Effects of On-Demand Ridesourcing on U.S. Vehicle Ownership, Travel Patterns, and Energy Use Externalities

Jeremy Michalek, Inês Azevedo, Costa Samaras, Pedro Ferreira and Nicholas Muller
Carnegie Mellon University (CMU)

We propose to capitalize on the staggered market entry timing of on-demand ridesourcing services, like Uber and Lyft, across U.S. cities and the expansion of service areas within these cities over time to answer two lines of questioning: (1) what are the effects of on-demand ridesourcing service availability on energy use, vehicle ownership, vehicle miles traveled, transit ridership, and air emissions, and (2) what are the externality cost implications of these effects?

1. INTRODUCTION

New personal transportation options that provide on-demand mobility services, including transportation network companies (TNCs) such as Uber and Lyft, have already changed how many urban travelers move. The impact of these services on energy use, vehicle ownership, and travel patterns is uncertain. On the one hand, TNCs may induce a shift away from privately owned vehicle use toward a broader set of transportation modes, such as TNCs and transit. On the other hand, the low cost and convenience of TNC travel may divert transit passengers, change the types of vehicles purchased for TNC drivers, or induce new vehicle travel (with associated energy consumption and emissions).

Preliminary studies examining on-demand ridesourcing provide promising but inconclusive evidence about the net effects of these mobility services. Survey-based efforts have suggested that 9% of TNC users in seven major U.S. cities report disposing of one or more household vehicles[1], and Austin, Texas users reported a 9% increase in vehicle ownership following the departure of Uber and Lyft[2]. The same studies suggest that 49% to 61% of ride-hailing trips are associated with increased vehicle miles traveled (VMT)[1] but that the departure of Uber and Lyft in Austin resulted in a 23% increase in trips for individuals who transitioned from TNC-use to a personal vehicle mobility paradigm[2]. Econometric studies have found that Uber market entry decreases urban traffic congestion in the United States[3] and that Uber entry is associated with an 8% increase in new vehicle ownership in China[4]. The effect of TNC entry on energy use and the related factors of VMT, transit use, and air emissions have not been studied.

2. METHODS

Because TNCs entered different cities at different times since 2005 and expanded service zones within cities over time, a difference-in-difference (DiD) regression model can be used to distinguish TNC market entry effects from other trends and to estimate causal effects. Our proposed model will estimate effects at the zip-code level using recently-obtained monthly vehicle registration data from IHS Markit. In our preliminary model, we estimate state level effects. The state-level econometric model specification is:

$$y_{st} = \boldsymbol{\beta}'\mathbf{x}_{st} + \boldsymbol{\alpha}'\mathbf{z}_{st} + \lambda_s + \theta_t + \varepsilon_{st} \qquad (1)$$

where y_{st} is the dependent variable of interest for state s and year t; $\mathbf{x}_{st}$ is the vector of treatment effects (i.e., a TNC/ridesharing indicator) with coefficient vector $\boldsymbol{\beta}$ (the prime indicates transpose); $\mathbf{z}_{st}$ is a vector of controls (including population, gas price, real personal income per capita, and Section 177 status--a proxy for state air quality regulatory stringency) with coefficient vector $\boldsymbol{\alpha}$; λ_s is the fixed effect for state s; θ_t is the fixed effect for year t; and ε_{st} is unobserved error. To further control for systematic differences

of states where TNCs enter and those where TNCs do not enter, we apply propensity score weighting with inverse probability of treatment weights (IPTW) using a logistic regression model:

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

where p_{st} is the probability of treatment for state s and year t; $\boldsymbol{\gamma}$ is the vector of control variable coefficients; and ξ_{st} is unobserved error. We examine the balance of the weighted sample to ensure control and treatment groups are comparable and use the resulting estimates of p_{st} as IPTW weights in Eq.(1) to conduct state-level regression analyses for four dependent variables: gasoline use, vehicle registration, VMT, and emissions. Three specifications were applied: (1) a binary model ($x_{st} = 1$ if Uber or Lyft are present in state s in year t and 0 otherwise) to estimate the average effect of entry over the analysis period; (2) a discrete annual model to test for a potentially dynamic effect over time, and (3) a population-share model that accounts for the share of each state's population served by Uber each year. Statistical and diagnostic tests used to structure the regression include a Box-Cox test, a correlation matrix, and generalized additive models, and robustness checks include examination of residual errors, randomized treatment permutation testing, leave-one-out analysis, leave-multiple-out analysis, and alternative model specifications (including an unweighted regression).

To estimate externality costs of these effects, we adopt models and estimates from the literature, including the AP2[5] and EASIUR[6] models of monetized location-specific air pollution damages, social cost of carbon estimates from the Interagency Working Group[7], estimates of accident and congestion externalities per VMT[8], and oil premium estimates of gasoline consumption.[8-9]

3. DATA

3.1 Dependent variables:

- *Energy use (measured):* The U.S. Department of Transportation (DOT) has published motor fuel sales data from state motor fuel tax agencies in their State Statistical Abstract series since 2008,[10] and earlier data are available in DOT's Highway Statistics Series.[11]
- *Vehicle ownership (measured):* IHS/R.L. Polk maintains data on the number, location, and type (market segment, size, fuel economy, etc.) of light-duty vehicle registrations in the U.S.; we recently obtained an annual time series of these data for 2010–2016. For the preliminary analysis we adopt vehicle registration data by state for each year for light-duty passenger vehicles from Ward's Automotive.[12] Ward's data are based on data published in U.S. DOT's State Statistical Abstracts, which is the set of official vehicle registration data published by state DOTs.
- *Transit ridership (measured)*: the American Public Transit Association publishes a quarterly time-series of unchained passenger trips by public transit agency (typically roughly congruous with a metropolitan statistical area), as originally reported to the U.S. Department of Transportation (DOT) (as is legally required for transit agencies receiving DOT financial support).[13]
- *VMT (estimated):* State agencies estimate aggregate VMT based on vehicle count data measured on representative roadways and distributions of roadway type within the state, and these are reported in DOT's State Statistical Abstract series and Highway Statistics Series[10,11]. Existing agreements with CMU have also made available vehicle registration and odometer readings for Pennsylvania, Texas, and Colorado, as reported by the respective state agencies.
- *Emissions (estimated):* State-level emissions data are published annually in the U.S. Environmental Protection Agency's State Average Emissions Trend report, which, in turn, is informed by EPA's National Emission Index.[14] Emissions attributable to light-duty vehicles are estimated by the EPA

annually. DOE's Energy Information Administration (EIA) publishes an annual series of State Carbon Dioxide Emissions, with a roughly 2-year lag.[15]

3.2 Independent variables:

- *TNC market entry:* Uber/UberX market entry dates by city (or metropolitan area) for over 100 U.S. metropolitan regions from 2010 to 2016 have been aggregated from public announcements in three previously published papers[3,16,17], and Lyft directly provided their market launch data in response to our request.[18] As an alternative model specification, we estimate the portion of each state's population served by Uber each year, and we are also in the process of negotiating for more detailed data on the service region in each city over time, which would provide additional resolution.
- *Control variables*: the U.S. Census Bureau's American FactFinder database provides time-series data on relevant demographics and economics data (household size and income, age and race distribution, etc.) at the ZIP code level.[19] We also use information on gasoline price[20] and state policy (participation in Section 177 of the Clean Air Act)[21].

4. PRELIMINARY FINDINGS

In advance of and in support of the proposed ZIP-code level analysis, we conducted a preliminary analysis at the state level using the Uber and Lyft market entry data described above and associated data on energy use, vehicle registration, VMT, and emissions using publically available data at the state level (50 state-level observations over 11 years for a total of n=550 observations). Each state's annual share of population with TNC access was derived by summing within each state the population of each city where Uber is present and dividing by DOT-estimated total state population[10,19]. Other relevant data include: personal income data from the Bureau of Economic Analysis[22], average state gasoline price from the Energy Information Administration[20], and an indicator for whether a state has adopted California's more stringent vehicle emissions control requirements, pursuant to Section 177 of the Clean Air Act.[21]

Table 1. Summary of the estimated effect of TNC entry on gasoline use, vehicle registration, VMT, and emissions of NOx and VOCs from three regression models: (1) a binary (average effect) model, (2) a discrete annual (dynamic effect) model, and (3) a population-share model.

		Gasoline Use	Vehicle registrations	VMT	NOx	VOC
(1) Average effect of state entry		-4.9%**	-4.0%**	-4.0%**	-7.7%	-8.9%
		(2.0%)	(1.7%)	(2.0%)	(6.2%)	(6.6%)
(2) Dynamic effect of state entry	1st year	-3.9%**	-4.5%**	-3.3%*	-6.2%	-8.0%
		(1.8%)	(2.1%)	(1.8%)	(5.8%)	(6.1%)
	2nd year	-7.9%***	-6.4%**	-6.0%**	-10.9%	-10.6%
		(2.7%)	(2.6%)	(2.7%)	(8.5%)	(8.5%)
	>2 years	-11.3%***	-10.6%**	-8.5*	-11.0%	-8.8%
		(4.2%)	(4.6%)	(4.4%)	(13.4%)	(13.5%)
(3) Effect per 1% of state population served		-0.196%**	-0.135%**	-0.181%**	-0.280%**	-0.269%**
		(0.086%)	(0.051%)	(0.067%)	(0.119%)	(0.098%)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.01$

Table 1 summarizes treatment effect estimates from our results across three model specifications (control variables not shown). We estimate that TNC service availability in U.S. cities has reduced state per-capita gasoline consumption by 4.9% and reduced state per-capita vehicle ownership by 4.0%, on average, during the period 2005 to 2015 (relative to expected trends if the TNCs had not entered those states). This represents an average 0.20% drop in state per-capita gasoline consumption and a 0.14% drop in state per-capita vehicle registrations per 1% of the state's population that gains TNC access.

Further, using estimates of VMT from U.S. state Departments of Transportation, we estimate that TNC service availability has reduced state per-capita VMT by 4.0% on average or 0.18% per 1% of a state's population that gains access to TNC services. And using EPA estimates of passenger transportation emissions, we estimate that TNC service availability has reduced state per-capita emissions of CO, NH_3, NO_X, and VOCs by 0.23%, 0.28%, 0.28%, and 0.27%, respectively, per 1% of a state's population that gains TNC access (NOx and VOCs shown in Table 1).

5. INTERMEDIATE CONCLUSIONS AND PROPOSED NEXT STEPS

Our results suggest that access to TNC services has reduced per-capita gasoline consumption and vehicle registrations in U.S. states. The application of several diagnostic methods—visual inspection of regression residual errors, a permutation test using iterative resampling, synthetic control group matching, and a leave-one-out analysis—yields no evidence of systematic error or potential misspecifications.

Our results also suggest that TNC services have likely reduced per-capita VMT and emissions of several pollutants in U.S. states. Specifically, our preferred model specifications suggest that TNC services have caused a decrease in both VMT and emissions, and no model specification examined suggests an increase in VMT or emissions; however, both state VMT and state emissions data are estimated by government agencies rather than measured directly.

Our preliminary analysis focuses on changes in overall state-level outcomes after TNCs enter cities within those states. We cannot identify changes to fleet mix with the available data, and there are potentially multiple alternative narratives that might explain these trends. For example, it is possible that TNCs reduce gasoline consumption primarily by reducing VMT, but it is also possible that TNCs reduce gasoline consumption primarily by shifting VMT away from older, less efficient vehicles toward newer, more efficient vehicles that operate under hot steady-state conditions for a large portion of VMT. Newer vehicles are also associated with lower pollutant emissions: CO, NO_x, VOC, and PM emissions in transportation have declined 30-50% over the past ten years[23], although the EPA emissions estimates we use do not account for potential changes in cold start vs. hot operation ratios induced by TNCs, so any signal captured by our models and data is potentially attributable to a vehicle fleet transition but not likely to drive-cycle.

By extending our preliminary analysis using IHS ZIP-code level registration data, we expect to add precision and robustness to the preliminary analysis and yield additional insight about the mechanisms that produce the observed outcomes. We also intend to extend our analysis to examine the effect of TNC entry on transit use and geographically distributed socio-demographic populations), and we will estimate externality costs of these effects by drawing on estimates from the literature for accidents and congestion as a function of VMT[8], air pollution damages for each pollutant[5,6], as a function of location, and oil premium costs to the U.S. [8-9]

6. RESEARCHERS

- **Dr. Jeremy J. Michalek** (PI) is a Professor of Engineering and Public Policy, Professor of Mechanical Engineering, and Director of the Vehicle Electrification Group at Carnegie Mellon University. He has published studies on life cycle externality and oil premium implications of vehicle technologies and on effects of federal and state policy interactions on the light-duty fleet mix and its externalities.

- **Dr. Inês L. Azevedo** is a Professor of Engineering and Public Policy and Co-Director of the Center for Climate and Energy Decision-Making at Carnegie Mellon University. She has published on the impact of public policy on hybrid vehicle adoption, the rebound effect, and marginal emissions and externality estimates for energy policy interventions.
- **Dr. Constantine Samaras** is an Assistant Professor of Civil and Environmental Engineering and Director of the Center for Engineering and Resilience for Climate Adaptation at Carnegie Mellon University as well as an Adjunct Senior Researcher at the RAND Corporation. He has published on policies for, and social costs and benefits of, vehicle automation technologies.
- **Dr. Pedro Ferreira** is an Assistant Professor at the Carnegie Mellon Heinz College of Information Systems and Public Policy. He has published econometric studies and large-scale randomized field experiments on information and communication technology in education and media.
- **Dr. Nicholas Muller** is an Associate Professor of Economics and of Engineering and Public Policy at Carnegie Mellon University. He co-developed the APEEP model of location-specific air pollution externalities and has published studies on externalities from energy and transportation.

7. CONFLICT OF INTEREST STATEMENT

The authors declare no conflicting financial or other interests that might bear on the proposed work.

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