Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX

Robert C. Hampshire[a,1], Chris Simek[b], Tayo Fabusuyi[a], Xuan Di[c], Xi Chen[d]

[a] Transportation Research Institute, University of Michigan, 2901 Baxter Rd., Ann Arbor, MI 48109, USA
[b] Texas A&M Transportation Institute, Texas A&M University, 505 East Huntland Drive, Suite 455 Austin, Texas 78752, USA
[c] Department of Civil Engineering and Engineering Mechanics, Columbia University, 500 W. 120th St., 610 Mudd, New York, NY 10027, USA
[d] Department of Industrial and Manufacturing Engineering, University of Michigan-Dearborn, 2340 Heinz Prechter Engineering Complex (HPEC), Richard Dr, Dearborn, MI 48128

Abstract

On May 7, 2016, residents of Austin, Texas, voted against *Proposition 1*, which would have allowed ridesourcing/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 disruption provided for a natural experiment to evaluate the impact of Uber and Lyft on users' travel demand and the supply side implications of the entry of new players. Our paper focuses solely on the demand side user response to the disruption. 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 disruption on travel behavior.

In order to test our hypothesis of the impact of the service suspension on changes in travel mode choice and trip frequency we used regression analyses to model both the before and after travel behavioral pattern. Our analysis revealed that of the population surveyed, 45% switched to the use of personal vehicles after disruption while only 3% shifted to public transit. Individuals who switched to personal vehicles also include 8.9% of respondents who reported purchasing a vehicle in response to the service disruption. In addition, an individual who switched to a personal vehicle increased his or her probability of a higher trip frequency post disruption by 14%. The probability of a higher trip frequency for individuals who were satisfied with the quality of Uber and Lyft services pre-disruption however decreased from 21% to 6%.

Keywords: On-demand transportation, transportation network companies, service disruption, travel behavior

[1] Corresponding author. +1 734 763 7746; fax: +1 734 764 1221.
Email Addresses: hamp@umich (R.C. Hampshire), c-simek@tti.tamu.edu (C. Simek), Fabusuyi@umich.edu (T. Fabusuyi), sharon.di@columbia.edu (S. Di), xichenxi@umich.edu (X. Chen).

1. Introduction and Motivation

Over the last decade, there has been an appreciable increase in the adoption of 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 ridesourcing (e.g., uberX, Lyft,), and shuttle services (e.g., Bridj, Via), are leading the way. Of these services, ridesourcing 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 positive impacts 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 disruption in Austin Texas, triggered by the defeat of *Proposition 1*, provides for a natural experiment to measure the impact of ridesourcing services. The proposition would have allowed ridesourcing companies to continue using their own background check systems for drivers rather than utilize the system mandated by the City of Austin.[2]

In response to this public decision, Uber and Lyft suspended services in Austin. This disruption has had a direct impact on passengers by reducing the menu of mobility options. Shortly after the May 7, 2016, vote, several informal community efforts sprung up to offer ridesourcing services. As many as 12 app-based service providers 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 is the following: How has the service disruption of Uber and Lyft impacted travel behavior? This question is complicated by the entry of new ridesourcing platforms after the disruption. The Uber and Lyft exit had not only a demand side impact but also supply side implications. While it could be argued that the scale and resulting network effects of Uber and Lyft deterred market entry, this barrier was removed by the disruption – a development that introduced confounding factors into our analyses. Although we acknowledge this, we take the supply response as given and focus solely on the demand side - specifically changes in travel behavior.

We designed and implemented a travel survey of ridesourcing passengers in the Austin area with the primary objective of assessing the impact of the service disruption on travel mode choice and trip frequency. The survey, which utilized a non-random sampling methodology, was administered between November 1, 2016 and December 31, 2016. The survey data was not weighted, as the full universe of TNC users in Austin is not known. Given the non-random nature of our data set, we acknowledge that our findings may not be generalizable to the overall population of TNC users within the city of Austin. However, our respondents' socio-

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

demographic profile is comparable with ridesourcing users in Austin as presented in Lavieri et al., 2017a.

Our research results provide not only insights on the impact of the disruption on individuals' travel behavior but also adaptations that riders made in response to the disruption. Specifically, findings from our analysis demonstrate that the public transit system is not the best outside option for Uber and Lyft users in Austin. We also show that users who switched to a private vehicle have a higher probability of increasing their trip frequency post disruption. However, this effect on the cumulative change in trip frequency is counterbalanced by the decrease in trip frequency for individuals who were satisfied with Uber and Lyft services pre-disruption.

The balance of the paper is organized as follows. Section 2 provides a review of the existing literature. The third section identifies the data source and provides descriptive statistics of key variables of interest. Regression analyses including the interpretation of the results are addressed in the fourth section while section five discusses the findings. Section 6 concludes and provides insight on the caveats associated with the study.

2. Review of Existing Studies

We review the literature on the impact of ridesourcing on travel behavior, namely mode choice and trip frequency. Given the rapid expansion and pace of adoption of ridesourcing services much the literature on this topic is found in the grey literature, i.e. white papers, working papers, and non-peer reviewed reports. We review both peer reviewed and grey literature findings. We do *not* survey the literature on the impacts of ridesourcing on road congestion. While related, the congestion research crucially depends on the movement of ridesourcing vehicles when no passenger is in the car. This is beyond the scope of the current study.

Our review of existing literature focuses on three stated preference surveys that investigated the impact of ridesourcing on mode shift and trip frequency (Clewlow and Mishra, 2017; Rayle et al., 2014; Feigon and Murphy, 2016;). The report by Clewlow, R. R., & Mishra, G. S. (2017) presented a wide range of travel behavior insights derived from a representative survey sample from seven major cities in the United States - Boston, Chicago, Los Angeles, San Francisco, New York, Seattle and Washington D.C. The journal article by Rayle et al. (2014) provided exploratory evidence of the role of ridesourcing in the broader transportation ecosystem. It was based on intercept surveys of 380 people in San Francisco. Lastly, the report by the American Public Transportation Association (APTA) also presented findings based on a stated preference survey of 4,500 mobility consumers from 7 major cities in the United States -Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle and Washington, D.C. (Feigon and Murphy, 2016).

In contrast to these three studies based on aggregate survey results, several researchers have developed regression models based on travel surveys (Dias et al., 2017; Lavieri et al., 2017b) and trip-level ridesourcing data (Lavieri et al., 2017a). Notably, the journal article by Dias et al. (2017) developed a disaggregated choice model for the use of carsharing and ridesourcing using a regional travel survey in Seattle, WA. The study used regression analysis to analayze the impact of socio-economic variables, demographics, smartphone and population density on the user adoption of ridesourcing and carsharing.

Across these studies and particularly for those that explicitly address mode shift, there is no clear consensus on the impact of the availability of ridesourcing on travel mode shift. Several previous studies asked survey respondents what mode they would take if ridesourcing were not available (Clewlow and Mishra, 2017; Rayle et al., 2014; Feigon and Murphy, 2016;). The results varied across the studies. The results of a representative survey sample from seven cities showed that 39% of the trips would have been made by personal vehicle, 17% by walking, 15% by public transit, 7% by bicycle, 7% by taxi, and 22% of the trips would not have been made at all (Clewlow and Mishra, 2017). The APTA survey asked frequent ridesourcing users what mode they would use if ridesourcing were not available for their most frequent trip. They found that 34% of ridesourcing users would have shifted to a personal vehicle, 24% to carsharing, 14% to transit, 8% to taxi, 6 % walk and 4% to bikeshare (Feigon and Murphy, 2016). In San Francisco, researchers found via an intercept survey that 39% of survey respondents would have taken the trip via taxi, 33% by transit, and only 6% via personal vehicle (Rayle et al. 2014).

Two of the three studies found that a plurality of users would shift to a personal vehicle if ridesourcing were not available. In the third study, based on San Francisco, five times fewer people proportionally would have switched to a personal vehicle - 34% and 39% versus 6%. With regards to public transit, Rayle et al. found that twice as many people proportionally would have switched to public transit than found in either Clewlow and Mishra (2017) and Feigon and Murphy (2016) - 15% and 14% versus 33%. These results suggest that San Francisco may be a unique context with regards to mode choice compared to the multi-city averages presented in Clewlow and Mishra (2017) and Feigon and Murphy (2016).

In reference to public transit, both Rayle et al (2016) and Feigon and Murphy (2016) stated that their results support the hypothesis that ridesourcing is an effective first/last mile connection to public transit. The econometric results of Hall et al. (2017) found that ridesourcing mainly acts as a complement to the average public transit agency. These findings have had a large impact on practice, leading to many new partnerships between transit agencies and ridesourcing services nationwide.

However, several other studies provide evidence that complicates the narrative that ridesourcing complements public transit *writ large*. Clewow and Mishra (2017) presented a more nuanced view of the interaction of ridesourcing by considering different types of public transit, i.e. bus, rail, regional rail, etc. They found that ridesourcing is a competitor to bus services, but a complement to commuter rail services. In support of this more nuanced finding, Lavieri et al. (2017a) found a negative impact of bus frequency on ridesourcing usage in Austin. Furthermore, Hall et al. (2017) found that Uber reduces transit ridership in smaller cities. Our paper contributes to this debate about the impact of ridesourcing on public transit.

On trip frequency, there is growing evidence that the presence of ridesourcing increases trip frequency. Rayle et al. (2014) found that 8% of respondents would not have taken the trip if ridesourcing services were not available. Clewow and Mishra (2017) found that 22% of people would not have taken the trip if ridesourcing services were not available. However, by contrast, over 99% of the APTA survey participants reported they would continue to take their most frequent ridesourcing trip if ridesourcing was not available (Feigon and Murphy, 2016). The APTA question measured the "most frequent trip" as opposed to a "typical trip." This might explain the difference in the reported trip frequency.

In this paper, we measure the impact of the exit of Uber and Lyft on mode shift and trip frequency. This aim is different from the previous studies whose goal was to measure the impact of the availability of *any* ridesourcing platform on mode shift and trip frequency. Thus our results may not be directly comparable to the previous studies. However, our study has the benefit of capturing the revealed mode shift choices of users given the exit of Uber and Lyft, as opposed to stated preferences. Taking the supply response to the disruption as given, we develop disaggregate statistical models to gain further insight into the factors that influence the change in trip frequency. The catalyzing event that enables our analysis is the exit of Uber and Lyft from Austin.

3. Data Collection and Descriptive Statistics

We administered an online travel survey of TNC passengers between Nov 1, 2016 and Dec 31, 2016 to 1,840 respondents. The survey instrument allows for a detailed comparison of the pre and post disruption measures by anchoring the questions on the respondent's last or reference trip taken before the suspension of Uber and Lyft services. This approach leverages the fact that both the Uber and Lyft apps provide users with a detailed history of past trips thus affording us the opportunity of minimizing errors due to recall data. This approach generates a random sample of trips over the population of respondents. This is consistent with travel survey practices. For example, the National Household Travel Survey (NHTS) is based on a one day travel diaries. Of the 1,214 individuals that gave a response on their last Uber or Lyft trip before the disruption, 70% took the trip using Uber, while the balance of 30% was made up of Lyft patrons.

Table 1 provides the summary findings of the key questions of interest with percentages calculated based on the subset of respondents that provided valid answers for each question. Non-responses are coded as missing. Scaled responses are on a 1 to 5 Likert scale with only the 5-rating reflected for the pre and post-disruption satisfaction measures. Two-thirds of the reference trips were identified as social or recreational in nature, representing by far, the most popular trip purpose. Though not shown in the table, a near equal number of males and females responded to the survey – 689 males compared to 660 females.

Table 1: Summary Statistics

Mean of Pre and Post Disruption Measures				
Variable	*# of Obs.*	*Mean (Pre)*	*# of Obs.*	*Mean (Post)*
Average Trip Cost	1067	14.8	226	14.4
Trip Monthly Freq	1121	5.6	1312	2.1
Perception of Safety	1067	4.6	242	4.3
Binary Responses				
Question			*Yes*	
Have you ever used Uber/Lyft in Austin?			1572 (87%)	
Is purpose of reference trip social?			745 (67%)	
Was the trip taken using ride share?			134 (12%)	
Do you have access to an automobile?			1274 (94%)	
Scaled Responses (Likert 1-5)				
Statement			Extremely Positive (5)	
Pre-disruption TNC trip satisfaction			927 (82%)	
Post-disruption TNC trip satisfaction			242 (38%)	
Socio-Demographics (most predominant segment)				
Variable	*Segment*		*# of Obs.*	
Age	25 - 34		561 (41%)	
Household Size	2 – person		568 (42%)	
Race	White		1176 (84%)	
Household income	> $100,000		599 (44%)	
Others				
Employed			1252 (68%)	
Lives in/around Austin's city center			650 (48%)	

The summary table also compares pre- and post-disruption averages for trip cost, trip frequency and safety perceptions for respondents that reported using either Uber or Lyft (pre-disruption) and any of the existing TNCs (post disruption). Our findings reveal that pre-disruption trips were, on average, characterized by a slightly higher cost ($14.8 pre-disruption compared to $14.4 after). In addition, respondents were asked to identify the number of times per month they made the reference trip via any means, pre and post disruption. Respondents reported a much lower average monthly trip frequency of 2.1 post disruption compared to a relatively higher figure of 5.6 before the disruption of services by Uber and Lyft. The post-disruption average trip frequency was obtained using a much larger sample size compared to other mean post-disruption measures by imputing 0 for individuals who self-reported no longer making the trip or making it less than once a month. 42% of respondents no longer take the reference trip after the exit of Uber/Lyft.

Regarding mode shift, a majority of respondents switched to either a personal vehicle (45%) or another TNC (41%). After the disruption, only 2.9% of people took the reference trip via public transit, 3.7% by carsharing, 1.7% by taxi, 1.8% by bike, 0.7% walked and the remaining by other means. The next best choice of most respondents was a personal vehicle or another TNC. A clear take away from this result is that public transit is not an attractive option for a vast majority of Uber/Lyft riders in Austin.

We also used Likert scale questions to rate respondents' satisfaction with Uber/Lyft services prior to the disruption relative to the services of the TNCs in operation post-disruption. Our findings show that 82% of TNC users pre-disruption reported extreme satisfaction compared to 38% post-disruption. Although not shown in Table 1, a comparison of the mean of pre- and post-disruption satisfaction scores using the Likert scale revealed a 4.8 average pre-disruption score compared to 3.9 post-disruption score. Complementing the satisfaction question was a series of statements posed to respondents to evaluate the overall quality offered by Uber or Lyft pre-disruption and other TNCs post-disruption for trips. Forty % of the respondents felt that "the overall quality of Uber or Lyft services was the same as other TNCs," though fewer than one in five (18%) reported that "the overall quality of Uber or Lyft services was lower than other TNCs." The balance of 42% indicated that Uber and Lyft provide a higher service relative to the existing TNCs. We did not observe much variation in willingness to share rides pre and post-disruption. Of the 246 individuals that provided a response on the willingness to share rides, 67% reported that their willingness to share rides had not changed since Uber/Lyft suspended services; 13% said their willingness to share rides has increased while the balance of 20% said they are now less willing to share rides.

Rounding up the summary table is a set of socio-demographics questions posed to respondents. For conciseness, only the highest frequency segments are shown in the table. Segmenting the population by age, the 25 to 34 age cohort has the highest representation while a 2-person household is the most observed by household size. More than four out of every five respondents are White and an appreciable number of individuals (44%) belong to households making more than $100,000 income per annum. The socio-demographic profile of the respondents is consistent with several other ridesourcing aggregate surveys (Rayle et al., 2016; Clewlow, and Mishra, 2017; Feigon and Murphy, 2016; Smith, 2016; Kooti, et al.,2017). Lavieri et al. (2017) use trip-level data from the ridesourcing service Ride Austin to estimate the socio-demographics of the riders at the transportation analysis zone (TAZ) level. They do this by using census level socio-demographic data at the trip origins to estimate rider characteristics. Their estimates also find that riders are young and white from small households with access to a vehicle. However, our sample is more affluent and educated than their estimates.

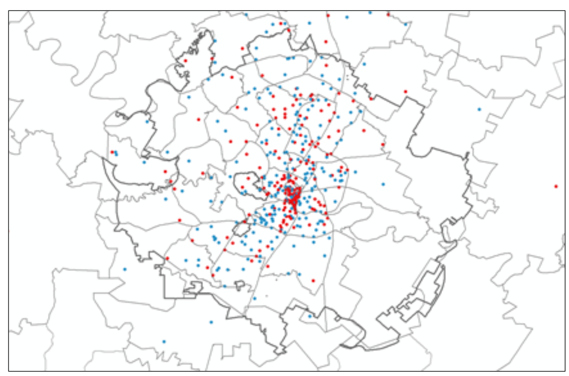

Figure 1: Respondents' home and work locations in the Austin area depicted in blue and red dots respectively

Although not shown in the table, the survey queried respondents about the impact of the service disruption on their vehicle acquisition decisions. With regards automobile acquisition, 119 individuals (8.9% of the 1,334 responses obtained) reported acquiring a vehicle because of the disruption, a figure consistent with Clewlow and Mishra's (2017) finding on vehicle acquisition from study conducted around the same time as our survey. Finally, we provided information on respondents' places of work and abode using zip codes. A visual representation of the information is shown in Figure 1 where work locations are depicted with red dots and places of residence are shown in blue.

4. Regression Analyses

To gain more insight into the factors influencing these descriptive summary statistics, we ran regression models for travel mode switch and changes in trip frequency. Variables used in the regressions are either related to trips such as trip type or trip frequency, mode choice and socio-demographic attributes including respondents' places of abode. Dependent variables are either categorical, ordered or continuous variables while all regressors are dummies except for pre-trip monthly frequency and household size that are continuous.

Travel mode switch
How did the suspension of Uber/Lyft services impact passengers' travel mode choices and what covariates explain the mode switch? To answer these questions, we ran a multinomial probit (MNP) regression model with travel mode as the dependent variable. Mode equaled 0 if the respondent continued using any of the existing TNCs post disruption; it equaled 1 if the respondent switched to private vehicle and all other travel options are classified as 2. The explanatory variables include:

- *Satisfied*: a dummy variable which equaled 1 if the individual's response to the question on satisfaction with Uber/Lyft quality of service had the highest Likert rating of 5, and 0 otherwise. This variable applied only to the pre-disruption trips.
- *Social:* a trip dummy that equaled 1 if the trip's purpose was social or recreational, and 0 otherwise.
- *Educ:* an education dummy that equaled 1 if the individual had at least a bachelor's degree, and 0 otherwise.
- *Pre_trip_freq:* the average pre-disruption 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.
- *Rich:* a dummy variable that equaled 1 for individuals from households with incomes in excess of $100,000 and 0 otherwise.
- *Core:* a dummy variable that equaled 1 for individuals who live in Austin's urban core and 0 otherwise.
- *Millennial:* a dummy variable that equaled 1 if respondent is within the 25 to 34 age range and 0 otherwise

Table 2 provides coefficient estimates of the MNP regressions and the associated standard errors. The base outcome is all travel modes (taxi, carsharing, walking etc.) excluding personal vehicles and existing TNCs. All the explanatory variables are dummies except for the average monthly pre-disruption trip frequency. Individuals assigned a core dummy value of 1 are restricted to respondents who live in 15 zip codes in the center of the city. A regressor of interest is the "satisfied" dummy that captures the quality of Uber/Lyft service offering before the disruption. Coefficient estimates are shown in columns two and three for personal vehicles and post-disruption TNCs respectively.

Relative to the excluded group, the estimated coefficients for *satisfied*, *vehicle_access*, and *rich* with personal vehicle as the travel mode are all positive and significant at the 0.01 significance level except for *rich* that is significant at the 0.05 significance level. Since these are all dummies, a value of 1 for any of these variables increased the probability of an individual making the shift to a personal vehicle travel mode relative to the base outcome. However, the variable *core*, with an estimated coefficient value of -0.683 and p-value < 0.001 has an opposite effect. Relative to the excluded travel mode options, individuals that live in the core have a lower incentive to switch to personal vehicles as the travel mode post disruption. This may be related to a richer menu of travel options available in the city center compared to individuals who live in the peripheries. The magnitude of the pre-disruption trip frequency or being a millennial had no explanatory power either with regards to the choice of personal vehicle or switching to any of the existing TNCs post-disruption.

Individuals who are employed have the highest probability of continued usage of any of the existing TNCs post-disruption. What is particularly noteworthy is that coming from a household with a vehicle does not negatively impact on the probability of using an existing TNCs post-disruption given the positive coefficient estimate that is significant at the 0.01 significance level. Trip purpose, represented here using the dummy for social or recreational trip, increases the probability of using the existing TNCs post-disruption. Relative to the base outcome, the variables *rich* and *educ*, though significant at the 0.05 significance level, exert contradictory effect on the continued usage of any of the TNCs available post-disruption with being associated with a household making more than $100,000 increasing the probability and having at least an undergraduate degree decreasing the probability.

Table 2: MNP regression for travel mode

Travel-Mode†	Personal Vehicle	Existing TNCs
Satisfied	0.945***	-0.458*
	(0.263)	(0.246)
Employed	0.538	1.251***
	(0.398)	(0.425)
Veh-access	1.712***	1.028***
	(0.432)	(0.383)
Social	0.286	0.643***
	(0.228)	(0.230)
Pre-disruption trip frequency	0.006	0.005
	(0.015)	(0.016)
Rich	0.496**	0.495**
	(0.225)	(0.226)
Core	-0.683***	0.092
	(0.227)	(0.233)
Educ	-0.401	-0.715**
	(0.356)	(0.356)
Millennial	-0.271	-0.094
	(0.249)	(0.253)
_cons	-1.436**	-1.076*
	(0.633)	(0.613)
Chi-square	**102.56**	
Observations	**459**	

† *base outcome = All travel mode excluding personal vehicle and existing TNCs*

Significant at the .10 level; ** at the .05 level and * at the .01 level*

To better illustrate the impact of the regressors on the probability of exercising a specific mode option, marginal effect estimates are provided in Table 3. Table 3 improves on the previous table by reporting both the predicted probabilities for each travel mode and the regressors' marginal effects that document the predicted impact of the independent variables on the travel model options. The adjusted predicted probability for switching to the use of a personal vehicle post-disruption is estimated at 46.6% while the probability of the continued use of any of the existing TNCs post-disruption is 38.5%. The balance of 14.9% represents all other travel mode options excluding personal vehicle and existing TNCs.

Table 3: Predicted probabilities and marginal effect estimates

	Personal Vehicle	**Existing TNCs**	**All Others**
Predicted probability	0.466	0.385	0.149
Regressors' marginal effects[a,b]			
Satisfied	0.328***	-0.289***	-0.038
Employed	-0.086	0.227**	-0.141**
Vehicle access	0.258**	-0.043	-0.215***
Social	-0.042	0.115**	-0.073**
Rich	0.039	0.038	-0.079**
Core	-0.194***	0.147***	0.047

[a]*Marginal change represents a change of 0 to 1 for each variable*

[b]*Regressors limited to those significant for at least one of the travel mode options*

***Significant at the .05 level; and *** at the .01 level*

The computed marginal effect estimates are based on a marginal increase, from 0 to 1 given that all the regressors that featured in the table are dummies, with all the other regressors held constant at their mean. Statistically significant changes in preferences are reported with asterisks. Being satisfied with Uber/Lyft service offerings pre-disruption increases the probability of an individual switching to the use of personal vehicle post-disruption by more than 32%.

Living in the city's core, as defined by the geographical area representing the 15 zip-codes in the city's central area, reduces the probability to switch to a personal vehicle by approximately 20%. The same change in place of abode, holding other things constant, is associated with a 15% increase in the preference for switching to any of the existing TNCs. The most impactful variable for exhibiting a preference for continued usage of any of the existing TNCs is being employed. Respondents who reported being satisfied with Uber/Lyft services pre-disruption are predicted to have an almost 29% reduction in the probability of continuing using the existing TNCs. Individuals embarking on trips that are recreational in nature, relative to those that are not, exhibit a preference for using existing TNCs in making the trip.

Trip frequency

We expected the service disruption to reduce trip frequency. We anticipated that the decrease in trip frequency post-disruption would be more pronounced for respondents who reported being satisfied with the quality of Uber/Lyft services before the disruption. Thus, we hypothesized that there would be a significant reduction in average trip frequency for individuals who are part of this cohort. The dependent variable for the regressions was the net difference in the number of trips traveled pre and post disruption.

We ran two regression models – 1) an ordinary regression with the net difference in continuous form and 2) an ordinal logistic regression with the net difference in trip frequency as an ordered categorical variable. The ordinal data were classified into three categories—*increase*, where an increase was observed in trip frequency post-disruption; *neutral*, where no change in trip frequency was observed pre and post- disruption; and *decrease*, where a decrease in trip frequency was observed post-disruption. Explanatory variables used for the regression included trip purpose dummies (*work*, *social*, and *airport*); *personal_veh*; *satisfied, core, rich, millennial* and *veh_access*, as defined in the MNP regression; and the *male* dummy which equaled 1 if the individual is male and 0 otherwise.

Table 4: Changes in trip frequency regressions

Trip Frequency	OLS	Ordered Logit
work	-1.410	-0.275
	(0.859)	(0.283
social	0.007	-0.233*
	(0.697)	(0.236)
airport	2.463***	0.534*
	(0.925)	(0.291)
personal_veh	3.072***	1.676***
	(0.547)	(0.175)
veh_access	1.187	-0.275
	(1.056)	(0.362)
male	-1.184***	0.145
	(0.429)	(0.149)
core	-1.358***	-0.049
	(0.424)	(0.143)
rich	0.211	-0.112
	(0.438)	(0.149)
satisfied	-4.703***	-1.746***
	(0.563)	(0.173)
millennial	-1.173***	-0.438***
	(0.436)	(0.150)
_cons	-0.078	n/a
	(1.305)	
cut1	n/a	-1.035
cut2	n/a	0.919
(Pseudo) R-Square	**12.3%**	**11.7%**
Observations	**978**	

Significant at the .10 level; ** at the .05 level and * at the .01 level*

The OLS regression was a linear-linear relationship and coefficient estimates could be interpreted in a straightforward manner. For example, being male reduced the net difference by ~1.18 trips, while switching to a personal vehicle post disruption increased it by about 3.1. The 3.1 increase is relative to all other travel modes that were not personal vehicle. Individuals who reported being extremely satisfied with the quality of Uber/Lyft services pre-disruption experienced the most predicted decrease in trip frequency – a reduction of 4.7 trips, an estimate significant at the 0.001 significance level. Reductions in trip frequency at the same level of significance with much lower magnitude were also observed for millennials and individuals who live in the city's core. The coefficient estimate for airport trips was positive and significant at the 99% confidence level. As usual, these coefficient estimates should be interpreted relative to the excluded group.

We also estimated a second regression using an ordinal logistic model. Here, the dependent variable was a latent variable divided into three categories—increase, neutral, and decrease—with associated estimated cut-points that triggered a category change when the variable crossed the cut-points. A few observations are relevant with regards to the overall model. For one, a chi-square value of 195 and an associated $p<0.0001$ shows that the coefficients in the model are statistically, significantly different from zero. Second, the reported coefficients are in log-odds and thus cannot be interpreted just like the estimates obtained from the OLS regression method. Predicted probabilities, calculated at the mean values of the explanatory variables, showed that, on average, 65% of the respondents decreased their trip frequency, 26% made no change in trip frequency, and 9% of respondents increased their trip frequency.

In demonstrating the effect of the estimated coefficients on the ordinal trip frequency, we focused on personal vehicle travel mode as the primary factor influencing the increase in trip frequency given that it was the only regressor with statistically significant positive 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 who switched to the use of a personal vehicle increased his or her probability of experiencing higher trip frequency post disruption from 5% to 19%. The figure was computed relative to the excluded group of respondents that did not use a personal vehicle in meeting their trip demand. A decrease of 3% (from 8 to 5%) in the probability of trip frequency increase was observed among millennials while individuals who reported being satisfied with Uber/Lyft service pre-disruption witnessed a 15% predicted decrease in the probability of increasing their trip frequency – from 21% to 6%.

5. Discussion of Findings

We reiterate the basic tenet that underpins the present study—the notion that a service disruption may have 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 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. The analyses we carried out were informed by the hypothesis that the loss in welfare would be more pronounced among the cohort of individuals that reported being extremely satisfied with Uber/Lyft services pre-disruption and it would be among this segment of respondents that the most pronounced changes in travel behavior would be observed. It was on this basis that we framed our testable hypotheses with regards to the impact of the disruption on travel behavior.

On mode switch, 246 individuals or 40% of all the responses mentioned shifting to the use of personal vehicles post-disruption, with an appreciable fraction – four out of every five, reporting being satisfied with Uber/Lyft services pre-disruption. Individuals who live in the city center have the highest probability for the increased use of any of the existing TNCs post–disruption, a preference that was more pronounced when the trip purpose was recreational in nature. Only 3%

shifted to public transit. A larger than expected number of respondents (8.9%) reported buying an automobile because of the service disruption.

Across all respondents, we obtained a statistically significant decrease in post trip frequency compared to the period before the service disruption. However, the change in average trip frequency was appreciably smaller and not statistically significant among the subset of respondents that continue to make the reference trip at least once a month post-disruption. This is explained by the contradictory effect exerted on trip frequency by the disruption as described in the next paragraph.

On the one hand, an impact similar to a direct effect, individuals who reported being satisfied with the quality of Uber and Lyft services pre-disruption experienced the largest decrease in trip frequency post-disruption. On the other hand, an effect that is indirect in nature, it is precisely this cohort that are most likely to switch to the use of personal vehicle – a transition that is associated with a predicted 14% increase in the probability of the individual reporting higher trip frequency. This diametrically opposite effect explains in large part the attenuated impact of the disruption on trip frequency changes among this segment.

We would like to reiterate that the aforementioned findings are reflective of the two-month window—November 1, 2016, to December 31, 2016—within which the data were collected. One might expect that as new entrants refine their business and service models, service quality will improve. It is relevant to mention that the viewpoint underscores the need to gather and use data not simply in a cross-sectional manner but, at a minimum, in a panel data or repeated cross-sectional format. In addition, we have not attempted to determine if statistically significant differences existed across subsets of the respondents. Oftentimes, this is the case because of the skewed nature of the data set. For example, 85% of respondents who provided information on race were white.

6. Conclusion[3]

We studied the travel behavioral impact of the TNC service disruption, created by the defeat of Proposition 1 in the city of Austin on May 7, 2016. Though we acknowledge both the demand and supply side implications of the disruption, our analyses focused solely on the demand side. We carried out a detailed a regression analyses to evaluate the impact on individuals' travel behavior along two dimensions—travel mode and trip frequency.

The disruption led to 45% of Uber and Lyft patrons switching to the use of personal vehicles post disruption. Users who switched to a private vehicle had a higher probability of increasing their trip frequency post disruption. Only 3% shifted to public transit – a finding that buttress the viewpoint that the demand for TNC services complement public transit. This finding also supports the hypothesis that ridesharing complements public transit. Additionally, we found evidence that supports the notion that the presence of Uber and Lyft increases trip frequency.

[3] We would like to update the reader on the Uber and Lyft situation in Austin, TX. After an extraordinary act by the Texas state legislature, Uber and Lyft returned to Austin a year after the service suspension. Our future work will analyze the impact of their re-entry on travel behavior in Austin.

Individuals who lived in the city center were less likely to switch to a personal vehicle after the disruption compared to those outside of the city center. A higher than expected number of respondents (8.9%) reported that they purchased an automobile in response to the disruption.

The entry of new TNCs after the exit of Uber and Lyft calls for a more nuanced interpretation of the results. We found that users viewed the newer TNCs as having lower quality than Uber and Lyft. They were also less satisfied with them. The exit of Uber and Lyft left users with lower quality TNCs in addition to the existing mode choices. In essence, the natural experiment allowed us to measure the impact of the *change in quality* of TNC service on travel behavior. We would like to reiterate that the aforementioned findings are reflective of the two-month window—November 1, 2016, to December 31, 2016—within which the data were collected. One might expect that as new entrants refine their business and service models, service quality will improve.

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Authors' contribution

RC Hampshire: Survey Design, Manuscript writing and editing
C. Simek: Survey Design, Survey Implementation, Manuscript writing and editing
T. Fabusuyi: Survey Design, Survey Analysis, Manuscript writing and editing
X. Di: Survey Design, Survey Analysis, Manuscript writing and editing
X. Chen: : Survey Design, Manuscript editing

Conflict of Interest Statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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