Measuring the Impact of an Unanticipated Suspension of Ride-Sourcing in Austin, Texas

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Abstract

On May 7, 2016 residents of Austin, TX voted against Proposition 1, which would have allowed transportation networking companies (TNCs) to continue using their own background check systems. The defeat of the proposition prompted Uber and Lyft to suspend services in Austin indefinitely. The suspension provided for a natural experiment to measure the impact of the suspension on travel behavior. In examining the impact, we conducted an online survey that combines stated and revealed preference questions (N=1,840) of former Uber and/or Lyft users in Austin to explore the effect of the suspension on travel behavior.

Regression analyses, modeled to capture both the before and after travel behavioral pattern of the suspension, were used to test our hypothesis of the impact of the service suspension on travel behavior along three dimensions—mode choice, trip frequency, and vehicle ownership. Our analysis finds that 42 percent of respondents who had used Uber or Lyft to make a trip prior to the suspension reported transitioning to another TNC as the means by which similar trips were most often made after the suspension. A near equal proportion (41 percent) reported transitioning to a personal vehicle, while 3 percent transitioned to public transit. The analysis also suggests that, when looking at trips made for the same purpose pre and post suspension, individuals that transitioned from Uber or Lyft to a personal vehicle were more likely (23 percent more likely) to make more trips than individuals transitioning from Uber or Lyft to another TNC. Additionally, approximately 9 percent reported purchasing an additional vehicle in response to the service suspension. The vehicle acquisition trend was driven primarily by respondents who were inconvenienced by the service suspension—the odds of acquiring a car for an inconvenienced respondent was more than five times that of an individual who was not. These results suggest that TNCs may contribute to reduced car ownership and trip making.

Keywords: On-demand transportation, ride-sourcing, ride-hailing, transportation network companies, service suspension, travel behavior, vehicle ownership, mode shift

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1. Introduction and Motivation

Over the last decade, there has been an appreciable increase in innovative shared mobility services in the transportation sector (Chan and Shaheen, 2012; Shaheen et al., 2013; Shaheen et al., 2006; Shaheen and Cohen, 2012; Shaheen et al., 2012). These services promise to improve quality of life, health, and economic activity (Taylor et al., 2015). Shared mobility services, like carsharing (e.g., Zipcar), one-way carsharing (e.g., car2go), bikesharing, ridesharing/carpooling, on-demand ride-sourcing (e.g., uberX, Lyft,), and shuttle services (e.g., Bridj, Via), are leading the way. Of these services, ride-sourcing has seen the largest growth (Hughes and McKenzie, 2016), and its adoption is the focus of this paper.

The potential public benefits of these services include the positive impact on the environment, energy consumption, road congestion, affordability, and accessibility (Light, 2017). However, empirical evidence for many of these benefits has yet to appear in the research literature. A service suspension in Austin, Texas, provided for a natural experiment to measure the impact of ride-sourcing services.

On May 7, 2016, Austin residents voted 56 percent to 44 percent against *Proposition 1*, which would have allowed ride-sourcing companies to continue using their own background check systems for drivers rather than utilizing the system mandated by the City of Austin.[2] In response to this public decision, Uber and Lyft suspended services in Austin indefinitely. This suspension has had a direct impact on passengers, who have faced a reduced menu of mobility options. Shortly after the May 7, 2016, vote, several informal community efforts sprang up to offer ride-sourcing services. As many as 12 app-based service providers were launched to fill the void left by Uber and Lyft in Austin. While many of these platforms have subsequently closed shop, several are still in business.

Our motivating research question was the following: How has the ride-sourcing service suspension impacted travel behavior? This question is important because policy makers need scientific evidence on the impact of these services on their city and citizens to help guide the development of sound transportation public policy. The number of trips, mode share, and change in vehicle ownership are key facets of travel behavior and the subject of this article. The aim of this article is to provide information on the proportionate number of respondents switching to other new-entrant ride-hailing companies, switching to public transit, or driving their own car. We also estimate the impact of the service suspension on the frequency of trip activities. Finally, ride-sourcing service quality pre and post suspension is compared, allowing us to make an assessment on the extent that TNC patrons within the city of Austin were inconvenienced by the suspension and the attendant effect on their travel behavior.

In order to address the research question, pre-suspension ride-sourcing users were asked to complete an online travel survey. The survey was administered between November 1, 2016, and December 31, 2016, a time window when many of the new TNC services had already launched.

[2] http://money.cnn.com/2016/05/08/technology/uber-lyft-austin-vote-fingerprinting/

2. Review of Existing Studies

The relevant research literature considers the impact of ride-sourcing on mode shift, vehicle miles traveled, and vehicle ownership. For the sake of comparison, we also review the analogous research findings for one-way carsharing because it is the shared mode that is most similar to ride-sourcing. We do not review the well-established body of literature on traditional carsharing, which finds that carsharing members reduce their vehicle miles traveled and vehicle ownership (Cervero, 2003; Cervero and Tsai, 2004; Cervero et al., 2007; Martin and Shaheen, 2010).

Our point of departure is a recent report (Feigon and Murphy, 2016) sponsored by the American Public Transportation Association (APTA) that discloses the findings from a stated preference survey of 4,500 mobility consumers. The aim of the APTA report is to analyze public transit's relationship to shared transportation modes such as bikesharing, carsharing, and ride-sourcing. The respondents answered questions related to mode shift, trip frequency, and vehicle ownership. The findings from the APTA report have had a large impact on practice, leading to many new partnerships between transit agencies and ride-sourcing services nationwide. A motivation for our study was to test the validity of the APTA findings within the context of the ride-sourcing service suspension in Austin, Texas.

2.1 Mode Shift

Regarding mode shift, a key finding of the APTA report is that ride-sourcing complements public transit (Feigon and Murphy, 2016). The survey asked frequent ride-sourcing users what mode they would use if ride-sourcing was not available for their most frequent trip. The resulting mode shares were 15 percent public transit, 4 percent bikeshare, 24 percent carsharing, 6 percent walk, 34 percent drive alone or with a friend, and 8 percent other/taxi. In contrast, other research has found that one-way carsharing competes with public transportation (Martin and Shaheen, 2016).

2.2 Trip Frequency

Whether ride-sourcing induces travel demand is still undetermined. Over 99 percent of the APTA survey participants reported they would continue to take their most frequent ride-sourcing trip if ride-sourcing was not available (Feigon and Murphy, 2016). This finding suggests that ride-sourcing does not induce a large amount of travel. In contrast, the analogous results for one-way carsharing suggest that in aggregate, users reduce their vehicle miles traveled (VMT) by 6 percent to 16 percent (Martin and Shaheen, 2016). The service suspension in Austin allowed us to measure the resulting change in trip frequency.

2.3 Vehicle Ownership

Users of shared modes report lower car ownership rates than those who have not used a shared mode (Feigon and Murphy, 2016). However, it is difficult to determine causality in this relationship in the APTA findings. Do shared mobility users own fewer cars because of their usage of shared mobility? Or do they use shared mobility because they own fewer cars? Based on a survey of 347 one-way carsharing users, Le Vine and Polk (2017) overcame the causality problem with carefully worded survey questions to find that 30 percent of respondents did not purchase a car that they would have otherwise bought, and 4 percent got rid of a car due to their usage of one-way carsharing. In Germany, a stated preference survey found that over 25 percent of car2go members would forgo the purchase of a vehicle if car2go were offered permanently (Firnkorn, 2011). Martin and Shaheen (2016) found that between seven to 11 vehicles are removed per one-way carsharing vehicle. We seek to contribute to this literature by capturing the change of vehicle ownership after the service suspension.

Perhaps the most unique aspect of this research is the use of a natural experiment to measure the impact of the service suspension on mode shift, trip frequency, and change in vehicle ownership.

3. Data Collection and Descriptive Statistics

We used a micro dataset to analyze the impact of the suspension on travel mode shift, vehicle acquisition, and changes in trip frequency. The data set obtained from a survey conducted by the Texas A&M Transportation Institute (TTI) is a cross-sectional data set obtained from a 10-minute online questionnaire administered between November 1, 2016, and December 31, 2016. This was a non-probability (opt-in) survey, and the resulting data set was not adjusted to be representative of a broader population. As such, the estimates are only representative of the respondents who completed the survey.

3.1 Survey Design and Administration

The instrument was designed to allow for a detailed comparison of the pre- and post-suspension measures by anchoring the questions on the respondents' last trip taken before the suspension of Uber and Lyft services. This trip was considered the reference trip. This approach leveraged the fact that both the Uber and Lyft apps provide users a detailed history of past trips. The relevant questions were classified into three broad categories: pre-suspension, post-suspension, and respondent socio-demographic attributes.

The pre-suspension survey questions relied on the trip history menu in both the Uber and Lyft smartphone apps. The respondents selected their most recent Uber or Lyft trip that originated within the Austin city limits and respond to a series of questions explicitly tied to the reference trip. These questions included the following: What was the cost of your trip? What was the trip distance? What was the primary purpose of the trip? How many times per month did you make this type of trip? A set of questions related to the trip quality were also included.

The post-suspension questions generally mirrored the pre-suspension questions. In answering these questions, respondents were asked to think about the ways they made trips similar to the reference trip after the suspension of service by Uber and Lyft. The survey ended with a series of demographic and household-level questions. These questions covered car access, employment status, home and work location, age, marital status, household size, race, household income, and gender.

Partners across the Central Texas region assisted in advertising and distributing the survey link. These partners include government, neighborhood, and civic organizations. TTI also utilized its social media accounts as a means to advertise the survey. Additionally, local television and newspaper outlets promoted this study and provided the survey link on their websites.

3.2 Key Variables and Summary Statistics

A total of 1,840 respondents participated in the survey. A series of qualifying questions were asked of participants based on (a) their past use of Uber or Lyft for a trip that began in the city of Austin, and (b) the presence of the Uber or Lyft app on their smartphone. Once this subset had been identified, they were asked to tell us about the last trip they made beginning in the city of Austin, using either Uber or Lyft. Of the 1,214 respondents that provided an answer, 70 percent took the last trip using Uber, while the balance of 30 percent was made up of Lyft patrons. Unless otherwise noted, pre-suspension details are based on the information collected from these 1,214 respondents. Unless otherwise noted, post-suspension details are based on the information collected from 184 respondents that used either Uber or Lyft before the service disruption and another TNC post suspension to make a trip with a similar purpose to the reference trip.

It should also be noted that the estimates presented in this section are only based on the subset of respondents that provided valid answers. Item non-response was coded as "missing."

Table 1 presents a partial snapshot of survey respondents that provided demographic information, based on the most predominant demographic attributes. Because the sample frame was not well defined either demographically or geographically, it is difficult to draw conclusions based on comparisons made to U.S. Census distributions.

Demographic	Most Predominant	Frequency	Percent
Age	25–34	561	41%
Gender	Male	681	50%
Household Size	2-person household	568	42%
Race	Caucasian	1,176	84%
Household Income	>$100,000	599	44%

Table 1: Survey Respondent Demographic Snapshot

Table 2 presents some details regarding the reference trip for respondents that provided this information. Two-thirds of the trips were identified as social or recreational purposes, which was by far the most popular trip purpose. Furthermore, slightly more than one of 10 trips (12 percent) were made using UberPool or Lyft Line.

Reference Trip Attribute	Frequency of "yes" responses	Percent of "yes" responses
Was the trip purpose "social or recreational"?	745	67%
Was the trip purpose "work related"?	155	14%
Was the trip purpose "travel to or from the airport"?	110	10%
Was UberPool or Lyft Line used?	134	12%

Table 2: Reference Trip Purpose Distribution

Table 3 compares pre- and post-suspension means for trip cost and trip frequency for respondents that reported using either Uber or Lyft (pre suspension) and a different TNC (post suspension). The data suggest that pre-suspension trips were, on average, characterized by a slightly lower cost ($12.96 pre suspension compared to $14.03 post suspension). In addition, respondents were asked to identify the number of times per month they made the reference type of trip via any means, pre and post suspension. A much lower average figure of 2.1 was reported post service suspension compared to a relatively higher figure of 5.6 before the suspension of services by Uber and Lyft.

Variable	Pre-suspension Mean	Post-suspension Mean
Trip Cost	$12.96	$14.03
Monthly Trips	5.6	2.1

Table 3: Pre- and Post-suspension Means—Cost, Frequency, and Safety Score

Similarly, respondents that reported using either Uber or Lyft (pre suspension) and a different TNC (post suspension) were presented a 5-point Likert scale (1=*not at all satisfied*; 5=*extremely satisfied*), and asked to rate their satisfaction with with TNC services for trips starting within the city of Austin. The survey findings presented in Table 4 suggest that 44 percent of these respondent's reported extreme satisfaction compared to 36 percent post suspension.

TNC trip satisfaction	Frequency of "extremely positive"	Percent of "extremely positive" responses
Pre suspension	111	44%
Post suspension	91	36%

Table 4: Pre- and Post-suspension TNC Trip Satisfaction Score

Complementing the satisfaction question was a series of statements posed to respondents to evaluate the overall quality offered by Uber or Lyft pre suspension and other TNCs post suspension for trips. Our analysis revealed that nearly the same proportion of respondents (40 percent) felt that "the overall quality of Uber or Lyft services was the same as other TNCs" as did the proportion of respondents (42 percent) that felt like "the overall quality of Uber or Lyft services was higher than other TNCs." However, fewer than one in five felt that "the overall quality of Uber or Lyft services was lower than other TNCs."

Sentiment	Frequency	Percent
The overall quality of Uber or Lyft services was the same as other TNCs	98	40%
The overall quality of Uber or Lyft services was higher than other TNCs	105	42%
The overall quality of Uber or Lyft services was lower than other TNCs	45	18%

Table 5: Overall Quality of TNC Service—Pre and Post Suspension

A close variant of the TNC trip satisfaction survey question used a Likert scale from 1 (*not at all inconvenienced*) to 5 (*extremely inconvenienced*) to ascertain the degree to which all respondents may have been inconvenienced by the suspension of Uber and Lyft services. The distribution of responses is presented in Table 6. The overall average inconvenience score for the 1,343 respondents was 3.7. Finer segmentation by age group revealed that, relative to the overall average figure, the four youngest age groups (18–24, 25–34, 35–44, 45–54) reported higher inconvenience scores. The two oldest age cohorts (55–64, 65 and older) were characterized by inconvenience scores less than the average overall score.

Inconvenience Score	Frequency	Percent
1—Not at all inconvenienced	194	14%
2	91	7%
3	185	14%
4	310	23%
5—Extremely inconvenienced	563	42%

Table 6: Level to Which Respondents Were Inconvenienced by Suspension

4. Empirical Strategy

The empirical strategy examined the impact of the suspension on travel behavior along three dimensions: trip frequency, travel mode choice, and vehicle acquisition probability. The central tenet of this analysis was that users of TNC services pre suspension were not indifferent to the service suspension. We expected that the suspension would lead to a decline in the quality of existing services post suspension. The inconvenience created by this development is what would compel patrons to make changes to ameliorate the impact.

The empirical strategy was divided into two analyses: a preliminary analysis that focused on the three dimensions of changes in travel behavior and a more rigorous analysis that was carried out using regression models. We provide detailed information on the variables of interest in the preliminary analysis below. Where relevant, simple formal tests were carried out to determine if statistically significant differences existed in the data collected pre and post suspension for the relevant variables.

4.1 Preliminary Analysis on Travel Behavior

Given our research question—How did the ride-sourcing service suspension impact travel behavior?—we focused on questions that provided information on the observed shift in travel mode choice, trip purpose, and trip frequency. Apart from going beyond the insights gleaned from the summary statistics on these variables, this section provides richer insight and serves as a precursor for the subsequent regression analyses discussion.

4.1.1 Travel Mode

Respondents were asked how they presently make the pre-suspension reference trip. Figure 1 shows that a majority of respondents switched to either a personal vehicle or another TNC. A more detailed analysis revealed that a higher number of individuals (78 percent) who were extremely inconvenienced by the suspension of services by Uber and Lyft switched to private vehicles compared to only 16 percent for those who self-reported not being inconvenienced by the development.

As shown in Figure 1, about four of 10 respondents continued to use a TNC, while the same proportional representation had transitioned to a personal vehicle. Respondents reporting using “another TNC” were asked to identify which TNC they used most frequently for trips of the same purpose as the reference trip. Figure 2 reveals that nearly half selected Ride Austin, and slightly more than a third selected Fasten.

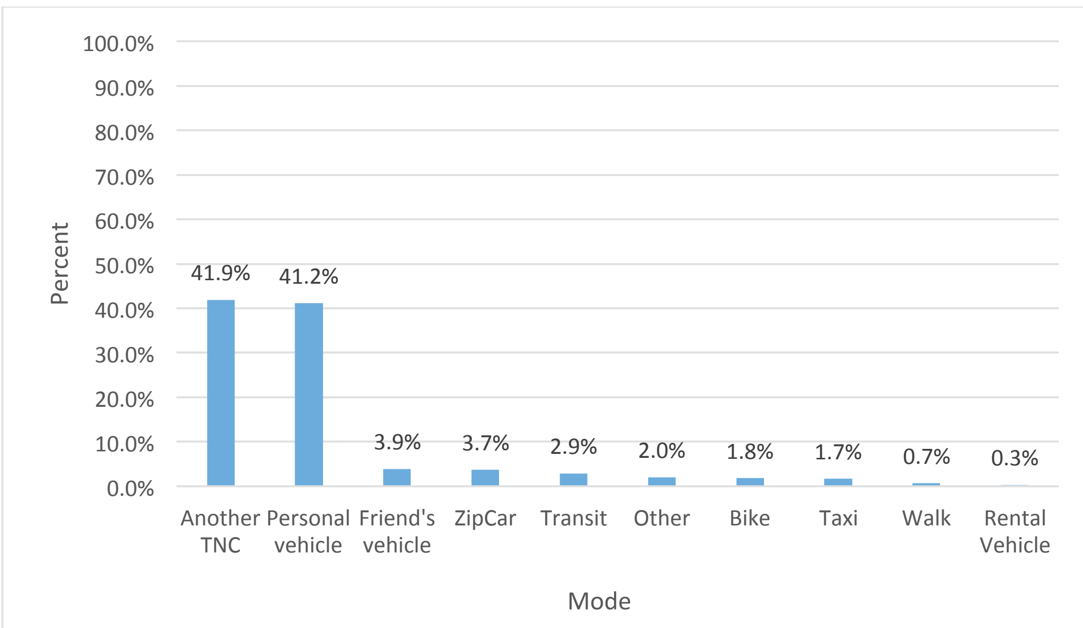

Figure 1: Mode Used Most Often—Post Suspension

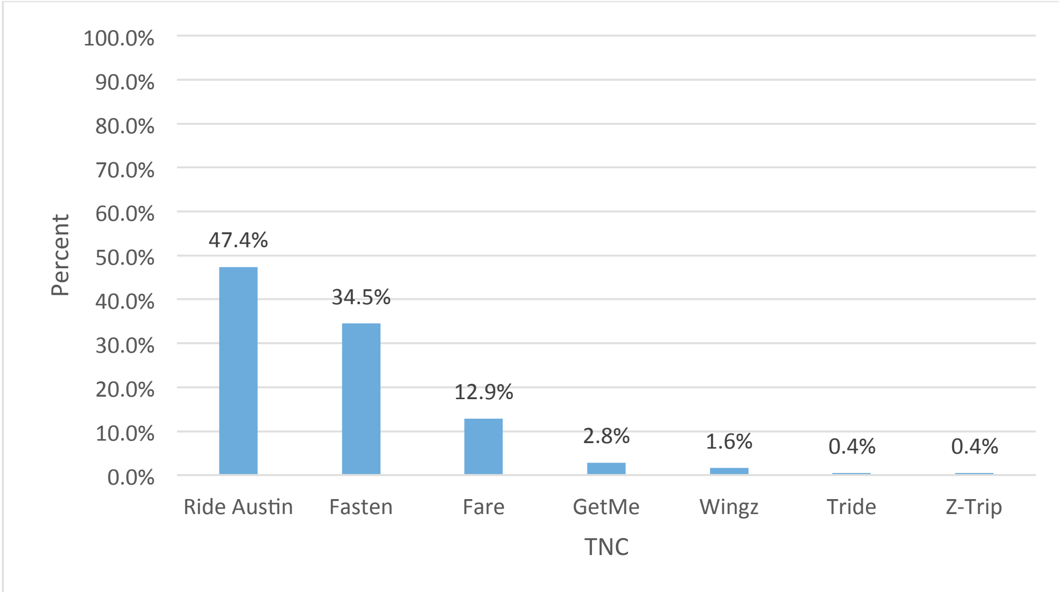

Figure 2: TNC Service Used—Post Suspension

4.1.2 Trip Frequency and Vehicle Acquisition

Table 7 suggests that the average monthly frequency of the reference trips decreased after the service suspension from 5.65 to 2.01. The trip frequency, post suspension, includes all trips irrespective of the travel mode. We carried out a paired t-test under a null hypothesis that assumed the mean difference in pre- and post-suspension frequency was zero against an alternative that assumed otherwise. The resulting analysis suggests that the two means were significantly different. Table 7 also shows that the largest decrease in mean trips was for work-related trips.

	Frequency	Mean	SD	Min	Max
Trip Frequency					
Pre-suspension frequency	1,080	5.65	6.99	0	60
Post-suspension frequency	1,080	2.01	4.09	0	40
Trip Purpose					
Work related	145	−4.9	10.9	−50	36
Shopping	30	−3.2	5.1	−16	6
Social or recreational	715	−3.7	5.9	−50	27
Personal	38	−4.7	11.5	−60	3

Table 7: Pre- and Post-trip Means and Mean Decrease

The survey specifically queried respondents about the impact of the service suspension on their vehicle acquisition decisions. As suggested in Table 8, more than eight of 10 respondents (83 percent) did not consider acquiring a vehicle as a result of the service suspension.

Automobile Acquisition	Frequency	Percent
Acquired	119	8.9%
Considered	113	8.5%
Not Considered	1,103	82.6%

Table 8: Automobile Acquisition

We also found a discernable wealth effect with the decision to acquire automobiles. Consequently, we expected individuals from higher-income households to have a higher propensity of automobile acquisition compared to respondents from lower-income households. A Pearson's chi-square test was run to determine if automobile acquisition and household income were independent of each other. The corresponding result of a Pearson chi-square value of 16.12 and an associated P value = 0.041 suggest a statistically significant relationship between the two variables.

4.2 Regression Analyses

To quantify how the suspension in service impacted travel behavior, we ran regression models for each of the following dimensions: changes in trip frequency, changes in travel mode, and changes in vehicle acquisition. We used *inconvenience* as a proxy for the impact of the service suspension. This approach allowed us to perceive resiliency of the system using a variable that is representative of the ability of the system to meet demand and, if that demand is met, the quality of services provided.

4.2.1 Impact of the Suspension on Travel Mode

In examining the impact of the suspension on travel mode, we hypothesized that individuals would switch to the use of personal vehicles because they were negatively impacted by the service suspension. To test this hypothesis, we ran regression models to determine if the hypothesis would hold after controlling for other potential explanatory variables. We carried out two different binary regression models with travel mode as the dependent variable. Mode equaled 1 if the respondent switched to private vehicle post suspension and 0 if he or she continued using any of the existing TNC services. The explanatory variables used included:

- *Happy*: a dummy variable for satisfied, with happy = 1 if satisfied had the highest Likert rating of 5, and 0 otherwise; this variable applied only to the pre-suspension trips.
- *Purpose:* a trip dummy that equaled 1 if the trip's purpose was social or recreational, and 0 otherwise.
- *Bach:* an education dummy that equaled 1 if the individual had at least a bachelor's degree, and 0 otherwise.
- *Convenience:* a dummy for the Likert-scale inconvenience measure, with convenience = 1 if the score was 5, and 0 otherwise.
- *Pre_trip_freq:* the average pre-suspension monthly trip frequency.
- *Employed:* an employment dummy that equaled 1 if the respondent was employed, and 0 otherwise.

- *Vehicle_access:* a dummy variable that equaled 1 if the individual had access to a vehicle, and 0 otherwise.

Table 9 provides coefficient estimates of the logistic regressions and the associated standard errors for mode shift given the explanatory variables itemized above. Model 1 contains only dummy explanatory variables, while Model 2 has an extra explanatory variable that is a continuous variable—average pre-suspension monthly trip frequency. The frequency of trips before the suspension of service by Uber and Lyft was included in Model 2 to examine if the variable had any predictive power given the assumption that if an individual used Uber of Lyft appreciably before the suspension, the same individual may be inclined to use one of the other TNCs post suspension.[3]

In Table 9, the coefficients for *happy*, *vehicle_access*, and *convenience* are all positive and significant at the 0.01 significance level. Moreover, the coefficient estimate for the frequency of pre-suspension trips reflected in Model 2 is not statistically significant. Since these are all dummies, a value of 1 for any or all of these variables increased the probability of an individual making the shift to a personal vehicle travel mode.

To better illustrate the impact of the regressors on mode shift, we used the odds ratio to explain the effects of the independent variables. If a respondent was very happy with the Uber/Lyft services before suspension, then his or her odds of switching to a personal vehicle were 3.17 times greater than someone who did not self-report a similar level of satisfaction, holding all other variables constant. The use of dummies made for easier interpretations given the limited options the variable could assume. Still, the odds ratio did not provide us with any information about the magnitude of the implied change in the probability of making the mode change (Freese and Long, 2005).

[3] This may not be the case given the way the question was worded. In addition, we may have needed to explicitly control for differences in service quality across the regimes.

	Model 1	Model 2
Variable		
happy		
variable coefficient	1.155***	1.256***
standard error	0.235	0.29
odds ratio	3.174	3.510
employed		
variable coefficient	−0.328	−0.516
standard error	0.419	0.484
odds ratio	0.720	0.597
vehicle_access		
variable coefficient	1.4**	1.273*
standard error	0.508	0.589
odds ratio	4.056	3.571
bach		
variable coefficient	−0.0462	0.0572
standard error	0.276	0.326
odds ratio	0.955	1.059
Convenience		
variable coefficient	1.479***	1.566***
standard error	0.235	0.267
odds ratio	4.388	4.788
Purpose		
variable coefficient	−0.401	−0.404
standard error	0.222	0.247
odds ratio	0.700	0.667
pre_trip_freq		
variable coefficient	n/a	−0.029
standard error	n/a	0.0173
odds ratio		0.972
Constant		
coefficient	−1.958**	−1.661*
standard error	0.606	0.732
Pseudo R-square	16.95%	17.20%
BIC	614.5	503.6
Chi-square	116.6	94.68
Observations	496	399

* p<0.05, ** p<0.01, *** p<0.001.

Table 9: Changes in Travel Mode

4.2.2 Service Suspension Impact on Trip Frequency

We expected the service suspension to have a negative impact on trip frequency. In order words, lower average trip frequencies post suspension would be observed compared to pre-suspension figures. The differences were anticipated to be more pronounced for the cohort of respondents who self-reported being inconvenienced by the suspension. Thus, we hypothesized that a reduction in average trip frequency would be observed for individuals who were inconvenienced by the service suspension.

For this regression, the dependent variable was the net difference in the number of trips traveled pre and post suspension. Two forms of regressions were run—an ordinary regression with the net difference in continuous form (Table 10, Model 1) and an ordinal logistic regression model with the net difference in trip frequency as an ordered categorical variable as the dependent variable (Table 10, Model 2). The ordinal data were classified into three categories—*increase*, where an increase was observed in trip frequency post suspension; *neutral*, where no change in trip frequency was observed pre and post suspension; and *decrease*, where a decrease in trip frequency was observed post suspension. The number of observations for the regression was 1,080. Of this number, 696 individuals reported a decrease in trip frequency; no change in trip frequency was observed for 279 respondents, and the balance was made up of those who experienced an increase in trip frequency post suspension. Explanatory variables used for the regression included trip purpose dummies (work, social, and airport trips); travel mode dummies (personal and ride share); *convenience* and *vehicle_access*, as defined in the earlier regression; the male dummy; and *conveh*, an interaction term for convenience and vehicle access dummies.

Given that there were no higher-order explanatory variables, the ordinary regression was a linear-linear relationship and could be interpreted in a straightforward manner. For example, being male reduced the net difference by ~1.2 trips, while switching to a personal travel mode post suspension increased it by about 3.6. The 3.6 increase was relative to all other travel modes that were not personal vehicle. It is also pertinent to point out that, when measured relative to the excluded group, there was also a statistically significant increase in trip frequency by TNC users, denoted by the *ride_share* variable. However, just as we observed for the travel mode, the most impactful variable was *convenience*, which represented individuals who self-reported being inconvenienced by the suspension.

A second regression using an ordinal logistic model, with results shown under the Model 2 column, was also estimated. Here, the dependent variable was a latent variable divided into three categories—increase in trip frequency post disruption, neutral, and decrease in trip frequency post disruption—with associated estimated cut-points that triggered a category change when the variable crosses these thresholds. Regression coefficient results are reported in log-odds and thus could not be interpreted just like the estimates obtained from the ordinary least square methods. Predicted probabilities, calculated at the mean values of the explanatory variables, showed, on average, a 68 percent decrease in trip frequency, a 26 percent of no change in trip frequency, and a 6 percent increase in trip frequency.

In demonstrating the effect of the estimated coefficients on the ordinal trip frequency, we focused on trip mode as the primary factor influencing trip frequency given that they were the only regressors with statistically significant coefficient estimates for the ordinal regression model at the 0.01 significance level. Further analysis using marginal changes to estimate predicted probabilities revealed that an individual with a personal vehicle increased his or her probability of experiencing higher trip frequency post suspension from 4 percent to 27 percent. Probabilities obtained for continued use of TNC services produced similar, albeit smaller, changes. For example, the use of a TNC service post suspension translated to an increase in the probability of a trip frequency increase from ~4 percent to 17 percent. These figures were computed relative to the excluded group of respondents that neither used a personal vehicle nor a TNC service in meeting their trip demand. Again, the explanatory variables of interest were all dummies, so a marginal change in each variable meant a change from one of the binary states to the other.

	Model 1	Model 2
Variable		
work_trip		
variable coefficient	−1.088	−0.0987
standard error	0.788	0.274
social_trip		
variable coefficient	−0.0247	−0.353
standard error	0.636	0.223
airport_trip		
variable coefficient	1.848*	0.436
standard error	0.857	0.284
personal		
variable coefficient	3.617***	2.228***
standard error	0.515	0.181
ride_share		
variable coefficient	1.932***	1.453***
standard error	0.558	0.182
vehicle_access		
variable coefficient	0.953	0.48
standard error	1.4	0.459
convenience		
variable coefficient	4.738**	−0.764
standard error	1.716	0.611
male		
variable coefficient	−1.200**	0.0567
standard error	0.388	0.14
conveh		
variable coefficient	0.427	−0.958
standard error	1.763	0.626

Constant			
	coefficient	−1.817	n/a
	standard error	1.442	n/a
cut1			
	coefficient	n/a	0.476
	standard error	n/a	0.48
cut2			
	coefficient	n/a	2.552***
	standard error	n/a	0.491
R-squared		0.149	0.1766†
AIC		7053	1550.5
BIC		7102.9	1605.4
Chi-square		n/a	327.8
Observations		1,080	1,080

* p<0.05, ** p<0.01, *** p<0.001.
† indicates pseudo R-Squares.

Table 10: Changes in Trip Frequency

4.2.3 Service Suspension Impact on Vehicle Acquisition

Is there a higher propensity to acquire vehicles post suspension? If so, what factors help explain this behavior? In addressing these questions, we framed and tested the hypothesis that vehicle acquisition would increase for individuals negatively impacted by the suspension by running a binary regression model, the findings for which are provided in Table 11. The dependent variable was *bought*, a binary variable that equaled 1 if the individual bought a vehicle as a result of being inconvenienced by the suspension, and 0 otherwise. The table reports both coefficient estimates for explanatory variables and their associated odds ratios. All the explanatory variables were defined previously except for:

- *Rich:* a dummy variable that equaled 1 if the individual belonged to a household with an annual income in excess of $100,000, and 0 otherwise.
- *Satisfied:* a dummy variable that dichotomized the 1-5 Likert scale for the Uber and Lyft satisfaction measure with the highest satisfaction rating of 5 being 1 and all other 0.
- *Household_size:* a variable that measured the number of individuals within the household.

		Model 1
Variable		
rich		
	variable coefficient	−0.776**
	standard error	0.243
	odds ratio	0.46
social_trip		
	variable coefficient	−0.810**

standard error	0.249
odds ratio	0.445
airport_trip	
variable coefficient	−0.583
standard error	0.456
odds ratio	0.558
convenience	
variable coefficient	1.630***
standard error	0.489
odds ratio	5.102
male	
variable coefficient	0.611*
standard error	0.242
odds ratio	1.842
household_size	
variable coefficient	0.312***
standard error	0.0899
odds ratio	1.366
pre_month_freq	
variable coefficient	0.0570***
standard error	0.0121
odds ratio	1.059
satisfied	
variable coefficient	1.473*
standard error	0.726
odds ratio	4.362
Constant	
coefficient	−11.48**
standard error	3.552
R-squared	17.56%
AIC	550.2
BIC	594.4
Chi-square	113.4
Observations	999

* p<0.05, ** p<0.01, *** p<0.001.

Table 11: Changes in Vehicle Acquisition

The vehicle acquisition model was implemented using logistic regression. For each regressor, we determined the estimated coefficient, the standard error, and the odds ratio associated with each coefficient estimate. Measures on the overall fit of the model were also determined. These included information criteria measures, chi-square number with an associated <0.0001 p-value, and a pseudo R-square figure of 0.176. Given that we were running the same model irrespective of its coefficient estimates or odds ratios, we do not provide information on the statistical significance of the odds ratio herein since it is the same as with the coefficient estimates. The standard errors are different, but the conclusions drawn on the statistical significance of the estimated coefficient, or the lack thereof, are the same. The average predicted probability of buying a vehicle was 9.1 percent.

Except for trips to the airport, all the explanatory variables were statistically significant, though at different significance levels. As shown with the odds ratio figures, positive coefficient estimates indicated variables with increased odds of buying a car relative to the excluded group, while variables with negative coefficients had decreased odds relative to the reference group. For example, the odds of acquiring an automobile for an individual who self-reported being inconvenienced by the suspension was 5.1 times that of another individual who reported not being inconvenienced by the suspension. Being satisfied with the quality of Uber and Lyft produced a similar effect, though with less magnitude.

The variable *rich* seemed to exert a contradictory effect given the 0.46 odds ratio, an indication that rich households have a lower probability of buying a vehicle relative to the excluded group - households making less than $100,000/years. A plausible explanation is that the need to acquire a vehicle by rich households may not arise given that rich households typically own cars. In addition, estimated marginal effects revealed that being inconvenienced increased the probability of buying a car by approximately 12 percent and a one standard deviation (1.25) increase in the household size at the mean from 2.34 to 3.59 increased the probability of buying a car by 3.3 percent.

5. Discussion of Findings and Policy Implications

It is appropriate to commence the discussion section by reiterating the basic tenet that underpins the present study—the notion that a service suspension by Uber and Lyft has an associated welfare loss for patrons either with demand for TNC services not being met or with demand only being fulfilled with lower-quality services. This way of thinking emphasizes the fact that resiliency in the present context goes beyond merely a binary construct, as in a request for TNC service being or not being met to a finer gradation of the quality of the service provided. Differences in service standards pre and post suspension were captured by the *inconvenience* variable. It was on this basis that our testable hypotheses with regard to the impact of the suspension on travel behavior were framed.

Our findings show that when respondents were asked the degree to which they had been inconvenienced by Uber and Lyft suspending service, three out of every four respondents reported either being very or extremely inconvenienced by the service suspension. Of even greater significance is how the state of being inconvenienced altered their travel behavior patterns. The inconvenience variable was a recurring factor across the dimensions of travel behavior we examined. Of all the explanatory variables, the convenience variable had the most impact in terms of being statistically significant at the highest significance level and having the greatest magnitude across the regressions run for changes in vehicle acquisition, trip frequency, and travel mode. This insight underscores the fact that the system's resiliency in bridging the shortfall created by the exit of Uber and Lyft goes appreciably beyond being able to provide

TNC services and also includes the quality of the service provided. The cohort of TNC users that were inconvenienced were more likely to demonstrate changes in behavior.

We highlight a couple of results that run contrary to conventional wisdom. For one, *rich*, the dummy for individuals who were from households with incomes in excess of $100,000, exerted a contradictory effect on the inclination to acquire a vehicle. Minimal changes were observed in the willingness to carpool pre and post suspension. Nonetheless, we caution against inferring any policy insight from this finding. Network effect may dictate that carpooling is only feasible for dense, thick networks characterized by both high demand for sharing rides and a high supply of agents to meet this demand. Given the increasing sophistication of their matching algorithm, Uber and Lyft may have the potential to improve on their carpooling services. Unfortunately, given the suspension, we cannot establish the counterfactual. As such, comparing the recent carpooling willingness to what existed pre-suspension results in an apples-to-oranges comparison.

We would like to point out that these findings are based on data collected from November 1, 2016, to December 31, 2016. This is approximately 6 months after Uber and Lyft suspended service in Austin. The length of this time period may have impacted the ease with which some respondents recalled trip details, particularly those that could not be accessed through the TNC smartphone app. Additionally, the reader must be reminded that, while TNCs other than Uber and Lyft were available in the city of Austin both prior to and following the suspension, these newer entrants into the TNC market had not been in existence as long as Uber and Lyft. One would expect that as these new entrants refine their business and service models over time, their service quality will also improve. As such, it is not unreasonable to theorize that, if this survey were administered now, the data might lead to findings much different than those presented here. Finally, we acknowledge that given the non-probability sampling of respondents that contributed to the data set, these findings should not be generalized to the overall population of TNC users within the city of Austin or the Austin region.

6. Conclusions

We studied the travel behavioral impact of the TNC service suspension, created by the defeat of Proposition 1 in the city of Austin on May 7, 2016. In estimating the impact of the suspension, we examined changes in travel behavior along three dimensions—travel mode, trip frequency, and vehicle acquisition. Numerous salient findings were obtained from the investigation, with the findings anchored on differences in service quality pre and post suspension. After controlling for relevant explanatory variables, we found that the inconvenience variable had a statistically significant and sizable influence on changes in all three dimensions.

Our findings provide evidence for pre and post suspension regional mobility patterns that are different from one another. Although the findings obtained are not generalizable to the population of all TNC users within the city of Austin, the study provides crucial insights with policy relevance. A 30 percent increase in the probability of switching to personal vehicles relative to any of the existing TNCs for an individual who is inconvenienced by the service suspension provides strong support for policies that help reduce the likelihood of occurrence of such a suspension. The case for this need is made stronger when one considers that this transition may be associated with a 23 percent increase in trip making.

Given that these findings are obtained using a cross sectional data, we will encourage that further research be conducted to better understand the changing attitudes and travel behavior of Austin residents in response to the service suspension impact. It is our opinion that a future study would benefit from a design that specifically investigates how the maturation of TNC models operating in the Austin region has affected and continues to influence residents' travel behavior.

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