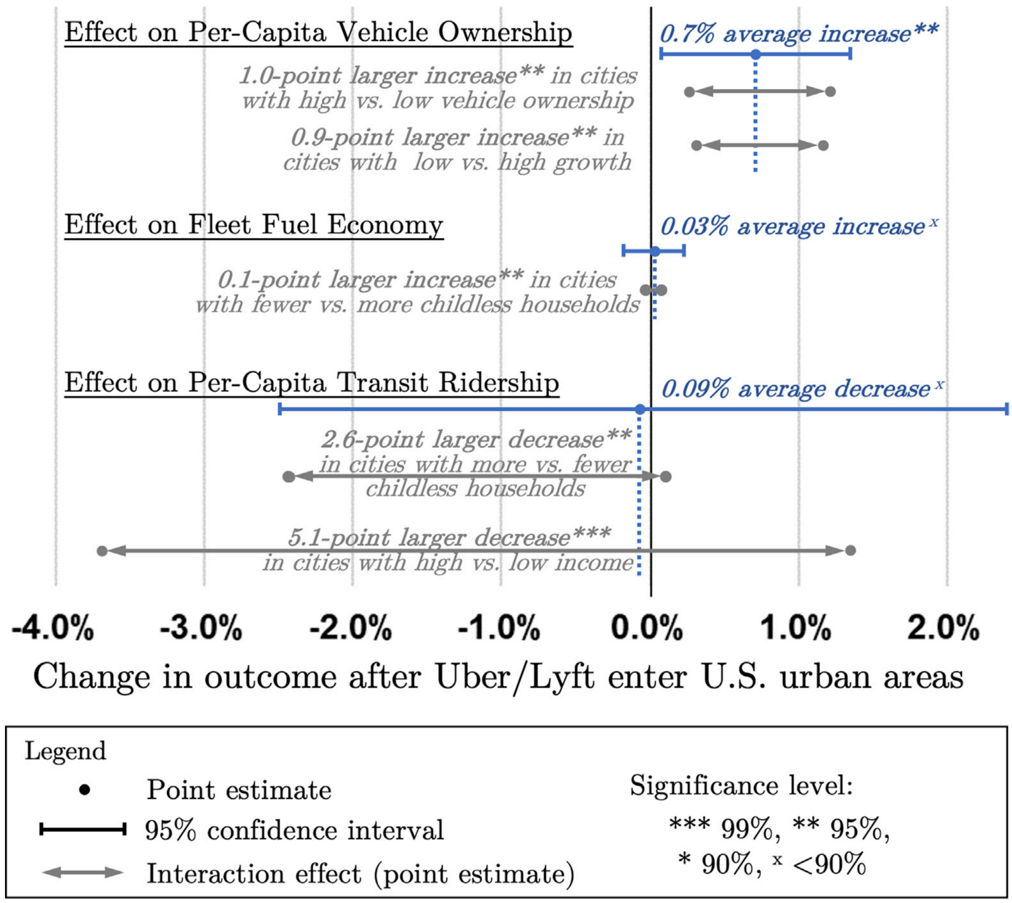

Figure 4. Summary of results for primary model specification

Visual summary of regression model findings estimating TNC market entry effects on vehicle ownership, fuel economy, and transit ridership. Average effects for each outcome are shown in blue (with an error bar indicating a 95% confidence interval), and heterogeneous effects are shown in gray (with arrows indicating the estimated interaction effects). Data from Tables 1 and 4.

Interpreting the estimated effects presented here as causal relies on three key assumptions of the difference-in-difference approach: (1) exogeneous intervention, (2) parallel trends, and (3) no spillover. For the exogeneous intervention condition, informal discussions with TNCs about market entry strategy suggests that decisions were not made by monitoring differential nonlinear changes in trends across urban area variables other than monitoring frequency of local web searches for terms like "uber" and "lyft". Our event study results (Figure S6) are consistent with exogeneous intervention because, for registrations as the dependent variable, we observe no statistically significant effects prior to entry and observe statistically significant and positive effects every year after entry. For the parallel trends condition, use of linear time trends provides flexibility in establishing parallel trends relative to potentially distinct linear trends in each urban area, and it is encouraging that our event study (Figure S6), which does not assume parallel trends, also produces a positive (although larger) effect estimate after entry. For the spillover condition, we view it as safe to assume the effect of residents in one city changing vehicle ownership or transit ridership patterns in response to entry of TNCs in other cities is negligible.

Our analysis identifies net overall outcomes after TNCs enter urban areas. We cannot identify more detailed changes to vehicle fleet mix or changes in specific cities with the available data, and there are potentially multiple alternative—and sometimes competing—narratives that might explain these trends. Additional study of the effect of TNC market entry on vehicle fleet composition and travel behavior across the fleet is needed for deeper insight about the mechanisms that produce these outcomes. Our analysis is also constrained to a relatively short time period and relatively simple measures of TNC availability and use; whereas, future study can build on this work with more detailed data. Given the global growth trends of TNC services, vehicle manufacturing, and travel-related GHG, and air pollutant emissions, understanding and mitigating the environmental impacts of TNC use in urban areas is critical.

Resource availability

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Jeremy Michalek (jmichalek@cmu.edu).

Materials availability

This study did not generate new unique reagents.

Data and code availability

The data set and code used in this study have been deposited to Mendeley Data [https://doi.org/10.17632/8tpstn78dh.1], with the exception of vehicle registration and fuel economy data. Vehicle registration and fuel economy data are propriety to and available from IHS Markit; restrictions apply to the availability of these data, which were used under license for the current study, and so are available for purchase from IHS Markit.

METHODS

All methods can be found in the accompanying Transparent Methods supplemental file.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2020.101933.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: J. W. Ward conducted the literature review and led all data collection, model development and implementation, analysis, interpretation, and documentation. J. J. Michalek, C. Samaras, and I. L. Azevedo contributed to model development, interpretation, and documentation. A. Henao contributed to structuring models and interpreting model findings. C. Rames iteratively prepared data for analysis. T. Wenzel contributed to structuring models and independently verifying regression analysis findings.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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Supplemental Information

The impact of Uber and Lyft on vehicle ownership, fuel economy, and transit across U.S. cities

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1. TRANSPARENT METHODS

We use difference-in-difference (DID) models to estimate effects of the intervention (TNC entry into U.S. urban areas) by comparing the trends of treated and untreated groups before and after the treatment occurs. The DID technique is a quasi-experimental method that enables our models to isolate and estimate a TNC entry effect, even without a randomized controlled experiment. These specifications can control explicitly for relevant covariates as well as implicitly for potentially unobserved (or otherwise omitted) covariates (to the extent they are time invariant within each urban area or affect urban areas similarly over time) that could otherwise bias our estimates by differencing away similarities between treated and untreated groups (both of which are ostensibly similarly affected by any potentially omitted covariates). DID methods have been used previously to evaluate the effect of TNCs on transportation and several other outcomes. We employ inverse probability of treatment weighting (IPTW) to ensure that our control and treated groups are comparable and mitigating confounding (e.g.: TNCs systematically entering certain kinds of urban areas first). The details of our DID and IPTW implementations are described below.

1.1. Difference-in-Difference Model

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

$$y_{ut} = \beta x_{ut} + \boldsymbol{\alpha}^\top \mathbf{z}_{ut} + \gamma_u + \delta_t + \gamma_u t + \varepsilon_{ut} \tag{1}$$

where y_{ut} is the dependent variable of interest for urban area u and year t and represents either 1) vehicle registrations per capita, 2) average fuel economy, or 3) transit ridership. x_{ut} is the treatment (TNC indicator) with coefficient β. $\mathbf{z}_{ut}$ is a vector of controls (population, unemployment rate, income, portion of households with no children, percent of population commuting by transit, and state average gas price), with corresponding coefficients $\boldsymbol{\alpha}$. γ_u and δ_g are fixed-effects dummies for urban area u and year t, respectively; $\gamma_u t$ allows for linear time trends by urban area; and ε_{ut} is unobserved error.

Propensity Score

A potential concern arises if treatment (TNC entry) is conflated with other attributes of the treated and untreated groups (e.g.: if densely populated cities are treated more frequently than less densely populated cities). So, to control for potential systematic differences between treated and untreated groups, we apply both control variables and inverse probability of treatment weights (IPTW) in a weighted least-squares model. This model compares post-treatment trends in treated units with weighted trends in non-treated units, probabilistically weighted to resemble the treated states along attribute dimensions that are correlated with treatment. After estimating the probability of treatment, we compare measures of balance to confirm that the propensity score weights succeed in matching the control states' weighted pretreatment characteristics to those of the unweighted treatment states (that is, that the weighted control and unweighted treatment group are balanced).

We estimate propensity scores using gradient boosting (Friedman et al., 2000), which previous studies have shown as superior to simple logistic regression models for propensity score estimation (McCaffrey et al., 2013), to approximate the logistic model:

$$\log\left(\frac{p_{gt}(\mathbf{z}_{ut})}{1-p_{ut}(\mathbf{z}_{ut})}\right) = \sum_m f_m(\mathbf{z}_{ut}) + \epsilon_{ut}, \tag{2}$$

where p_{ut} is the probability of treatment for urban area u and year t; $\mathbf{z}_{ut}$ is the same vector of covariates for urban area u and year t as in equation (1), and ϵ_{ut} is unobserved error. We estimate the additive function f_m using gradient boosting, given the treatment and covariate data, and compute estimated probability of treatment $\hat{p}_{ut}$ for each urban area and year. The resulting estimates for probability of treatment are then used in a weighted regression for equation (1) (Austin and Stuart, 2015). Table S4 reports the resulting weights used; Table S3 summarizes improvements of balance of attributes across treated and untreated urban areas after weighting, and Figure S2 presents an influence diagram. Table S6 compares regression results with and without IPTW weighting. Figure S3 provides diagnostic plots for the IPTW regression.

Heterogeneous Treatment Effects Analysis

We estimate heterogeneous treatment effects by individual urban area in the following variation of our baseline specification:

$$y_{ut} = \beta_u x_{ut} + \boldsymbol{\alpha}^\top \mathbf{z}_{ut} + \gamma_u + \delta_t + \gamma_u t + \varepsilon_{ut}, \tag{3}$$

such that the coefficient β_u now takes on unique values for each urban area u. We subsequently fit an additional linear model to identify significant differences between urban areas where treatment effects are positive versus negative using the following specification:

$$\tau_u = \boldsymbol{\alpha}^\top \mathbf{z}_{ut} + \varepsilon_{ut}, \tag{4}$$

where τ_u is a binary indicator for whether the treatment effect is significant and positive or significant and negative (urban areas without significant estimated effects are excluded). Detailed results for the HTE model are presented in Table S5 and Figure S5.

1.2. Cluster Analysis

We use hierarchical clustering to identify groups of urban areas that are similar in terms of their observable features, employing an agglomerative (rather than divisive) algorithm, in hopes of finding larger groups of similar urban areas, and computing [dis]similarity across urban areas using Euclidean distances and Ward's minimum variance method (Murtagh and Legendre, 2011). For a given number of clusters, n, we re-specify our regression as:

$$y_{ut} = \boldsymbol{\kappa}_u^\top \boldsymbol{\beta} x_{ut} + \boldsymbol{\alpha}^\top \mathbf{z}_{ut} + \gamma_u + \delta_t + \gamma_u t + \varepsilon_{ut}, \tag{5}$$

where $\boldsymbol{\kappa}_u^\top = [\kappa_{1\mathrm{u}}\ \kappa_{2u} \dots\ \kappa_{nu}]$ is a vector indicating the cluster to which urban area u belongs ($\kappa_{iu} = 1$ if urban area u is in cluster i and $\kappa_{iu} = 0$ otherwise) and $\boldsymbol{\beta} = [\beta_1\ \beta_2 \dots \beta_n]^\top$ is the vector of treatment coefficients for each cluster. We run a series of models sweeping from $n \in \{2, 3, \dots, 10\}$ clusters and estimate cluster-specific TNC entry effects as described.

We test the sensitivity of our clustering analysis by varying the clustering algorithm (divisive rather than agglomerative), the distance measure (Manhattan rather than Euclidean), the linkage function (complete rather than Ward's method) and by using a subset (rather than all) of urban area features: vehicle registrations per capita, population, population density, and percent of population commuting by transit.

We again fit an additional linear model to identify significant differences between clusters of urban areas where treatment effects are positive and significant versus insignificant using the following specification:

$$\boldsymbol{\tau}_u = \boldsymbol{\alpha}^\top \mathbf{z}_{ut} + \varepsilon_{ut}, \tag{6}$$

where τ_u is a binary indicator for whether the treatment effect for the cluster to which an urban area belongs is significant and positive or not. Results for 3-cluster models are summarized in Table 3. Results for 3- and 4-cluster models are presented in Table S6.

1.3. Interaction Analysis

In a final variation on the primary regression in equation (1), we interact specific variables with treatment. We specify these interaction regressions as:

$$y_{ut} = \beta_1 x_{ut} + \beta_2 x_{ut} \zeta_{ut} + \boldsymbol{\alpha}^\top \mathbf{z}_{ut} + \gamma_u + \delta_t + \gamma_u t + \varepsilon_{ut}, \tag{7}$$

where β_1 is the average treatment coefficient and β_2 is a treatment interaction coefficient estimating how the average treatment varies with ζ_u, an element of $\mathbf{z}_{ut}$. We interact a categorical measure of ζ_{ut}: 1 indicates a value greater than the median for a given UA in a given year; while, 0 indicates not (Table S7 provides summary statistics). We use pre-treatment year 2011 for all categorical control variables except for the following: when the interaction term is vehicle registrations per capita, to avoid endogeneity problems (as a function of modeling a dependent measure of vehicle registrations per capita with an independent measure of the same), the interaction term refers to a pre-treatment categorization from 2010.

1.4. Robustness

We subject our results to a variety of checks including a set of robustness checks, sensitivity analysis, and event studies. We discuss each below. All significant effects in our primary model are robust (i.e., still estimated as significant at similar magnitude) to five robustness checks, with exceptions noted in Table S9, as follows:

(1) *Randomized Treatment*: we conduct placebo tests, in which we reassign the set of true TNC entry dates to other urban areas at random and re-specify our regressions, to ensure that the effects we estimate are unique to the particular observed pattern of treatments, rather than a result of the structure of the model (Figure S7). Estimated effects are considered robust if they fall in the tails (>95%) of the distribution of randomized treatment-estimated effects;
(2) *Leave-One-Out*: we conduct leave-one-out tests to ensure that our estimates do not hinge on accuracy of the timing of TNC entry in, or the data from, any one urban area. (Figure S8-Figure S9) Estimated effects are considered robust if they remain significant when systematically leaving each urban area out;
(3) *Leave-Multiple-Out*: because some dependent variables exhibit what could be perceived as discontinuities resulting from data collection/input or other error for several urban areas, we incrementally remove urban areas that exhibit the largest year-on-year change in decreasing order (Figure S10). Estimated effects are considered robust if estimated magnitude and significant are similar after systematically excluding up to 25 urban areas;
(4) *Alternative Quantiles*: in our targeted interaction regressions, we increase the number of quantiles (the top and bottom 50%iles are compared in the main text) to confirm significant treatment interaction terms are robust and consistent across varying categorical interaction variable quantile sizes (Figure S10);
(5) *Continuous Interaction*: in our targeted interaction regressions, we replace the categorical with a continuous measure of the interaction term to test whether interaction effects are linear (Table S16);
(6) *Alternative Clustering*: in our cluster analysis, we change the urban area features and algorithms used for clustering (including Manhattan instead of Euclidean distance measures, a complete linkage function instead of Ward's linkage function, a divisive instead of agglomerative algorithm, and an alternative feature selection, including only those features identified as significant in our HTE analysis) to confirm correlations between TNC effects on vehicle registration and fuel economy outcomes are consistent independent of clustering features and/or method (Figure S12-Figure S13); and
(7) *Event Study*: we model an event study by adding relative time indicators for the number of years before and after TNC entry to confirm the presence of post-treatment (i.e., post-TNC entry) effects without pre-treatment anticipation (i.e., estimated effects occur only after treatment) (Figure S6).

Robustness test results are summarized in Table S9.

1.5. Data

We describe and identify data sources, resolution, and other data quality descriptions for dependent variables, treatment, and control variables below (Table S1 provides summary statistics):

Dependent Variables:

- *Vehicle registrations and fuel economy:* IHS Markit (formerly Polk) collects and sells vehicle registration information from U.S. state agencies responsible for vehicle registration data (IHS Markit, 2019). We rely on annual versions of the dataset from 2010–2017 that report individual vehicle make, model, and engine size for each of the approximately 240 million light-duty vehicles registered in the U.S. Data are provided to us at the ZIP code level, and we aggregate vehicle counts to and average fuel economies by urban area.
- *Transit ridership:* U.S. DOT's Federal Transit Administration (FTA) reports annual summary statistics, including ridership by transit mode (train, bus, demand response, or other), on more than 660 transit providers receiving federal funding in the National Transit Database (Federal Transit Administration, 2019). We focus on transit providers that consistently report data for all years of this analysis (2010–2017) and aggregate individual transit agencies by urban area, per classification in the database, resulting in transit data for only 55% of the urban areas in our dataset.

Treatment 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 (Bi, 2014) 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. Forbes 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 (Bi, 2014; Brazil and Kirk, 2016) as well as the authors' own systematic comparison with local newspaper announcements. 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 for the rest of the analysis period (through 2017). Lyft market launch dates were requested from and provided by Lyft (Gigante, 2016). While Uber and Lyft launch dates are published to the day, we use an annualized measure (to align with our other annual indicators) of the first entry date (Uber or Lyft) in our analysis to indicate when on-demand mobility became available for each urban area (annualized Lyft market entry years are the same or later than annualized Uber market entry years in all but several cases in upstate New York). Market entry begins in 2012 with 5 urban areas, grows through 2014 with 114 urban areas, and then declines through the end of our analysis period (and likely beyond) with 25 urban areas treated in 2017. Table S2 in presents details on market entry timing by urban area and is accompanied by Figure S4, which presents a Goodman-Bacon decomposition diagnostic plot of difference-in-difference weights by treatment timing cohort.

Control Variables

- Control variables are 5-year American Community Survey (ACS) estimates reported by the U.S. Census annually and include: (i) population, (ii) unemployment rate, (iii) income, (iv) portion of households without children, and (v) percent of population commuting by transit. A state-level measure of gasoline price, published annually by the Energy Information Administration, is also included as a control variable (U.S. Energy Information Administration, 2020). Additional ACS variables used to determine IPTW weights include: population density, portion of the population over age 16 and 65, respectively, and percent of population that is female.

2. SUPPLEMENTAL FIGURES

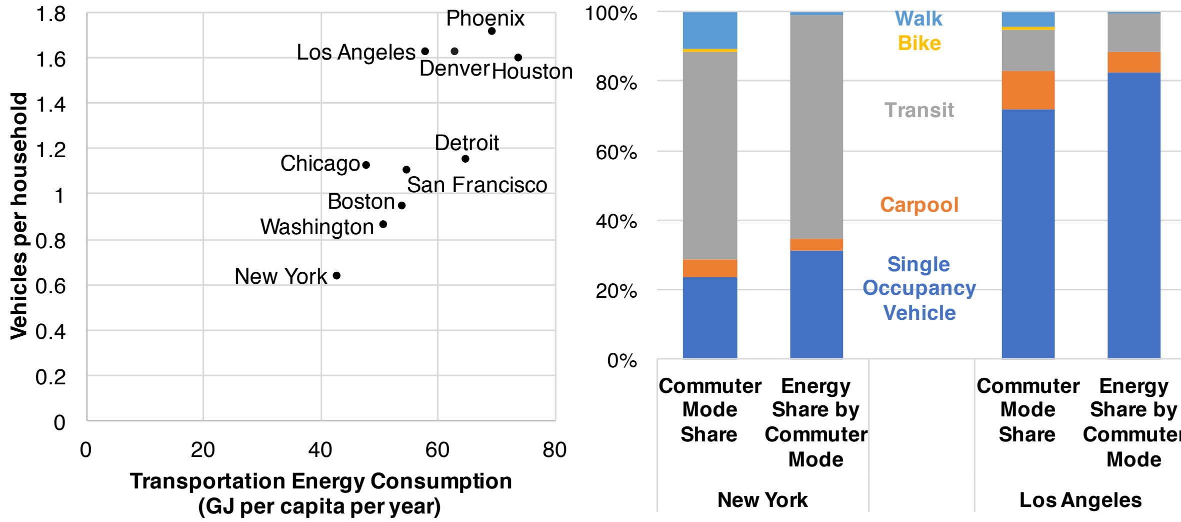


Figure S1. Vehicle Ownership, Transportation Energy Consumption, and Commute Modes in US Cities. Transportation energy consumption is positively correlated with vehicle ownership, shown for 10 major U.S. cities (left; data from U.S. Census and Newman and Kenworthy, 2006), and private vehicle travel consumes proportionally greater energy, compared to commuter transportation modes, as energy shares of those commuter transportation modes for New York and Los Angeles shows (right; data from U.S. Census and Banister, 2011). Related to Figure 1.

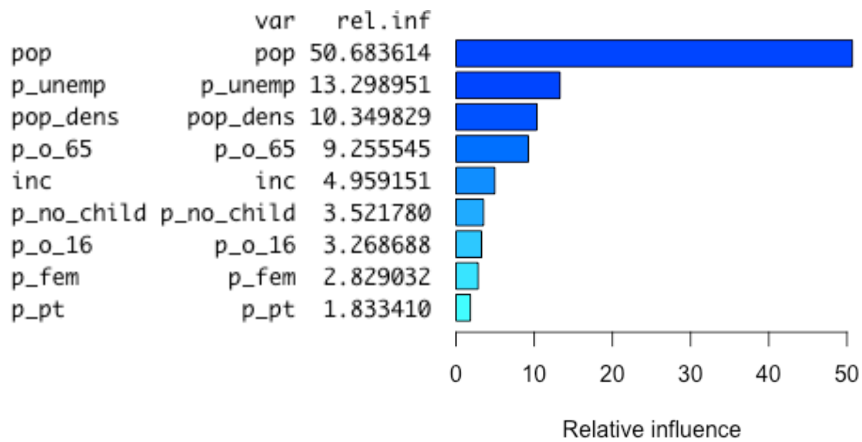


Figure S2. IPTW influence diagram. Relative influence of urban area features in determining the estimated probability of treatment (i.e., TNC entry in a given urban area in a given year). The influence diagram indicates that urban area population ("pop") is the most important urban area feature in determining estimated probability of treatment, followed by unemployment rate ("p_unemp"), population density ("pop_dens"), percentage of population over 65 ("p_o_65"), income ("inc"), childless household rate ("p_no_child"), percentage of population over 16 ("p_o_16"), percentage female ("p_fem"), and public transit commuting rate ("p_pt"). Population alone accounts for just over 50% of the variance that influences estimated probability of treatment. Related to Table 1.

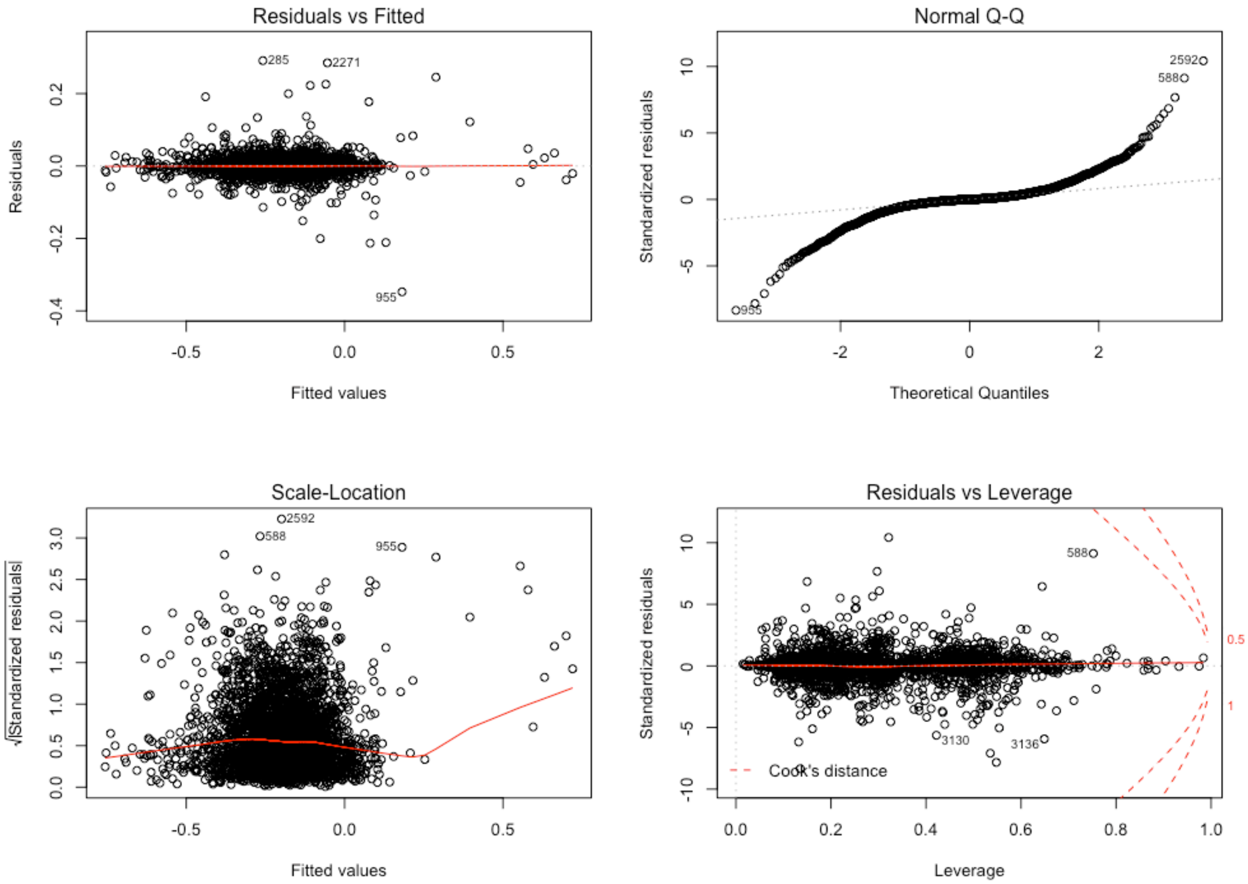


Figure S3. IPTW diagnostic plots. Shown for model estimating average effect on vehicle ownership. The residuals-vs.-fitted values plot (top, left) confirms no structure in residual error; the normal quantile-quantile plot (top, right) illustrates a generally normal distribution of residual errors with heavy tails; the scale-location plot (bottom, left) suggests residuals are generally randomly spread over the range of fitted values (and our main text reports cluster-robust standard errors); and the residuals-vs.-leverage plot suggests no disproportionately influential observations. Related to Table 1.

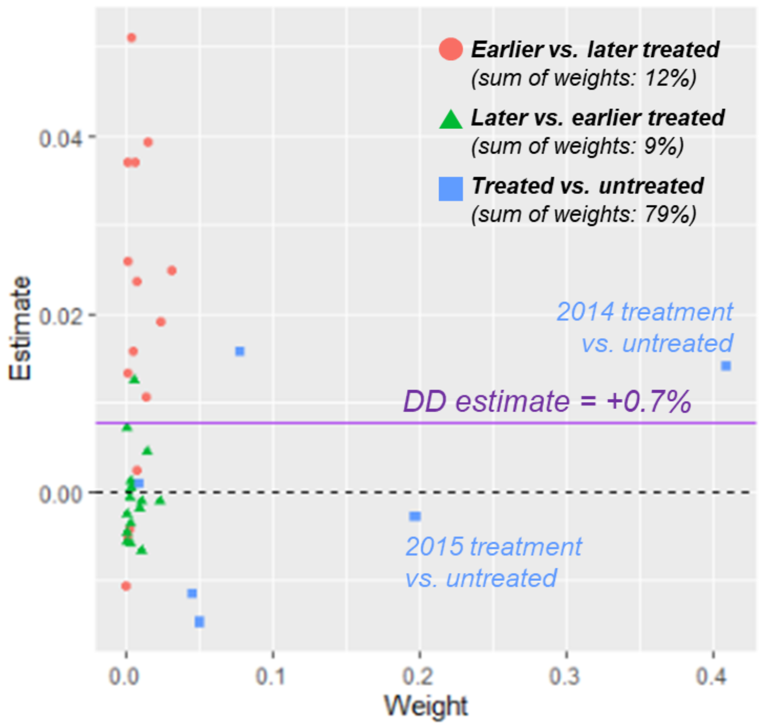


Figure S4. Goodman-Bacon decomposition diagnostic plot. This figure shows the OLS difference-in-difference coefficient estimate and weight in the overall average treatment effect for each respective cohort. The largest weights are associated with the difference between untreated urban areas and urban areas treated in 2014 and 2015, which corresponds both to the middle of the analysis period and the years in which the greatest number of urban areas are treated (48% and 22% in 2014 and 2015, respectively). Related to Table 1 and Table S2.

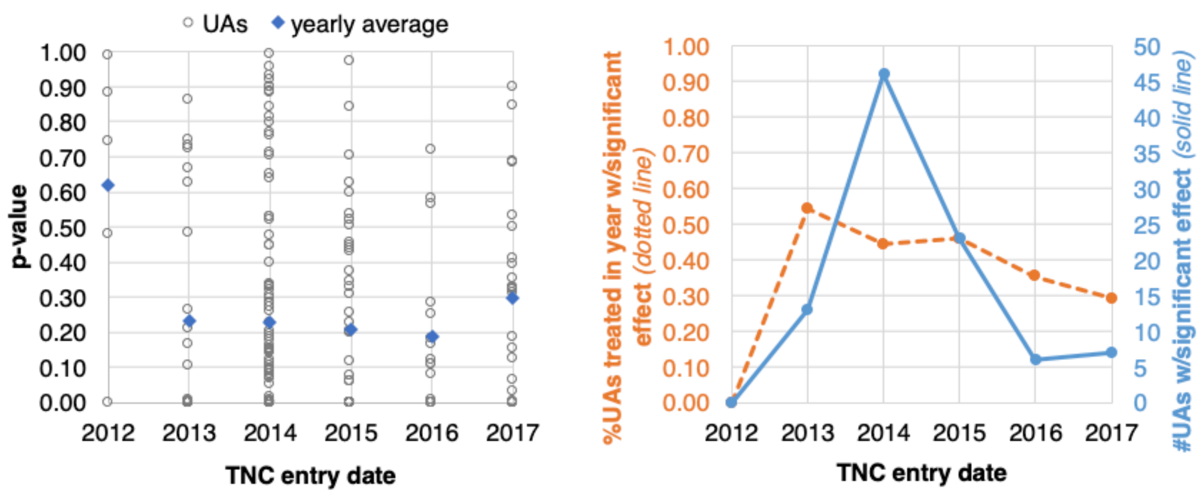


Figure S5. Heterogeneous treatment effect model results. At left, a comparison of the level of significance (p-value) of all estimated urban area-specific TNC entry treatment effects on vehicle ownership as a function of TNC entry date into each urban area, as well as the average level of significance by TNC entry year. At right, the percentage of urban areas with a significant estimated TNC entry effect on vehicle ownership by TNC entry year as well as the distribution of the number of urban areas with a significant estimated TNC entry effect on vehicle ownership by TNC entry year. Related to Figure 2.

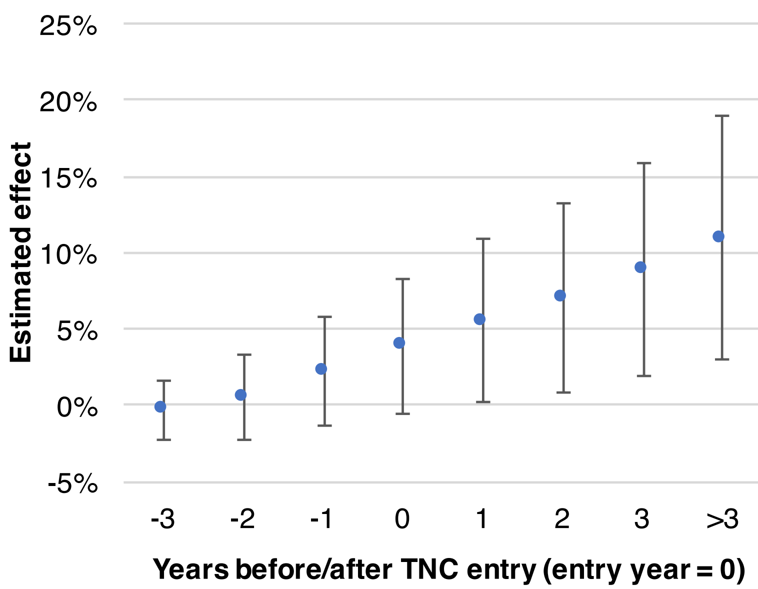


Figure S6. Event study. An event study showing estimated relative time effect of TNC entry on vehicle registrations per capita. Estimated effects are not significant before the year of entry and are significant and positive after the year of entry, providing supporting evidence for primary conclusions. However, both the smooth monotonic visual trend and the larger magnitude of the estimated effect post treatment in the event study relative to the primary model suggest caution. Neither average fuel economy nor transit ridership are analyzed, as regressions modeling those dependent variables in the main text did not identify a significant TNC entry effect to test. Related to Table 1.

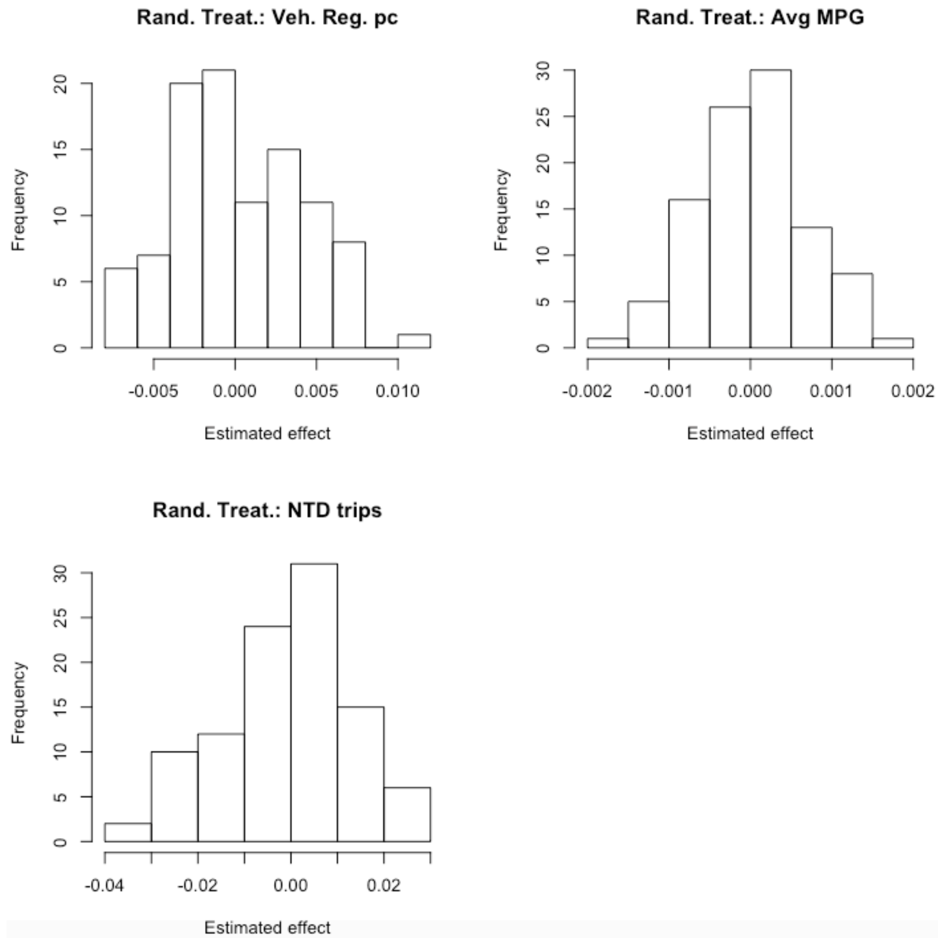


Figure S7. Robustness check: randomized treatment. Distributions of average TNC entry effect estimated on vehicle registrations per capita (top left), average fuel economy (top right), and transit ridership (bottom left) after randomizing TNC entry across urban areas. In general, the distributions are centered about zero and symmetric, suggesting that the estimated effects in the main text are not the inadvertent result of model structure. Related to Table 1.

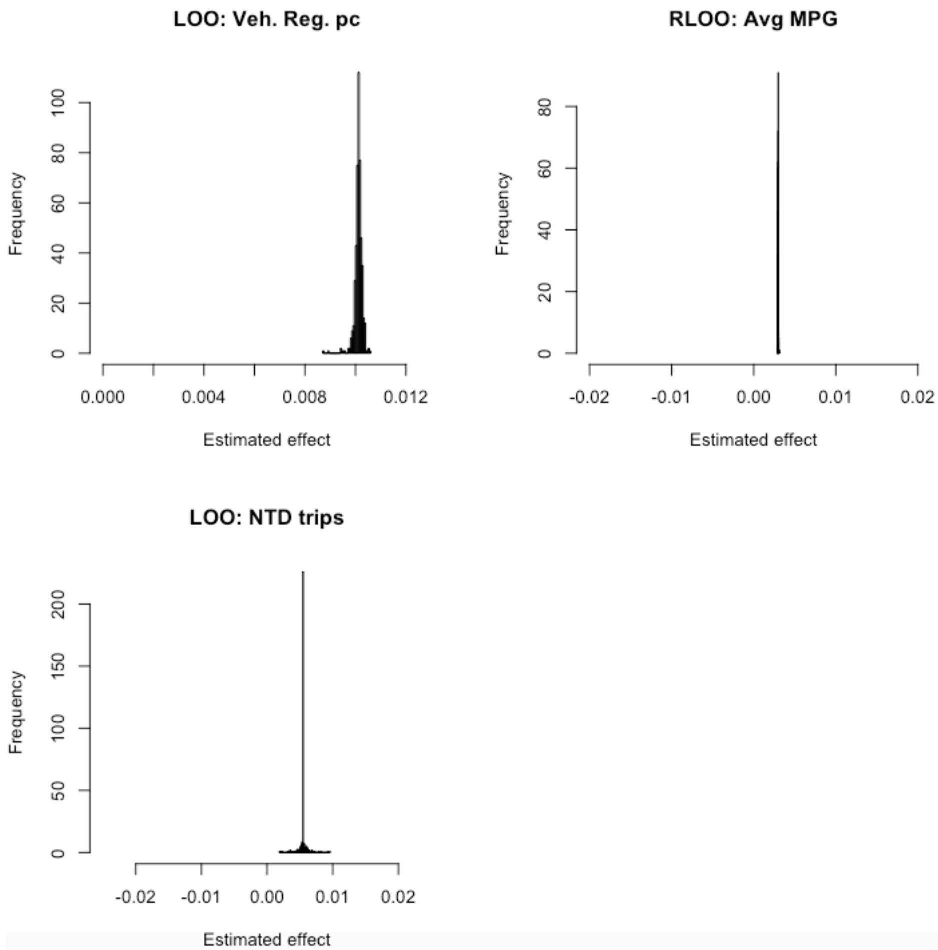


Figure S8. Robustness check: leave-one-out analysis for average effect. Distributions of average TNC entry effect estimated on vehicle registrations per capita (top left), average fuel economy (top right), and transit ridership (bottom left) after systematically excluding one urban area at time. Limits of the x-axis are set to match the confidence interval presented in the main text, such that the tightness of the distribution is meaningful. In general, the distributions are centered tightly about the value estimated including all urban areas, suggesting no one urban area has undue influence in biasing or driving the estimates presented in the main text. Related to Table 1.

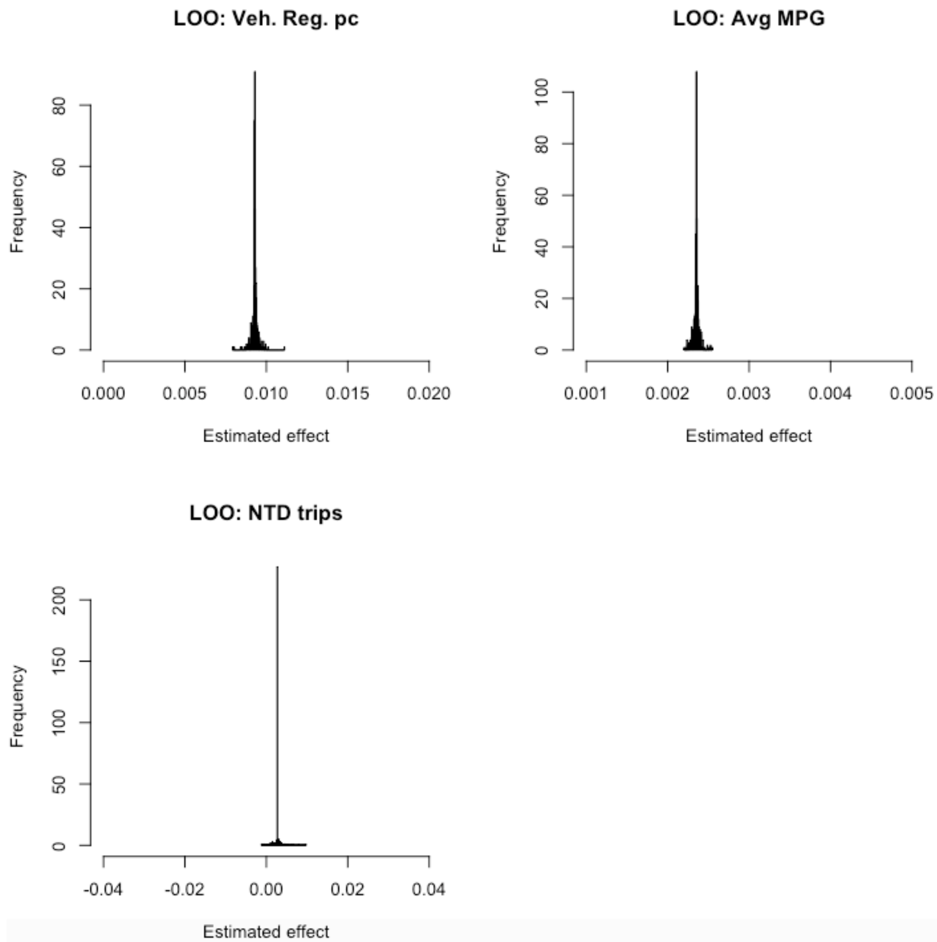


Figure S9. Robustness check: leave-one-out analysis for interaction effects. Distributions of the estimated interaction effect between TNC entry and a categorical measure of income on vehicle registrations per capita (top left), average fuel economy (top right), and transit ridership (bottom left) after systematically excluding one urban area at time. Limits of the x-axis are set to match the confidence interval presented in the main text, such that the tightness of the distribution is meaningful. In general, the distributions are centered tightly about the value estimated including all urban areas, suggesting no one urban area has undue influence in biasing or driving the estimates presented in the main text. Related to Table 1.

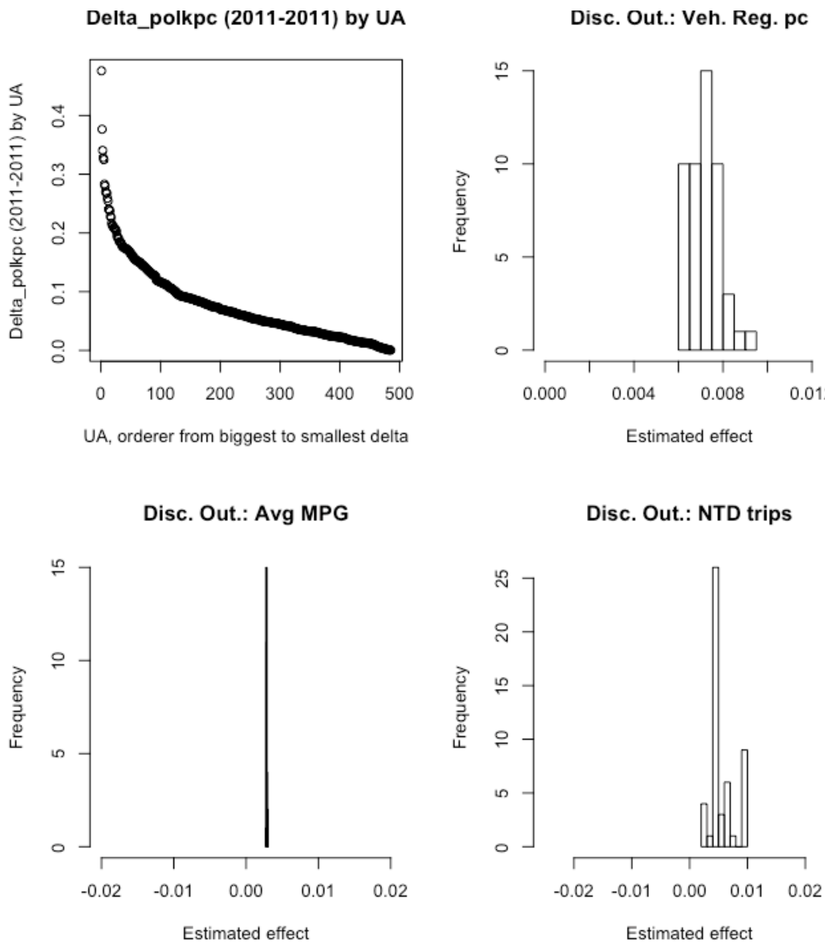
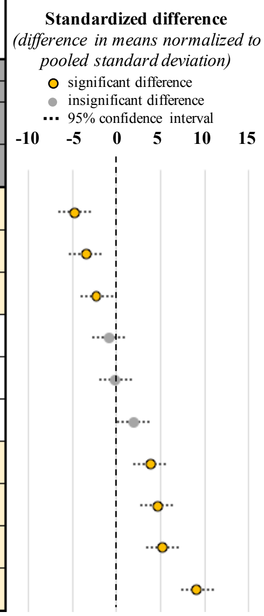


Figure S10. Robustness check: leave-multiple-out analysis. Distribution of changes in per-capita vehicle registrations over the 2011–2017 analysis period by urban are (top left) as well as distributions of the estimated interaction effect between TNC entry and a categorical measure of income on vehicle registrations per capita (top right), average fuel economy (bottom left), and transit ridership (bottom right) after systematically excluding an increasing number of urban areas in order greatest change in vehicle ownership over the analysis period. Limits of the x-axis are set to match the confidence interval presented in the main text, such that the tightness of the distribution is meaningful. In general, the distributions are centered tightly about the value estimated including all urban areas, suggesting no one urban area has undue influence in biasing or driving the estimates presented in the main text. Related to Table 1.

	Mean Value		t-stat	p-value
	Big, dense UAs	Other UAs		
# UAs in cluster	33	258		
% UAs treated	81.8	51.2		
Vehicle Reg. Effect	0.026*** (0.009)	-0.002 (0.005)		
Fuel Economy Effect	0.008 (0.008)	0.007 (0.011)		
Vehicle Reg. per cap	0.743 (0.077)	0.813 (0.090)	-4.782	0.000
Unemployment Rate	0.074 (0.017)	0.086 (0.025)	-3.515	0.000
Δ % Transit Commuters	0.008 (0.023)	0.032 (0.162)	-2.227	0.026
Δ Population Density	0.010 (0.006)	0.011 (0.009)	-0.840	0.401
Δ Population	0.011 (0.006)	0.012 (0.011)	-0.166	0.868
% Households w/no children	0.678 (0.06)	0.657 -0.074	1.854	0.064
Income	67642 (18692)	55001 (12359)	3.781	0.000
Population	2576968 (2836340)	326420 (460281)	4.550	0.000
Population Density	3522 (2513)	1227 (911)	5.201	0.000
% Transit Commuters	0.074 (0.038)	0.014 (0.013)	9.168	0.000



	Mean Value		t-stat	p-value
	Slow growth UAs	Other UAs		
# UAs in cluster	193	258		
% UAs treated	42.5	51.2		
Vehicle Reg. Effect	0.004*** (0.001)	-0.002 (0.005)		
Fuel Economy Effect	0.020*** (0.005)	0.007 (0.011)		
Δ Population Density	-0.001 (0.006)	0.011 (0.009)	-16.90	0.000
Δ Population	0.001 (0.005)	0.012 (0.011)	-13.26	0.000
Income	51748 (10606)	55001 (12359)	-3.002	0.003
Δ % Transit Commuters	0.007 (0.068)	0.032 (0.162)	-2.179	0.029
Population	257826 (343914)	326420 (460281)	-1.811	0.070
Population Density	1116 (815)	1227 (911)	-1.361	0.174
Unemployment Rate	0.085 (0.022)	0.086 (0.025)	-0.394	0.693
% Transit Commuters	0.014 (0.012)	0.032 (0.162)	-0.077	0.938
Vehicle Reg. per cap	0.869 (0.112)	0.813 (0.090)	5.677	0.000
% Households w/no children	0.689 (0.036)	0.657 (0.074)	6.110	0.000

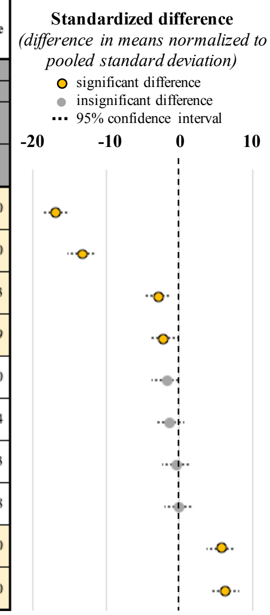


Figure S11. Robustness check: cluster analysis results for the 4-cluster case. A comparison of the average characteristics of "Big, dense UAs" versus "Other UAs" (left), and "Slow growth UAs" versus "Other UAs" (right). Highlighted cells indicate significant differences ($p<0.05$). "Big, dense UAs" is a cluster where TNC entry results in increased per capita vehicle registrations, and "Slow growth UAs" is a cluster where TNC entry results in increased per capita registrations and increased fleet average fuel efficiency. Related to Table 3.

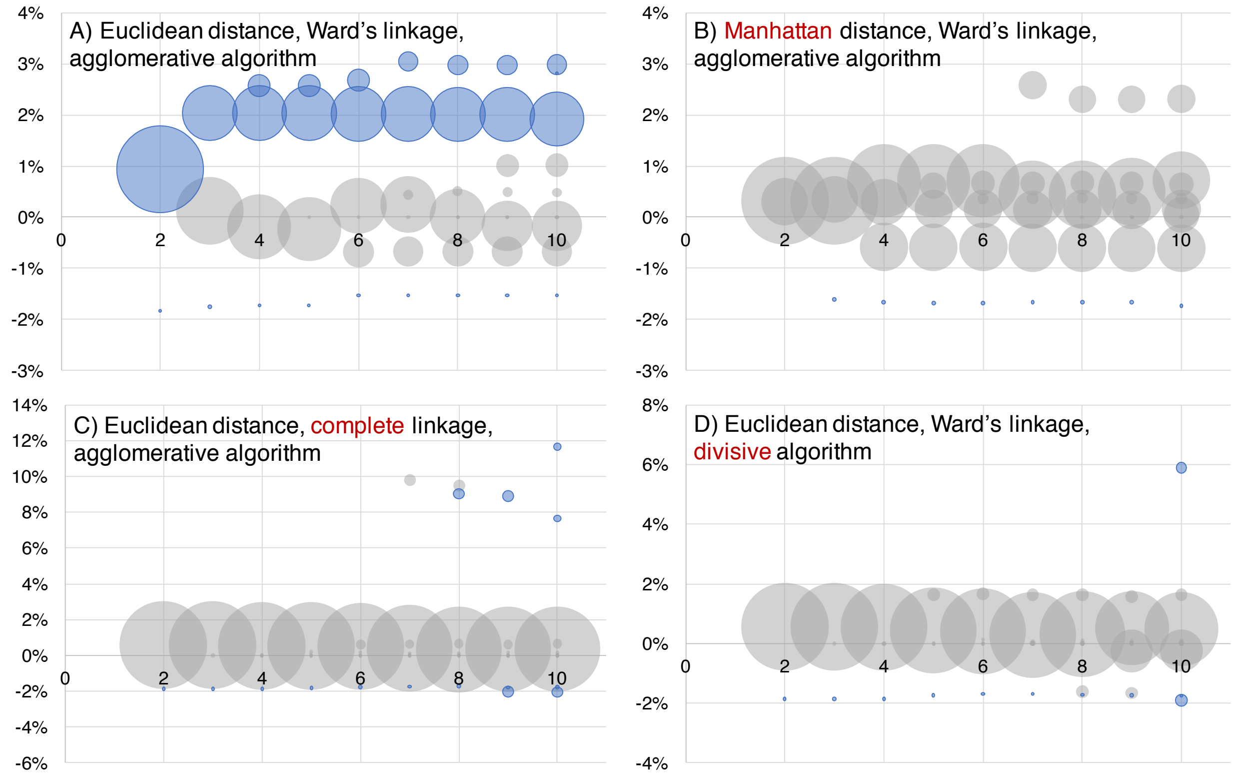


Figure S12. Robustness check: alternative clustering methods. TNC treatment effect on the change in per-capita vehicle registrations varying by urban area typology and as a function of clustering method: Euclidean vs. Manhattan distance (panel A vs. B), Ward's vs. complete linkage (panel A vs. C), and agglomerative vs. divisive algorithm (panel A vs. D). In all cases, statistically significant effects are highlighted in blue, and estimates that are not significant are grey. The size of each circle reflects the number of urban areas in each cluster. Related to Figure 3.

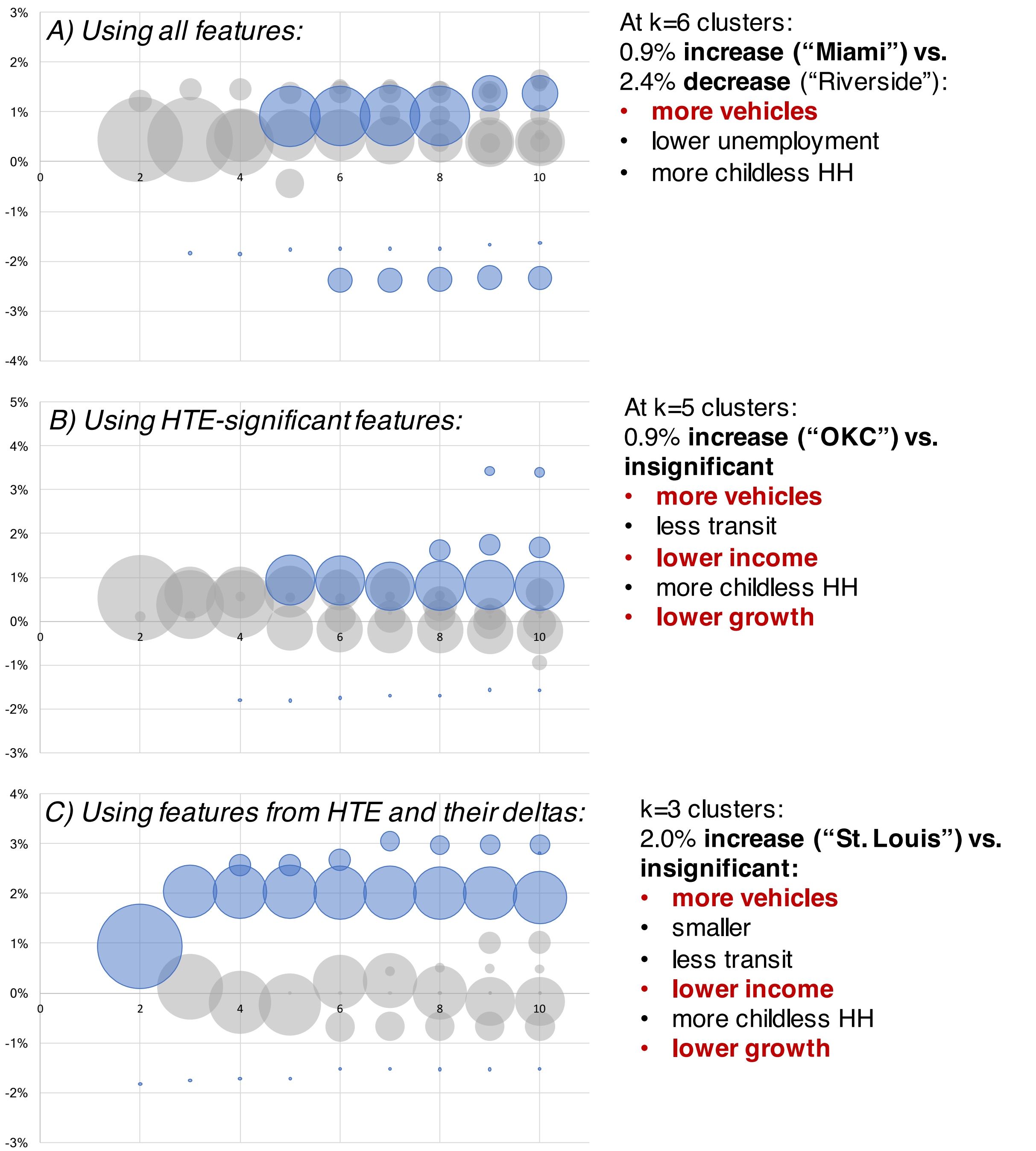


Figure S13. Robustness check: alternative clustering features. TNC treatment effect on the change in per-capita vehicle registrations varying by urban area typology and as a function of the urban area features used for classification: all features (panel), only significant features identified in the HTE analysis (panel B), and significant features identified in the HTE analysis plus a measure of their rates of change (panel C). In all cases, statistically significant effects are highlighted in blue, and estimates that are not significant are grey. The size of each circle reflects the number of urban areas in each cluster. Red text indicate items common across all three plots. Related to Figure 3.

3. SUPPLEMENTAL TABLES

Table S1. Descriptive statistics (means and standard deviations) across n=485 urban areas annually for the analysis period 2011–2017. Related to Tables 1-4.

Variable	Units	Coded as	2011	2012	2013	2014	2015	2016	2017
Vehicle registrataions	# vehicles	polk_reg	361898 (843768)	368543 (864999)	371413 (862048)	380005 (888522)	390421 (914096)	401301 (937200)	404148 (940863)
Average fuel economy	miles per gallon	avg_mpg	20.5 (0.5)	20.9 (0.5)	21.1 (0.6)	21.3 (0.6)	21.6 (0.7)	21.9 (0.7)	22.1 (0.8)
Transit trips	# trips	NTDtrips	36726260 (258009100)	37093390 (259439800)	37476220 (266073200)	37906230 (271915700)	37005930 (265042100)	36229950 (265285600)	35420920 (262407400)
Urban areas with TNC service	%	treat	0% (0%)	1% (10.1%)	6.4% (24.5%)	29.9% (45.8%)	41.2% (49.3%)	44.7% (49.8%)	49.9% (50.1%)
Population	# persons	pop	478538 (1291134)	482988 (1299632)	485327 (1304244)	489862 (1314047)	493613 (1322095)	498169 (1330433)	502986 (1344081)
Population density	# persons / sq. mi.	pop_dens	1363 (1595)	1371 (1606)	1378 (1619)	1390 (1638)	1398 (1652)	1407 (1661)	1415 (1678)
Unemployment rate	%	p_unemp	8.6% (2.4%)	9.3% (2.7%)	9.7% (2.8%)	9.2% (2.7%)	8.3% (2.4%)	7.5% (2.2%)	6.7% (2%)
Average household income	current $	inc	53228 (12340.94)	53456 (12463.93)	53480 (12578.51)	53980 (12787)	54375 (12927.58)	55735 (13316.58)	57969 (13999.23)
Childless households	%	p_no_child	66.1% (6.4%)	66.4% (6.5%)	66.8% (6.4%)	67.1% (6.3%)	67.4% (6.3%)	67.8% (6.2%)	68.1% (6.1%)
Transit commuting rate	%	p_pt	1.8% (2.5%)	1.8% (2.5%)	1.8% (2.6%)	1.9% (2.6%)	1.9% (2.6%)	1.9% (2.6%)	1.9% (2.7%)
Gasoline price	$/MMBtu	Gas_Price	28.7 (1.3)	29.6 (1.6)	28.7 (1.4)	27.6 (1.5)	20.4 (2.3)	18.2 (1.8)	20.4 (2)
Portion of population over age 16	%	p_o_16	78.9% (3.2%)	79% (3.2%)	79.2% (3.1%)	79.3% (3.1%)	79.5% (3.1%)	79.6% (3.1%)	79.8% (3.1%)
Portion of population over age 65	%	p_o_65	13.2% (4.1%)	13.4% (4.2%)	13.7% (4.3%)	14.1% (4.3%)	14.5% (4.4%)	14.9% (4.5%)	15.3% (4.6%)

Table S2. TNC market entry timing by urban area. Market entry begins in 2012 with 5 urban areas, grows through 2014 with 114 urban areas, and then declines through the end of our analysis period (and likely beyond) with 25 urban areas treated in 2017. Related to Figure 1.

Uber Entry Year	Number of Urban Areas	Share of Urban Areas	Treatment Share
2012	5	1%	86%
2013	26	5%	71%
2014	114	24%	57%
2015	55	11%	43%
2016	17	4%	29%
2017	25	5%	14%
Untreated	243	50%	--

Table S3. Balance table for inverse probability of treatment weights (IPTW). Significant differences across population, density, unemployment, income, female population percentage, and transit commuting rate in the unweighted data are balanced (i.e., no significant differences) in the weighted sample (except for unemployment rate, which, though still statistically significantly different, is practically similar at 7.7% and 8.1% for the treated and control groups, respectively). Related to Table 1.

Unweighted							
	Treatmed Mean	**Treated Std. Dev.**	**Control Mean**	**Control Std. Dev.**	**Stand'ized Effect Size**	**t-Statistic**	**p-Value**
pop	86432.046	2176640.67	294194.305	763528.149	0.364	10.346	0.000
pop_dens	2284.468	2504.109	1094.597	1067.59	0.475	13.383	0.000
p_unemp	0.077	0.022	0.087	0.027	-0.451	-10.652	0.000
inc	59775.76	13117.84	52903.037	12521.718	0.524	13.325	0.000
p_o_16	0.795	0.028	0.793	0.033	0.067	1.609	0.108
p_o_65	0.141	0.039	0.142	0.046	-0.015	-0.349	0.727
p_no_child	0.673	0.054	0.67	0.066	0.048	1.132	0.258
p_fem	0.51	0.008	0.508	0.013	0.307	6.335	0.000
p_pt	0.027	0.039	0.016	0.019	0.306	8.538	0.000
Weighted							
	Treatmed Mean	**Treated Std. Dev.**	**Control Mean**	**Control Std. Dev.**	**Stand'ized Effect Size**	**t-Statistic**	**p-Value**
pop	86432.046	2176640.67	900627.294	1873260.74	0.085	1.263	0.207
pop_dens	2284.468	2504.109	2161.548	2319.981	0.049	0.642	0.521
p_unemp	0.077	0.022	0.081	0.022	-0.181	-3.717	0.000
inc	59775.76	13117.84	58856.287	13746.753	0.07	1.235	0.217
p_o_16	0.795	0.028	0.794	0.027	0.005	0.106	0.916
p_o_65	0.141	0.039	0.14	0.04	0.026	0.524	0.600
p_no_child	0.673	0.054	0.673	0.051	-0.008	-0.159	0.874
p_fem	0.51	0.008	0.511	0.008	-0.045	-0.889	0.374
p_pt	0.027	0.039	0.028	0.038	-0.01	-0.136	0.892

Table S4. IPTW weights used in IPTW regressions. Urban areas with TNC access receive unity weights (i.e., a weight of 1); control urban areas and pre-treatment urban areas that are eventually treated are weighted as the quotient calculated by dividing probability of treatment by one minus the probability of treatment. Weights range from 0.01 (for several smaller urban areas) to 6.28 (for San Francisco, CA in the pre-treatment year 2011). Related to Table 1 and Table 4.

	2011	2012	2013	2014	2015	2016	2017
Aberdeen--Bel Air South--Bel Air North, MD	1.21	1.09	1.03	1.58	1.00	1.00	1.00
Abilene, TX	0.26	0.24	0.25	0.25	0.22	0.25	0.30
Akron, OH	0.36	0.25	0.27	1.00	1.00	1.00	1.00
Albany--Schenectady, NY	1.39	1.25	0.80	1.50	2.52	3.44	1.00
Albany, GA	0.01	0.01	0.01	0.00	0.00	0.01	0.01
Albany, OR	0.04	0.02	0.02	0.01	0.02	0.03	0.04
Albuquerque, NM	1.40	0.78	0.89	1.00	1.00	1.00	1.00
Alexandria, LA	0.04	0.05	0.05	0.05	0.05	0.05	0.06
Allentown, PA--NJ	1.00	1.14	0.85	1.23	1.00	1.00	1.00
Alton, IL--MO	0.05	0.04	0.04	0.04	0.05	0.06	0.06
Altoona, PA	0.04	0.04	0.05	0.05	0.04	0.04	0.05
Amarillo, TX	0.66	0.52	0.48	0.48	1.00	1.00	1.00
Ames, IA	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Anchorage, AK	0.16	0.14	0.16	0.14	0.14	0.72	1.00
Anderson, IN	0.05	0.04	0.04	0.05	0.05	0.08	0.06
Anderson, SC	0.02	0.02	0.01	0.01	0.02	0.02	0.05
Ann Arbor, MI	0.18	0.18	0.15	1.00	1.00	1.00	1.00
Anniston--Oxford, AL	0.03	0.04	0.01	0.01	0.01	0.01	0.02
Antioch, CA	0.09	0.08	0.11	0.12	0.11	0.13	0.47
Appleton, WI	1.11	1.41	1.43	1.58	1.00	1.00	1.00
Arroyo Grande--Grover Beach, CA	0.09	0.08	0.09	0.09	0.09	0.09	0.11
Asheville, NC	0.45	0.45	0.45	1.00	1.00	1.00	1.00
Athens-Clarke County, GA	0.20	0.15	0.12	1.00	1.00	1.00	1.00
Atlanta, GA	0.15	1.00	1.00	1.00	1.00	1.00	1.00
Atlantic City, NJ	0.36	0.37	0.40	1.00	1.00	1.00	1.00
Auburn, AL	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Augusta-Richmond County, GA--SC	0.37	0.34	0.26	0.34	1.00	1.00	1.00
Austin, TX	0.32	0.26	0.48	1.00	1.00	1.00	1.00
Avondale--Goodyear, AZ	0.06	0.13	0.12	0.15	0.39	0.64	0.53
Bakersfield, CA	0.08	0.08	0.11	1.00	1.00	1.00	1.00
Baltimore, MD	1.02	1.02	1.00	1.00	1.00	1.00	1.00
Bangor, ME	0.01	0.01	0.01	0.01	0.01	0.01	0.03
Barnstable Town, MA	1.03	1.81	1.00	1.00	1.00	1.00	1.00
Baton Rouge, LA	0.39	0.44	0.32	1.00	1.00	1.00	1.00
Battle Creek, MI	0.01	0.01	0.01	0.01	0.02	0.03	0.02
Bay City, MI	0.02	0.01	0.01	0.02	0.02	0.02	0.02
Beaumont, TX	0.12	0.10	0.08	0.13	0.17	0.39	0.59
Beckley, WV	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Bellingham, WA	0.31	0.30	0.33	0.45	1.00	1.00	1.00
Beloit, WI--IL	0.03	0.03	0.02	0.02	1.00	1.00	1.00
Bend, OR	0.01	0.01	0.01	0.01	0.02	0.21	0.24
Benton Harbor--St. Joseph--Fair Plain, MI	0.01	0.01	0.01	0.01	0.02	0.03	0.03
Billings, MT	0.38	0.71	0.79	0.75	0.81	1.00	1.00
Binghamton, NY--PA	0.19	0.20	0.19	0.20	0.59	0.40	1.00
Birmingham, AL	0.78	0.58	0.78	1.39	1.00	1.00	1.00
Bismarck, ND	0.02	0.01	0.01	0.01	0.01	0.02	0.02
Blacksburg, VA	0.01	0.01	0.01	0.01	0.02	0.04	0.06
Bloomington--Normal, IL	0.10	0.12	0.07	0.19	0.30	0.42	0.69
Bloomington, IN	0.01	0.05	0.08	1.00	1.00	1.00	1.00
Bloomsburg--Berwick, PA	0.01	0.02	0.02	0.01	0.01	0.02	0.03
Boise City, ID	0.34	0.61	1.15	1.00	1.00	1.00	1.00
Bonita Springs, FL	1.26	1.23	0.93	1.00	1.00	1.00	1.00
Boston, MA--NH--RI	2.61	2.64	1.00	1.00	1.00	1.00	1.00
Boulder, CO	0.40	0.40	0.15	1.00	1.00	1.00	1.00
Bowling Green, KY	0.01	0.01	0.01	0.01	0.02	0.03	0.04
Bremerton, WA	0.29	0.30	0.24	0.42	0.28	1.41	2.29
Bridgeport--Stamford, CT--NY	0.54	0.48	0.46	1.00	1.00	1.00	1.00
Bristol--Bristol, TN--VA	0.10	0.05	0.04	0.06	0.10	0.09	0.10
Brownsville, TX	0.06	0.05	0.05	0.05	0.05	0.05	0.12
Brunswick, GA	0.01	0.02	0.03	0.01	0.03	0.02	1.00
Buffalo, NY	0.56	0.57	0.52	0.76	0.91	1.42	1.00
Burlington, NC	0.05	0.04	0.04	0.09	0.07	0.17	0.34
Burlington, VT	0.25	0.29	0.25	0.26	0.44	0.47	1.03
Camarillo, CA	0.08	0.08	0.08	0.09	0.08	0.10	0.11
Canton, OH	0.44	0.36	0.39	1.00	1.00	1.00	1.00
Cape Coral, FL	0.70	0.52	0.52	1.00	1.00	1.00	1.00
Cape Girardeau, MO--IL	0.01	0.01	0.01	0.01	0.01	0.02	0.02
Carbondale, IL	0.01	0.01	0.01	0.01	0.01	0.02	0.02
Carson City, NV	0.02	0.02	0.02	0.01	0.02	0.02	0.03
Cartersville, GA	0.00	0.01	0.01	0.01	0.01	0.02	0.02
Casa Grande, AZ	0.02	0.02	0.02	0.02	0.02	0.03	0.03
Casper, WY	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Cedar Rapids, IA	0.69	0.69	0.63	1.00	1.00	1.00	1.00
Chambersburg, PA	0.05	0.03	0.02	0.02	0.03	0.03	0.04
Champaign, IL	0.51	0.47	0.45	0.45	1.00	1.00	1.00
Charleston--North Charleston, SC	0.25	0.24	0.39	1.00	1.00	1.00	1.00
Charleston, WV	0.34	0.33	0.29	0.29	0.34	0.46	0.46
Charlotte, NC--SC	1.24	0.93	1.00	1.00	1.00	1.00	1.00
Chattanooga, TN--GA	0.30	0.24	0.41	1.00	1.00	1.00	1.00
Cheyenne, WY	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Chicago, IL--IN	0.92	1.12	1.00	1.00	1.00	1.00	1.00

	2011	2012	2013	2014	2015	2016	2017
Chico, CA	0.03	0.03	0.03	0.06	1.00	1.00	1.00
Cincinnati, OH--KY--IN	0.77	1.13	1.60	1.00	1.00	1.00	1.00
Clarksville, TN--KY	0.05	0.08	0.08	0.07	0.14	1.00	1.00
Cleveland, OH	0.31	0.40	0.55	1.00	1.00	1.00	1.00
Cleveland, TN	0.01	0.02	0.02	0.02	0.02	0.03	0.03
Coeur d'Alene, ID	0.05	0.08	0.11	0.16	0.20	0.20	0.25
College Station--Bryan, TX	0.04	0.03	0.03	0.03	0.09	0.16	0.23
Colorado Springs, CO	0.30	0.33	0.34	1.00	1.00	1.00	1.00
Columbia, MO	0.07	0.06	0.07	0.13	0.15	0.13	0.12
Columbia, SC	0.33	0.26	0.32	1.00	1.00	1.00	1.00
Columbus, GA--AL	0.19	0.20	0.13	0.16	0.20	1.00	1.00
Columbus, IN	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Columbus, OH	0.38	0.51	0.51	1.00	1.00	1.00	1.00
Concord, CA	0.90	0.46	0.43	0.37	1.12	1.66	1.87
Concord, NC	0.22	0.19	0.13	0.10	1.00	1.00	1.00
Conroe--The Woodlands, TX	0.37	0.38	0.38	0.56	0.57	0.64	1.35
Conway, AR	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Corpus Christi, TX	0.72	1.03	1.15	1.00	1.00	1.00	1.00
Corvallis, OR	0.02	0.02	0.01	0.01	0.01	0.02	0.02
Cumberland, MD--WV--PA	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Dallas--Fort Worth--Arlington, TX	0.34	0.35	1.00	1.00	1.00	1.00	1.00
Dalton, GA	0.02	0.01	0.02	0.01	0.02	0.04	0.05
Danbury, CT--NY	0.48	0.26	0.56	1.00	1.00	1.00	1.00
Danville, IL	0.01	0.01	0.01	0.02	0.02	0.03	0.04
Daphne--Fairhope, AL	0.02	0.02	0.02	0.02	0.02	0.03	0.03
Davenport, IA--IL	1.44	1.50	2.28	2.27	1.00	1.00	1.00
Davis, CA	0.01	0.01	0.01	0.02	0.05	0.05	0.10
Dayton, OH	0.44	0.45	0.50	1.00	1.00	1.00	1.00
Decatur, AL	0.01	0.01	0.01	0.01	0.01	0.01	0.03
Decatur, IL	0.03	0.02	0.02	0.02	0.03	0.03	0.05
DeKalb, IL	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Delano, CA	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Deltona, FL	0.35	0.28	0.19	1.00	1.00	1.00	1.00
Denton--Lewisville, TX	0.25	0.22	0.15	0.16	0.19	0.25	0.81
Denver--Aurora, CO	0.55	0.37	0.55	1.00	1.00	1.00	1.00
Des Moines, IA	0.38	0.38	0.51	0.57	0.89	2.11	2.11
Detroit, MI	1.10	1.10	1.00	1.00	1.00	1.00	1.00
Dothan, AL	0.01	0.01	0.02	0.03	0.03	0.04	0.02
Dover--Rochester, NH--ME	0.13	0.22	0.24	0.32	0.32	0.36	0.38
Dover, DE	0.20	0.18	0.18	0.20	0.20	0.27	0.38
Dubuque, IA--IL	0.05	0.06	0.06	0.06	0.06	0.06	0.05
Duluth, MN--WI	0.31	0.43	0.43	0.40	1.02	1.32	1.00
Durham, NC	0.34	0.35	0.41	1.00	1.00	1.00	1.00
East Stroudsburg, PA--NJ	0.02	0.01	0.01	0.01	0.01	0.01	0.02
Eau Claire, WI	0.07	0.11	0.15	0.17	0.17	0.37	1.00
El Centro--Calexico, CA	0.02	0.01	0.01	0.01	0.02	0.04	0.05
El Paso de Robles (Paso Robles)--Atascadero, CA	0.01	0.01	0.01	0.01	0.01	0.01	0.02
El Paso, TX--NM	0.16	0.34	0.34	1.00	1.00	1.00	1.00
Elizabethtown--Radcliff, KY	0.01	0.02	0.03	0.03	0.07	0.06	0.06
Elkhart, IN--MI	0.08	0.08	0.10	1.00	1.00	1.00	1.00
Elmira, NY	0.03	0.03	0.04	0.05	0.06	0.05	0.06
Erie, PA	0.56	0.50	0.58	0.93	1.00	1.00	1.00
Eugene, OR	0.26	0.24	0.22	0.26	0.34	0.85	2.45
Evansville, IN--KY	0.93	0.93	0.49	0.88	1.59	1.77	1.00
Fairbanks, AK	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Fairfield, CA	0.12	0.13	0.09	0.14	0.15	0.20	0.35
Fargo, ND--MN	0.28	0.27	0.31	0.34	1.00	1.00	1.00
Farmington, NM	0.01	0.01	0.02	0.03	0.03	0.03	0.04
Fayetteville--Springdale--Rogers, AR--MO	0.44	0.35	0.64	1.00	1.00	1.00	1.00
Fayetteville, NC	0.35	0.29	0.26	1.00	1.00	1.00	1.00
Flagstaff, AZ	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Flint, MI	0.18	0.22	0.22	1.00	1.00	1.00	1.00
Florence, AL	0.02	0.04	0.04	0.06	0.07	0.10	0.07
Florence, SC	0.06	0.06	0.06	0.06	0.06	0.08	0.10
Fond du Lac, WI	0.05	0.06	0.07	0.07	0.08	0.08	0.08
Fort Collins, CO	0.21	0.34	0.67	1.00	1.00	1.00	1.00
Fort Smith, AR--OK	0.20	0.17	0.10	0.11	0.13	0.18	0.26
Fort Walton Beach--Navarre--Wright, FL	0.62	0.58	0.59	1.00	1.00	1.00	1.00
Fort Wayne, IN	0.88	0.67	0.51	0.95	1.00	1.00	1.00
Frederick, MD	0.18	0.28	0.77	0.42	1.00	1.00	1.00
Fredericksburg, VA	0.08	0.09	0.12	0.09	0.33	0.38	0.53
Fresno, CA	0.55	0.50	0.50	1.00	1.00	1.00	1.00
Gadsden, AL	0.01	0.01	0.00	0.00	0.01	0.01	0.01
Gainesville, FL	0.53	0.47	0.26	1.00	1.00	1.00	1.00
Gainesville, GA	0.22	1.00	1.00	1.00	1.00	1.00	1.00
Gastonia, NC--SC	0.15	0.15	0.15	0.15	0.15	0.27	0.76
Gilroy--Morgan Hill, CA	0.01	0.01	0.01	0.01	0.03	0.05	0.05
Glens Falls, NY	0.06	0.07	0.08	0.08	0.07	0.07	0.07
Goldsboro, NC	0.01	0.01	0.00	0.01	0.01	0.01	0.01
Grand Forks, ND--MN	0.00	0.01	0.01	0.01	0.01	0.02	0.09
Grand Island, NE	0.01	0.01	0.01	0.01	0.01	0.01	0.01

	2011	2012	2013	2014	2015	2016	2017
Grand Junction, CO	0.96	0.55	0.54	0.48	1.00	1.00	1.00
Grand Rapids, MI	0.21	0.29	0.58	1.00	1.00	1.00	1.00
Grants Pass, OR	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Great Falls, MT	0.03	0.04	0.04	0.04	0.04	0.03	0.04
Greeley, CO	0.04	0.04	0.05	1.00	1.00	1.00	1.00
Green Bay, WI	0.95	1.19	0.66	1.00	1.00	1.00	1.00
Greensboro, NC	0.58	0.38	0.43	0.37	1.00	1.00	1.00
Greenville, NC	0.07	0.03	0.08	0.06	1.00	1.00	1.00
Greenville, SC	0.28	0.21	0.21	1.00	1.00	1.00	1.00
Gulfport, MS	0.40	0.26	0.16	0.19	0.37	1.00	1.00
Hagerstown, MD--WV--PA	0.69	0.49	0.24	0.24	1.00	1.00	1.00
Hammond, LA	0.01	0.01	0.00	0.01	0.01	0.01	0.03
Hanford, CA	0.01	0.01	0.01	0.01	0.02	0.02	0.03
Hanover, PA	0.06	0.05	0.05	0.05	0.05	0.05	0.05
Harlingen, TX	0.01	0.01	0.02	0.02	0.03	0.03	0.02
Harrisburg, PA	1.90	1.73	2.63	2.34	1.00	1.00	1.00
Harrisonburg, VA	0.02	0.02	0.02	0.02	0.02	0.02	0.04
Hartford, CT	0.57	0.47	0.36	1.00	1.00	1.00	1.00
Hattiesburg, MS	0.02	0.02	0.03	0.02	0.01	0.03	0.06
Hazleton, PA	0.04	0.04	0.03	0.02	0.03	0.03	0.05
Hemet, CA	0.07	0.07	0.03	0.04	0.05	0.17	0.17
Hickory, NC	0.07	0.06	0.05	0.06	0.07	0.17	0.26
High Point, NC	0.10	0.08	0.09	0.08	1.00	1.00	1.00
Hilton Head Island, SC	0.03	0.03	0.03	0.04	0.04	0.07	0.10
Hinesville, GA	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Holland, MI	0.09	0.09	0.09	0.12	0.13	0.12	1.00
Homosassa Springs--Beverly Hills--Citrus Springs, FL	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Hot Springs, AR	0.01	0.00	0.01	0.00	0.00	0.00	0.00
Houma, LA	0.12	0.13	0.22	0.13	0.11	0.13	0.12
Houston, TX	0.68	0.56	0.60	1.00	1.00	1.00	1.00
Huntington, WV--KY--OH	0.83	0.46	0.46	0.46	0.69	1.00	1.00
Huntsville, AL	0.64	0.57	0.45	0.64	0.73	1.00	1.00
Idaho Falls, ID	0.00	0.00	0.00	0.01	1.00	1.00	1.00
Indianapolis, IN	0.72	0.69	1.00	1.00	1.00	1.00	1.00
Indio--Cathedral City, CA	0.77	0.66	0.60	1.00	1.00	1.00	1.00
Iowa City, IA	0.10	0.14	0.12	0.24	0.73	1.00	1.00
Ithaca, NY	0.01	0.02	0.02	0.02	0.02	0.04	0.05
Jackson, MI	0.04	0.04	0.04	0.03	0.05	0.06	0.07
Jackson, MS	0.76	0.65	0.76	1.00	1.00	1.00	1.00
Jackson, TN	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Jacksonville, FL	1.03	1.14	1.01	1.00	1.00	1.00	1.00
Jacksonville, NC	0.01	0.00	0.01	0.01	0.00	0.00	0.00
Janesville, WI	0.03	0.03	0.02	0.03	0.03	0.03	0.03
Jefferson City, MO	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Johnson City, TN	0.07	0.08	0.08	0.12	0.14	0.14	0.29
Johnstown, PA	0.10	0.08	0.07	0.05	0.04	0.05	0.08
Jonesboro, AR	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Joplin, MO	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Kahului, HI	0.05	0.03	0.03	0.02	0.02	0.04	0.04
Kailua (Honolulu County)--Kaneohe, HI	0.25	0.21	0.21	0.35	0.34	0.44	0.42
Kalamazoo, MI	0.19	0.20	0.28	1.00	1.00	1.00	1.00
Kankakee, IL	0.03	0.03	0.03	0.04	0.03	0.05	0.05
Kansas City, MO--KS	1.76	1.74	1.70	1.00	1.00	1.00	1.00
Kennewick--Pasco, WA	0.36	0.31	0.29	0.40	1.12	1.00	1.00
Kenosha, WI--IL	0.19	0.18	0.13	0.18	1.00	1.00	1.00
Killeen, TX	0.11	0.10	0.09	0.10	0.09	0.09	0.06
Kingsport, TN--VA	0.08	0.04	0.08	0.05	0.03	0.06	0.08
Kingston, NY	0.04	0.03	0.03	0.03	0.03	0.07	0.03
Kissimmee, FL	0.13	0.11	0.12	1.00	1.00	1.00	1.00
Knoxville, TN	1.53	1.29	1.18	1.00	1.00	1.00	1.00
Kokomo, IN	0.01	0.01	0.01	0.02	0.02	0.02	0.03
La Crosse, WI--MN	0.11	0.13	0.12	0.12	0.13	0.17	1.00
Lady Lake--The Villages, FL	0.03	0.03	0.03	0.05	0.15	0.32	0.46
Lafayette--Louisville--Erie, CO	0.01	0.01	0.01	0.01	0.01	0.03	0.08
Lafayette, IN	0.11	0.11	0.11	1.00	1.00	1.00	1.00
Lafayette, LA	0.31	0.30	0.57	1.13	1.00	1.00	1.00
Lake Charles, LA	0.10	0.08	0.08	0.10	0.11	0.27	0.34
Lake Havasu City, AZ	0.01	0.01	0.02	0.01	0.00	0.01	0.01
Lake Jackson--Angleton, TX	0.01	0.01	0.01	0.02	0.01	0.02	0.01
Lakeland, FL	0.36	0.48	0.31	1.00	1.00	1.00	1.00
Lancaster--Palmdale, CA	0.04	0.05	0.05	0.11	0.13	0.15	0.20
Lancaster, PA	2.55	2.12	1.12	2.03	1.00	1.00	1.00
Lansing, MI	0.54	0.33	0.45	1.00	1.00	1.00	1.00
Laredo, TX	0.05	0.12	0.12	0.12	0.15	0.17	0.24
Las Cruces, NM	0.11	0.09	0.08	0.08	1.00	1.00	1.00
Las Vegas--Henderson, NV	0.37	0.23	0.56	0.57	1.00	1.00	1.00
Lawrence, KS	0.01	0.01	0.02	0.02	0.02	0.03	0.02
Lawton, OK	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Lebanon, PA	0.04	0.04	0.04	0.04	0.04	0.04	0.07
Lee's Summit, MO	0.06	0.15	0.17	1.00	1.00	1.00	1.00
Leesburg--Eustis--Tavares, FL	0.33	0.17	0.06	0.05	0.10	0.13	0.14

	2011	2012	2013	2014	2015	2016	2017
Leominster--Fitchburg, MA	0.21	0.18	0.13	0.18	1.00	1.00	1.00
Lewiston, ID--WA	0.01	0.02	0.01	0.01	0.01	0.01	0.02
Lewiston, ME	0.02	0.04	0.02	0.02	0.02	0.02	0.03
Lexington Park--California--Chesapeake Ranch Estates, MD	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Lexington-Fayette, KY	0.36	0.20	0.25	1.00	1.00	1.00	1.00
Lima, OH	0.01	0.01	0.02	0.02	0.02	0.03	0.03
Lincoln, NE	0.47	0.58	0.89	1.00	1.00	1.00	1.00
Little Rock, AR	0.62	0.62	0.65	1.00	1.00	1.00	1.00
Livermore, CA	0.00	0.00	0.01	0.01	0.01	0.01	0.01
Lodi, CA	0.02	0.02	0.02	0.04	0.03	0.03	0.04
Logan, UT	0.01	0.00	0.00	0.01	0.02	0.02	1.00
Lompoc, CA	0.00	0.00	0.01	0.01	0.01	0.01	0.01
Longmont, CO	0.03	0.04	0.04	0.04	0.04	0.04	0.04
Longview, TX	0.07	0.05	0.07	0.06	0.07	0.05	0.13
Longview, WA--OR	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Lorain--Elyria, OH	0.13	0.11	0.12	0.14	0.17	0.18	0.44
Los Angeles--Long Beach--Anaheim, CA	0.61	0.71	1.00	1.00	1.00	1.00	1.00
Los Lunas, NM	0.01	0.01	0.01	0.00	0.00	0.01	0.01
Louisville/Jefferson County, KY--IN	0.50	0.35	0.56	1.00	1.00	1.00	1.00
Lubbock, TX	0.45	0.59	0.56	1.00	1.00	1.00	1.00
Lynchburg, VA	0.13	0.17	0.21	0.25	1.00	1.00	1.00
Macon, GA	0.05	0.07	0.20	0.05	0.04	1.00	1.00
Madera, CA	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Madison, WI	0.53	0.47	0.54	1.00	1.00	1.00	1.00
Manchester, NH	0.71	0.64	0.64	1.00	1.00	1.00	1.00
Mandeville--Covington, LA	0.10	0.08	0.11	0.14	0.09	0.08	0.11
Manhattan, KS	0.01	0.00	0.01	0.01	0.01	0.01	0.01
Mankato, MN	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Mansfield, OH	0.03	0.02	0.02	0.02	0.03	0.03	0.03
Manteca, CA	0.01	0.02	0.02	0.03	0.03	0.03	0.05
Marysville, WA	0.11	0.13	0.09	0.11	1.00	1.00	1.00
Mauldin--Simpsonville, SC	0.17	0.09	0.25	1.00	1.00	1.00	1.00
McAllen, TX	0.05	0.05	0.05	0.05	0.05	0.08	0.08
McKinney, TX	0.52	0.52	1.00	1.00	1.00	1.00	1.00
Medford, OR	0.07	0.07	0.07	0.07	0.08	0.19	1.00
Memphis, TN--MS--AR	0.40	0.40	0.38	1.00	1.00	1.00	1.00
Merced, CA	0.04	0.04	0.02	0.03	0.04	0.04	0.04
Miami, FL	1.25	1.18	1.10	1.00	1.00	1.00	1.00
Michigan City--La Porte, IN--MI	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Middletown, NY	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Middletown, OH	0.12	0.15	0.13	1.00	1.00	1.00	1.00
Midland, MI	0.01	0.01	0.01	0.02	0.02	0.01	0.01
Midland, TX	0.33	0.47	0.27	0.30	1.00	1.00	1.00
Milwaukee, WI	1.02	0.72	0.66	1.00	1.00	1.00	1.00
Minneapolis--St. Paul, MN--WI	0.91	0.99	1.00	1.00	1.00	1.00	1.00
Mission Viejo--Lake Forest--San Clemente, CA	1.25	1.00	0.56	1.38	2.02	2.17	2.49
Missoula, MT	0.04	0.05	0.05	0.13	0.10	0.10	0.12
Mobile, AL	0.28	0.24	0.23	0.23	1.00	1.00	1.00
Modesto, CA	0.34	0.40	0.42	1.00	1.00	1.00	1.00
Monessen--California, PA	0.04	0.13	0.14	1.00	1.00	1.00	1.00
Monroe, LA	0.06	0.06	0.06	0.06	0.06	0.06	1.00
Monroe, MI	0.02	0.01	1.00	1.00	1.00	1.00	1.00
Montgomery, AL	0.33	0.29	0.29	0.42	0.55	1.00	1.00
Morgantown, WV	0.02	0.03	0.04	0.04	0.04	0.05	0.08
Morristown, TN	0.01	0.01	0.01	0.01	0.01	0.02	0.02
Mount Vernon, WA	0.01	0.01	0.01	0.01	0.02	0.02	0.01
Muncie, IN	0.01	0.01	0.01	0.01	0.01	0.02	0.02
Murfreesboro, TN	0.03	0.07	0.08	0.10	0.14	0.14	0.16
Murrieta--Temecula--Menifee, CA	0.15	0.11	0.11	0.18	0.40	0.43	0.79
Muskegon, MI	0.07	0.07	0.07	0.07	0.10	0.17	1.00
Myrtle Beach--Socastee, SC--NC	0.19	0.19	0.16	1.00	1.00	1.00	1.00
Nampa, ID	0.04	0.06	0.07	0.12	0.18	0.20	0.31
Napa, CA	0.01	0.01	0.01	0.02	0.02	0.02	0.02
Nashua, NH--MA	0.30	0.52	1.00	1.00	1.00	1.00	1.00
Nashville-Davidson, TN	0.51	0.31	1.00	1.00	1.00	1.00	1.00
New Bedford, MA	0.23	0.20	0.18	0.19	0.51	0.45	0.38
New Bern, NC	0.01	0.01	0.01	0.01	0.01	0.01	0.01
New Haven, CT	0.42	0.44	0.41	1.00	1.00	1.00	1.00
New Orleans, LA	0.22	0.23	0.27	0.34	1.00	1.00	1.00
New York--Newark, NY--NJ--CT	3.97	1.00	1.00	1.00	1.00	1.00	1.00
Newark, OH	0.09	0.05	0.11	0.12	0.12	0.14	0.17
Norman, OK	0.06	0.08	0.20	1.00	1.00	1.00	1.00
North Port--Port Charlotte, FL	0.57	0.10	0.08	0.08	0.10	0.19	0.36
Norwich--New London, CT--RI	1.02	1.13	1.39	1.39	1.33	1.00	1.00
Ocala, FL	0.15	0.04	0.06	0.06	0.06	0.18	0.27
Odessa, TX	0.20	0.20	0.28	0.31	0.23	0.21	0.18
Ogden--Layton, UT	0.54	0.57	0.57	0.57	1.00	1.00	1.00
Oklahoma City, OK	2.76	2.54	1.00	1.00	1.00	1.00	1.00
Olympia--Lacey, WA	0.54	0.34	0.54	0.52	0.79	1.00	1.00
Omaha, NE--IA	0.54	0.54	0.50	1.00	1.00	1.00	1.00
Orlando, FL	0.36	0.33	0.39	1.00	1.00	1.00	1.00

	2011	2012	2013	2014	2015	2016	2017
Oshkosh, WI	0.05	0.05	0.04	0.04	0.09	0.11	0.15
Owensboro, KY	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Oxnard, CA	0.51	0.34	0.77	1.00	1.00	1.00	1.00
Palm Bay--Melbourne, FL	0.91	0.75	0.62	1.00	1.00	1.00	1.00
Palm Coast--Daytona Beach--Port Orange, FL	1.98	1.02	0.88	1.00	1.00	1.00	1.00
Panama City, FL	0.20	0.14	0.12	1.00	1.00	1.00	1.00
Parkersburg, WV--OH	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Pascagoula, MS	0.01	0.01	0.02	0.04	0.01	0.02	0.03
Pensacola, FL--AL	0.28	0.45	0.70	1.00	1.00	1.00	1.00
Peoria, IL	0.84	0.84	1.27	1.27	1.00	1.00	1.00
Petaluma, CA	0.03	0.03	0.02	0.02	0.02	0.05	0.07
Philadelphia, PA--NJ--DE--MD	1.27	0.76	0.74	1.00	1.00	1.00	1.00
Phoenix--Mesa, AZ	3.49	3.79	1.00	1.00	1.00	1.00	1.00
Pine Bluff, AR	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pittsburgh, PA	4.40	3.39	1.79	1.00	1.00	1.00	1.00
Pittsfield, MA	0.03	0.02	0.02	0.02	0.02	0.03	0.08
Pocatello, ID	0.01	0.01	0.01	0.02	0.02	0.02	0.02
Port Arthur, TX	0.16	0.17	0.09	0.09	0.13	0.20	0.40
Port Huron, MI	0.06	0.06	0.06	0.06	0.08	0.09	0.14
Port St. Lucie, FL	0.62	0.62	0.62	1.00	1.00	1.00	1.00
Porterville, CA	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Portland, ME	1.58	2.15	2.09	1.00	1.00	1.00	1.00
Portland, OR--WA	0.26	0.42	0.54	0.95	1.00	1.00	1.00
Portsmouth, NH--ME	0.04	0.04	0.08	0.10	0.10	0.10	0.08
Pottstown, PA	0.33	0.28	0.28	0.27	0.59	0.93	0.93
Poughkeepsie--Newburgh, NY--NJ	0.53	0.28	0.32	0.45	0.45	0.86	1.00
Prescott Valley--Prescott, AZ	0.02	0.03	0.01	0.02	0.03	0.08	0.04
Providence, RI--MA	1.02	0.75	1.00	1.00	1.00	1.00	1.00
Provo--Orem, UT	0.32	0.24	0.21	0.24	1.00	1.00	1.00
Pueblo, CO	0.08	0.07	0.09	0.07	0.07	0.10	0.11
Racine, WI	0.36	0.23	0.17	0.22	1.00	1.00	1.00
Raleigh, NC	0.27	0.21	0.34	1.00	1.00	1.00	1.00
Rapid City, SD	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Reading, PA	0.62	0.46	0.54	0.35	1.00	1.00	1.00
Redding, CA	0.06	0.06	0.06	0.06	0.08	1.00	1.00
Reno, NV--CA	0.58	0.50	0.43	0.49	1.00	1.00	1.00
Richmond, VA	0.66	0.67	0.67	1.00	1.00	1.00	1.00
Riverside--San Bernardino, CA	0.19	0.22	0.25	1.00	1.00	1.00	1.00
Roanoke, VA	2.86	2.86	2.48	1.00	1.00	1.00	1.00
Rochester, MN	0.08	0.09	0.11	0.11	0.11	0.17	0.22
Rochester, NY	0.40	0.52	0.53	0.59	0.74	0.99	1.00
Rock Hill, SC	0.03	0.04	0.04	0.04	0.06	0.09	0.14
Rockford, IL	0.36	0.34	0.26	0.34	1.00	1.00	1.00
Rocky Mount, NC	0.02	0.01	0.01	0.01	0.01	0.01	0.02
Rome, GA	0.01	0.00	0.00	0.00	0.01	0.01	0.01
Round Lake Beach--McHenry--Grayslake, IL--WI	0.26	0.20	1.00	1.00	1.00	1.00	1.00
Sacramento, CA	1.83	1.70	1.00	1.00	1.00	1.00	1.00
Saginaw, MI	0.10	0.07	0.06	0.06	0.05	0.06	0.09
Salem, OR	0.27	0.24	0.30	0.22	0.27	0.66	1.00
Salinas, CA	0.07	0.07	0.09	1.00	1.00	1.00	1.00
Salisbury, MD--DE	0.20	0.24	0.25	0.48	1.00	1.00	1.00
Salt Lake City--West Valley City, UT	0.25	0.20	0.75	1.00	1.00	1.00	1.00
San Angelo, TX	0.02	0.02	0.02	0.02	0.06	0.10	0.08
San Antonio, TX	0.93	0.47	0.60	1.00	1.00	1.00	1.00
San Diego, CA	1.10	1.19	1.00	1.00	1.00	1.00	1.00
San Francisco--Oakland, CA	6.28	1.00	1.00	1.00	1.00	1.00	1.00
San Jose, CA	0.98	1.28	1.00	1.00	1.00	1.00	1.00
San Luis Obispo, CA	0.02	0.02	0.02	0.03	0.02	0.02	0.01
San Marcos, TX	0.00	0.00	0.00	0.00	0.01	0.01	0.01
Santa Barbara, CA	0.89	0.63	1.00	1.00	1.00	1.00	1.00
Santa Clarita, CA	0.07	0.07	0.04	0.20	1.00	1.00	1.00
Santa Cruz, CA	0.81	0.81	0.83	1.00	1.00	1.00	1.00
Santa Fe, NM	0.05	0.03	0.02	0.03	0.03	0.05	0.04
Santa Maria, CA	0.22	0.21	0.17	0.27	0.32	0.59	0.48
Santa Rosa, CA	0.58	0.44	0.42	1.00	1.00	1.00	1.00
Sarasota--Bradenton, FL	1.60	1.50	1.53	1.00	1.00	1.00	1.00
Saratoga Springs, NY	0.04	0.04	0.03	0.03	0.04	0.08	0.13
Savannah, GA	0.71	0.49	0.32	0.69	1.00	1.00	1.00
Scranton, PA	1.77	0.99	0.99	1.11	1.00	1.00	1.00
Seaside--Monterey, CA	0.14	0.10	0.21	1.00	1.00	1.00	1.00
Seattle, WA	0.72	1.66	1.00	1.00	1.00	1.00	1.00
Sebastian--Vero Beach South--Florida Ridge, FL	0.08	0.08	0.08	0.08	0.09	0.11	0.17
Sebring--Avon Park, FL	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sheboygan, WI	0.04	0.09	0.05	0.06	0.06	0.06	0.06
Sherman, TX	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Shreveport, LA	0.55	0.55	0.54	0.77	0.94	1.18	1.00
Sierra Vista, AZ	0.01	0.01	0.01	0.01	0.02	0.02	0.01
Simi Valley, CA	0.09	0.06	0.19	1.00	1.00	1.00	1.00
Sioux City, IA--NE--SD	0.15	0.17	0.20	0.17	0.24	0.28	1.00
Sioux Falls, SD	0.33	0.38	0.30	0.65	0.68	1.60	1.00
Slidell, LA	0.03	0.05	0.05	0.08	0.12	0.12	0.08

	2011	2012	2013	2014	2015	2016	2017
South Bend, IN--MI	0.26	0.27	0.23	0.25	0.53	0.60	1.00
South Lyon--Howell, MI	0.16	0.34	1.00	1.00	1.00	1.00	1.00
Spartanburg, SC	0.22	0.12	0.12	0.12	1.00	1.00	1.00
Spokane, WA	0.54	0.42	0.37	1.00	1.00	1.00	1.00
Spring Hill, FL	0.72	0.20	0.38	1.00	1.00	1.00	1.00
Springfield, IL	0.36	0.37	0.54	0.47	1.00	1.00	1.00
Springfield, MA--CT	0.58	0.39	0.41	0.36	1.00	1.00	1.00
Springfield, MO	1.03	0.58	0.58	0.55	1.11	1.00	1.00
Springfield, OH	0.04	0.03	0.03	0.04	0.04	0.07	0.06
St. Augustine, FL	0.06	0.03	0.05	0.08	0.07	0.07	0.05
St. Cloud, MN	0.12	0.17	0.18	0.32	0.48	0.67	1.00
St. George, UT	0.05	0.07	0.10	0.18	0.25	0.32	0.31
St. Joseph, MO--KS	0.03	0.03	0.03	0.03	0.03	0.03	0.05
St. Louis, MO--IL	0.75	0.66	0.52	0.66	1.00	1.00	1.00
State College, PA	0.03	0.03	0.03	0.03	0.04	0.11	0.10
Staunton--Waynesboro, VA	0.01	0.02	0.02	0.02	0.02	0.02	0.02
Stockton, CA	0.35	0.19	0.15	1.00	1.00	1.00	1.00
Sumter, SC	0.01	0.01	0.01	0.01	0.03	0.01	0.02
Syracuse, NY	0.67	0.32	0.42	0.42	0.41	1.32	1.00
Tallahassee, FL	0.36	0.25	0.24	1.00	1.00	1.00	1.00
Tampa--St. Petersburg, FL	1.65	1.28	1.28	1.00	1.00	1.00	1.00
Temple, TX	0.09	0.08	0.08	0.07	1.00	1.00	1.00
Terre Haute, IN	0.13	0.13	0.06	0.06	0.07	0.07	0.11
Texarkana--Texarkana, TX--AR	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Texas City, TX	0.23	0.26	0.18	1.00	1.00	1.00	1.00
Thousand Oaks, CA	1.14	0.66	0.59	1.00	1.00	1.00	1.00
Titusville, FL	0.04	0.03	0.03	0.03	0.05	0.04	0.06
Toledo, OH--MI	0.24	0.24	0.24	1.00	1.00	1.00	1.00
Topeka, KS	0.32	0.28	0.34	0.48	1.00	1.00	1.00
Tracy, CA	0.02	0.02	0.01	0.01	0.01	0.01	0.01
Trenton, NJ	0.60	0.46	0.57	1.00	1.00	1.00	1.00
Tucson, AZ	0.28	0.30	0.26	0.29	0.54	1.00	1.00
Tulsa, OK	2.13	1.85	1.99	1.00	1.00	1.00	1.00
Turlock, CA	0.03	0.06	0.06	1.00	1.00	1.00	1.00
Tuscaloosa, AL	0.12	0.12	0.10	0.16	0.16	0.32	0.31
Twin Rivers--Hightstown, NJ	0.47	1.00	1.00	1.00	1.00	1.00	1.00
Tyler, TX	0.19	0.19	0.18	0.18	0.52	0.49	0.48
Uniontown--Connellsville, PA	0.01	0.01	0.00	0.00	0.01	0.03	0.01
Urban Honolulu, HI	2.67	1.58	1.73	1.00	1.00	1.00	1.00
Utica, NY	0.38	0.39	0.36	0.39	0.39	0.44	1.00
Vacaville, CA	0.02	0.02	0.03	0.06	0.06	0.04	0.04
Valdosta, GA	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Vallejo, CA	0.08	0.09	0.08	0.08	0.13	0.14	0.26
Victoria, TX	0.06	0.07	0.06	0.06	0.05	0.06	0.11
Victorville--Hesperia, CA	0.08	0.07	0.06	0.11	0.11	0.11	0.17
Villas, NJ	0.03	0.03	0.03	0.05	0.05	0.07	0.06
Vineland, NJ	0.02	0.02	0.02	0.02	0.03	0.03	0.03
Virginia Beach, VA	1.18	1.07	1.44	1.00	1.00	1.00	1.00
Visalia, CA	0.14	0.10	0.10	0.12	0.14	0.17	0.21
Waco, TX	0.09	0.18	0.25	1.00	1.00	1.00	1.00
Waldorf, MD	0.07	0.14	0.16	0.16	1.00	1.00	1.00
Walla Walla, WA--OR	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Warner Robins, GA	0.17	0.14	0.06	0.10	0.21	0.20	0.20
Washington, DC--VA--MD	1.70	1.41	1.00	1.00	1.00	1.00	1.00
Waterbury, CT	0.30	0.23	0.27	0.42	0.30	0.20	0.27
Waterloo, IA	0.06	0.05	0.05	0.06	0.09	0.11	1.00
Watertown, NY	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Watsonville, CA	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Wausau, WI	0.01	0.01	0.02	0.02	0.02	0.02	0.02
Weirton--Steubenville, WV--OH--PA	0.01	0.01	0.01	0.02	0.05	0.05	0.05
Wenatchee, WA	0.01	0.01	0.01	0.01	0.02	0.02	0.02
West Bend, WI	0.01	0.01	0.01	0.02	0.02	0.02	0.01
Westminster--Eldersburg, MD	0.15	0.10	0.14	0.14	0.17	0.19	0.29
Wheeling, WV--OH	0.02	0.02	0.03	0.05	0.05	0.06	0.07
Wichita Falls, TX	0.07	0.07	0.04	0.03	0.07	0.08	0.07
Wichita, KS	0.99	0.99	0.99	1.00	1.00	1.00	1.00
Williamsburg, VA	0.04	0.05	0.08	0.05	0.05	0.05	0.04
Williamsport, PA	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Wilmington, NC	0.70	0.47	0.42	1.00	1.00	1.00	1.00
Winchester, VA	0.04	0.04	0.04	0.04	0.04	0.05	0.06
Winston-Salem, NC	0.41	0.23	0.23	0.25	1.00	1.00	1.00
Winter Haven, FL	0.19	0.09	0.09	1.00	1.00	1.00	1.00
Woodland, CA	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Worcester, MA--CT	1.06	1.06	1.00	1.00	1.00	1.00	1.00
Yakima, WA	0.24	0.15	0.15	0.22	0.26	1.00	1.00
York, PA	0.61	0.43	0.45	0.88	1.00	1.00	1.00
Youngstown, OH--PA	0.30	0.28	0.39	0.62	0.99	1.00	1.00
Yuba City, CA	0.04	0.04	0.04	0.05	0.05	0.05	0.05
Yuma, AZ--CA	0.21	0.13	0.12	0.11	0.09	0.10	0.14
Zephyrhills, FL	0.05	0.07	0.09	1.00	1.00	1.00	1.00

Table S5. Urban area-specific heterogeneous treatment effects. Estimates from the heterogeneous treatment effect (HTE) regressions modeling vehicle registrations, fuel economy, and transit ridership. Related to Figure 2.

Urban Area	Vehicle Reg's.	Fuel Economy	Transit Ridership	Urban Area	Vehicle Reg's.	Fuel Economy	Transit Ridership	Urban Area	Vehicle Reg's.	Fuel Economy	Transit Ridership
Aberdeen-Bel Air South-Bel Air North, MD	-0.039*** (0.007)	0.003*** (0.001)	-	Cincinnati, OH-KY-IN	0.054*** (0.004)	0.005*** (0.001)	-0.026* (0.018)	Gulfport, MS	-0.012*** (0.004)	-0.002** (0.001)	0.005 (0.021)
Akron, OH	0.015*** (0.004)	0.004*** (0.001)	0.008 (0.017)	Clarksville, TN-KY	0.050** (0.022)	-0.003* (0.002)	-	Hagerstown, MD-WV-PA	0.130*** (0.006)	-0.006*** (0.002)	-
Albany-Schenectady, NY	0.003 (0.003)	0.002*** (0.001)	-0.015 (0.012)	Cleveland, OH	0.010*** (0.004)	0.009*** (0.001)	-0.069*** (0.017)	Harrisburg, PA	0.039*** (0.004)	-0.003*** (0.001)	-0.089*** (0.017)
Albuquerque, NM	-0.032*** (0.005)	0.001 (0.001)	-0.068*** (0.022)	Colorado Springs, CO	0.030*** (0.005)	-0.010*** (0.001)	0.177*** (0.016)	Hartford, CT	-0.004 (0.005)	0.000 (0.001)	0.069*** (0.020)
Allentown, PA-NJ	0.050*** (0.003)	-0.005*** (0.001)	0.006 (0.014)	Columbia, SC	0.018*** (0.003)	-0.005*** (0.001)	0.411*** (0.013)	High Point, NC	-0.034*** (0.004)	0.001 (0.001)	-
Amarillo, TX	0.006* (0.005)	-0.008*** (0.001)	-	Columbus, GA-AL	-0.040*** (0.005)	-0.003*** (0.001)	-	Holland, MI	-0.005 (0.010)	-0.014*** (0.002)	-0.014 (0.036)
Anchorage, AK	-0.084*** (0.004)	-0.004*** (0.001)	-0.050*** (0.013)	Columbus, OH	0.000 (0.004)	0.003*** (0.001)	0.048*** (0.014)	Houston, TX	0.070*** (0.014)	-0.009*** (0.004)	0.041 (0.040)
Ann Arbor, MI	-0.025*** (0.005)	0.005*** (0.002)	0.035* (0.021)	Concord, NC	-0.060*** (0.006)	-0.002** (0.001)	-	Huntington, WV-KY-OH	-0.017*** (0.003)	-0.006*** (0.001)	0.065*** (0.016)
Appleton, WI	0.011*** (0.004)	-0.003*** (0.001)	-0.006 (0.021)	Corpus Christi, TX	-0.013*** (0.004)	0.004*** (0.001)	-0.015 (0.018)	Huntsville, AL	-0.008** (0.003)	-0.003*** (0.001)	0.330*** (0.013)
Asheville, NC	-0.033*** (0.005)	-0.001 (0.001)	0.267*** (0.024)	Dallas-Fort Worth-Arlington, TX	0.082*** (0.011)	-0.002 (0.003)	-0.021 (0.030)	Idaho Falls, ID	0.031*** (0.003)	-0.010*** (0.001)	-
Athens-Clarke County, GA	0.013** (0.007)	0.006*** (0.001)	-0.196*** (0.023)	Danbury, CT-NY	0.020*** (0.003)	0.004*** (0.001)	-0.064*** (0.017)	Indianapolis, IN	0.007* (0.005)	-0.003*** (0.001)	0.046*** (0.014)
Atlanta, GA	0.011* (0.008)	0.011*** (0.002)	-0.052** (0.023)	Davenport, IA-IL	-0.035*** (0.005)	-0.005*** (0.001)	0.025 (0.020)	Indio-Cathedral City, CA	0.034*** (0.012)	0.020*** (0.002)	0.042 (0.035)
Atlantic City, NJ	0.001 (0.006)	0.006*** (0.001)	-0.047** (0.021)	Dayton, OH	0.025*** (0.005)	-0.001* (0.001)	0.054*** (0.017)	Iowa City, IA	-0.012** (0.006)	0.000 (0.001)	-0.039** (0.020)
Augusta-Richmond County, GA-SC	-0.010** (0.006)	-0.004*** (0.001)	-	Deltona, FL	0.036*** (0.006)	0.018*** (0.002)	-	Jackson, MS	0.002 (0.004)	-0.004*** (0.001)	-
Austin, TX	0.049*** (0.005)	0.012*** (0.001)	0.347*** (0.021)	Denver-Aurora, CO	0.063*** (0.007)	-0.011*** (0.002)	0.028 (0.022)	Jacksonville, FL	0.029*** (0.004)	0.008*** (0.001)	0.064*** (0.014)
Bakersfield, CA	0.013** (0.006)	0.003*** (0.001)	-0.082*** (0.017)	Detroit, MI	0.027*** (0.006)	0.004*** (0.001)	-0.185*** (0.027)	Kalamazoo, MI	-0.020*** (0.005)	-0.008*** (0.001)	0.023 (0.024)
Baltimore, MD	-0.023*** (0.004)	0.002** (0.001)	0.005 (0.015)	Duluth, MN-WI	0.011*** (0.003)	-0.008*** (0.001)	-0.013 (0.018)	Kansas City, MO-KS	0.006* (0.004)	-0.003*** (0.001)	-0.117*** (0.016)
Barnstable Town, MA	0.004 (0.005)	-0.001 (0.001)	0.108*** (0.017)	Durham, NC	-0.048*** (0.004)	0.004*** (0.001)	-0.009 (0.015)	Kennewick-Pasco, WA	-0.030*** (0.005)	-0.005*** (0.001)	-0.099*** (0.017)
Baton Rouge, LA	-0.096*** (0.005)	-0.008*** (0.001)	0.121*** (0.019)	Eau Claire, WI	0.010** (0.005)	-0.004*** (0.001)	0.003 (0.016)	Kenosha, WI-IL	0.005 (0.007)	0.002 (0.002)	-0.024 (0.022)
Bellingham, WA	-0.016*** (0.005)	0.000 (0.001)	-0.082*** (0.016)	El Paso, TX-NM	0.004 (0.010)	0.003** (0.001)	-0.046** (0.026)	Kissimmee, FL	0.038*** (0.005)	0.014*** (0.001)	-
Beloit, WI-IL	-0.008*** (0.003)	-0.008*** (0.001)	-	Elkhart, IN-MI	0.019*** (0.007)	-0.011*** (0.001)	0.188*** (0.028)	Knoxville, TN	-0.004 (0.004)	-0.006*** (0.001)	-0.062*** (0.017)
Billings, MT	-0.012*** (0.004)	-0.023*** (0.001)	-0.114*** (0.017)	Erie, PA	0.013*** (0.004)	0.000 (0.001)	-0.071*** (0.014)	La Crosse, WI-MN	0.014*** (0.004)	-0.003*** (0.001)	-0.034** (0.018)
Binghamton, NY-PA	-0.011*** (0.004)	0.003*** (0.001)	-0.040*** (0.015)	Evansville, IN-KY	-0.013*** (0.003)	-0.001* (0.001)	-0.161*** (0.017)	Lafayette, IN	-0.013** (0.006)	-0.006*** (0.001)	-0.038** (0.017)
Birmingham, AL	-0.005** (0.003)	-0.003*** (0.001)	0.066*** (0.013)	Fargo, ND-MN	0.012** (0.006)	-0.007*** (0.001)	-0.014 (0.020)	Lafayette, LA	-0.046*** (0.003)	0.000 (0.001)	0.194*** (0.017)
Bloomington, IN	-0.005 (0.005)	-0.002* (0.001)	0.078*** (0.025)	Fayetteville-Springdale-Rogers, AR-MO	0.008* (0.006)	-0.002* (0.001)	0.111*** (0.017)	Lakeland, FL	0.019*** (0.006)	0.013*** (0.001)	0.115*** (0.020)
Boise City, ID	0.033*** (0.006)	-0.003*** (0.001)	-	Fayetteville, NC	-0.099*** (0.012)	0.005*** (0.002)	-0.015 (0.031)	Lancaster, PA	0.018*** (0.003)	-0.006*** (0.001)	-
Bonita Springs, FL	0.043*** (0.008)	0.012*** (0.001)	-0.147*** (0.026)	Flint, MI	0.013** (0.006)	-0.011*** (0.001)	-0.084*** (0.035)	Lansing, MI	0.071*** (0.003)	-0.003*** (0.001)	-0.036** (0.016)
Boston, MA-NH-RI	0.002 (0.006)	-0.002 (0.003)	-0.011 (0.019)	Fort Collins, CO	0.011*** (0.003)	-0.010*** (0.001)	0.070*** (0.014)	Las Cruces, NM	-0.003 (0.005)	-0.005*** (0.001)	-
Boulder, CO	0.162*** (0.005)	0.005*** (0.001)	-	Fort Walton Beach-Navarre-Wright, FL	-0.012*** (0.004)	0.002*** (0.001)	-0.115*** (0.017)	Las Vegas-Henderson, NV	0.018*** (0.007)	0.006*** (0.001)	0.149*** (0.025)
Bridgeport-Stamford, CT-NY	0.050*** (0.006)	0.001 (0.002)	-0.010 (0.026)	Fort Wayne, IN	0.011** (0.006)	-0.005*** (0.001)	-0.021 (0.022)	Lee's Summit, MO	-0.001 (0.004)	0.000 (0.001)	-
Brunswick, GA	-0.024*** (0.008)	0.002 (0.002)	-	Frederick, MD	-0.059*** (0.004)	0.000 (0.001)	-0.187*** (0.017)	Leominster-Fitchburg, MA	0.075*** (0.003)	0.004*** (0.001)	0.001 (0.017)
Buffalo, NY	-0.012*** (0.003)	0.004*** (0.001)	0.004 (0.013)	Fresno, CA	-0.017*** (0.006)	0.004*** (0.001)	-0.026 (0.021)	Lexington-Fayette, KY	-0.016*** (0.004)	-0.001** (0.001)	-0.179*** (0.018)
Canton, OH	0.017*** (0.005)	-0.001 (0.001)	0.059*** (0.017)	Gainesville, FL	0.169*** (0.006)	0.010*** (0.001)	0.014 (0.023)	Lincoln, NE	-0.015*** (0.003)	-0.008*** (0.001)	0.109*** (0.017)
Cape Coral, FL	0.019*** (0.006)	0.011*** (0.001)	-0.003 (0.028)	Gainesville, GA	-0.001 (0.005)	0.003*** (0.001)	-	Little Rock, AR	-0.017*** (0.003)	-0.002*** (0.001)	-0.013 (0.014)
Cedar Rapids, IA	-0.021*** (0.004)	-0.008*** (0.001)	0.103*** (0.018)	Grand Junction, CO	-0.002 (0.009)	-0.012*** (0.002)	-	Logan, UT	-0.003 (0.006)	-0.007*** (0.001)	-0.103*** (0.019)
Champaign, IL	-0.013*** (0.004)	-0.002*** (0.001)	0.084*** (0.017)	Grand Rapids, MI	0.004 (0.004)	-0.006*** (0.001)	-0.077*** (0.020)	Los Angeles-Long Beach-Anaheim, CA	0.030*** (0.008)	0.024*** (0.001)	-0.038** (0.020)
Charleston-North Charleston, SC	0.003 (0.004)	-0.001 (0.001)	-0.107*** (0.015)	Greeley, CO	0.070*** (0.007)	-0.019*** (0.002)	-	Louisville/Jefferson County, KY-IN	-0.009** (0.004)	-0.001 (0.001)	-0.061*** (0.019)
Charlotte, NC-SC	-0.034*** (0.005)	0.003*** (0.001)	-0.072*** (0.015)	Green Bay, WI	0.001 (0.004)	-0.001 (0.001)	-0.072*** (0.018)	Lubbock, TX	0.004 (0.004)	-0.001** (0.001)	0.048*** (0.016)
Chattanooga, TN-GA	-0.026*** (0.003)	0.000 (0.001)	0.000 (0.016)	Greensboro, NC	-0.039*** (0.007)	0.004*** (0.001)	-0.077*** (0.022)	Lynchburg, VA	-0.007** (0.003)	-0.012*** (0.001)	-0.043*** (0.018)
Chicago, IL-IN	0.042*** (0.004)	0.006*** (0.001)	-0.030** (0.015)	Greenville, NC	-0.035*** (0.006)	0.002** (0.001)	-	Macon, GA	0.016** (0.008)	-0.002* (0.001)	-
Chico, CA	0.009* (0.006)	-0.003*** (0.001)	0.005 (0.017)	Greenville, SC	0.054*** (0.009)	-0.009*** (0.001)	0.215*** (0.024)				

Madison, WI	0.011*** (0.005)	0.004*** (0.001)	-0.017 (0.017)	**Pittsburgh, PA**	0.006 (0.005)	0.001 (0.001)	0.060*** (0.023)	**South Bend, IN-MI**	0.010** (0.004)	-0.004*** (0.001)	-0.125*** (0.019)
Manchester, NH	0.041*** (0.005)	0.009*** (0.001)	-	**Port St. Lucie, FL**	-0.002 (0.005)	0.011*** (0.001)	0.227*** (0.031)	**South Lyon-Howell, MI**	0.041*** (0.006)	0.001 (0.001)	-
Marysville, WA	-0.003 (0.005)	-0.006*** (0.001)	-	**Portland, ME**	0.009** (0.005)	0.008*** (0.001)	0.122*** (0.020)	**Spartanburg, SC**	0.079*** (0.004)	-0.008*** (0.001)	-
Mauldin-Simpsonville, SC	0.034*** (0.007)	-0.005*** (0.002)	-	**Portland, OR-WA**	-0.007* (0.005)	-0.001 (0.002)	0.026** (0.015)	**Spokane, WA**	0.006 (0.005)	-0.018*** (0.001)	0.024* (0.018)
McKinney, TX	0.059*** (0.005)	0.010*** (0.002)	-	**Poughkeepsie-Newburgh, NY-NJ**	-0.004 (0.004)	-0.001 (0.001)	0.175*** (0.017)	**Spring Hill, FL**	-0.014** (0.008)	0.010*** (0.001)	-
Medford, OR	0.013** (0.007)	-0.005*** (0.001)	0.053** (0.024)	**Providence, RI-MA**	-0.005* (0.004)	0.001 (0.001)	-0.019 (0.015)	**Springfield, IL**	-0.006* (0.004)	-0.002** (0.001)	0.020 (0.020)
Memphis, TN-MS-AR	0.048*** (0.005)	-0.001 (0.001)	-0.090*** (0.017)	**Provo-Orem, UT**	-0.010*** (0.003)	-0.004*** (0.001)	-	**Springfield, MA-CT**	-0.066*** (0.004)	-0.006*** (0.001)	0.142*** (0.017)
Miami, FL	0.044*** (0.013)	0.004 (0.003)	-0.086*** (0.035)	**Racine, WI**	0.014* (0.010)	-0.003** (0.001)	-0.086*** (0.025)	**Springfield, MO**	-0.012*** (0.004)	-0.003*** (0.001)	-0.068*** (0.018)
Middletown, OH	0.143*** (0.008)	0.003** (0.001)	-	**Raleigh, NC**	-0.030*** (0.005)	0.004*** (0.001)	-0.117*** (0.015)	**St. Cloud, MN**	0.033*** (0.005)	-0.001 (0.001)	-0.075*** (0.015)
Midland, TX	-0.021** (0.011)	-0.025*** (0.004)	-	**Reading, PA**	0.075*** (0.004)	-0.006*** (0.001)	-	**St. Louis, MO-IL**	0.047*** (0.003)	0.006*** (0.001)	-0.042*** (0.014)
Milwaukee, WI	0.001 (0.004)	0.002*** (0.001)	-0.091*** (0.017)	**Redding, CA**	-0.115*** (0.006)	-0.002** (0.001)	-0.023 (0.033)	**Stockton, CA**	-0.002 (0.007)	0.000 (0.001)	0.099*** (0.032)
Minneapolis-St. Paul, MN-WI	0.010** (0.005)	-0.002** (0.001)	-0.014 (0.018)	**Reno, NV-CA**	0.015*** (0.006)	-0.003*** (0.001)	0.438*** (0.021)	**Syracuse, NY**	-0.007** (0.003)	0.006*** (0.001)	0.108*** (0.016)
Mobile, AL	-0.029*** (0.003)	-0.003*** (0.001)	-0.094*** (0.018)	**Richmond, VA**	-0.002 (0.005)	-0.001 (0.001)	0.008 (0.017)	**Tallahassee, FL**	0.002 (0.006)	0.005*** (0.001)	-0.152*** (0.023)
Modesto, CA	0.029*** (0.006)	0.000 (0.001)	-0.032* (0.023)	**Riverside-San Bernardino, CA**	0.040*** (0.008)	0.012*** (0.001)	-0.050** (0.021)	**Tampa-St. Petersburg, FL**	0.001 (0.006)	0.007*** (0.001)	0.005 (0.018)
Monessen-California, PA	0.032*** (0.005)	-0.007*** (0.002)	-0.021 (0.024)	**Roanoke, VA**	0.001 (0.006)	-0.008*** (0.001)	0.003 (0.021)	**Temple, TX**	-0.052*** (0.008)	0.000 (0.001)	-
Monroe, LA	-0.039*** (0.005)	-0.005*** (0.002)	-	**Rochester, NY**	-0.012*** (0.004)	0.006*** (0.001)	-0.076*** (0.016)	**Texas City, TX**	0.034*** (0.004)	-0.001* (0.001)	0.361*** (0.017)
Monroe, MI	0.015* (0.010)	-0.007** (0.003)	-	**Rockford, IL**	0.012*** (0.003)	-0.006*** (0.001)	0.016 (0.018)	**Thousand Oaks, CA**	0.028** (0.015)	0.030*** (0.002)	-
Montgomery, AL	0.028*** (0.003)	0.001 (0.001)	-0.203*** (0.014)	**Round Lake Beach-McHenry-Grayslake, IL**	0.034*** (0.005)	0.015*** (0.002)	-	**Toledo, OH-MI**	0.019*** (0.004)	-0.007*** (0.001)	-0.050** (0.023)
Muskegon, MI	-0.006 (0.005)	-0.011*** (0.001)	-	**Sacramento, CA**	-0.064*** (0.006)	0.010*** (0.001)	-0.059*** (0.015)	**Topeka, KS**	-0.010*** (0.003)	-0.013*** (0.001)	0.058*** (0.014)
Myrtle Beach-Socastee, SC-NC	0.043*** (0.004)	0.004*** (0.001)	-	**Salem, OR**	0.018*** (0.005)	-0.008*** (0.001)	0.021 (0.026)	**Trenton, NJ**	0.009** (0.005)	0.000 (0.001)	-
Nashua, NH-MA	-0.014*** (0.005)	0.008*** (0.001)	0.008 (0.018)	**Salinas, CA**	0.055*** (0.007)	0.002* (0.001)	-	**Tucson, AZ**	0.001 (0.005)	-0.003*** (0.001)	-0.047*** (0.017)
Nashville-Davidson, TN	0.011** (0.006)	0.007*** (0.001)	0.048*** (0.017)	**Salisbury, MD-DE**	-0.026*** (0.003)	0.000 (0.001)	-0.010 (0.014)	**Tulsa, OK**	0.082*** (0.004)	0.010*** (0.001)	0.076*** (0.018)
New Haven, CT	-0.018* (0.012)	0.000 (0.002)	-0.052* (0.032)	**Salt Lake City-West Valley City, UT**	-0.051*** (0.006)	-0.003** (0.002)	0.088*** (0.016)	**Turlock, CA**	0.037*** (0.006)	0.003*** (0.001)	0.149*** (0.026)
New Orleans, LA	-0.045*** (0.006)	0.004*** (0.001)	0.038** (0.019)	**San Antonio, TX**	0.037*** (0.006)	0.003** (0.001)	-0.109*** (0.021)	**Twin Rivers-Hightstown, NJ**	0.000 (0.006)	0.008*** (0.002)	-
New York-Newark, NY-NJ-CT	0.014* (0.010)	-0.008*** (0.003)	0.003 (0.029)	**San Diego, CA**	0.116*** (0.007)	0.022*** (0.002)	0.110*** (0.021)	**Urban Honolulu, HI**	0.030*** (0.006)	0.004** (0.002)	-0.006 (0.024)
Norman, OK	-0.015*** (0.004)	-0.002** (0.001)	-	**San Francisco-Oakland, CA**	0.058*** (0.008)	0.018*** (0.004)	0.028 (0.024)	**Utica, NY**	0.015*** (0.004)	0.009*** (0.001)	-
Norwich-New London, CT-RI	0.014*** (0.005)	0.003* (0.002)	-0.031* (0.022)	**San Jose, CA**	0.045*** (0.007)	0.038*** (0.004)	-0.002 (0.025)	**Virginia Beach, VA**	0.018*** (0.005)	0.000 (0.001)	-0.109*** (0.023)
Ogden-Layton, UT	-0.030*** (0.003)	-0.007*** (0.001)	-	**Santa Barbara, CA**	0.070*** (0.008)	0.016*** (0.002)	-0.055** (0.025)	**Waco, TX**	0.000 (0.004)	0.000 (0.001)	0.188*** (0.015)
Oklahoma City, OK	0.038*** (0.004)	-0.002** (0.001)	0.126*** (0.015)	**Santa Clarita, CA**	0.043*** (0.007)	0.017*** (0.001)	-0.139*** (0.017)	**Waldorf, MD**	-0.022*** (0.006)	0.009*** (0.002)	0.223*** (0.022)
Olympia-Lacey, WA	-0.028*** (0.006)	0.004*** (0.001)	-0.005 (0.020)	**Santa Cruz, CA**	0.026*** (0.006)	0.020*** (0.001)	0.030** (0.016)	**Washington, DC-VA-MD**	-0.009 (0.009)	0.000 (0.002)	-0.047* (0.031)
Omaha, NE-IA	-0.004 (0.006)	-0.008*** (0.001)	-0.044*** (0.016)	**Santa Rosa, CA**	0.021*** (0.006)	0.016*** (0.001)	-0.203*** (0.019)	**Waterloo, IA**	-0.044*** (0.004)	-0.008*** (0.001)	-
Orlando, FL	0.063*** (0.006)	0.021*** (0.001)	-0.037** (0.021)	**Sarasota-Bradenton, FL**	0.016** (0.007)	0.009*** (0.001)	-0.002 (0.024)	**Wichita, KS**	-0.006* (0.004)	-0.006*** (0.001)	-0.184*** (0.016)
Oxnard, CA	0.048*** (0.006)	0.008*** (0.001)	0.086*** (0.017)	**Savannah, GA**	-0.002 (0.006)	0.002* (0.002)	-	**Wilmington, NC**	-0.043*** (0.004)	0.004*** (0.001)	-0.137*** (0.017)
Palm Bay-Melbourne, FL	0.010*** (0.004)	0.011*** (0.001)	-	**Scranton, PA**	0.037*** (0.004)	-0.005*** (0.001)	-0.134*** (0.016)	**Winston-Salem, NC**	-0.022*** (0.004)	-0.001* (0.001)	-0.098*** (0.017)
Palm Coast-Daytona Beach-Port Orange, FL	0.029*** (0.005)	0.013*** (0.001)	0.004 (0.022)	**Seaside-Monterey, CA**	0.036*** (0.006)	0.010*** (0.001)	0.073*** (0.017)	**Winter Haven, FL**	0.036*** (0.008)	0.015*** (0.001)	-
Panama City, FL	-0.002 (0.006)	-0.002* (0.001)	-0.101*** (0.023)	**Seattle, WA**	0.011** (0.006)	0.002 (0.002)	0.092*** (0.017)	**Worcester, MA-CT**	0.026*** (0.005)	0.006*** (0.001)	0.096*** (0.019)
Pensacola, FL-AL	-0.036*** (0.012)	-0.003** (0.002)	0.653*** (0.033)	**Shreveport, LA**	-0.038*** (0.005)	0.001 (0.002)	-0.094*** (0.022)	**Yakima, WA**	-0.029*** (0.007)	-0.013*** (0.001)	-0.105*** (0.019)
Peoria, IL	-0.016*** (0.004)	-0.004*** (0.001)	-0.048*** (0.019)	**Simi Valley, CA**	0.021*** (0.008)	0.017*** (0.001)	-	**York, PA**	0.059*** (0.005)	-0.005*** (0.001)	0.162*** (0.024)
Philadelphia, PA-NJ-DE-MD	0.040*** (0.005)	0.001 (0.001)	0.036** (0.018)	**Sioux City, IA-NE-SD**	0.020*** (0.004)	-0.013*** (0.001)	-0.116*** (0.023)	**Youngstown, OH-PA**	0.006** (0.003)	0.001** (0.001)	0.083*** (0.015)
Phoenix-Mesa, AZ	0.062*** (0.007)	0.001 (0.001)	0.138*** (0.018)	**Sioux Falls, SD**	0.003 (0.005)	-0.009*** (0.001)	-0.067*** (0.015)	**Zephyrhills, FL**	0.066*** (0.003)	0.012*** (0.001)	-

Table S6. Cluster Analysis Results. Estimated effects on vehicle registrations per capita and average fuel economy and descriptive statistics by cluster for clusters of urban areas estimated in a 3-cluster and 4-cluster analysis. Related to Figure 3.

Cluster		Largest Urban Area	n	% treated	Estimated Effect on Vehicle Registrations per capita			Estimated Effect on Average Fuel Economy		
					Estimate	Cluster s.e.	p-value	Estimate	Cluster s.e.	p-value
3-cluster results	1	St. Louis, MO--IL Urbanized Area	193	42.5	2.04%	0.52%	0.000	0.43%	0.11%	0.000
	2	Los Angeles--Long Beach--Anaheim, CA Urbanized Are	291	54.6	0.13%	0.46%	0.781	0.12%	0.09%	0.147
	3	New York--Newark, NY--NJ--CT Urbanized Area	1	100	-1.75%	0.32%	0.000	0.02%	0.04%	0.562
4-cluster results	1	St. Louis, MO--IL Urbanized Area	193	42.5	2.04%	0.52%	0.000	0.43%	0.11%	0.000
	2	Detroit, MI Urbanized Area	258	51.2	-0.19%	0.50%	0.711	0.13%	0.09%	0.163
	3	Los Angeles--Long Beach--Anaheim, CA Urbanized Are	33	81.8	2.58%	0.89%	0.004	-0.02%	0.24%	0.950
	4	New York--Newark, NY--NJ--CT Urbanized Area	1	100	-1.72%	0.32%	0.000	0.03%	0.04%	0.484

Cluster		Largest Urban Area	Vehicle Registrations per capita	Population	Population Density	Transit Commuting Rate	Unemployment Rate	Household income	Childless Households	Population Growth Rate
3-cluster results	1	St. Louis, MO--IL Urbanized Area	0.869	257826	1116	1.4%	8.5%	51748	68.9%	0.1%
	2	Los Angeles--Long Beach--Anaheim, CA Urbanized Are	0.805	581637	1488	2.1%	8.5%	56435	65.9%	1.2%
	3	New York--Newark, NY--NJ--CT Urbanized Area	0.545	18735857	25304	32.5%	8.7%	72644	65.5%	0.5%
4-cluster results	1	St. Louis, MO--IL Urbanized Area	0.869	257826	1116	1.4%	8.5%	51748	68.9%	0.1%
	2	Detroit, MI Urbanized Area	0.813	326420	1227	1.4%	8.6%	55002	65.7%	1.2%
	3	Los Angeles--Long Beach--Anaheim, CA Urbanized Are	0.743	2576968	3522	7.4%	7.4%	67643	67.8%	1.1%
	4	New York--Newark, NY--NJ--CT Urbanized Area	0.545	18735857	25304	32.5%	8.7%	72644	65.5%	0.5%

Table S7. Summary statistics of urban areas by bin. A comparison of mean and standard deviation for the lower and upper 50%ile for each respective interaction term: vehicle registrations per capita, population, change in population, household income, and transit commuting rate. Related to Table 4.

	Lower 50%ile Mean (Std. Dev.)	Upper 50%ile Mean (Std. Dev.)
Vehicle Registrations per capita	0.752 (0.063)	0.908 (0.095)
Population	97,482 (25,909)	883,140 (1,773,708)
Change in Population	-0.10% (1.34%)	1.58% (2.02%)
Household Income	45,254 (3,877)	63,955 (12,200)
Transit Commuting Rate	0.60% (0.27%)	3.15% (3.16%)

Table S8. Comparison of heterogeneity findings across model specifications. Summary of influence of urban area characteristics on TNC entry effect sign estimated for vehicle registrations per capita, average fuel economy, and transit ridership using the HTE model, cluster analysis, and our primary specification with interaction terms for urban area covariates of pre-treatment vehicle registrations per capita, population, population growth, childless household rate, household income, transit commuting rate, unemployment rate, and gasoline price. The HTE and cluster analysis results, shown in gray, are used as exploratory models to identify a set of interaction variables to test in our primary specification. For the HTE results, + or − indicates the attribute is significant (at the p=0.05 level) in predicting whether the an urban area with a significant HTE TNC entry effect estimate will be positive or negative (Table 2). For the cluster analysis results, + or – indicates the attribute is significant (at the p=0.05 level) in predicting whether an urban area will belong to a cluster that has a TNC entry effect estimate that is positive or not statistically significant (Table 3). For the interaction effects model, our primary specification, we test only those urban area attributes identified in either the HTE analysis or the cluster analysis as being significant in predicting differences in TNC entry effect estimates. Related to Table 2, Table 3, and Table 4.

	Vehicle Registrations per capita			Average Fuel Economy			Transit Ridership		
	HTE	Cluster	Interaction	HTE	Cluster	Interaction	HTE	Cluster	Interaction
Vehicle Registrations per capita	+	+	+	+	+				
Population	−	−		−	−				
Population Growth		−	−		−				
Childless household rate	+	+		−	+	−			−
Household Income	−	−		−	−				−
Transit Commuters	+			+					
Unemployment Rate			N/A			N/A			N/A
Gasoline Price			N/A			N/A			N/A

Table S9. Summary of robustness tests and results. Related to Table 1 and Table 4.

	Estimated Effect	Randomized Treatment	Leave-One-Out	Leave-Multiple-Out	Alternative Quantile	Continuous Interaction	Alternative Clustering	Event Study
Vehicle Ownership								
Average Effect	0.007**	●	●	●	○	●	n/a	●
Interaction Effects								
Veh. Reg. per capita	0.009**	●	●	●	●	○	●	n/a
Population Growth	-0.009**	●	●	●	◒	◒	●	n/a
Average Fuel Economy								
Average Effect	3.00E-4	○	○	○	○	○	n/a	○
Interaction Effects								
Childless Household	-0.001**	●	●	●	●	○	●	n/a
Transit Ridership								
Average Effect	5.19E-4	○	○	○	○	○	n/a	○
Interaction Effects								
Childless Household	-0.001**	●	●	●	●	○	●	n/a
Income	-0.051***	●	●	●	●	◒	●	n/a

Notes: ● denotes "robust", i.e., same sign and similar magnitude and significance level; ◒ denotes near-"robust", i.e., same sign and similar magnitude but reduced significance level; and ○ denotes not robust, i.e., changes to sign, magnitude, or significance level or, alternatively, that the initial estimate wasn't significant to begin with

Table S10. Robustness check: comparison of IPTW and OLS results. Regression results estimating the effect of TNC market entry ("Treatment") on three dependent variables of interest—vehicle ownership, fleet fuel efficiency, and transit ridership—as a function of control variables (coefficients shown) both with inverse probability of treatment weighting (IPTW) and without (i.e., ordinary least squares, OLS). Year and urban-area fixed effect estimates are omitted for brevity and readability. Related to Table 1.

	Dependent variable: log, per cap.					
	Vehicle Registrations		Fuel Economy		Transit Trips	
	IPTW	OLS	IPTW	OLS	IPTW	OLS
Treatment	0.007**	0.010***	0.0003	0.003***	-0.001	0.005
	(0.003)	(0.004)	(0.0009)	(0.001)	(0.012)	(0.015)
Population	-0.118***	-0.136**	0.029***	0.051***	0.041	0.046
	(0.038)	(0.055)	(0.009)	(0.011)	(0.096)	(0.099)
Unemp. Rate	0.382	0.529	0.057	-0.045	-3.771	-2.795
	(0.513)	(0.515)	(0.113)	(0.092)	(2.38)	(2.133)
Unemp. Rate^2	-5.68***	-5.799***	-0.322	0.260	16.431	8.053
	(1.886)	(2.011)	(0.462)	(0.376)	(9.986)	(8.900)
Income	3.275***	2.11**	1.618***	0.812***	7.357*	9.457**
	(1.155)	(0.895)	(0.448)	(0.282)	(4.02)	(4.143)
Childless Households	0.524	0.46*	0.148**	0.121***	2.587**	0.465
	(0.358)	(0.252)	(0.063)	(0.033)	(1.312)	(1.022)
Transit Commuting	-0.419	-0.028	0.324*	0.308*	1.683	0.695
	(0.547)	(0.461)	(0.175)	(0.121)	(1.804)	(1.724)
Gasoline Price	0.006***	0.008***	0.005***	0.004***	0.006	0.006
	(0.002)	(0.003)	(0.001)	(0.000)	(0.009)	(0.008)
Observations	3395	3395	3395	3395	1848	1848
Deg. Freedom	2895	2895	2895	2895	1569	1569
Adjusted R-Sq.	0.948	0.914	0.979	0.975	0.998	0.997

Notes: *Time and group fixed effects and group time trend coefficient estimates not shown; *p<0.1; **p<0.05; ***p<0.01*

Table S11. Robustness check: alternative data resolution. Comparison of estimated TNC entry effect on vehicle registration from analysis at the state and urban area level. Our primary regression analysis (middle column) finds an increase in average per-capita vehicle registrations after TNC entry at the urban area level, whereas Ward et al. (2019) found a decrease in a state-level analysis (left column). We replicate the state level analysis using urban area-level data by aggregating (or population-weighting) urban area data by state and re-specifying the state-level regression model. We find that the urban area data produces a significant negative estimate when aggregated to the state level, consistent with the state-level analysis in Ward et al. (2019). This suggests that the change in sign is not a result of using a different data source but, rather, differences in results when averaged across different units of observation suggests heterogeneity: If TNC entry has different effects in different cities, averaging effects across urban areas can yield different results than averaging effects across states. Related to Table 1.

	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

Table S12. Robustness check: alternative treatment encoding. Results of a replication of regression results from Table 1 using a one-year lag in treatment. The estimated effects of lagged TNC entry on vehicle registrations, average fuel economy, and transit ridership are comparable to those estimated in the main text: a significant increase in per-capita vehicle registrations and no significant effect on either average fuel economy or per-capita transit trips. A pairwise comparison by outcome of results in Table 1 with those here confirms that the 95% confidence intervals of all estimates overlap. Related to Table 1.

	Dependent variable, log:		
	Vehicle Registrations, Per Capita	Average Fuel Economy	Transit Trips, Per Capita
Treatment Effect, lagged one year	0.007**	0.022	0.001
	(0.003)	(0.018)	(0.012)
Observations	3395	3395	1848
Deg. Freedom	2895	2895	1569
Adjusted R-Sq.	0.948	0.976	0.995

Notes: Covariate controls, time fixed effects, group fixed effects, and group time trend coefficient estimates not shown.
*p<0.1; **p<0.05; ***p<0.01

Table S13. Robustness check: disaggregation of transit ridership data. A comparison of the estimated TNC effect on per-capita transit ridership (from Table 1) with a disaggregation of transit ridership (which includes bus, rail, demand response, and other trips) by bus and rail. The TNC effect on neither per-capita bus ridership nor per-capita bus ridership is significant. Note that estimates are less precise than those presented in the main text due to the fewer number of urban areas for which bus and rail data (especially) are available. Related to Table 1.

	Dependent variable, log, per capita:		
	Transit Trips, Per Capita	Bus Trips, Per Capita	Rail Trips, Per Capita
Treatment Effect	5.19E-4	-0.008	0.008
	(1.16E-2)	(0.011)	(0.035)
Observations	1848	1792	231
Deg. Freedom	1569	1521	183
Adjusted R-Sq.	0.998	0.993	0.990

Notes: Covariate controls, time fixed effects, group fixed effects, and group time trend coefficient estimates not shown.
*p<0.1; **p<0.05; ***p<0.01

Table 14. Robustness check: correction for multiple hypothesis tests. A Benjamini-Hochberg test for False Discovery Rate (FDR) for multiple hypotheses, showing the estimated average effect of TNC entry on vehicle registration is robust to FDRs as low as 12% when considering the 3 average-effect hypothesis only, and, when considering all 21 hypothesis regarding average and interaction effects, all effects estimated as significant are robust to FDRs as low as 14%. Values highlighted in green are robust at the false detection rate of the corresponding column. Related to Table 1 and Table 4.

	Estimate	Std. Error	t value	Pr(>|t|)	p-value rank	Critical values as f(FDR*)					min. FDR*
						1%	2%	5%	10%	20%	
Veh Reg - average	**0.7%**	**0.4%**	**1.75**	**0.040**	**1**	**0.003**	**0.007**	**0.017**	**0.033**	**0.067**	**12.0%**
Avg MPG - average	0.0%	0.1%	0.34	0.366	2	0.007	0.013	0.033	0.067	0.133	54.9%
Transit - average	0.1%	1.2%	0.04	0.482	3	0.010	0.020	0.050	0.100	0.200	48.2%

	Estimate	Std. Error	t value	Pr(>|t|)	p-value rank	Critical values as f(FDR*)					min. FDR*
						1%	2%	5%	10%	20%	
Avg MPG - p_no_child	**-0.1%**	**0.0%**	**-3.10**	**0.001**	**1**	**0.000**	**0.001**	**0.002**	**0.005**	**0.010**	**2.0%**
Transit - inc	**-5.1%**	**1.7%**	**-2.95**	**0.002**	**2**	**0.001**	**0.002**	**0.005**	**0.010**	**0.019**	**1.7%**
Veh Reg - polkpc	**1.0%**	**0.4%**	**2.18**	**0.015**	**3**	**0.001**	**0.003**	**0.007**	**0.014**	**0.029**	**10.3%**
Transit - p_no_child	**-2.6%**	**1.3%**	**-1.97**	**0.024**	**4**	**0.002**	**0.004**	**0.010**	**0.019**	**0.038**	**12.8%**
Veh Reg - D_pop	**-0.9%**	**0.4%**	**-1.97**	**0.025**	**5**	**0.002**	**0.005**	**0.012**	**0.024**	**0.048**	**10.4%**
Veh Reg - average	**0.7%**	**0.4%**	**1.75**	**0.040**	**6**	**0.003**	**0.006**	**0.014**	**0.029**	**0.057**	**14.0%**
Avg MPG - D_pop	-0.1%	0.0%	-1.34	0.090	7	0.003	0.007	0.017	0.033	0.067	26.9%
Avg MPG - p_pt	-0.1%	0.0%	-1.32	0.093	8	0.004	0.008	0.019	0.038	0.076	24.4%
Transit - p_pt	2.7%	2.0%	1.31	0.095	9	0.004	0.009	0.021	0.043	0.086	22.2%
Transit - pop	2.5%	2.1%	1.18	0.119	10	0.005	0.010	0.024	0.048	0.095	25.0%
Avg MPG - inc	0.0%	0.0%	-1.05	0.148	11	0.005	0.010	0.026	0.052	0.105	28.2%
Veh Reg - pop	-0.6%	0.8%	-0.82	0.206	12	0.006	0.011	0.029	0.057	0.114	36.1%
Veh Reg - p_no_child	0.3%	0.4%	0.76	0.222	13	0.006	0.012	0.031	0.062	0.124	35.9%
Veh Reg - p_pt	0.4%	0.5%	0.70	0.242	14	0.007	0.013	0.033	0.067	0.133	36.3%
Avg MPG - average	0.0%	0.1%	0.34	0.366	15	0.007	0.014	0.036	0.071	0.143	51.2%
Transit - polkpc	-0.2%	1.3%	-0.19	0.426	16	0.008	0.015	0.038	0.076	0.152	55.9%
Transit - D_pop	-0.2%	1.3%	-0.14	0.445	17	0.008	0.016	0.040	0.081	0.162	55.0%
Avg MPG - pop	0.0%	0.1%	0.12	0.451	18	0.009	0.017	0.043	0.086	0.171	52.6%
Veh Reg - inc	0.0%	0.5%	0.07	0.472	19	0.009	0.018	0.045	0.090	0.181	52.2%
Avg MPG - polkpc	0.0%	0.0%	-0.05	0.479	20	0.010	0.019	0.048	0.095	0.190	50.3%
Transit - average	0.1%	1.2%	0.04	0.482	21	0.010	0.020	0.050	0.100	0.200	48.2%

Table S15. Robustness check: alternative quantiles for interaction effects. Estimated TNC entry effects and interaction effects on vehicle registrations per capita, average fuel economy, and transit trips per capita using three quantiles (rather than two, as is presented in the main text) for pre-treatment values of each of several interaction variables: vehicle registrations per capita, population growth rate, childless household rate, and income (population and transit commuting rate not shown to match Table 5 in the main text). Related to Table 4.

	Dependent variable, log:		
	Vehicle Registrations Per Capita	Average Fuel Economy	Transit Trips Per Capita
TNC entry in middle 33%ile	0.006	0.0005	0.040
(of all interaction variables)	(0.007)	(0.0006)	(0.025)
Pre-treatment vehicle registrations per capita			
TNC entry interaction	0.0003	-0.0003	-0.020
(middle vs. lower 33%ile)	(0.007)	(0.0005)	(0.015)
TNC entry interaction	0.008	-0.0006	-0.020
(middle vs. upper 33%ile)	(0.005)	(0.0005)	(0.018)
Pre-treatment population growth rate			
TNC entry interaction	0.004	0.0009**	0.005
(middle vs. lower 33%ile)	(0.005)	(0.0005)	(0.016)
TNC entry interaction	-0.0002	0.0005	-0.013
(middle vs. upper 33%ile)	(0.006)	(0.0005)	(0.015)
Pre-treatment childless household rate			
TNC entry interaction	-0.009	0.0003	0.025
(middle vs. lower 33%ile)	(0.006)	(0.0005)	(0.016)
TNC entry interaction	0.004	-0.0009*	-0.034**
(middle vs. upper 33%ile)	(0.005)	(0.0005)	(0.017)
Pre-treatment income			
TNC entry interaction	-0.0002	-0.0002	0.028
(middle vs. lower 33%ile)	(0.007)	(0.0005)	(0.028)
TNC entry interaction	-0.002	0.0002	-0.035***
(middle vs. upper 33%ile)	(0.005)	(0.0005)	(0.013)
Other treatment interactions	Y	Y	Y
Covariate controls	Y	Y	Y
Time fixed effects	Y	Y	Y
Group fixed effects	Y	Y	Y
Group time trends	Y	Y	Y
Observations	3395	3395	1848
Deg. Freedom	2401	2401	1296
Adjusted R-Sq.	0.972	0.996	0.998

	Dependent variable, log:		
	Vehicle Registrations Per Capita	Average Fuel Economy	Transit Trips Per Capita
Sum of middle 33%ile effect and vehicle registrations per capita interaction effect			
TNC entry in lower	0.006	0.0002	0.019
33%ile†	(0.011)	(0.0008)	(0.028)
TNC entry in upper	0.014*	-0.0001	0.020
33%ile†	(0.008)	(0.0008)	(0.020)
Sum of middle 33%ile effect and population growth rate interaction effect			
TNC entry in lower	0.010	0.0014*	0.009
33%ile†	(0.009)	(0.0008)	(0.038)
TNC entry in upper	0.006	0.0010	0.015
33%ile†	(0.010)	(0.0009)	(0.027)
Sum of middle 33%ile effect and childless household rate interaction effect			
TNC entry in lower	-0.002	0.0008	0.064*
33%ile†	(0.009)	(0.0009)	(0.037)
TNC entry in upper	0.010	-0.0004	0.006
33%ile†	(0.009)	(0.0009)	(0.031)
Sum of middle 33%ile effect and income interaction effect			
TNC entry in lower	0.006	0.0003	0.068*
33%ile†	(0.009)	(0.0009)	(0.038)
TNC entry in upper	0.004	0.0007	0.005
33%ile†	(0.009)	(0.0007)	(0.029)

Notes: Covariate, time and group fixed effects, and group time trend coefficient estimates not shown

†computed post-hoc and not directly estimated

*p<0.1; **p<0.05; ***p<0.01;

Table S16. Robustness check: continuous variables for interaction effects. Treatment effects of TNC entry in the U.S. from regression models estimating vehicle registrations per capita, average fuel economy, and transit ridership per capita using continuous measures (rather than categorical measures) of interaction variables. Related to Table 4.

	Dependent variable, log:		
	Vehicle Registrations Per Capita	Average Fuel Economy	Transit Trips Per Capita
TNC entry effect, *assuming all interaction variables at mean value*	0.006**	2.3E-5	0.003
	(0.002)	(2.4E-4)	(0.008)
TNC entry interactions with continuous measures of pre-treatment values of:			
Vehicle registrations per capita	-0.005	-0.003	-0.077
	(0.032)	(0.003)	(0.068)
Population growth rate	-0.170*	0.002	-0.303
	(0.095)	(0.008)	(0.712)
Childless household rate	0.097*	-0.002	-0.298*
	(0.059)	(0.004)	(0.175)
Income	0.165	0.063**	-0.952
	(0.260)	(0.026)	(0.693)
Other treatment interactions	Y	Y	Y
Covariate controls	Y	Y	Y
Time fixed effects	Y	Y	Y
Group fixed effects	Y	Y	Y
Group time trends	Y	Y	Y
Observations	3395	3395	1848
Deg. Freedom	2407	2407	1302
Adjusted R-Sq.	0.972	0.996	0.998

Notes: Covariate, time and group fixed effects, and group time trend coefficient estimates not shown; *p<0.1; **p<0.05; ***p<0.01;

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