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Ride-Sharing Services and Environmental Sustainability: An Empirical Investigation of UberX Entry and Gas Emissions

Ramah Al Balawi
University of Illinois at Chicago, ralbal2@uic.edu

Ecem Basak
University of Illinois at Chicago, ebasak2@uic.edu

Ali Tafti
University of Illinois at Chicago, atafti@uic.edu

Mary Beth Watson-Manheim
University of Illinois at Chicago, mbwm@uic.edu

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Completed Research

Ramah Al Balawi
University of Illinois at Chicago
ralbal2@uic.edu

Ecem Basak
University of Illinois at Chicago
ebasak2@uic.edu

Ali Tafti
University of Illinois at Chicago
atafti@uic.edu

Mary Beth Watson-Manheim
University of Illinois at Chicago
mbwm@uic.edu

Abstract

On-demand ride-sharing services, such as Uber and Lyft, promote themselves as an innovation that solves old transportation problems and as sustainable transportation systems that reduce traffic congestions and environmental impact. Despite the increasing studies that examine the societal and economic impact of on-demand ride-sharing services, little is known on the environmental impact of these services. Using data collected from 46 Metropolitan Statistical Areas in the United States, we employ difference-in-differences framework to investigate the impact of the entry of an on-demand ride-sharing service, UberX, on gas emission levels. The results suggest an increase in the maximum levels of gas emissions after the introduction of UberX.

Keywords

UberX, environmental sustainability, gas emission, difference-in-differences

Introduction

The transportation industry is considered one of the largest producers of pollutants, accounting for nearly 30% of greenhouse gas emissions within the United States (U.S.). [1] The environmental impact of transportation has increasingly captured the interest of both scholars and policy makers (Gwilliam and Geerlings 1994; Martin and Shaheen 2011). Different policies and strategies have been proposed over the past decades to address the environmental effect of fossil-fuel burning vehicles and to create more sustainable transportation systems. A key strategy that has shown significant economic, societal and environmental impact is ride-sharing, which purportedly reduces gas emission levels of personal transportation through promoting fuel sharing and reducing vehicle kilometers travelled (VKT) (Jacobson and King 2009).

On-demand ride-sharing services (ODRS), such as Uber and Lyft, are digital ride-sharing services that allow users (riders) to submit ride requests and match with car-owner drivers (drivers) who provide transportation services. Ride-sharing is the sharing of rides among drivers and passengers that have similar origin or destination points, and ride-sharing platforms are information technology systems that enable ODRS (Shaheen et al. 2020). These platforms have promoted themselves as sustainable transportation systems that aim to improve transportation efficiency, reduce congestion, and lower environmental impact. In keeping with this image, ride-sharing companies have announced initiatives, such as Lyft's Green Cities initiative,[2] to commit to their sustainable mobility goals, e.g., reduce the number of on-road vehicles and reduce fuel consumption. These initiatives are expected to beneficially influence pollutant gas emissions and climate change. ODRS platforms have received remarkable attention from policy makers and media outlets, particularly those that explore economic and social impacts of these platforms.[3] However, the assessments of environmental impact have some apparent contradictions. Despite existing analysis on the environmental benefit of ride-sharing usage (Caulfield 2009; Yu et al. 2017), recent media reports claim that ODRS platforms are actually hurting the environment.[4] Therefore, a robust estimate of the environmental impact of ORDS could resolve the ongoing argument.

Previous academic studies investigating environmental consequences of ride-sharing adoption have relied on case studies which do not establish the causal link between ride-sharing and environmental outcomes (Caulfield 2009; Yin et al. 2018; Yu et al. 2017). These studies lack methodological rigor, for example due to a lack of longitudinal data. Therefore, in this paper we exploit a natural experiment setting to examine the effect of the introduction of UberX, a low-cost service introduced by Uber in 2012, into U.S. Metropolitan Statistical Areas (MSAs) on environmental outcomes. When Uber was first founded, it only offered a luxury ride service, Uber Black, a more expensive and less available service due to specific car requirements (i.e. black exterior or luxury sedan or SUV). With the introduction of UberX, low-cost hybrid cars have been used for this service, and the requirements for UberX have not been stringent as Uber Black, making UberX more accessible and affordable to use.

We employ a difference-in-differences (DID) framework to estimate the effect. Thus, our research question is: What is the impact of the introduction of on-demand ride-sharing services on environmental outcomes?

Our empirical analysis yields interesting results and show that the introduction of UberX into an MSA leads to an overall increase in the gas emissions. This study makes the following contributions. First, it sheds some light on the on-going debate about whether ODRS platforms are environmentally sustainable or hurt the environment. Second, to the best of our knowledge, this study is amongst the first to empirically test the effect of ODRS introduction on environmental outcomes. Moreover, we overcome the methodological limitations in prior studies by simulating an experiment with observational data to estimate the causal effect. Lastly, we contribute to the growing body of literature that examines the societal and economic impact of ODRS platforms (e.g. Babar and Burtch 2019; Gong et al. 2017).

Background

Ride-sharing has been in existence for decades, and it has been promoted as a successful alternative to a sustainable transportation mode (Clewlow and Mishra 2017; Jacobson and King 2009). Given the numerous societal, economic and environmental benefits associated with ride-sharing, policy makers and scholars have considered ride-sharing to be a powerful way to help alleviate traffic congestion while reducing gas emissions (Chan and Shaheen 2012). In a survey study conducted with members of ride-sharing programs in North America, Martin and Shaheen (2011) found that ride-sharing significantly reduces green-house gas emission, with a decline in the average VKT per year by 27%. Jacobson and King (2009) found a considerable fuel savings from increased ride-sharing in the U.S., with an annual fuel savings 0f 0.80 to 0.82 billion gallons of fuel when one passenger is added to every 100 vehicles. They also found a savings of 7.54 to 7.74 billion gallons of fuel when one passenger is added to every 10 vehicles. Based on their simulation study to examine the benefits of ride-sharing in a West Midland's county in the United Kingdom, Fellows and Pitfield (2000) argued that ride-sharing will reduce the number of vehicles as well as the annual VKT. In theory, therefore, one could argue that ODRS leads to a reduction in VKT that in turn could ultimately result in reduction in emissions.

Over the past decade, ODRS platforms have gained popularity as an alternative mode of urban transportation that leverages advances in information technology. These platforms use mobile applications to match and connect riders to drivers. Riders could be influenced to adopt these platforms due to the reduction in cost and information uncertainty, such as ride cost and arrival estimates, and improved access to information relevant to choosing a ride service, such as customer ratings (Basak et al. 2020). However, these platforms also promote themselves as a convenient and environmentally sustainable alternative to car ownership. Academic research has examined a range of economic and societal effects of these platforms. For example, Greenwood and Wattal (2017) examined the influence of Uber entry on alcohol-related motor vehicle fatalities, and found significant reduction in incidents after the introduction of the ride-sharing platform. Burtch et al. (2018) examined the effect of Uber entry on entrepreneurial activity, and found significant decrease in such activity after the introduction of Uber. Li et al. (2016) studied the impact of the introduction of Uber on traffic congestion in U.S. urban areas, and found a decrease in traffic congestion time and cost. Despite the initial contribution of ride-sharing services to better utilization of cars, research on the adoption of ODRS has also shown negative, and unexpected externalities created by these services. For instance, in contrast to the results from Li et al. (2016), Clewlow and Mishra (2017) showed that these services add more vehicle miles travelled. Using a causal mediation analysis, Basak et al. (2020) in their working paper found that UberX entry decreases public bus ridership, which in turn increases traffic congestion. Gong et al. (2017) studied the effect of Uber entry on new vehicle ownership in China, and their results suggest an association between Uber entry and the number of new car registrations. Ge et al. (2016) found significant evidence of racial discrimination by ride-sharing drivers. Other reports showed that ODRS have actually increased miles travelled annually by 5.7 billion miles, and increased car ownership across major U.S. cities between 2012 and 2016 (Schaller 2018).

On one hand, ODRS platforms promote themselves as an innovation that solves old transportation issues through reducing the cost and uncertainty associated with ride-sharing. In this case, these platforms may lead to the same societal, economic and environmental benefits of ride-sharing. In other words, we expect ODRS platforms to reduce traffic congestion, car ownership, and subsequently gas emission levels. However, empirical evidence shows that ODRS platforms are creating externalities that do not conform to the benefits of ride-sharing as an alternative transportation strategy. ODRS platforms could increase traffic congestion, and are bringing more private vehicles to the roads. In addition, drivers could be increasing traffic congestion while waiting for ride requests. Jacobson and King (2009) found that the fuel savings from ride-sharing was offset by the additional travel to pick up riders. In this case, it is plausible that ODRS platforms would have negative impact on environmental outcomes, i.e. increase gas emission levels. Therefore, we empirically test the impact of the introduction of ODRS on the levels of gas emissions.

Methods

Data and Variables

Our dataset comes from multiple resources. We collected UberX entry data for 46 MSAs from Uber's website and other internet sources. Environment data comes from U.S. Environmental Protection Agency (EPA),[5] which contains unbalanced daily maximum and average emission concentrations for Carbon Monoxide (CO) measured in parts-per-million (ppm), Nitrogen Dioxide (NO2) measured in part-per-billion (ppb), and Volatile Organic Compounds (VOCs) measured in ppb for core-based statistical areas (i.e. metropolitan statistical area and micropolitan statistical area) in the U.S. Primary sources of gas emissions are electricity, transportation,[6] and industrial processes such as agriculture, manufacturing, and mining[7]. Data on electricity is adapted from Energy Information Administration (EIA), which is a monthly dataset of electricity generation from natural resources by state. Industrial processes data come from U.S. Census Bureau, which is an annual number of establishments by sector. The Census data also includes population and income levels by MSA. We collected data on temperature, an important factor related to emission levels, from the National Oceanic and Atmospheric Administration, which keeps track of daily and monthly weather data. Federal and state government agencies are charged with reducing air pollution caused by gas emissions. We consider the Cross-State Air Pollution Rule,[8] which requires member states in the eastern half of the U.S. to reduce annual power plant emissions such as SO_2, NO_x and Ozone (O_3) to help downwind states attain and maintain clean air standards. In contrast to other policies implemented much earlier than UberX's first entry, this rule was implemented during the period of our study, in January 1st, 2015. When combined, our final dataset is an unbalanced panel dataset compromising of 46 MSAs from January 2012 to December 2016.

Using EPA data, we compute an aggregated monthly level of emissions taking the mean of the daily values of the maximum CO, NO2, and VOCs, which are the dependent variables. Our treatment variable is $UberX_{ij}$, which is coded as 1 indicating the availability of UberX in MSA i in all months j such that j >= j'. A list of UberX entry time into different MSAs is given in Table 1.

MSA	UberX Entry	MSA	UberX Entry
Birmingham, AL	Dec/2015	Raleigh, NC	Apr/2014

Phoenix-Mesa, AZ	Aug/2013	Charlotte, NC-SC	Sep/2013
Los Angeles-Long Beach-Anaheim, CA	Jun/2013	Las Vegas-Henderson, NV	Sep/2015
Riverside-San Bernardino, CA	Apr/2014	Kansas City, MO-KS	May/2014
Sacramento, CA	Sep/2013	Milwaukee, WI	Mar/2014
San Diego, CA	May/2013	New York-Newark, NY-NJ-CT	Sep/2012
San Francisco-Oakland, CA	Jun/2012	Cleveland, OH	Apr/2014
San Jose, CA	Jul/2013	Columbus, OH	Feb/2014
Denver-Aurora, CO	Oct/2013	Cincinnati, OH-KY-IN	Mar/2014
Hartford, CT	Oct/2014	Oklahoma City, OK	Oct/2013
Detroit, MI	Nov/2013	Portland, OR-WA	Dec/2014
Jacksonville, FL	Apr/2014	Pittsburgh, PA	Mar/2014
Miami, FL	Jun/2014	Philadelphia, PA-NJ-DE-MD	Oct/2014
Orlando, FL	Jun/2014	Virginia Beach, VA	May/2014
Tampa-St. Petersburg, FL	Apr/2014	Nashville-Davidson, TN	Dec/2013
Atlanta, GA	Jun/2013	Memphis, TN-MS-AR	Apr/2014
Chicago, IL-IN	Apr/2013	St. Louis, MO-IL	Sep/2015
Indianapolis, IN	Sep/2013	Dallas-Fort Worth-Arlington, TX	Nov/2013
Louisville/Jefferson County, KY-IN	Apr/2014	Houston, TX	Feb/2014
New Orleans, LA	Apr/2015	San Antonio, TX	Mar/2014
Boston, MA-NH-RI	Feb/2013	Salt Lake City-West Valley City, UT	May/2014
Baltimore, MD	Oct/2013	Richmond, VA	Aug/2014
Minneapolis-St. Paul, MN-WI	Sep/2013	Seattle, WA	Apr/2013

Table 1. UberX Entry Time into Different MSAs

We also include population (Population), per capita income (Income), number of manufacturing establishments (Manufacturing), number of mining establishments (Mining), number of agriculture establishments (Agriculture), average temperature (Temperature), a dummy variable for CSAPR (CSAPR) coded as 1 indicating the implementation of the rule, thousand megawatt hours of electricity generation by coal (Coal), and thousand megawatt hours of electricity generation by natural gas (Gas). Table 2 presents the summary statistics.

	Obs.	**Mean**	**Std. Dev**	**Min**	**Max**
Max CO	2,617	0.52	0.24	0.11	2.9
Max NO2	2,645	21.87	7.46	5.16	51.9
Max VOCs	2,204	4.14	12.05	0.05	180.95
Population	2,760	3,491,301	3,349,567	1107434	20,031,443
Income	2,760	3,8481.77	4,633.86	31215	54,214
Manufacturing	2,760	3,193.73	3,344.18	731	17,504
Mining	2,760	151.42	309.61	8	1,557

Agriculture	2,760	87.52	84.31	11	451
Temperature	2,760	60.71	16.26	8	97.1
CSAPR	2,760	0.17	0.38	0	1
Coal	2,760	3,452.79	3,256.88	0.04	15,394.98
Gas	2,760	5,295.83	5,355.19	29.1	25,789.16

Table 2. Summary Statistics

Difference-in-Differences Estimation Framework

We use the DID estimation framework to estimate the effect of UberX entry on the level of gas emissions. This DID framework exploits a natural experiment using observational data. It is an appropriate method to compare the differences in the level of gas emissions before and after UberX entry to the differences for untreated MSAs. Conducting a DID analysis helps us estimate the causal effect by simulating an experiment with observational data (Angrist and Pischke 2008). We estimate the effect using the following equation:

$$y_{ij} = \beta UberX_{ij} + \gamma W_{ij} + \theta_j + \mu_i + \varepsilon_{ij} \tag{1}$$

where y_{ij} is the maximum level of CO, NO2, or VOCs in MSA i during month j, θ_j is time fixed-effects, μ_i is MSA fixed-effects, W_{ij} is the set of control variables, and ε_{ij} is the error term. In the analysis, we use the log transformed values of gas emissions and control variables except for temperature and CSAPR to interpret the percentage change and to address the possible non-normality in the distribution of the error term (Greenwood and Wattal 2017).

Results

Table 3 reports the coefficient estimates of Equation (1). As shown in Column (1), we estimate an increase in rate of log maximum CO emission by 0.052 ppm (p = 0.23; 95% confidence interval, 0.011–0.092) after UberX entry. Econometrically, this result suggests an average increase in the maximum CO emission by 5.3% (rounded from the following: [exp(0.052) - 1] * 100 = 5.33%)[9] in MSAs treated by UberX; however, this estimate is imprecise and non-statistically significant. In Column (2), we observe an association between the maximum NO2 emission and UberX entry, and find an increase in rate of logged maximum NO2 emission by 0.021 ppb (p = 0.43; 95% confidence interval, -0.008–0.051). This result suggests an average increase in the maximum NO2 by 2.1%. This exposure is more imprecise than the coefficient of the maximum CO. In Column (3), we see that UberX entry increases rate of log maximum VOCs by 0.166 ppb (95% confidence interval, 0.064–0.269). Econometrically, this result suggests an average increase in the maximum VOCs by 18%. This estimate is more precise compared to the maximum CO and NO2.

	(1) ln(Max CO)	**(2) ln(Max NO2)**	**(3) ln(Max VOCs)**
UberX	0.052	0.021	0.166*
	(0.043)	(0.027)	(0.099)
ln(Population)	0.974	0.025	-3.610**
	(0.625)	(0.394)	(1.575)
ln(Income)	0.977	-0.642	7.309**
	(1.509)	(1.134)	(3.722)
ln(Manufacturing)	1.223	0.291	3.575
	(1.031)	(0.688)	(2.688)
ln(Mining)	0.186	0.026	0.399
	(0.189)	(0.107)	(0.469)
ln(Agriculture)	0.562***	0.273	-0.188

	(0.180)	(0.197)	(0.505)
Temperature	0.010***	0.006***	0.019***
	(0.002)	(0.002)	(0.004)
CSAPR	-0.091	0.013	0.136
	(0.061)	(0.039)	(0.154)
ln(Gas)	-0.003	0.009	-0.005
	(0.030)	(0.015)	(0.062)
ln(Coal)	0.012	0.008	-0.006
	(0.012)	(0.013)	(0.023)
MSA fixed-effects	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes
Observations	2617	2645	2204
R-squared	0.089	0.040	0.070
Robust standard errors are given in parentheses; *** p<0.01 ** p<0.05 * p<0.10			

Table 3. Difference-In-Differences Results

Robustness Tests

Relative Time Model

One critical assumption of DID is that no pre-treatment trend should exist across treated and untreated units before the treatment (Angrist and Pischke 2008). Relative time models have been used in the literature to determine if significant differences between treated and untreated units before the treatment exist, in order to determine whether untreated units are an acceptable control group (Burtch et al. 2018; Greenwood and Wattal 2017). Following prior literature, we set time dummies that represent the relative temporal distance, k, between an observation period, j, and the timing of UberX entry in urban area i. The relative time model is specified as follows:

$$y_{ij} = \sum_k \beta_k \; UberX_{ij}(k) + \gamma W_{ij} + \theta_j + \mu_i + \varepsilon_{ij} \qquad (2)$$

where y_{it} is the log-transformed number of the maximum CO, NO2, and VOCs in MSA i during month j, θ_j is time fixed-effects, μ_i is MSA fixed-effects, W_{ij} is the set of control variables, and $UberX_{ij}(k)$ is the vector of relative time dummies, which is set to one if the relative temporal distance between UberX's entry into MSA i during month j is k.

Results of Equation (2) are given in Table 4. First, the results are consistent with the DID model. Second, we do not observe statistical significance in the pre-treatment time dummies, indicating that there are no common trends across MSAs that receive UberX treatment; this supports the no pre-treatment trend assumption.

	(1) ln(Max CO)	(2) ln(Max NO2)	(3) ln(Max VOCs)
$UberX_{-5}$	-0.109***	-0.076***	0.067
	(0.041)	(0.027)	(0.092)
$UberX_{-4}$	0.017	0.007	0.017
	(0.030)	(0.018)	(0.058)
$UberX_{-3}$	0.059*	0.013	-0.043
	(0.033)	(0.027)	(0.066)
$UberX_{-2}$	0.041	0.016	0.013
	(0.044)	(0.015)	(0.063)

$UberX_{-1}$	Baseline: UberX-1 omitted		
UberX	0.036	0.033	0.091
	(0.046)	(0.031)	(0.081)
$UberX_1$	0.022	0.001	0.005
	(0.033)	(0.024)	(0.046)
$UberX_2$	-0.018	-0.005	0.053
	(0.038)	(0.022)	(0.094)
$UberX_3$	-0.018	0.017	-0.010
	(0.040)	(0.023)	(0.068)
$UberX_4$	-0.010	-0.029	0.043
	(0.035)	(0.019)	(0.084)
$UberX_5$	-0.005	-0.009	-0.079
	(0.031)	(0.021)	(0.061)
$UberX_6$	-0.038	0.009	0.069
	(0.040)	(0.027)	(0.081)
MSA fixed-effects	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2617	2645	2204
R-squared	0.102	0.054	0.069
Robust standard errors are given in parentheses; *** p<0.01 ** p<0.05 * p<0.10			

Table 4. Relative Time Model Results

Other On-Demand Ride-Sharing Services

So far, our analysis focused only on the effect of one ODRS platform on gas emissions; however, there might be other ORDSs that have launched before UberX entered to the MSA. Their presence could evoke the observed impact on gas emissions as UberX. Therefore, we focus on Uber's two main competitors: Lyft and SideCar. We chose these companies as they are second and third entrants in the market. In 12 MSAs such as Seattle, WA; Pittsburgh, PA; and Miami, FL[10], these services started their operations before UberX arrived. We replicated our analysis using these entry times. Results in Table 5 show that our findings are consistent with our main model results.

	(1) ln(Max CO)	**(2) ln(Max NO2)**	**(3) ln(Max VOCs)**
Ride-Sharing Entry	0.035	0.017	0.161*
	(0.046)	(0.025)	(0.092)
ln(Population)	0.984	0.026	-3.610**
	(0.625)	(0.393)	(1.570)
ln(Income)	0.950	-0.658	7.169*
	(1.516)	(1.127)	(3.806)
ln(Manufacturing)	1.205	0.280	3.497
	(1.033)	(0.684)	(2.712)
ln(Mining)	0.187	0.027	0.432
	(0.193)	(0.107)	(0.478)
ln(Agriculture)	0.567***	0.274	-0.196

	(0.179)	(0.197)	(0.505)
Temperature	0.010***	0.006***	0.019***
	(0.002)	(0.002)	(0.004)
CSAPR	-0.093	0.012	0.125
	(0.061)	(0.038)	(0.155)
ln(Gas)	-0.003	0.009	-0.004
	(0.030)	(0.015)	(0.061)
ln(Coal)	0.012	0.009	-0.006
	(0.012)	(0.013)	(0.023)
MSA fixed-effects	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes
Observations	2617	2645	2204
R-squared	0.088	0.040	0.070
Robust standard errors are given in parentheses; *** p<0.01 ** p<0.05 * p<0.10			

Table 5. Difference-In-Differences Results for Other Ride-Sharing Companies

Discussion and Conclusion

ODRS platforms, such as Uber, promote themselves as sustainable systems. Sustainability is often described as the intersection of three pillars: economic, societal and environmental effects. Prior research examining the sustainability of ODRS platforms have mainly investigated the economic and societal effects of these platforms (e.g. Babar and Burtch 2019; Gong et al. 2017; Greenwood and Wattal 2017). However, there is lack of systematic research that examines the effect of the introduction of ODRS platforms on environmental outcomes. In this work, we fill this gap by examining the impact of UberX entry on the environment outcomes. Our findings suggest that the introduction of UberX increases gas emissions in 46 MSAs.

The results have important research implications for on-demand ride-sharing services. Ride-sharing among commuters has traditionally been recognized as a sustainable transportation mode. Motor vehicle transportation is reduced as riders share a vehicle during a trip. ODRS platforms have promoted their services as 'ride-sharing' with increased convenience for riders; the ODRS model leverages information technology and sophisticated algorithms to enable on-demand transportation service for riders. Thus, unlike traditional ride-sharing options, this on-demand matching of riders with car-owning drivers actually introduces additional vehicles into the transportation system. We turn to institutional theory to further interrogate the debate on the position of ODRS platforms in the transportation system and their environmental effect.

Institutional theory suggests that organizations are social and cultural systems embedded within an institutional context. This institutional context sets certain expectations on what is considered legitimate behavior (Hinings et al. 2018). However, and according to institutional theorists, organizations could sustain their legitimacy and distract external attention from practices that could be deemed controversial or unacceptable by adopting visible and institutionalized structures which conform to social norms (Elsbach and Sutton 1992; Meyer and Rowan 1997). For example, an institutional isomorphism with environmental institutions could result in the success of organizations (Meyer and Rowan 1997). In the context of ODRS, these platforms could face an institutional pressure to comply with societal, economic and environmental expectations in order to be accepted and adopted. However, these platforms might face challenges when deviating from institutionalized structures given the innovation in the technology and services they provide. To overcome these challenges, these platforms may implement specific impression management tactics, which are concerned with controlling and creating desired attribution and perception and aim at providing positive interpretation of controversial actions while maintaining their legitimacy (Elsbach and Sutton 1992).

ODRS platforms may conform to the institutional structure of prior ride-sharing programs. With the reduced cost of coordination and matching riders with drivers, ODRS could overcome the inconsistent proportion level of share that the ride-sharing modality has experienced in the past (Chan and Shaheen 2012). This could be attributed to psychological factors, such as privacy and security concerns (Chan and Shaheen 2012). However, empirical studies and media reports show that these on-demand ride-sharing services are shifting passenger behavior away from complementary modes of transportation, such as public transit and commuter rail, causing increases in traffic congestion (Clewlow and Mishra 2017). These externalities deviate from the institutionalized structures that conform with certain expectations. Therefore, ODRS platforms might have to overcome this institutional pressure using impression tactics, such as promoting sustainability programs, in order to position the services provided by their platforms as new forms of ride-sharing and not as digital tax-services.

This study makes several contributions. First, it sheds some light on the on-going debate about whether ODRS platforms are environmentally sustainable. Second, to the best of our knowledge, our study is amongst the first to examine the environmental impact of the introduction of ODRS platforms. Third, while some studies found environmental benefits of ride-sharing services (Yin et al. 2018; Yu et al. 2017), our study provides a rigorous analysis to uncover the causal effect of ODRS on environmental outcomes. Finally, we contribute to the growing literature on the impact of ODRS platforms.

This study has important implications for policy and decision makers. It would be inappropriate at this point to make a definitive conclusion regarding the environmental effect of the introduction of ODRS platforms. However, our preliminary results could be informative to policy makers on the environmental effects of these platforms. Although ride-sharing platforms are promoted as sustainable, environmental-friendly alternatives that solves transportation problems, proper supporting measures that ensure these benefits are achieved are required.

It is important to note that this study is subject to multiple limitations. First, although the results in this study indicate that UberX entry increases gas emission, it is important to note that these are preliminary results. However, further improvement to the estimation model could yield more accurate results, and this is our future task. Second, availability of other environmental outcome measures such as CO2 and greenhouse gas could further provide more insights.

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Endnotes

[1] See https://www.epa.gov/transportation-air-pollution-and-climate-change/carbon-pollution-transportation

[2] See https://blog.lyft.com/posts/lyft-commits-to-full-carbon-neutrality-and-100-renewable-energy

[3] See https://www.chicagotribune.com/news/breaking/ct-biz-ride-share-congestion-loop-20190520-story.html

[4] See https://www.independent.co.uk/news/business/analysis-and-features/uber-lyft-climate-change-ipo-environment-global-warming-a8852396.html

[5] US Environmental Protection Agency. Air Quality System Data Mart available at http://www.epa.gov/ttn/airs/aqsdatamart. Accessed August 15, 2019.

[6] On-demand ride-sharing platforms could have an impact on transportation such as congestion, public transit ridership, and car ownership. Therefore, transportation is not included in our main model as variables like congestion and public transit riders could also be impacted by the introduction of ride-sharing platforms.

[7] See https://www.census.gov/en.html

[8] See https://www.epa.gov/csapr

[9] http://www.bzst.com/2009/09/interpreting-log-transformed-variables.html

[10] The complete MSA list is: Seattle, WA; Los Angeles-Long Beach-Anaheim, CA; Denver-Aurora, CO; Dallas-Fort Worth-Arlington, TX; Pittsburgh, PA; Salt Lake City-West Valley City, UT; Virginia Beach, VA; Miami, FL; and Philadelphia, PA-NJ-DE-MD