

TRANSPORT FINDINGS

Inferred Switching Behavior in Response to Re-entry of Uber and Lyft: A Revealed Study in Austin, TX

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Findings

In May 2016, Uber and Lyft suspended services following the defeat of Proposition 1 in Austin, TX. In response, several ridesourcing services entered the market. This paper provides information on the individuals most likely to switch back to Uber or Lyft after service restoration using estimated indifference bands. We hypothesize that people will not switch back unless a given trip's cost saving is beyond a positive threshold due to boundedly rational behavior. The study revealed, among others, that those who use TNC for social purposes, have lower indifference bands and are more likely to switch to Uber or Lyft.

RESEARCH QUESTION AND HYPOTHESIS

We investigate the impact of the service network disruption and restoration in Austin, TX due to the Uber and Lyft service suspension (Dinges 2017). Our motivating research question is: "To what degree does bounded rationality impact mode switching behavior when an on-demand service is involved?" We developed and implemented a model that provides insight on users' mode switching behavior after Uber and Lyft resumed services. We hypothesize that fewer people will return to Uber and Lyft than predicted by a model that assumes fully rational actors. Our analysis reflects a more nuanced and complex environment (for example, the use of subsidies and trip discounts by Uber and Lyft (Dinges 2017)).

METHODS AND DATA

We administered an online travel survey of transportation network company (TNC) passengers between November 1, 2016 and December 31, 2016. Participants were asked a series of qualifying questions based on their past use of Uber or Lyft for trips that began in the city of Austin, the presence of the Uber or Lyft app on their smartphones, and the last trip they made before Uber and Lyft service was suspended. More details about the survey can be found in (Hampshire et al. 2017)

A total of 1,840 respondents participated in the survey. Of the 1,214 respondents that provided an answer on the last trip taken pre-suspension, 70% took the last trip using Uber and 30% used Lyft. (Of particular interest to the present study is a cohort of 184 passengers who used either Uber or

Lyft prior to suspension and then switched to another TNC post-suspension; however, our focus is on switching behavior after Uber and Lyft reenter the Austin market.) Although Uber and Lyft resumed services in Austin on May 29, 2017, the survey data used for the present study predates the service restoration date. The survey conducted between November 1, 2016 and December 31, 2016 was intended to investigate the impact of service suspension rather than service reentry. However, we believe that the users' perception of service suspension offers rich information about their potential switching behavior, affording us the opportunity to make inferences about their switching behavior after service restoration. We would like to infer people's mode switching behavior from their perception of the service disruption and willingness to switch once the TNC market becomes stable. Assuming that Uber and Lyft maintain the prior level of service after reentry, participants who said that the overall quality of Uber or Lyft was no better compared to other TNCs are assumed to stay with their post-suspension TNC companies, while those who said that the quality of Uber or Lyft was higher than other TNCs are assumed to switch back to Uber or Lyft. The respondents were divided into two groups: Group A if the respondent said that the overall quality of Uber or Lyft was no better compared to other TNCs, and Group B if they said that the overall quality of Uber or Lyft was higher than other TNCs. Group A consisted of 94 responses and Group B consisted of 90 responses. Based on our assumption, we labeled Group A as "Stayers" and Group B as "Switchers." We pulled both groups' pre-suspension trip records from the Uber or Lyft app. We also culled the average travel cost estimate of the same trip post-suspension. Denote c_{UL} as the travel cost pre-suspension of either Uber or Lyft; this was used as the proxy for the stable cost of Uber or Lyft post-suspension. Let c_{TNC} be the average travel cost post-suspension paid to other TNCs. As subjects' travel costs may not be in the same magnitude, travel cost saving proportion instead of absolute travel cost saving was used. Denote $\Delta^{(n)}$ as the n^{th} traveler's cost saving proportion by taking Uber or Lyft for traveler n . Then $\Delta^{(n)} = \frac{c_{UL}^{(n)} - c_{TNC}^{(n)}}{c_{TNC}^{(n)}}$. We provide summary statistics in Table 1.

In Figure 1, the red and blue lines represent the respective proportions of switchers and stayers in each bin. As the travel cost savings from Uber or Lyft increases, the proportion of switchers increases while that of stayers decreases. The exceptions occur when the cost savings is less than 50% or higher than 50%; i.e., switchers decrease, and stayers increase. We hypothesize that there exists a probabilistic threshold (i.e., indifference band [IB]) beyond which people prefer switching than staying. The approach of estimation of IBs is borrowed from route-switching models used to predict route choices after the collapse and replacement of the I-35 W bridge in Minneapolis, MN (Di et al. 2013, 2014, 2015; Di, Liu, and Ban 2016; Di et al. 2016; Di and Liu 2016).

Table 1: TNC Cost Saving Statistics

Statistics	Stayers (Group A)	Switchers (Group B)	Total
Distribution			
Counts	94	90	184
Percentage (%)	51.1	48.9	100.0
Average TNC cost			
Before	13.2	16.5	14.8
After	13.7	12.5	13.1
Average cost saving percentage (%)			
Average	-12.2	20.9	—
Minimum	-300.0	-141.2	—
Maximum	79.2	83.3	—
Median	-1.0	25.5	—

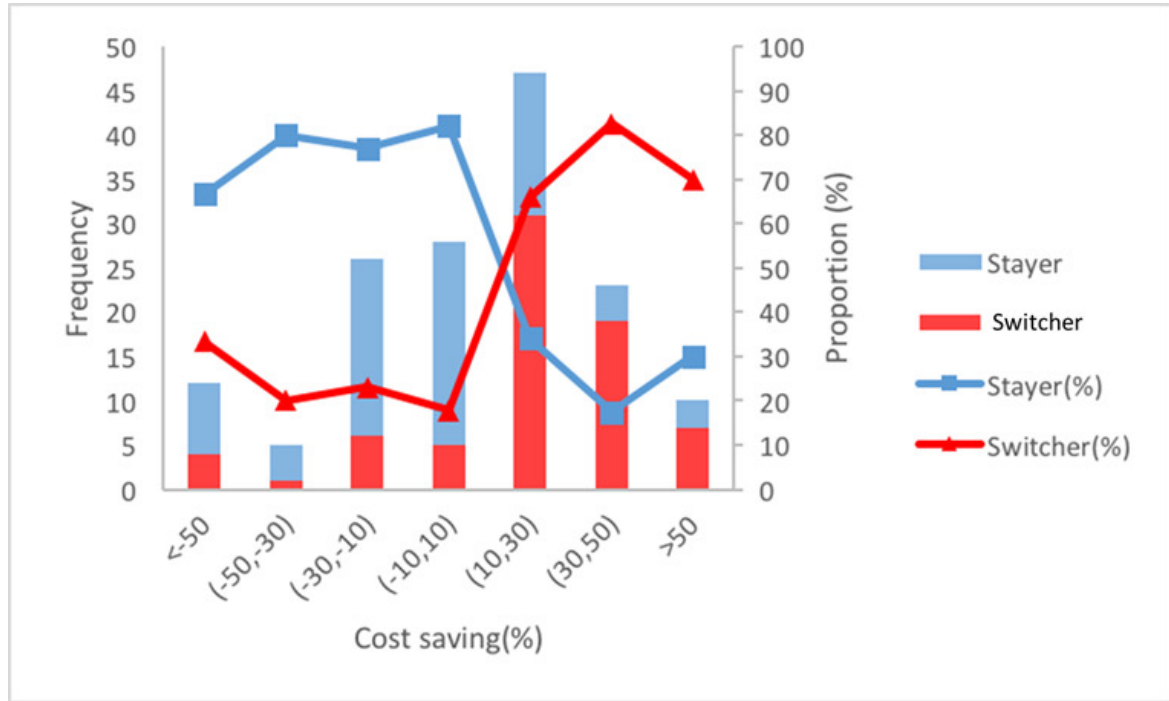


Figure 1: Histogram of Travel Cost Savings for Two Groups

Probit regression estimation: Borrowing from Di et al. (2016), let η_1 be a random variable normally distributed with mean $\mu = 0$ and standard deviation $\sigma > 0$ with $\varepsilon^{(n)}$ representing traveler n 's IB, then:

$$\varepsilon^{(n)} = \exp \left(\sum_i \theta_i X_i^{(n)} + \eta_1 \right) \sim \text{Normal} \left(\exp \left(\sum_i \theta_i X_i^{(n)} \right), \sigma^2 \right),$$

Equation 1

where $X_i^{(n)}$ is traveler n 's i^{th} explanatory variable, and θ_i is the coefficient before the i^{th} variable.

The hypothesis is that traveler n will not switch to Uber or Lyft unless their travel cost savings by taking Uber or Lyft is greater than their personal IB:

Table 2: Independent Variables and Coefficient Estimates

Variables	Definition				
Δ	Travel cost saving proportion				
Inconveniences (Inc)	0=Not extremely inconvenienced, 1=Extremely inconvenienced				
Purpose (Purp)	1=Work, 2=Social, 3=Others				
Frequency decreased (Freq_dec)	0=Same or increased, 1=Decreased				
Post TNC type (Post_TNC)	1=Fasten & Fare, 2=RideAustin, 3=Other TNCs				
Age	1=[18,24], 2=[25,34], 3=[35,44], 4=[45,54], 5=[55,64], 6=65+				
	Estimate	Std. Error	z value	p value	Significance level
(Intercept)	-0.47	1.05	-0.44	0.66	
$\Delta^{(n)}$	1.15	0.4	2.85	0	**
Inc=1	2.54	0.69	3.7	0	***
Purp=2	1.7	0.6	2.81	0	**
Purp=3	1.2	0.67	1.8	0.07	.
Freq_dec=1	1.74	0.34	5.06	0	***
Post_TNC=2	-0.69	0.3	-2.3	0.02	*
Post_TNC=3	0.13	0.72	0.19	0.85	
Age=2	-1.74	0.91	-1.92	0.05	.
Age=3	-1.58	0.92	-1.71	0.09	.
Age=4	-1.69	0.94	-1.8	0.07	.
Age=5	-2.04	1.04	-1.96	0.05	*
Age=6	-1.58	1.27	-1.24	0.21	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '.' 1

$$y^{(n)} = \begin{cases} 1, & \text{if } \Delta^{(n)} + \eta_2 > \log(\varepsilon^{(n)}) \\ 0, & \text{if } \Delta^{(n)} + \eta_2 \leq \log(\varepsilon^{(n)}) \end{cases}$$

The probability of switching for traveler n is then computed as:

$$P(y^{(n)} = 1 | \Theta) = P(\Delta^{(n)} > \log(\varepsilon^{(n)}) | \Theta) = P(\Delta^{(n)} + \eta_2 > \sum_i \theta_i X_i^{(n)} + \eta_1 | \Theta) = P(\eta$$

Equation 2

where $\eta_1 - \eta_2 \sim N(0, 2\sigma^2)$. The parameter vector is $\Theta = \{\theta_0, \theta_1, \dots, \theta_M, \sigma\}$, with $\theta'_1 = -\frac{1-\theta_1}{\sqrt{2}\sigma}$, $\theta'_i = -\frac{\theta_i}{\sqrt{2}\sigma}$, $i = 0, \dots, M$, where M is the total number of predictors.

FINDINGS

The parameters are estimated via maximum likelihood. Given our small sample size, a parsimonious model is fitted using only predictors with explanatory powers. The regressors and coefficient estimates are provided in Table 2. Except for travel cost savings, all covariates are either categorical or dummy variables. The regression has a p-value chi-square measure of fit of 0.000.

The expected value of $\varepsilon^{(n)}$ is:

Table 3: Four Types of People Utilizing TNCs

	Purpose	Frequency	TNC	Age	Mean μ_ϵ	SD σ_ϵ
Type 1	Other	Decreased	Other	[18,24]	0.40%	0.37%
Type 2	Social	Decreased	RideAustin	[25,34]	3.98%	3.67%
Type 3	Social	Increased/Same	Fasten/Fare	[45,54]	12.08%	11.16%
Type 4	Other	Increased/Same	RideAustin	[45,54]	45.32%	41.88%

$$\epsilon^{(n)} = \exp(\theta'_0 + \theta'_1 \Delta^{(n)} + \theta'_2 Inc + \theta'_3 Purp + \theta'_4 Freq_dec + \theta'_5 Post_TNC + \theta'_6 Age)$$

Equation 3

Indifference bands: Using Equation 3, we estimate IBs along two fronts for representative subsets of the population and to illustrate the impact of selected independent variables on IB estimates. The IB estimates are provided in the next two subsections. We assume a 40% cost savings and fix the inconvenience level to 1 (Extremely inconvenienced).

The statistics of IBs for people with combinations of various demographic and trip characteristics are shown in Table 3. The IB of Type 1 has the smallest mean and standard deviation values while that of Type 4 has the largest, indicating that a person of Type 1 may easily switch to Uber or Lyft while a person of Type 4 may likely stay with RideAustin.

Figure 2 plots the probability density function (PDF) of IBs against four groups of travelers. IB follows lognormal distribution. The flatness of the PDF is consistent with its standard deviation: the flatter the PDF is, the more the IB is spread out across the population (in other words, the more diverse people's switching behavior is across that population). The position of the peak of a PDF is consistent with its mean: Type 4's PDF peak is located to the right of Type 1 indicating a higher mean for Type 4 group. These observations show the consistent trend as illustrated in Table 3.

In examining the impacts of the independent variables on IB, in addition to these assumptions, we assume the trip purpose is social, that trip frequency remains the same or increased, that the TNC used is RideAustin, and that the traveler is between the age of 55 and 64. We subsequently vary the covariates one at a time while holding other factors constant. The PDFs of IBs are plotted in Figure 3.

IBs provide rich information about whether a traveler who used other TNCs during the suspension will switch back to Uber or Lyft post-suspension. Such switching decisions reflect a traveler's inertia, which is heterogeneous depending on not only cost savings but also individuals' characteristics. When individual features are fixed, the IB expressed in percent provides the lowest bound of travel cost savings at which a traveler is willing to switch. In other words, only when the travel cost saving brought by the return of Uber and Lyft goes above IBs do people consider switching. For example,

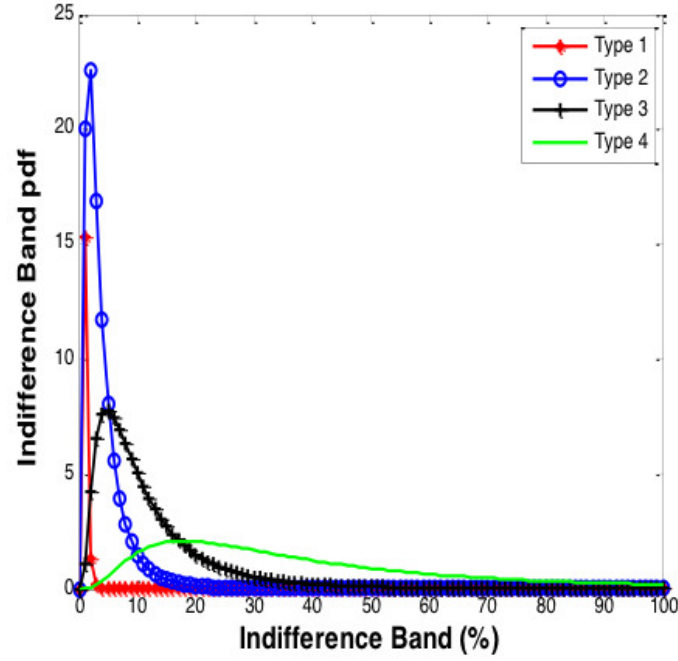


Figure 2: IBs for the Four Types of People

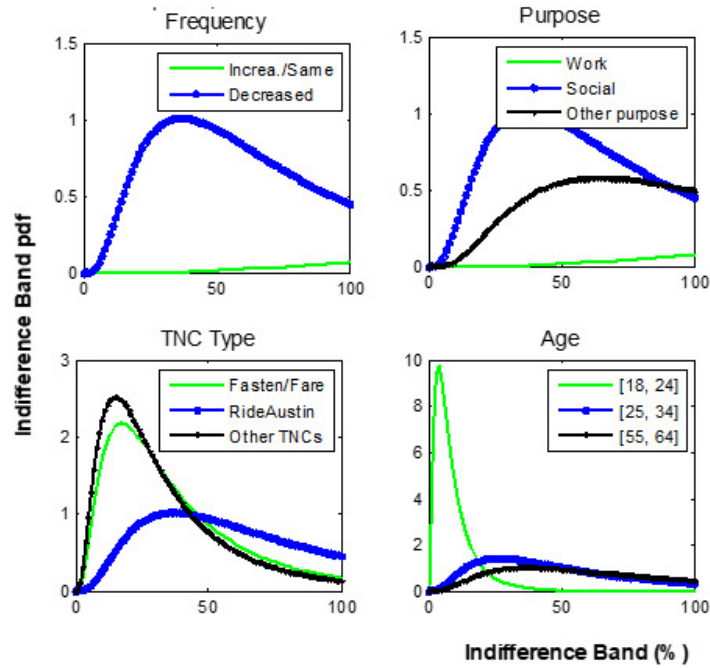


Figure 3: IB Comparison for Selected Independent Variables

RideAustin users have a flat IB PDF, indicating that the IB is spread out across the population. If the travel cost saving is above 50%, the proportion of RideAustin users who choose to switch is lower than that of other TNC users. Similarly, older travelers have a larger average IB compared to younger

people. In other words, given the same travel cost savings provided by a new TNC company, fewer older people tend to switch to this new TNC service compared to younger people, i.e., they have larger inertias in switching.

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