DISCERNING THE PREFERENCES OF CONSUMERS FOR RIDEHAILING AND AUTONOMOUS VEHICLES

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Akanksha Sinha

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ABSTRACT

Transportation Network Companies (TNCs) are changing the transportation ecosystem, but micro-decisions of drivers and users need to be better understood to assess the system-level impacts of TNCs. In this regard in the first paper, we contribute to the literature by estimating a) individuals' preferences of being a rider, a driver, or a non-user of TNC services; b) preferences of ridehailing users for ridepooling; c) TNC drivers' choice to switch to vehicles with better fuel economy, and also d) the drivers' decision to buy, rent or lease new vehicles with driving for TNCs being a major consideration. We use a unique sample (N= 11,902) of the U.S. population residing in TNC-served areas. Elicitation of drivers' preferences using a large sample is the key feature of this study. The population-weighted statistical analysis indicates that ridehailing services are mainly attracting personal vehicle users as riders, without substantially affecting demand for transit. Moreover, around 10% of ridehailing users reported postponing the purchase of a new car due to the availability of TNC services. The model estimation results indicate that the likelihood of being a TNC user increases with the increase in age for someone younger than 44 years, but the pattern is reversed post 44 years. This change in direction of the marginal effect of age is insightful as the previous studies have reported a negative association. Moreover, older ridehailing users with higher household vehicle ownership who live in suburban areas are less likely to pool rides. On the supply side, 65% of TNC drivers who work daily indicated that driving for TNCs was a consideration in vehicle purchase decisions. We also find that households with postgraduate drivers who drive

daily and live in metropolitan regions are more likely to switch to fuel-efficient vehicles. These findings can inform transportation planners and TNCs in developing policies to encourage ridepooling and to improve the average fuel economy of the TNC fleet.

In the second paper, we contribute to the literature by estimating a) Safety of children to use autonomous vehicles without any adult; specifically the question that we are analyzing is, “Once automated vehicles are running safely and reliably on all roadways, should a child of age 8, without a driver’s license, be permitted to travel alone in a driverless vehicle on trips up to 3 miles from his/her home?”; b) Preference to use either taxi in which the driver is unknown; ride-hailing services in which the rating of the driver is known or autonomous vehicles in which there is no driver; specifically, the question that we are analyzing is, “If the price and waiting time is the same, what would be the most preferred option among regular taxi, ride-hailing services and autonomous taxis?” and; c) The preference for the price of autonomous ride-hailing specifically Uber services. The question that we are analyzing is, “Should the cost of an automated Uber trip be higher or lower than the one served by a human driver and why?”. Our findings align with the previous work in that we find that males and younger individuals are more likely to use automated vehicles. They are also more likely to allow child to ride in an AV unsupervised. This information is useful for vehicle manufacturers to adjust their manufacturing standards and pricing, so that the modules they produce meet the preferences of the consumers.

BIOGRAPHICAL SKETCH

Akanksha has a bachelor's degree in Architecture and a Master of Science degree in Construction Engineering and Management.

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CHAPTER 1

ELICITING PREFERENCES OF RIDEHAILING USERS AND DRIVERS: EVIDENCE FROM THE UNITED STATES

1. Introduction

Ridehailing services such as Uber and Lyft (also known as Transportation Network Companies or TNCs) are rapidly changing the landscape of transportation. These companies have transformed the way people travel around cities. Schaller (2018) reveals that 2.61 billion passengers used TNCs in 2017 in the U.S., a 37% increase from 2016. This increase in the adoption of these services can be attributed to the ease of access using a smartphone application along with a higher availability compared to the regulated, traditional taxi services.

Proponents of these services emphasize positive impacts such as making travel easier by providing more travel options, especially in high-demand areas with uncertain and inefficient transit services (Alemi et al., 2018). There is also a possibility of partnerships between transit agencies and TNCs to improve the first and the last mile connectivity. In one such pilot project, Uber rides to and from a commuter rail station in a suburb of Orlando, Florida were subsidized in March 2016 (Shaheen and Chan, 2016). TNCs also provide users with an opportunity to give up vehicle ownership or reduce vehicle use. A few recent studies have provided evidence in support of this transition. Rayle et al. (2014) report that almost 40% of TNC users reduced driving due to the adoption of ridehailing services in San Francisco. Moreover, Clewlow and Mishra (2017) conclude that more frequent TNC users are more likely to reduce their household vehicle ownership. Similar to carsharing services, TNCs with ridepooling have immense potential to reduce vehicle miles traveled (VMT) and thus greenhouse

gas emissions and congestion arising from personal auto use (Martin and Shaheen, 2011). With these benefits in mind and to obtain a wider appeal among price-sensitive travelers, Uber and Lyft introduced their pooling services (UberPool and LyftLine) in 2014, which were heavily subsidized. Recently, Uber also introduced a new pooling service, UberPool Express, at an approximately 50% lower price than Uberpool and 75% lower than UberX (Hawkins, A., 2015). Additionally, given the higher mileage for vehicles used for taxis and ridehailing, high fuel economy and alternative fuel vehicles hold promise for adoption by ridehailing drivers and associated fleet providers. These strategies can also contribute toward lowering energy use and environmental impact associated with passenger auto travel.

Contrary to ridehailing's potential for improving societal welfare, a few studies have shown an adverse effect of these services, including induced demand for travel and a reduction in transit ridership in certain areas. For instance, in a survey across seven major cities in the United States, Clewlow and Mishra (2017) find that 49% to 61% of ridehailing trips would not have been made at all or could have been made by walking, biking, or public transit.

In sum, transportation planners and policymakers are uncertain about the impact of TNC services on energy use, the environment, and traffic congestion (Conway et al 2018). Whereas a decline in VMT and vehicle ownership can reduce greenhouse gas emissions (as established in the carsharing literature[1]), induced demand can compensate for such gains. These system-level impacts are manifestations of

[1] Greenblatt and Shaheen (2015) estimate an average reduction of 34% in greenhouse gas emissions per household because 25% to 71% of users avoided vehicle purchase due to the availability of carsharing services.

individual-level decisions, namely choice of ridehailing over transit or drive alone, preference to entirely depend on TNC services rather than owning vehicles, and TNC drivers' inclination toward buying fuel-efficient vehicles, among many others. However, in the absence of rich data sources, metropolitan planning organizations are unable to quantify the effect of TNCs on individual-level travel decisions, and system-level questions thus remain unanswered.

Previous studies have focused on understanding travelers' preferences to use or not use ridehailing services. These studies have shown that early adopters of TNC services are primarily well-educated young individuals who come from affluent families (Rayle et al., 2014; Clewlow and Mishra, 2017; Alemi et al., 2018). In the context of TNC drivers, some studies have touched upon driver safety (Feeney, 2015), driver wages (Berger and Frey, 2017), and sociodemographic characteristics (Kooti, 2017; Hall and Krueger, 2018), as well as personal attitude of individuals who are willing to become TNC drivers (Berliner and Tal, 2018). But, to the best of our knowledge, no previous study has explored preferences of TNC drivers (such as buying a vehicle with improved fuel economy), perhaps due to a lack of driver-level datasets.

This study takes an important step toward bridging this gap by analyzing a survey data, procured from Strategic Vision Incorporated, consisting of a sample (N= 11,902) of the U.S. population residing in TNC served areas. The survey included information on sociodemographic characteristics, personal attitudes toward adopting TNC services as a user or driver, and changes in travel mode and vehicle ownership preferences after using these services. Using this revealed preference data, we investigate association between sociodemographic characteristics and the following: a) individuals'

preferences for being a rider, a driver, or a non-user of TNC services; b) preferences of ridehailing users for ridepooling; c) ridehailing drivers' choice to switch to vehicles with better fuel economy, and also d) TNC drivers' decision to buy, rent or lease a new vehicle with driving for TNCs being a major contributing factor. We fit multinomial logistic regressions to answer the first and binary logistic regressions to answer the remaining research questions. We also provide insights about a) variation in individuals' frequency to use ridehailing services across different trip purposes and in absence of their preferred travel mode; b) impact of using ridehailing on vehicle ownership and other mobility decisions; c) preference of public transit users to adopt TNC services for first/last mile connectivity; d) activities undertaken by TNC drivers during downtime; e) and average pick-up time, across surveyed TNC drivers.

The remaining of the paper is organized as follows: section 2 provides a review of the relevant literature; section 3 discusses the survey data and key insights from the descriptive statistics of the sample and succinctly describes the methodology used in this study; section 4 summarizes main results; and conclusions and future research are discussed in section 5.

2. Literature Review

This section summarizes the contextual literature on individuals' preferences to use TNC services and the subsequent impacts on their mobility decisions. We first discuss the evolution of TNCs and then describe the sociodemographic and geographic characteristics of individuals who have a higher tendency to use TNC services. We then review the literature on how these services are changing the landscape of urban travel patterns by affecting vehicle ownership preferences and demand for other travel

modes. We conclude with a review of studies focusing on ridehailing drivers, followed by highlighting the research gap that we are addressing in this study.

In recent years, transportation has gone through a rapid transformation due to rapid deployment of emerging technologies such as smartphone and internet (Taylor et al., 2015). These technological advancements have mitigated geographic constraints and are the main drivers of TNCs rapid growth. As of 2016, ridehailing services are active in almost 500 cities in the United States (Murphy, 2016). However, these services are still not a regular mode of transport. From a survey of 4,787 American adults, the Pew Research Center finds that only 3% and 12% of TNC riders use these services on a daily or a weekly basis, respectively (Smith, 2016).

Some correlation studies have identified the characteristics of travelers with a higher propensity to use ridehailing services. Results of a survey across seven major US cities indicate that the adoption rate of these services is almost double among college-educated individuals as compared to those without a college degree (Clewlow and Mishra, 2017). Furthermore, travelers younger than 29 years and older than 65 years are found to be the most and least frequent users of ridehailing services, respectively. Kooti et al. (2017) also obtain similar findings by analyzing Uber data that was collected over a span of seven months and contains 59 million rides and 4.1 million riders. The authors conclude that whereas younger riders are more likely to take frequent, shorter rides; older travelers are more inclined toward infrequent, longer rides. In another study, Alemi et al. (2018) model individuals' lifestyles using the California Millennials Dataset to identify the factors affecting the adoption of ride-hailing services. The results of this study indicate that highly-educated independent

millennials who live in non-traditional households (living in core urban areas without owning personal vehicles) and without children have the highest adoption rate. In terms of personality traits, individuals with variety seeking and technology embracing attitudes are more likely to use ridehailing services.

Geographic context and built environment factors also play an important role in determining the usage frequency of ridehailing. According to Clewlow and Mishra (2017), the adoption of these services is comparatively higher in urban neighborhoods (29%) than those of suburban areas (15%). Alemi et al. (2018) also support a positive association between the demand for these services and the urbanization of the neighborhood. Along the same lines, the study by the Pew Research Center finds that a majority of users of these services are urban dwellers (21%), followed by suburban dwellers (15%) (Smith 2016). In a recent study, Yu and Peng (2019) investigate the relationship between different dimensions of the built environment and ridehailing demand using the 2016-2017 trip data from RideAustin, a local TNC company. The results support the findings of previous studies and also indicate that population density is a good predictor of ridehailing demand. Moreover, areas with higher roads and sidewalk densities are more likely to have a higher demand for TNC services.

TNC services are likely to reduce household vehicle ownership, but the extent of that reduction is not clear. The American Public Transportation Association (2016) reports that ridehailing users are more likely to own fewer cars. Similarly, Conway et al. (2018) use National Household Travel Survey (NHTS) data to examine the extent of the expansion of ridehailing services within the US and conclude that ridehailing users are more likely to be multimodal, owning fewer cars and using alternative modes of

transportation. The results of a survey in Austin, Texas by Hampshire et al. (2017) support this relationship as these authors find that 9% of the ridehailing users purchased a vehicle after a suspension of these services, and 41% of users went back to driving.

The impact of TNC services on public transit is also unclear. Sadowsky and Nelson (2017) implement a regression discontinuity design to measure the effect of TNCs on public transit across 28 major urban US cities. The authors find that the introduction of Uber led to an increase in the use of public transportation, however, the introduction of Lyft after a few months had a negative impact on transit ridership. Sadowsky and Nelson hypothesize that the competition between these TNCs led to a decrease in cost and wait time, making these services more attractive than transit. Dias et al. (2018) analyze around one million trips by RideAustin and find that individuals living in neighborhoods with lesser access to transit have higher inclination to use ridehailing services, but there is a synergy between transit and ridehailing services in other areas. In another study, Barbar et al (2017) use a difference-in-difference design to quantify the impact of ridehailing services and observe a significant decrease in road-based public transit service, especially in areas with poor transit coverage, but an increase in the demand of subway and commuter rail. Hall et al. (2018) also adopt a difference-in-difference design and find that Uber is, on average, complementary to transit. However, the more detailed analysis shows a negative impact of Uber on the transit ridership in smaller cities, but a positive impact in larger cities.

Although no previous study has focused on eliciting preferences of TNC drivers, a few studies have investigated the demographics of such drivers, and the relationship

between their desire to drive and personal attitudes. Hall and Kruger (2018) analyze data from two surveys in the US that were conducted in December of 2014 (N=601 drivers) and November of 2015 (N=632 drivers). Hall and Kruger find that 30% of the Uber drivers were between the ages of 30 and 39, 47.7% had college or advanced degrees, and only 14% were women. The authors also observe that more Uber drivers were single than married, and the married drivers had children at home. Berliner and Tal (2018) estimate the willingness of an individual to drive for TNCs using the stated preference data collected in Irvine, California in 2015. They find that the opportunity to make extra money followed by a fondness toward driving are key motivating factors behind an individual's willingness to drive for ridehailing services. Berliner and Tal also conclude that age, number of children, vehicle ownership, gender, and positive attitudes toward ridehailing have a significant role in estimating willingness to become a TNC driver.

This current research builds upon prior evidence on understanding the preferences of travelers and drivers for TNC services using revealed-preference, representative data of the TNC served areas in the United States. First, we expand the literature on understanding the socio-demographic characteristics of TNC users and drivers. Second, we help in identifying the demographic segments of TNC users who are interested in pooling rides. This question has received limited attention in the literature (Lavieri and Bhat, 2018), but it is crucial for policymakers to deploy pooling services faster and to make TNCs environmentally viable. Third, to further understand the impact of ridehailing services on greenhouse gas emissions, we recognize a group of TNC drivers who are willing to move toward fuel-efficient cars. Fourth, we also elicit

preferences of TNC drivers to buy new vehicles with driving TNCs being a major purchase consideration, which have also not been explored in the literature.

3. Data and Summary Statistics

In this section, we provide details of the survey data and weight calculation, followed by a discussion on travel behavior and vehicle purchase decisions of TNC users, non-users, and drivers using data summary statistics.

3.1.Data Collection and Weight Computation

We use data from a survey of ride-hailing users, drivers, and non-users, which was conducted by Strategic Vision Inc. in 2017 among 11,902 U.S. consumers residing in TNC served areas. Figure 1.1 shows the geographical distribution of the number of respondents across the contiguous states of the USA. The procured survey data includes information on household characteristics and attitudes, as well as information on ride-hailing usage and preferences. Household characteristics include respondents' age, gender, marital status, education level, household income, ethnicity, residential location, mode of commuting, and number of members in the household.

The sample either under- or over-represents some demographic groups. For example, women above 49 living in metropolitan or urban areas with income less than $100,000 using public or non-motorized transport are under-represented in the sample and men above 54 living in small town areas with annual income greater than $100,000 are over-represented in the sample. To address this concern, we estimate person-level weights using the iterative proportional fitting (IPF) technique (Bergmann, 2011). IPF matches the joint probability distribution of various demographic characteristics in the collected sample and the population-level datasets on urban and rural housing units

(2016 American Community Survey data and 2010 U.S. Census Bureau data). In other words, we compute weights by scaling the survey sample proportions, in four demographic classes or 32 categories (four gender- and age-based, two income-based, two travel mode-based, and two residence location-based groups), relative to the corresponding class-specific proportions in the population-level data. We implement this IPF method using the ipfweight package in Stata. The estimated weights vary between 0.15 - 4.65. All the results presented in this paper are based on the weighted sample.

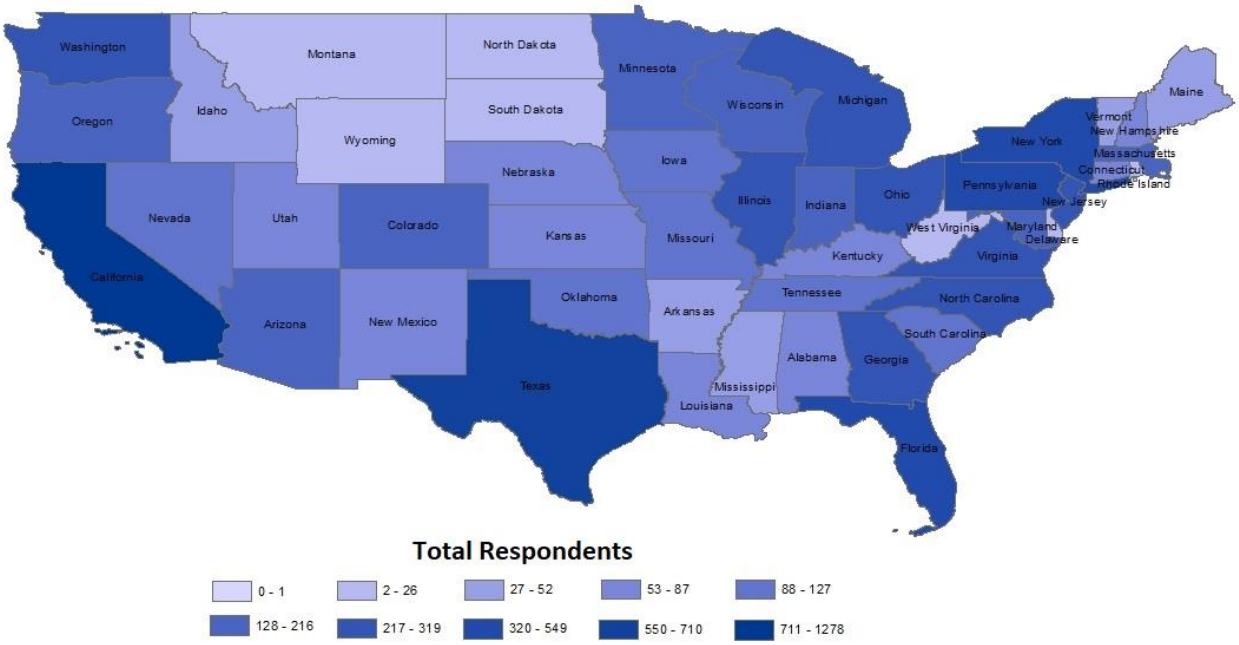

Figure 1. 1 Geographical distribution of "the number of respondents" at state-level (N=11,902)

3.2.Explanatory and Response Variables

Table 1.1 summarizes statistics of the population-weighted explanatory variables used in all logistic regression models of this study. The sample statistics are consistent with those of the population. For example, in the weighted sample, the proportion of males,

average age, and average annual income are 48%, 46.77 years and $94,909, respectively. These numbers for the population are 49%, 45.75 years and $81,346, respectively. Around 19% of respondents are early adopters of these ridehailing services. Among 1541 TNC drivers in the sample, around 25% drive daily.

Key summary statistics of the response variables are shown in Table 1. 2. The results indicate that the sample proportions of TNC users, drivers, and non-users are 29%, 29%, and 42%, respectively. Among the ridehailing users, 13% of them had used ridepooling services in the past. Among drivers, 53% of them indicated that they would be inclined to shift towards more fuel-efficient vehicles. When asked about the change in vehicle ownership preferences of drivers, 47% of them had a high propensity towards buying or leasing a new vehicle as a result of driving for TNCs.

Table 1. 1 Key explanatory variables

Explanatory Variables	**N**	**Mean**	**Median**	**SD**	**Min.**	**Max.**
Male indicator	8791	0.48	0	0.50	0	1
Single indicator	8791	0.35	0	0.48	0	1
Age (in years)	8791	46.77	47	15.73	18	100
Postgraduation indicator	8791	0.31	0	0.46	0	1
Annual Income (US$)	8791	94909	72500	90915	15000	1000000
Metropolitan resident indicator	8791	0.30	0	0.46	0	1
Household size 3+ indicator	8025	0.32	0	0.47	0	1
Total vehicle ownership	8791	2.15	2	1.17	0	6
Early adopter indicator	8791	0.19	0	0.39	0	1
Drive daily indicator	1541	0.25	0	0.43	0	1

Table 1. 2 Key response variables

Response variables (indicators)	**N**	**Mean**	**SD**
Model 1			
TNC driver	8791	0.29	0.45
TNC user	8791	0.29	0.45

TNC non-user	8791	0.43	0.49
Model 2			
Ridepooling user	2365	0.13	0.33
Model 3			
TNC drivers who would prefer to switch to fuel-efficient vehicles	1533	0.53	0.50
Model 4			
TNC drivers who considered driving for ridehailing services while buying or leasing a new vehicle	1540	0.47	0.50

3.3.Mobility Patterns of Ridehailing Users

We created a two-way table to understand the association between the most used mobility option by respondents and their TNC usage frequency (see Table 1. 3). We label "frequent TNC users" for those who use TNCs once or more times per week, and the remaining respondents fall in the category of "infrequent TNC users". The results suggest that personal vehicles and ridehailing are the most used travel modes by around 53-61% and 22-32% frequent TNC users, respectively. However, these proportions are 79-87% and 3-5% for the infrequent TNC users, with a marginal decline in the share of transit among the most used travel modes (4-10% for frequent vs. 3-6% for infrequent users). This pattern indicates that ridehailing does not impact transit demand significantly, but rather personal vehicle users are mainly shifting to TNCs.

In Table 1. 4, we analyze how the unavailability of the most used travel mode affect mobility patterns of travelers. Around 66% and 14% of those who mostly use ridehailing are likely to switch to driving personal vehicles and transit, respectively, in the absence of these services. Hampshire et al. (2017) also observed a similar trend where 41% of the riders went back to driving after the suspension of ridehailing

services in Austin. Among those who indicated their most used mode to be driving personal vehicles, 31% and 46% would shift to ridehailing and carpooling/carsharing, respectively, in the absence of their preferred mode. These proportions are 29% and 4% for the frequent transit users.[2] All these findings further strengthen our earlier result that ridesharing and carsharing services are mainly capturing personal-driving demand, without substantially affecting demand for transit. In contrast to Clewlow and Mishra (2017), we find evidence against the impact of ridehailing service on induced travel demand – only 0.45% of frequent ridehailing users would not have made those trips if these services were not available. These discrepancies can be attributed to different target samples of both studies. The sample used by Clewlow and Mishra (2017) had an oversampling of respondents in San Francisco and Los Angeles.

We present other insightful statistics about preferences of ridehailing users. Around 10% of ridehailing users reported postponing the purchase of a new car. This result is similar to that of Hampshire et al. (2017), who found that 9% of the ridehailing users purchased a vehicle after the suspension of these services in Austin. In terms of trip purpose, a high proportion (around 46%) of respondents selected ridehailing, carsharing or carpooling as their mobility options on trips to/from social events. This finding is consistent with the previous studies, which found that the most common usage of ridehailing trips was for recreational activities (Alemi et al., 2018; Lavieri and Bhat, 2018; Young and Farber 2019). The above finding is further supported by a sample statistic that around 21% of ridehailing users reported "didn't want to drive

[2] However, proportion of shift to ridehailing is similar for both personal vehicle and transit users, in absence of both services, personal vehicle users would mainly contribute to ridehailing market share due to their much higher current share (86% in the sample).

after drinking" as the most important reason for using ridehailing services. "Convenience" was reported as the other most important reason behind using ridehailing service by around 24% of respondents. These results are aligned with those of previous studies, which have also found these two factors to be the main reasons for preferring ridehailing (Rayle et. al. 2016, Alemi et. al. 2018, Conway et. al. 2018, Young and Farber 2019).

We further analyze that relatively small percentage,13%, of ridehailing users have used ridepooling services. Around 34% of ridehailing trips were pooled by these users in the past. When asked about the reasons for not using ridepooling services, a large percentage of the ridehailing users, around 50%, mentioned that they had not heard of these services. Another dominant reason, which was indicated by around 22% of the ridehailing users, is a preference for "private rides".

Table 1. 3 Most often used mobility options of the ridehailing users (N = 11,902)

Frequency of using ridehailing services or Taxis	**User Type**	**What mobility options do you use most often?**				
		Ridehailing	**Driving personal vehicle**	**Public Transit**	**Walk or Bike**	**Carsharing or carpooling**
Once or more a day	Frequent TNC Users	31.88	53.49	4.26	5.62	4.74
Once or more per week		21.91	60.73	10.13	5.4	1.83
Once or more per month; Once or more in 3 months	Infrequent TNC Users	5.41	79.13	6.08	6.41	2.97
Once or more a year; Once or more every		2.86	87.05	2.92	5.4	1.76

few years or Never						

Table 1. 4 Mobility option most used in the absence of their current travel mode

Mobility option used most often	**How would you make your most frequent trip if you're the most frequently used option was not available?**						
	N	**Ridehailing**	**Drive personal vehicle**	**Public transit**	**Walk or Bike**	**Carsharing or carpooling**	**Wouldn't make the trip**
Ridehailing	256	0	65.53	14.11	6.56	13.35	0.45
Drive personal vehicle	6369	30.64	0	9.4	7.8	46.11	6.04
Public transit	243	29.05	42.9	0	16.99	3.58	1.66
Walk or bike	372	12.42	59.84	16.88	0	5.51	5.35
Carsharing or carpooling	151	29.85	52.21	13.34	2.17	0	2.43

3.4.Preferences of non-users

We now discuss reasons for not using ridehailing by non-users. The highest proportion (around 36%) of the respondents mentioned that they would just prefer driving by themselves. Among the other reasons, around 21% of the nonusers did not need taxi or ridehailing services in the past. Non-users of TNCs, who use personal vehicles for first/last-mile transit connectivity, were asked about their preferences to switch to TNC services for the last-mile. Approximately 41.3% of these non-users reported their willingness to make that switch.

3.5.Preference of TNC Drivers

Drivers were asked about their emotional response to driving for TNCs. Whereas around 54% of the drivers reported their experience to be excellent, 28% and 18% felt

neutral and unsatisfactory, respectively. As expected, TNC drivers who work more frequently end up driving more miles per week. Specifically, the drivers working daily, and every other day drive 42 miles and 31 miles per week, on average, respectively, but those who work less than once per month, only drive an average of 16 miles per week.

We created a two-way table to understand the relationship between the decision to rent/lease/purchase a vehicle and their driving frequency (see Table 1. 5). Around 65% of drivers who work daily indicated that driving for TNCs was a consideration in terms of new vehicle ownership. As expected, this proportion declines to 51% and 40-46% for those who drive every other day and once a week or less, respectively. Moreover, around 93% of drivers use their primary vehicle to drive for ridehailing services. This proportion remains intact across different driving frequencies of drivers. We then asked about downtime activities of drivers. Around 29% of drivers reported that they drive to the busy parts of the city to get more rides, inducing extra vehicle miles traveled (VMT). Average pick-up time during peak and off-peak hours are 9 and 10 minutes, respectively, which further adds around 2-3 miles per trip to the induced VMT. In terms of inclination toward future fuel type, 26% of TNC drivers who work more than 20 hours per week would prefer Diesel, but this proportion is 8-11% for those who drive less frequently. Around 25% of drivers would like to drive a hybrid electric vehicle in the future.

Table 1. 5 Decision to rent/lease/purchase car based on the frequency of driving for ridehailing

Frequency of driving for ridehailing	**Number of**	**Was driving for ridehailing service a consideration in the decision to**

services	responses	rent/lease/purchase your primary vehicle?	
		Yes	**No**
Daily	478	65%	35%
Every other day	343	51%	49%
Once in a week	646	43%	57%
Once in a month	298	46%	54%
Less than once per month	353	40%	60%

4. Results and Discussion

Apart from parameter estimates of the link function of the logit models, we also report relative risk or odds-ratio estimates with 95% confidence intervals. We explore non-linear effects of continuous variables by plotting the predicted choice probabilities and marginal effect estimates over the support of the covariate. To compute these quantities at a given level of the covariate of interest, we fix all other covariates at their sample mean and make a unit change in the specific covariate of interest.

4.1.Model 1 – Preference of being a TNC Rider or a Driver

Table 1. 6 shows the parameter estimates and the relative risk ratios of the multinomial logistic model, which explains the association between individuals' sociodemographic characteristics and their preference for being a TNC rider, driver, or non-user.

The predicted choice probabilities and the marginal effects plots of age (see Figure 1. 2) indicate that the preference for being a TNC driver and non-user, respectively decreases and increases with an increase in age, keeping all other characteristics the same. This result is consistent with the findings of Hall and Krueger (2018) who also had a higher proportion of younger people among Uber drivers. Perhaps, platforms such as Uber provide new opportunities to the younger population who are more open to a flexible work schedule and are willing to take up multiple jobs. However, we

observe a non-linear effect of age on the propensity of being a TNC user. The likelihood of being a user increases with the increase in age for someone younger than 44 years, but the pattern is reversed post 44 years. This change in direction of the marginal effect of age at 44 years is insightful as the previous studies have reported a linear and negative association between age and propensity of being a TNC user (Kooti et al., 2017; Alemi et al 2018). Finally, the higher inclination of younger people toward being a TNC user or driver is also aligned with the education and psychology literature where previous studies have established that younger people are more likely to adopt information and communication technologies (Helsper and Eyon, 2010; Milojev and Sibley, 2017).

Higher income individuals have a higher inclination to ride TNC services, but a lower propensity to become a TNC driver. These results are consistent across all income values (see Figure 1. 3) and are also aligned with previous studies (Rayes et al 2014; Clewlow and Mishra 2017). A probable explanation of this relationship is higher affordability of wealthier individuals to ride TNC services and at the same time, lesser likelihood to become a TNC driver for additional income. After controlling for key covariates such as education, age, marital status, and gender, individuals with a higher household vehicle ownership are less likely to use TNCs in any form (driver or rider). However, variation in the predicted choice probabilities due to a change in vehicle ownership is very small (see relatively flat predicted choice probability plots in Figure 1. 4 indicate). This relationship is intuitive because TNC services in households with high vehicle ownership might serve as a convenient travel option rather than a

frequent mode of transport. On the same line, Bhat and Lavieri (2018) also report a decrease in ride-hailing frequency with the increase in vehicle availability.

Moreover, early adopters of technologies and residents of metropolitan areas are more inclined toward riding and driving ridehailing services, ceteris paribus. In fact, magnitudes of relative risk ratios indicate that these two covariates have the most practically significant relationship with the individual's preference to ride or drive TNC services. Being an early adopter and being a metropolitan resident increases the odds of being a driver (cf. being a nonuser) by factors of 4.81 and 1.94, respectively, and increases the odds of being a rider by factors of 1.36 and 1.53, respectively. These findings are consistent with the literature. For instance, Alemi et al. (2018) find that early adopters of TNC services are likely to be "technology-oriented" and thus they tend to adopt such services in bundle as a part of their modern lifestyle. Similarly, Hall and Krueger (2018) and Alemi et al. (2018) also observe higher inclination of metropolitan residents toward using these services. Lavieri and Bhat (2018) speculate three possible reasons for this tendency, namely parking restrictions in urban areas, lower trip costs due to shorter trip lengths, and higher reliability of TNC services. In fact, higher travel demand in metropolitan areas also explains residents' higher propensity of being a driver.

Finally, postgraduate degree holders and single individuals, everything else constant, are more likely to ride TNC services but are less likely to be a driver. These results are aligned with the findings of Lavieri and Bhat (2018).

Table 1. 6 Multinomial Logistic Parameter Estimates and Relative Risk Ratios (Model 1).

Explanatory Variables	Parameter estimates			Relative Risk ratios		
	Estimate	**Std. Err.**	**z-stat**	**Estimate**	**LB (95% CI)**	**UB (95% CI)**
	Ridehailing Driver					
Male indicator	-0.530	0.100	-5.28	0.589	0.484	0.717
Single indicator	-0.026	0.121	-0.22	0.974	0.769	1.234
Age	-0.134	0.005	-27.76	0.875	0.866	0.883
Postgraduation indicator	-0.620	0.120	-5.15	0.538	0.425	0.681
Annual Income (US$)	-5.07E-06	1.55E-06	-3.27	0.999995	0.999992	0.999998
Metropolitan resident indicator	0.665	0.112	5.93	1.945	1.561	2.423
HH Size 3+ indicator	0.485	0.108	4.49	1.625	1.315	2.008
Total vehicle ownership	-0.116	0.049	-2.38	0.890	0.809	0.980
Early adopter indicator	1.571	0.117	13.46	4.813	3.828	6.050
Constant	5.693	0.261	21.83			
	Ridehailing User					
Male indicator	-0.286	0.072	-3.97	0.751	0.652	0.865
Single indicator	0.292	0.092	3.17	1.339	1.118	1.604
Age	-0.045	0.003	-15.70	0.956	0.950	0.961
Postgraduation indicator	0.141	0.077	1.83	1.152	0.990	1.340
Annual Income (US$)	7.35E-06	5.82E-07	12.63	1.000007	1.000006	1.000008
Metropolitan resident indicator	0.425	0.088	4.83	1.529	1.287	1.817
HH Size 3+ indicator	-0.160	0.083	-1.93	0.852	0.724	1.002
Total vehicle ownership	-0.086	0.035	-2.47	0.918	0.857	0.982
Early adopter indicator	0.309	0.109	2.83	1.362	1.100	1.687
Constant	1.235	0.195	6.33			
N	8,086					
Loglikelihood	-6109.5					
Pseudo R-square	0.292					

Note: “Ridehailing Non-user” is a base category. LB (95% CI) and UB (95% CI) imply lower and upper bounds of 95% confidence interval.

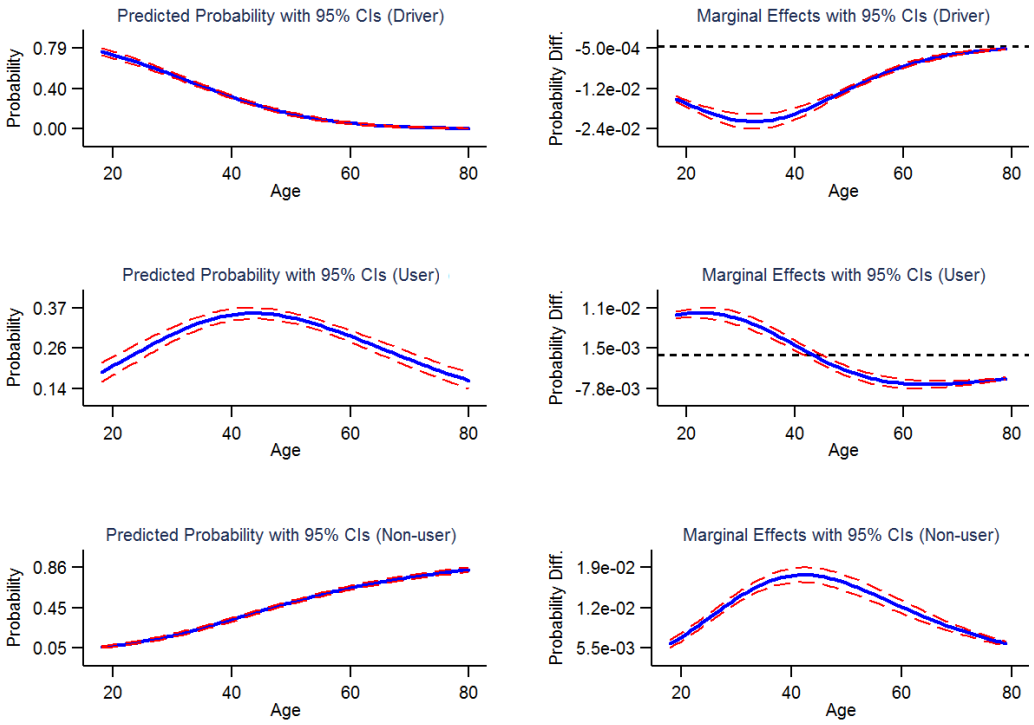

Figure 1. 2 Predicted Probability and Marginal Effect of "Age" (Model 1)

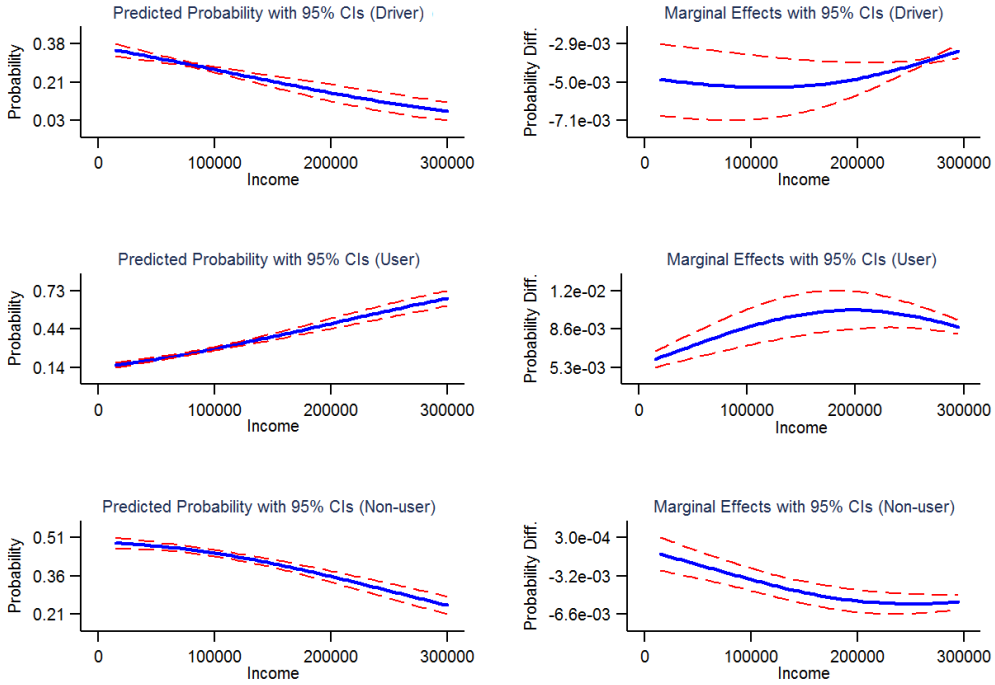

Figure 1. 3 Predicted Probability and Marginal Effect of "Annual Income" (Model 1)

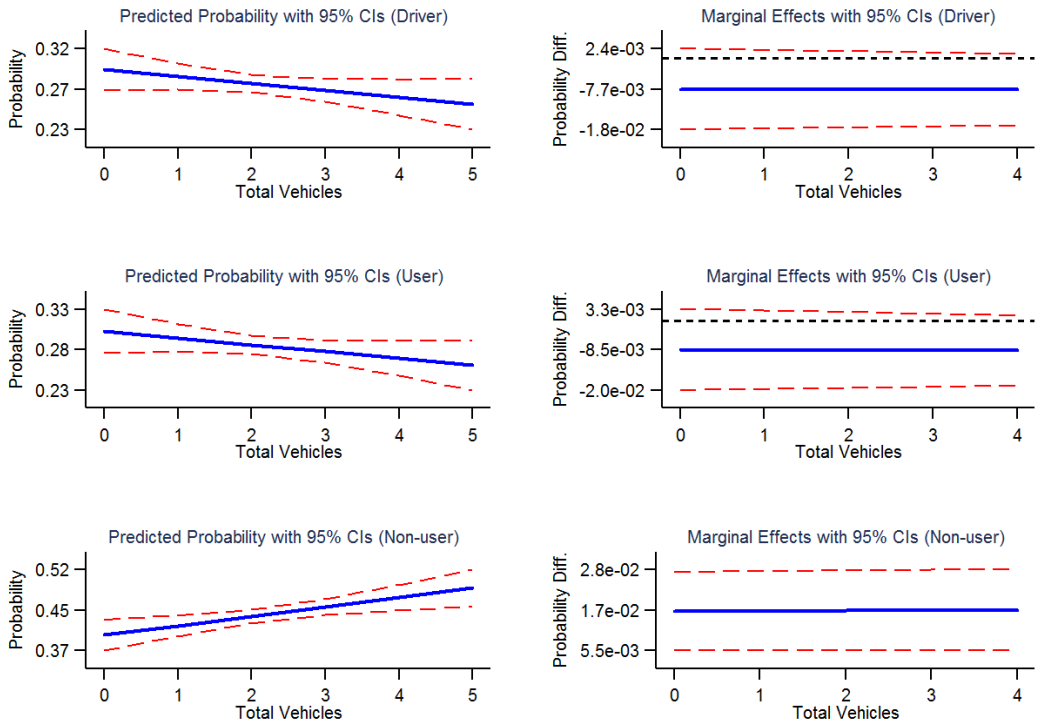

Figure 1. 4 Predicted Probability and Marginal Effect of "Total Vehicle Ownership" (Model 1)

4.2.Model 2 – Preference to Ridepool

Table 1. 7 shows the parameter estimates and the odds ratios of a binary logistic model which explain the preferences of TNC riders for ridepooling (base category: non-users of ridepooling). As the literature on ridepooling is still at a nascent stage, we have highlighted some of the similarities of our results with the results of carpooling/carsharing studies.

The predicted probability and marginal effect plots of age (see Figure 1. 5) indicate that the tendency of pooling consistently decreases with the increase in the age of TNC users. Lavieri and Bhat (2018) observe a similar trend, which they attribute to tech-savviness and variety-seeking behavior of the younger population. Carpooling is also more common among individuals between the ages of 25 and 55 (Shaheen et al.,

2016). However, the relationship between age and propensity to ridepool varies with sociodemographic characteristics such as education level (see Figure 1. 6) and gender (see Figure 1. 7). Clearly, the inclination of a male (and postgraduate) TNC user to pool is less severely affected by age as compared to that of females (and below postgrad), keeping all other characteristics the same. A young female TNC user is much more likely to pool than that of a young male. More specifically, a female TNC user who is younger than 54 years has a higher probability of pooling than a male user of the same age, but the trend reverses for users older than 54 years. The transition age for education effect is around 34 years. In other words, TNC user with education below postgraduation, who is younger than 34 years, is likely to have higher tendency to use pooling than a postgraduate TNC user of the same age, but the pattern is reversed for a TNC user older than 34 years. We thus provide new insights on the non-linear relationship between TNC riders' preference for ridepooling and their gender and education levels.

Household vehicle ownership is negatively associated with the preference of a TNC user to ridepool: odds of ridepooling by a TNC user due to the addition of a household vehicle decreases by a factor of 0.87. This relationship is consistent with the findings of Lee et al. (2018) in the context of carpooling. The predicted probability plot in Figure 1. 8 shows the linear nature of this relationship over the support of vehicle ownership.

Similar to the results of Model 1 in section 4.1, whereas metropolitan resident and early adopters are more inclined, males are less inclined to ridepool as compared to their counterparts, ceteris paribus. A few studies in the environmental psychology

literature (e.g., Glover et al. 1997) argue that females take a stronger standpoint on ethical, environmental and pro-social behavior as compared to males, which can be a plausible reason behind a higher inclination of females toward ridepooling. Residential location is the most practically significant predictor as reflected in odds ratios – living in metropolitan areas increase the odds of a TNC user to ridepool by a factor of 1.73 as compared to those living in suburban areas. This result is consistent with the findings of Almei et al (2018) and Lavieri and Bhat (2018).

Table 1. 7 Binary Logistic Parameter Estimates and Odds Ratios (Model 2).

Explanatory Variables	**Parameter estimates**			**Odds ratio**		
	Estimate	**Std. Err.**	**z-stat**	**Estimate**	**LB (95% CI)**	**UB (95% CI)**
Male indicator	-1.341	0.635	-2.11	0.262	0.075	0.908
Age	-0.047	0.014	-3.43	0.955	0.929	0.980
Postgraduation indicator	-0.614	0.662	-0.93	0.541	0.148	1.981
Metropolitan resident indicator	0.550	0.165	3.34	1.733	1.255	2.393
Total vehicle ownership	-0.138	0.084	-1.64	0.871	0.739	1.027
Early adopter indicator	0.321	0.201	1.6	1.378	0.930	2.042
Male indicator X Age	0.026	0.014	1.89	1.026	0.999	1.054
Postgrad indicator X Age	0.016	0.014	1.13	1.016	0.988	1.045
Constant	0.207	0.601	0.34			
N	2,504					
Loglikelihood	-853.9					
Pseudo R-square	0.048					

Note: “Ridepooling non-user” is a base category and parameter estimates are for “Ridepooling user”. LB (95% CI) and UB (95% CI) imply lower and upper bounds of 95% confidence interval.

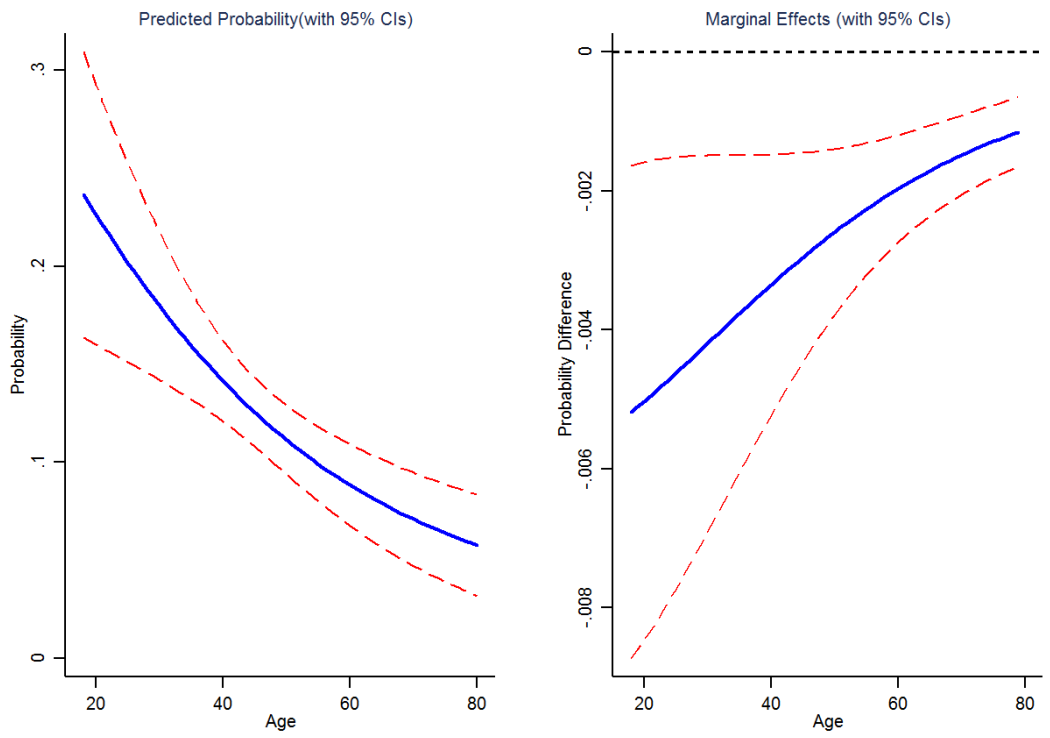

Figure 1. 5 Predicted Probability and Marginal Effect of "Age" (Model 2)

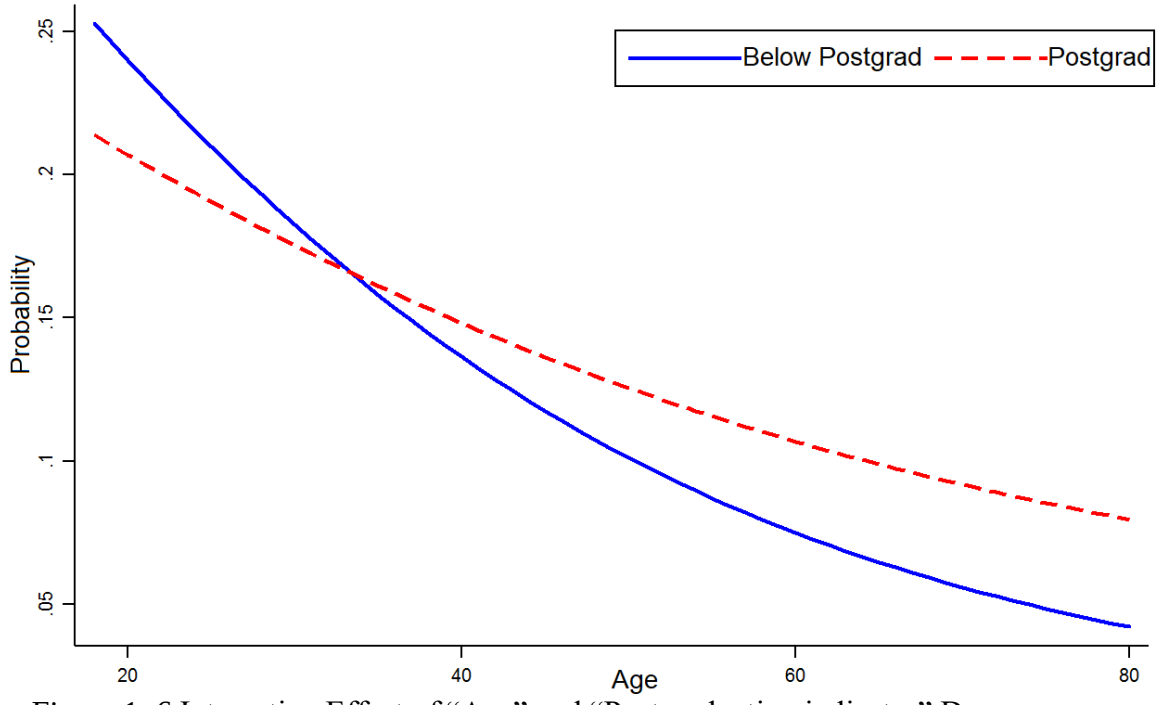

Figure 1. 6 Interaction Effect of "Age" and "Postgraduation indicator" Dummy (Model 2)

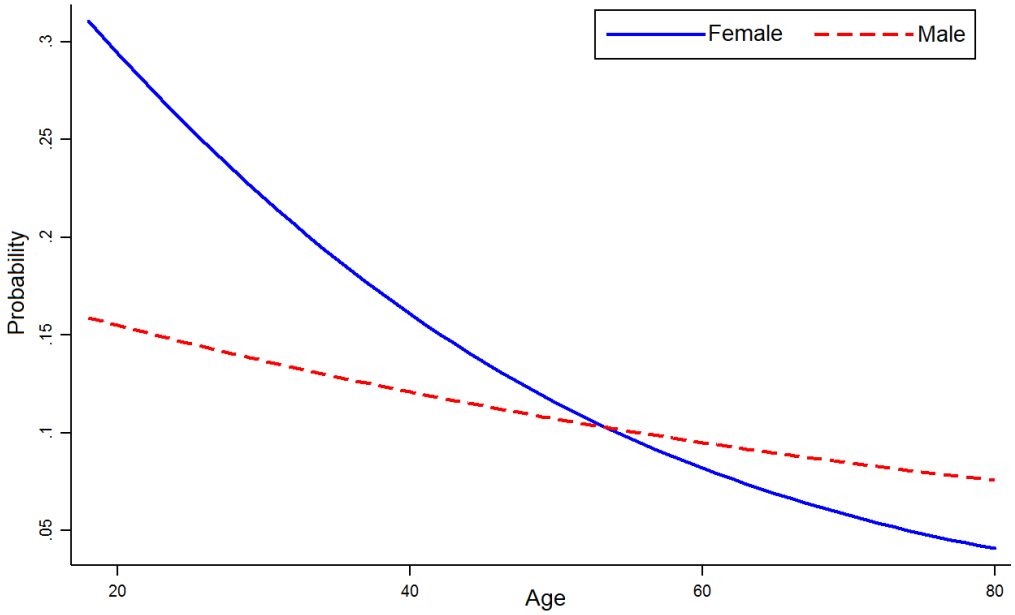

Figure 1. 7 Interaction Effect of "Age" and "Male indicator" Dummy (Model 2)

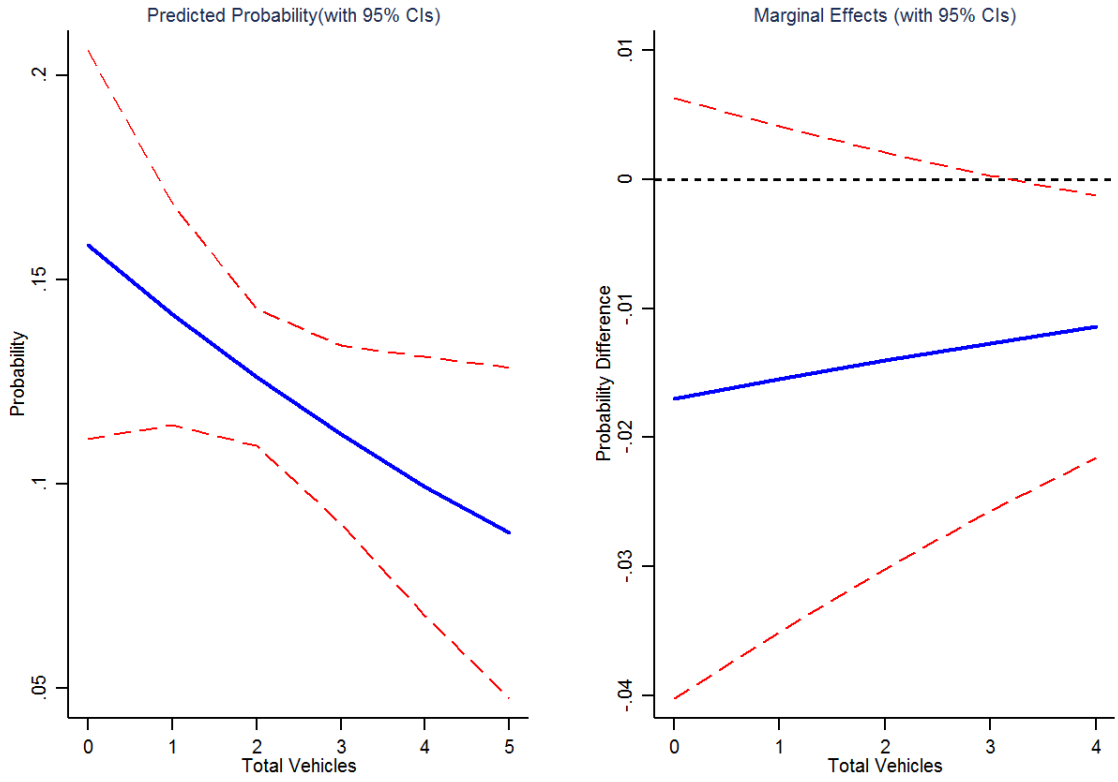

Figure 1. 8 Predicted Probability and Marginal Effect of "Total Vehicle Ownership" (Model 2)

4.3. Model 3 – Preferences of TNC Drivers for Fuel-efficient Vehicles

Table 1. 8 summarizes results of the binary logistic model that identifies the characteristics of TNC drivers who would prefer to switch to fuel-efficient vehicles (base category: prefer not to switch to fuel-efficient vehicles). Since there is no study on such preferences of TNC drivers, we highlight some similarities and differences between our results and the results of studies concerned with characteristics of electric vehicle (EV) buyers.

As expected, the predicted probability plot shows a negative correlation between the age of TNC drivers and their propensity to switch to fuel-efficient vehicles (see Figure 1. 9). Hidrue et al. (2011) observe a similar trend among EV buyers. The relationships between the inclination of a driver to switch to fuel-efficient vehicles and the driver's residential location (see Figure 1. 10), education attainment (see Figure 1. 11), and marital status (see Figure 1. 12) vary across age of the driver.

More specifically, postgraduate drivers who live in metropolitan areas are more prone to fuel-efficiency than their counterparts if their age is below 48 years, ceteris paribus. This pattern reverses for drivers older than 48 years because the inclination of these educated metropolitan residents toward fuel-efficient vehicles decreases more rapidly than their counterparts with the increase in their age. These results are consistent with the previous studies, which have found that younger and highly educated individuals are more prone to buy alternative fuel vehicles (Dütschke et al. 2013, Hackbarth and Madlener, 2013). As a matter of fact, being a postgrad and metropolitan resident are the two most significant predictors of propensity to switch to a more fuel-efficient vehicle. The individuals with higher education level have more awareness of the

environmental impacts of automobiles; and being a metropolitan resident is associated with having a variety-seeking lifestyle (Franzen and Volg, 2013; Laiveri and Bhat, 2018).

In addition, married drivers are more inclined to switch to fuel-efficient vehicles than their single counterparts for the age below 60 years. These results are consistent with those of Peter et al. (2011), who find that households with children are more likely to be EV buyers. In the context of this study, married drivers are probably even more conscious about fuel-efficiency of the vehicle because they might end up driving more miles than their single counterparts due to the use of the same vehicle for other household activities. A recent report by Ipsos (2017) also ascertains that married households are more inclined toward buying electric vehicles.

Drivers who are early adopters of ridehailing services are found to be more inclined to switch to fuel-efficient vehicles. In fact, being an early adopter increases the odds of a driver to switch to a fuel-efficient vehicle by a factor of 1.47. This observation makes intuitive sense because early adopters are likely to have a higher orientation toward technology and thus might be more interested in driving technologically advanced vehicles. The results of the survey conducted by CleanTechnica are also consistent with our findings where 38% of the respondents selected “love for new technology” as the reason for switching to the fuel-efficient vehicles.

TNC drivers who drive daily are more inclined to use fuel-efficient vehicles. Perhaps, these regular drives are more sensitive to fuel price and can foresee the benefits of investing in fuel-efficient vehicles due to their higher vehicle-miles-traveled. It is well established in the EV literature that early adopters of EVs drive a higher number of

kilometers (Plotz et al. 2014). In fact, an individual's willingness to pay for EVs is also primarily driven by savings in fuel costs, which is further associated with vehicle-miles-traveled (Hidrue et al., 2011).

Drivers with higher vehicle ownership also have a higher tendency to switch to fuel-efficient vehicles. The probability of switching linearly increases with the increase in the number of vehicles (see Figure 1. 13). Since the income of drivers is not controlled in the specification (because it was not statistically significant), perhaps the missing income effect is also reinforcing pro-fuel-efficiency behavior of drivers with high vehicle ownership. We observe similar relationships in the EV literature. Previous studies have shown that higher-income consumers are more likely to buy EVs (Erdem et al., 2010; Saarenpaa et al., 2013). Moreover, EVs are typically owned by high-income households with more than one car (Hjorthol, 2013).

Table 1. 8 Binary Logistic Parameter Estimates and Odds Ratios (Model 3).

Explanatory Variables	**Parameter estimates**			**Odds ratio**		
	Estimate	**Std. Err.**	**z-stat**	**Estimate**	**LB (95% CI)**	**UB (95% CI)**
Drive daily indicator	0.346	0.147	2.35	1.413	1.059	1.887
Single indicator	-1.026	0.431	-2.38	0.359	0.154	0.834
Age	-0.015	0.009	-1.64	0.985	0.967	1.003
Postgrad indicator	1.447	0.573	2.53	4.250	1.384	13.054
Metropolitan resident indicator	1.392	0.441	3.16	4.024	1.695	9.554
Total vehicle ownership	0.054	0.055	0.97	1.055	0.947	1.176
Early adopter indicator	0.385	0.129	2.98	1.470	1.140	1.895
Single indicator X Age	0.016	0.013	1.3	1.017	0.992	1.042
Postgrad indicator X Age	-0.032	0.016	-2.02	0.969	0.940	0.999
Metropolitan resident indicator X Age	-0.032	0.013	-2.5	0.969	0.945	0.993
N	1,534					
Loglikelihood	-994.3					

Pseudo R-square	0.06					

Note: "No preference of ridehailing drivers to switch to fuel efficient vehicles" is a base category and parameters are estimated for "Preference of ridehailing…". LB (95% CI) and UB (95% CI) imply lower and upper bounds of 95% confidence interval.

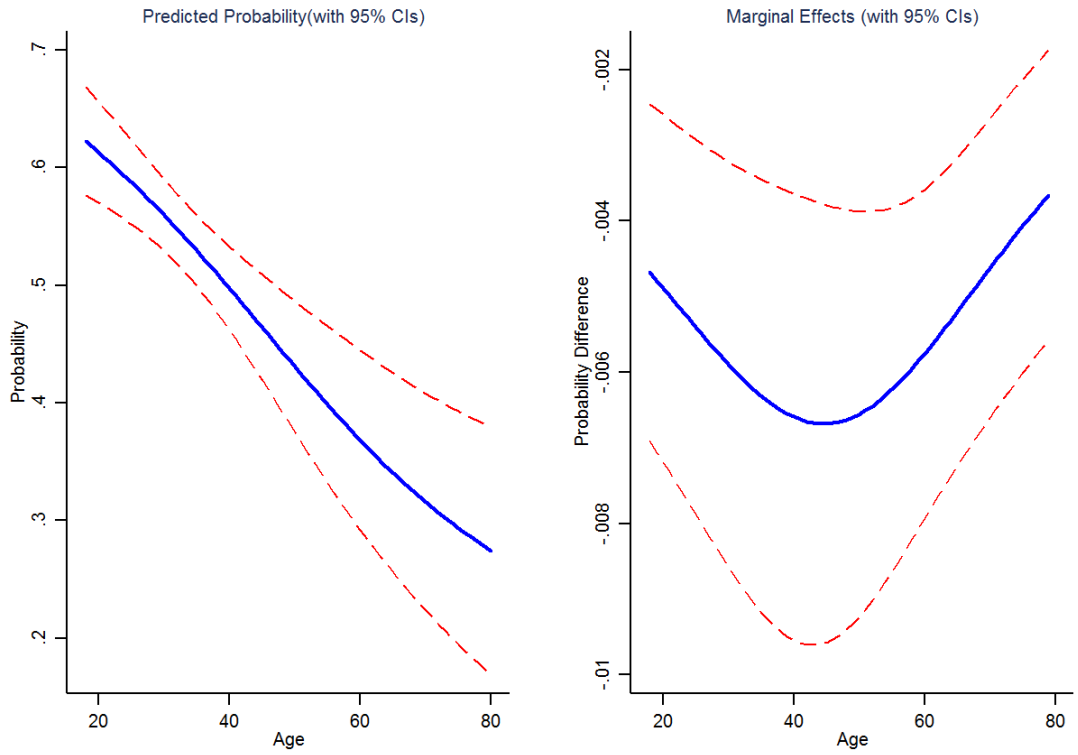

Figure 1. 9 Predicted Probability and Marginal Effect of "Age" (Model 3)

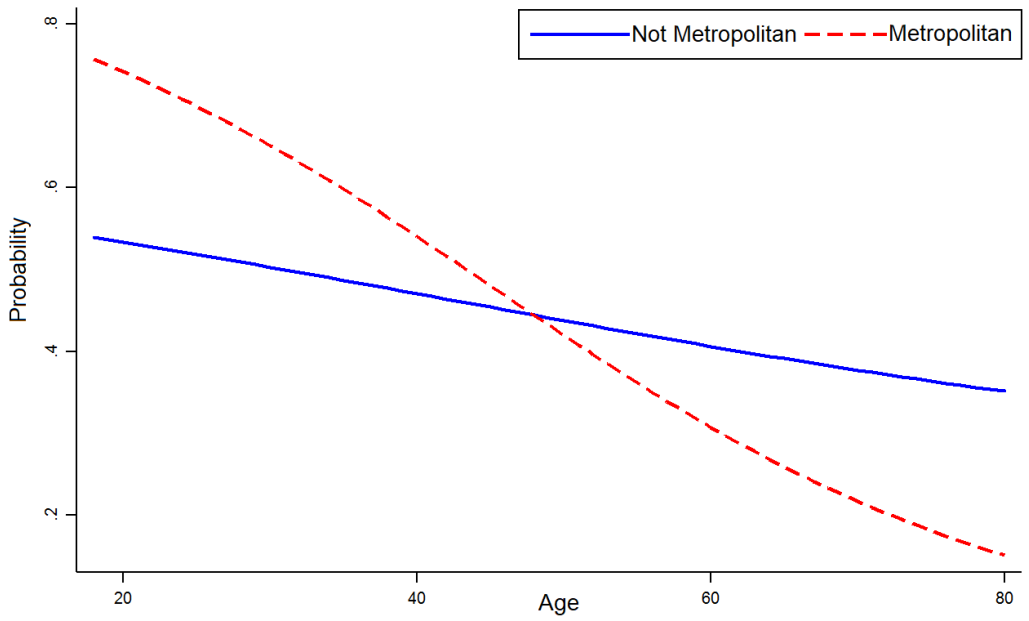

Figure 1. 10 Interaction Effect of "Age" and "Metropolitan Resident indicator" Dummy (Model 3)

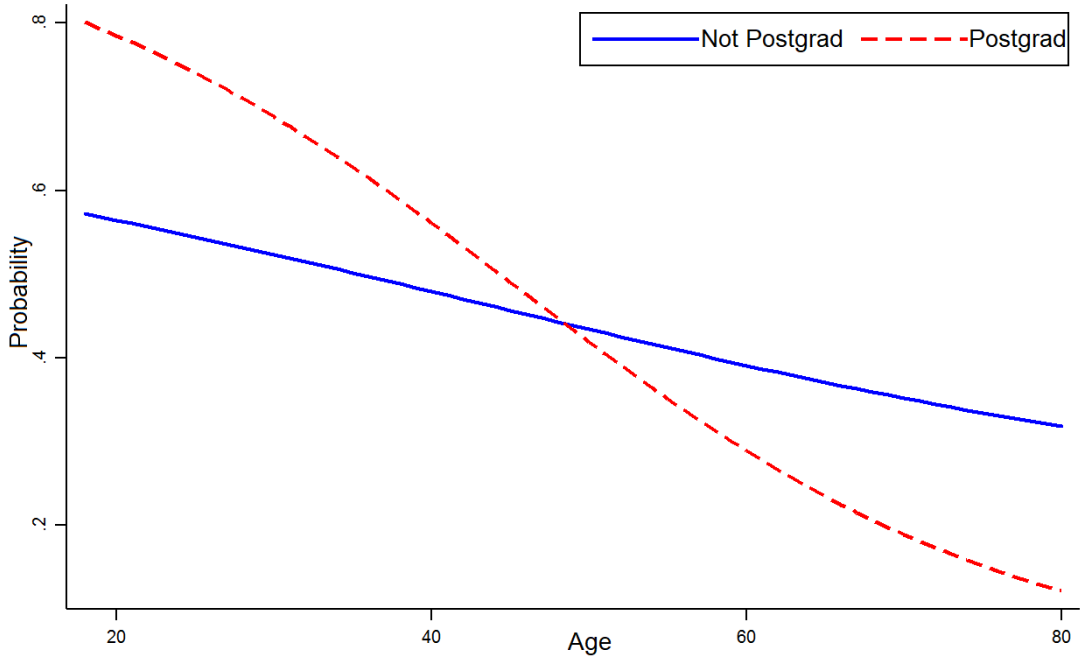

Figure 1. 11 Interaction Effect of "Age" and "Postgrad indicator" Dummy (Model 3)

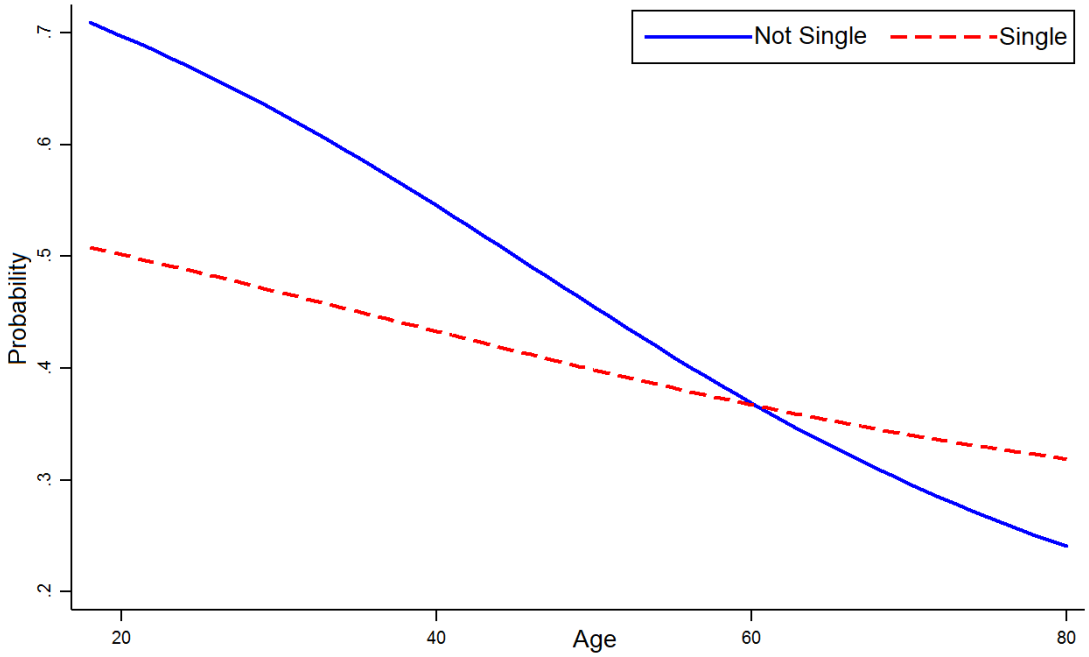

Figure 1. 12 Interaction Effect of "Age" and "Single indicator" Dummy (Model 3)

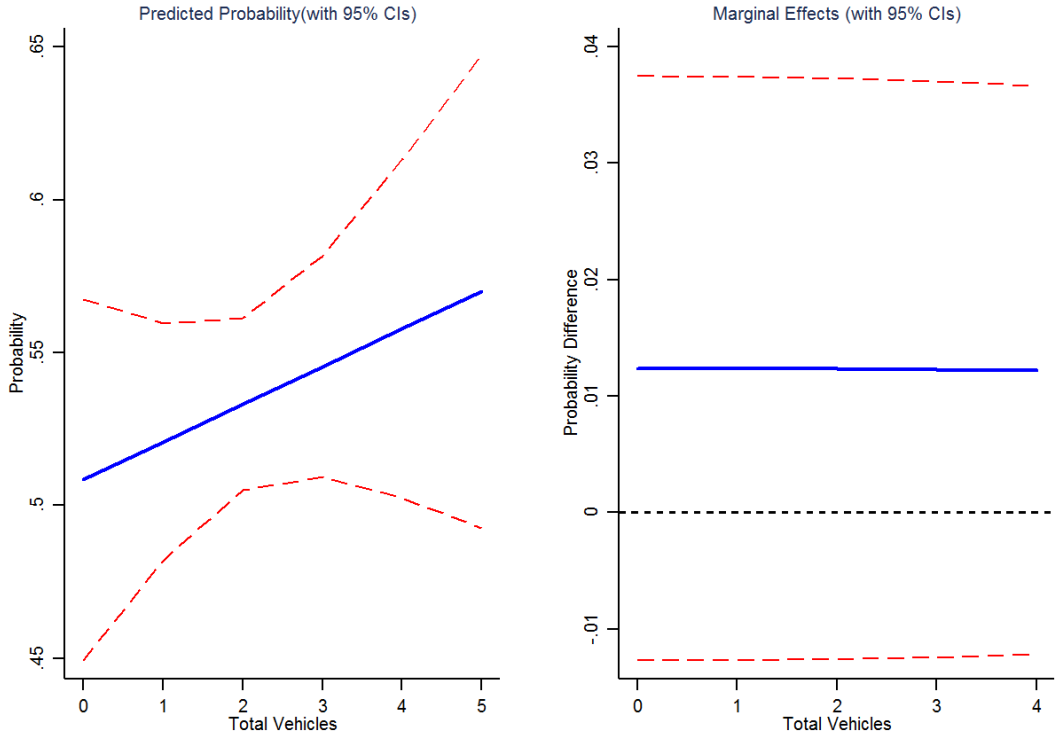

Figure 1. 13 Predicted Probability and Marginal Effect of "Total Vehicle Ownership" (Model 3)

4.4. Model 4 – Preference of TNC Drivers to Buy a New Vehicle

We use a binary logistic regression to estimate whether driving for a ridehailing service was a consideration in TNC drivers' decision to buy, rent or lease a new vehicle. Results are shown in Table 1. 9 (base category: no change in the preference to buy a new vehicle as a result of driving for TNCs).

The predicted probability and marginal effect plots (in Figure 1. 14), respectively, indicate that the tendency to buy a new vehicle with driving for TNCs being a major consideration decreases with the increase in age of the TNC driver, keeping everything else constant. For a large support of the driver's age (below 55 years), postgraduate and married drivers have higher propensity than their counterparts, but the pattern gets reversed for the older drivers (see Figures 1. 15 and 1. 16) because the negative effect of the increase in age is much higher for these drivers than their counterparts. Married drivers have higher incentives to buy an additional vehicle, perhaps because the additional vehicle can serve as the second vehicle for other household activities. Higher income drivers have a lower inclination to buy a vehicle with driving for TNCs as a consideration (see predicated probability and marginal effect in Figure 1. 17). Further investigation of this income effect within single and married drivers indicates that the increase in income of married drivers increases their probability, but the reverse effect is seen for single drivers (see Figure 1. 18). Overall, the negative income effect is a manifestation of the steeper rate of decline in the probability for single drivers as compared to the rate of increase in the probability for married drivers. For example, the predicted probability is the same (around 0.48) for a single and a married driver when the annual income is below $10,000, but this probability increases to 0.51

for a married driver and decreases to 0.38 for a single drive if the driver's income increases to $100,000, keeping all other characteristics the same. The high propensity of low-income single drivers to buy, lease, or rent a vehicle with driving for TNCs being a major consideration in part explains why some of TNCs offer such renting and leasing services to attract drivers from this demographic group.

A male driver residing in metropolitan areas, who is an early adopter, has higher vehicle ownership, and drives daily, is likely to have a higher inclination to buy a vehicle with driving for TNCs being a major purchase consideration than the counterpart, ceteris paribus. In terms of the strength of these relationships, being an early adopter of technologies increases the odds of changing the preference of a driver by a factor of 2.59, driving daily by a factor of 2.09, and being a metropolitan resident increases the odds by a factor of 1.90.

Table 1. 9 Binary Logistic Parameter Estimates and Odds Ratios (Model 4).

Explanatory Variables	**Parameter estimates**			**Odds ratio**		
	Estimate	**Std. Err.**	**z-stat**	**Estimate**	**LB (95% CI)**	**UB (95% CI)**
Drive daily indicator	0.736	0.159	4.620	2.09	1.53	2.85
Male indicator	0.459	0.120	3.840	1.58	1.25	2.00
Single indicator	-0.518	0.529	-0.980	0.60	0.21	1.68
Age	-0.032	0.010	-3.150	0.97	0.95	0.99
Postgraduation indicator	1.122	0.588	1.910	3.07	0.97	9.72
Annual Income (US$)	1.17E-06	6.18E-07	1.900	1.000001	1	1.000002
Metropolitan resident indicator	0.639	0.138	4.620	1.90	1.44	2.49
Total vehicle ownership	0.163	0.056	2.920	1.18	1.05	1.31
Early adopter indicator	0.953	0.135	7.060	2.59	1.99	3.38
Single indicator X Age	0.020	0.016	1.250	1.02	0.99	1.05
Postgrad indicator X Age	-0.024	0.017	-1.400	0.98	0.95	1.01
Single indicator X Annual Income	-5.64E-06	2.42E-06	-2.330	0.999994	0.999990	0.999999

Constant	-0.699	0.376	-1.860			
N	1,539					
Loglikelihood	-914.5					
Pseudo R-square	0.139					

Note: "No change in preference to buy/lease/rent a new vehicle with driving for TNCs being a major consideration" is a base category and parameters are estimated for "change in preference…". LB (95% CI) and UB (95% CI) imply lower and upper bounds of 95% confidence interval.

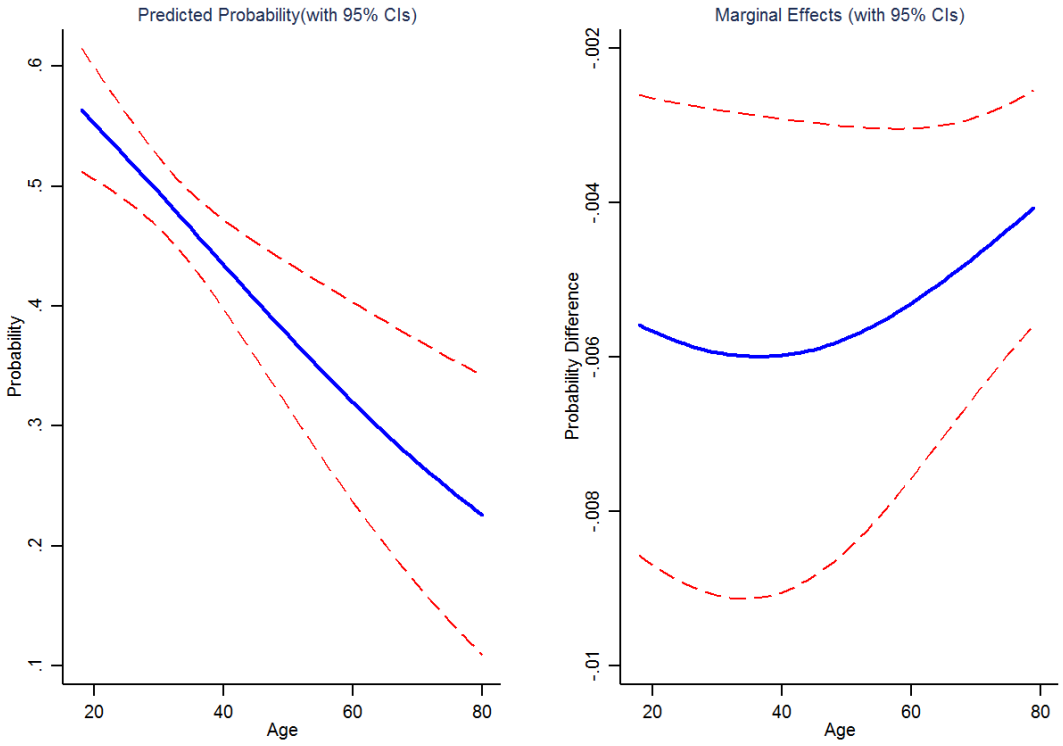

Figure 1. 14 Predicted Probability and Marginal Effect of "Age" (Model 4)

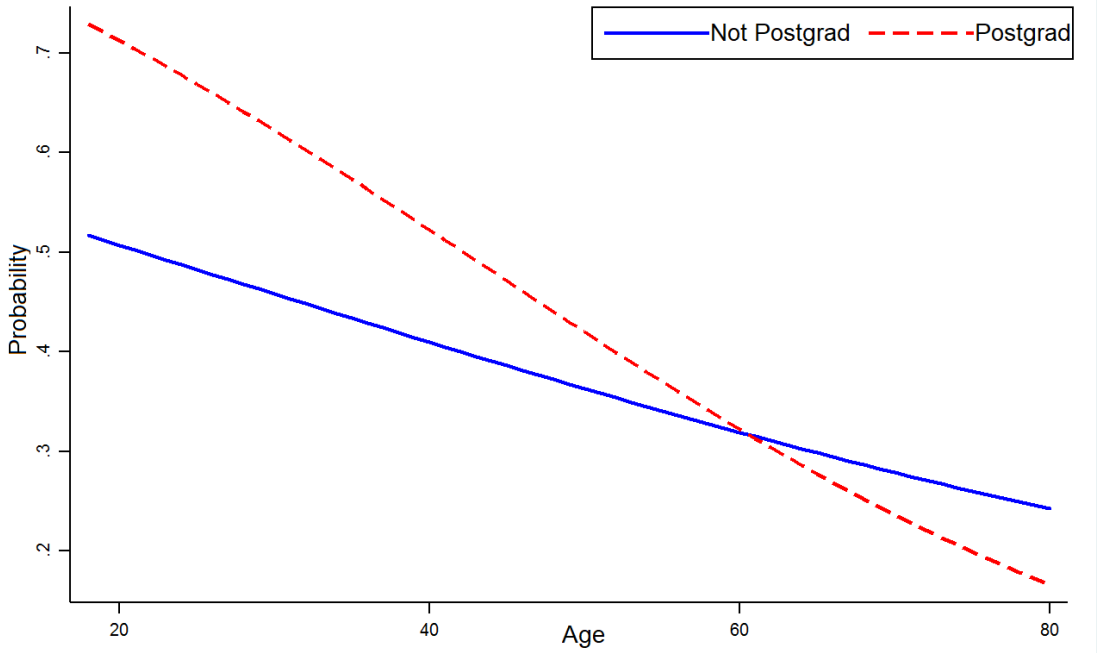

Figure 1. 15 Interaction Effect of "Age" and "Postgraduation indicator" Dummy (Model 4)

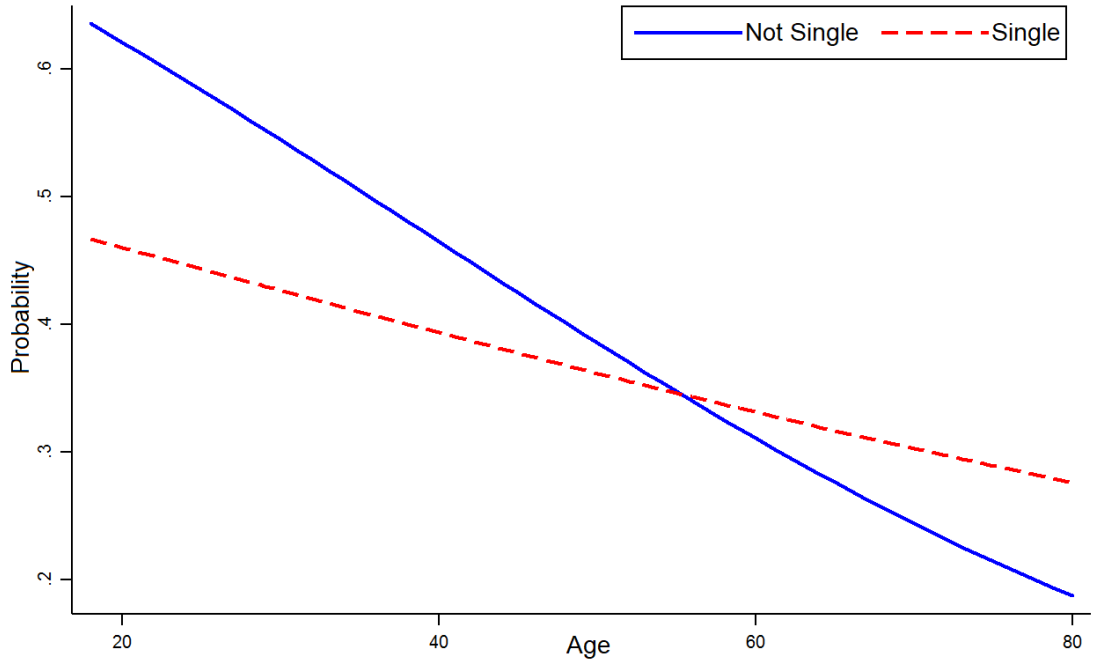

Figure 1. 16 Interaction Effect of "Age" and "Single indicator" Dummy (Model 4)

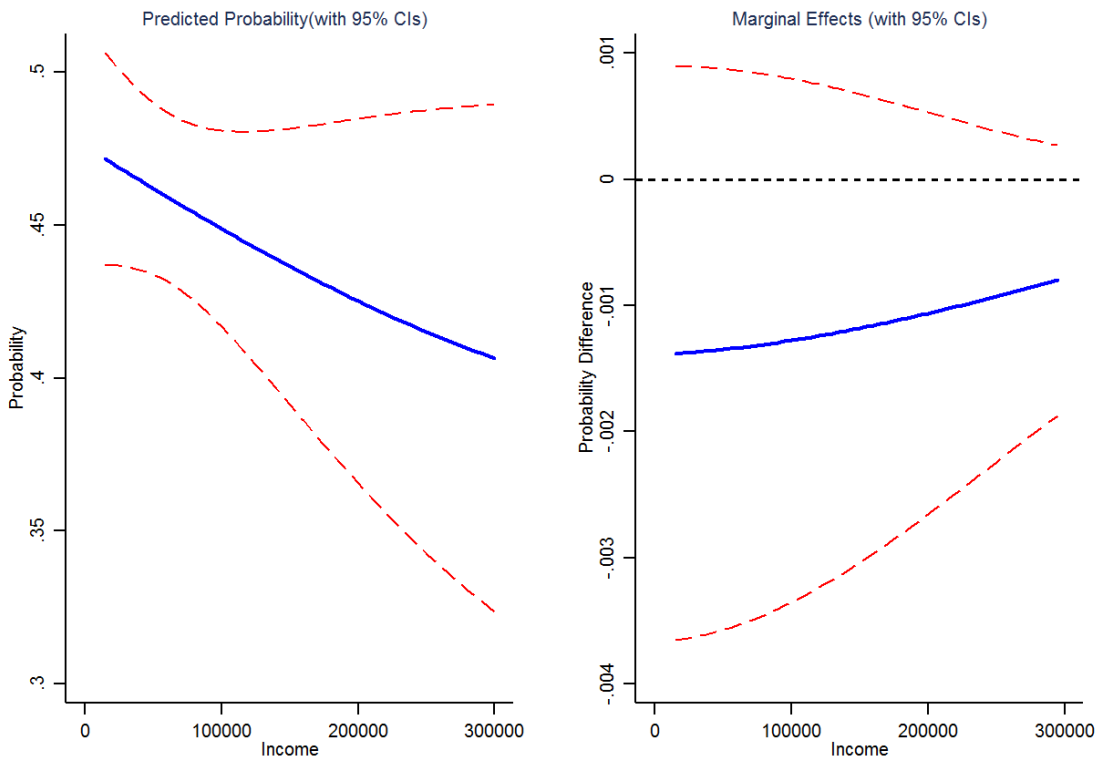

Figure 1. 17 Predicted Probability and Marginal Effect of "Annual Income" (Model 4)

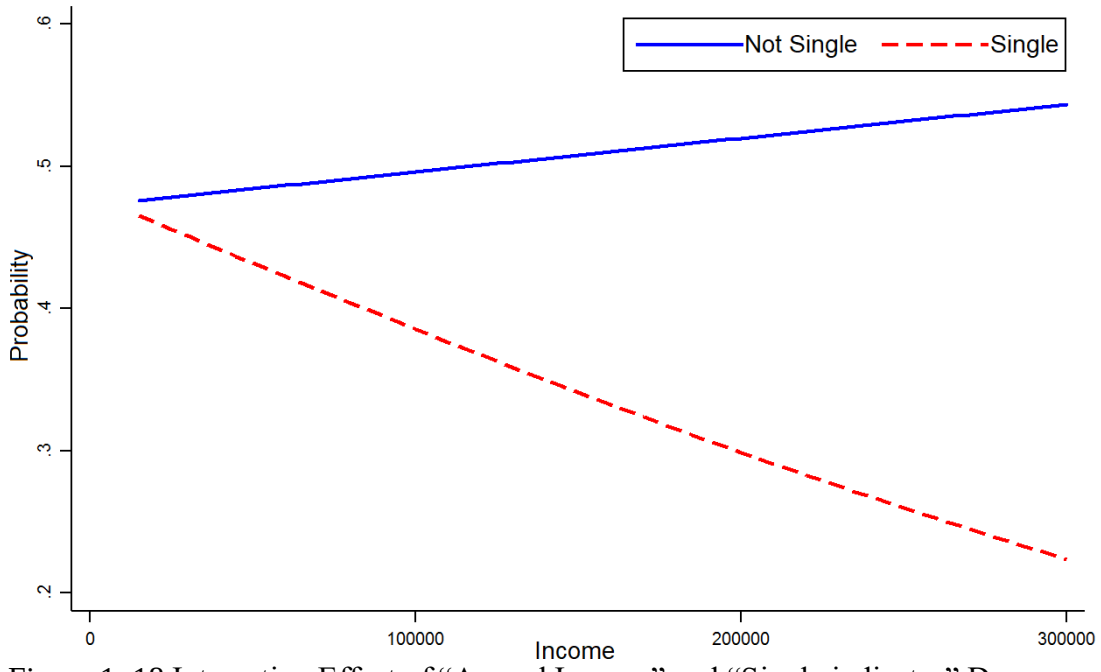

Figure 1. 18 Interaction Effect of "Annual Income" and "Single indicator" Dummy (Model 4)

5. Conclusions and Future Research

This study adds new insights to the existing literature on understanding preferences to use ridehailing services by identifying relationships of individuals' socio-demographic characteristics with their preferences to use ridehailing services (as a driver or a rider), and the willingness to ridepool by users. We have accomplished these findings by calibrating multinomial and binary logistic models using a unique dataset involving survey of respondents (N~11,000) in TNC served US cities in 2017. The uniqueness of this study stems from estimating preferences of TNC drivers to buy new vehicles with driving for TNCs being an influencing purchase consideration and to shift to fuel-efficient vehicles, which have not been explored in the literature. We also observe non-linear relationships by accounting for interaction effects of continuous covariates (e.g., age and income) with binary covariates (e.g., gender) while estimating preferences.

Results indicate that younger individuals who have achieved higher education levels, live in metropolitan areas, and belong to more affluent families are more likely to use ridehailing services. However, the relationship between the individuals' probability to use TNC services and their age is downward parabolic: it increases until the age of 48 years and then decreases. Households with higher vehicle ownership are less likely to associate themselves with TNCs in any form (as a driver or a rider). Further exploring the inclination of the ridehailing users to ridepool, we find that older travelers with higher household vehicle ownership who are living in suburban areas are less likely to pool rides. In terms of interaction effects, females with an education level below

postgraduation are more likely to ridepool than their counterparts if they are younger than 34 years, but the pattern gets reversed among travelers older than 54 years.

We now discuss key insights about the preferences of TNC drivers. Younger and married drivers who drive daily and own a higher number of vehicles are more likely to switch to fuel-efficient vehicles, ceteris paribus. These results are consistent with previous studies eliciting preferences for electric vehicles. Further, interaction effect estimates reveal that postgraduate drivers who live in metropolitan areas are more pro-fuel-efficiency than their counterparts if their age is below 48 years. Finally, the tendency of married TNC drivers to buy a new vehicle with driving for TNCs being a major consideration increases with income.

These findings can inform different stakeholders (such transportation planners, government agencies, automakers, and TNCs) in developing policies to encourage ridepooling and deployment of high fuel economy vehicles, which can further help in realizing system-level environmental benefits of these services. For instance, automotive manufacturers and auto-leasing companies could partner with TNCs to offer attractive leasing plans for the identified pro-fuel-efficiency drivers to encourage adoption of high fuel economy vehicles including electric vehicles. Such a partnership could be mutually beneficial for all parties. On one hand, it could help automakers meet their respective zero emission vehicle (ZEV) mandate targets in the ZEV states as well as their federal fleet fuel economy targets. On the other hand, it would also benefit the high mileage TNC drivers by helping them reduce their operating fuel costs. Finally, deployment of a higher number of fuel-efficient vehicles would allow TNCs to balance supply and demand for new environment-friendly initiatives (e.g.,

“green mode” initiative by Lyft (Price, 2019)), which allow riders to specifically call green vehicles. The attractive lease options offered by GM on Chevrolet Bolt for Uber and Lyft drivers is a case-in-point (Kurczewski, 2017).

A targeted campaign can be organized to spread awareness about the environmental benefits of ridepooling to encourage ridehailing users to pool rides. This is especially true as our research showed that younger female passengers, who are known to be more environmentally conscious, prefer ridepooling. To ensure passenger safety while pooling, automakers could be encouraged to provide tailor-made vehicles for pooling that include partitions.

Readers should be careful in interpreting results as this study does not identify causal relationships between individuals’ socio-demographic characteristics and their preferences, instead we only explore correlation patterns. Collaborations with TNCs to conduct randomized experiments in order to disentangle causal effects can be a potential avenue for future research.

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CHAPTER 2

DISCERNING THE OPINIONS FOR AUTONOMOUS VEHICLE USING RANDOM PARAMETER LOGIT MODELS AND MULTINOMIAL LOGISTICS REGRESSION

1. Introduction

Autonomous vehicles (AV) could provide a less expensive mode of mobility, and its demand is projected to skyrocket in the near future. Various technological advancements and innovations have been realized in the transportation industry in the past two decades to address the concerns of the consumers. The primary purpose of such developments is to improve the driving safety of individuals and reduce the number of lives lost annually due to irresponsible driving. The evolution of the industry has led to the introduction of autonomous vehicles which are commonly known as self-driving cars, and the prominent objective is to ensure the safety of the passengers even when they are intoxicated (Jiang et al., 2018).

According to recent statistics, the autonomous car by Google has self-driven for approximately 2 million miles while that of Tesla has autopilot itself for more than 300 million miles without any significant incidents as compared to those of manually operated vehicles (Dolgov, 2016 and Lambert, 2016). The California Department of Motor Vehicles reports in 2016 that only sixteen accidents occurred between 2014 and 2016 involving the self-driving cars and the majority of these were the crash type that happened in the rear-ending of the vehicle at a low speed (Jiang et al., 2018). This means that there were no major injuries associated with the car which makes them ideal for people to use since the risks of getting involved in an accident are reduced to

a considerable degree compared to those of noted for current ones. The data recorded is consistent with those of Schoettle and Sivak (2015) who conducted research in real-world driving and established that the autonomous vehicles were not at fault in the incidents they were involved in.

The number of deaths occurring on the roads is estimated to be 3,400, according to the World Health Organization (WHO), which totals up to approximately 1.2 million individuals dead or injured annually (World Health Organization, 2015). These numbers are high and mostly associated with human and performance errors. The human errors occur due to the inability of a person in control of the vehicle to process information fast. Hence, with autonomous vehicles, such will be dramatically reduced indicating the need for them as well as preferences of the consumers in the market. Additionally, the cars that run on an automated system will not be faced with instances of fatigue like humans do. The use of autonomous vehicles is one of the current technological developments that is likely to improve transport system all over the world. Individuals who purchase the autonomous vehicles may prefer owning them for luxury, or to benefit from the advantages such as higher levels of accuracy, as compared to the human controlled vehicles (Lambert, 2016). The self-driving cars also relieve the human brain and arms from being involved in the control process, hence can be used by physically challenged people. High automation vehicles are estimated to be in the market by 2050; thus, it is prudent to discern the preferences of the consumers for autonomous vehicle to determine the marketability of the advanced innovation.

The objective of this research is to investigate the association of different socio-economic attributes and demographics in relation to: a) Safety of children to use autonomous vehicles without any adult; specifically the question that we are analyzing is, "Once automated vehicles are running safely and reliably on all roadways, should a child of age 8, without a driver's license, be permitted to travel alone in a driverless vehicle on trips up to 3 miles from his/her home?"; b) Preference to use either taxi in which the driver is unknown; ride-hailing services in which the rating of the driver is known or autonomous vehicles in which there is no driver; specifically, the question that we are analyzing is, "If the price and waiting time is the same, what would be the most preferred option among regular taxi, ride-hailing services and autonomous taxis?" and; c) The preference for the price of autonomous ride-hailing specifically Uber services. The question that we are analyzing is, "Should the cost of an automated Uber trip be higher or lower than the one served by a human driver and why?"

The current research establishes the techno-economic aspects of the use of autonomous vehicles and its association with the various socio-economic and demographic groups. Vehicle manufacturers and traders can therefore find this information crucial for the adjustment of their manufacturing standards and pricing, so that the modules they produce meet the technical, demographic and economic preferences of the consumers. The findings of this research are also crucial for other stakeholders such as providers of taxi service and the society at large, such that sustainable pricing strategies can be formulated for the benefit of both the service providers and the users. Researchers and scholars can also use the findings of this

research as a basis for the formulation of other research topics regarding the autonomous vehicles and their use in the transport sector.

The next sections of the paper are organized as follows: chapter two presents the literature review, which provides the existing information regarding the safety standards of the autonomous vehicles and the price of their services as compared to those of conventional vehicles. This chapter also explains the research that has been done till now which investigates the association of demographics and their preferences for the use of autonomous vehicles. Chapter three explains the methodology that was used in conducting the research and chapter four explain the data of the survey. The results and discussions are presented in chapter five. Chapter six concludes the paper along with recommendations for future research.

2. Literature Review

The main objective of this section is to summarize the contextual literature on the preferences of autonomous vehicle users, and how they affect their perception on quality of services rendered by these vehicles. The review consists of literature on crucial factors affecting the users' preferences and how they have influenced their choice of the self-driving vehicles in consideration of the risk preferences. The section will conclude by reviewing studies that discern the inclinations of autonomous vehicle users before summarizing the findings of the various papers which will be referred to throughout the subsequent paragraphs.

2.1. Child Safety in Autonomous Vehicles

Legal measures are being developed to ensure that the safety of any child who uses the automated vehicles is maintained, according to (Karton, 2018). The proposed

legislations are to ensure the autonomous vehicles are manufactured and engineered for the protection of the unique safety needs of the children. The proposals highlight the need for the children to be protected from harm in case of a serious crash, or when the digital control system of the cars have failed on a busy highway. However, changes in the design systems of the vehicles can significantly affect their safety standards. The proposals also involve testing the vehicles for usability with having children as passengers. The safety standards of the autonomous vehicles are further identified as a factor that determines the acceptance of the society to use them in transportation, as clarified in (Zmud et al., 2016). The use of accessories such as airbags for the enhancement of security of autonomous vehicles is further explained in (Kalra, 2017). The tendency of consumers to let their children ride in autonomous vehicles has also been conducted by (Anania et al., 2018). The research establishes that most of the parents were not willing to let their children use autonomous buses while travelling to school. The research works introduce the relationship between safety, design of autonomous vehicles, legislation and the different scenarios or use of the autonomous vehicles, where children form a high proportion of the occupants. However, there is no study that investigates the association between the different demographic groups and their inclination towards their child using autonomous vehicles without any supervision.

2.2. Preference of Socio-Demographics for Autonomous Vehicles

A study conducted by Gurumurthy in the United States suggests that 36.4 percent of Americans enjoy driving and do not in any way plan to use autonomous vehicles (Gurumurthy, 2018). However, 29.4 percent posit that they love driving but will

change their preferences once the AVs become available for use, whereas 17.5 percent prefer both in equal measures (Gurumurthy, 2018). Among those who prefer both in equal measures, approximately 11.7 percent of them do not like driving and as such will prefer using autonomous vehicles while 2.9 percent prefer non-motorized modes of transport or travel and only 0.5 percent do not prefer both driving as well as the consideration for the usage of AVs. According to the same study and that of Krueger et al. (2016), some of the factors that determine the preference of the consumers' willingness to use autonomous vehicles include reliability as earlier addressed, self-parking, congestion relief, travel convenience, and safety improvements (Gurumurthy, 2018 and Krueger et al., 2016). The primary concerns, however, are faulty software, privacy breaches, tracking of location, confusion between human drivers and AVs on the road, and safety which is still questionable regarding crashes (Gurumurthy, 2018). Recent studies on vehicle automation and safety point out the need to understand the perceptions of the customer, their experiences, and attitudes towards the system. According to Abraham et al. (2017), the consumer's knowledge of the vehicles can be classified under five prominent constructs, for instance, safety, sustainability, flexibility, reliability, and liability. These are, however, objected-related but those considered objected related include desirability as well as trust. These constructs can be classified as the dimensions that resulted in the envisioning of vehicle automation as early as 1918 (Pendleton et al., 2017). The first concept of autonomous vehicles can nevertheless be traced back to General Motors in years that followed explicitly in 1939, as reported by (Shladover, 2018).

According to Faisal et al. (2019), various cities around the globe are changing urbanization plans with the primary goal of ensuring the accommodation for the new mode of transportation (Faisal et al., 2019). Presently, as per the Bloomberg studies, around 36 cities around the world are hosting autonomous vehicle tests whereby half of them are involved in long-range surveys of issues surrounding planning, regulating, and governing of the self-driving cars (Naughton, 2015). Some of these cities include Adelaide in Australia, Austin in the United States, Chiba in Japan, London in the United Kingdom, Zhuzhou in China, and Montreal in Canada (Faisal et al., 2019). Further research by Krueger et al. (2016) assert that the advent of the autonomous vehicle technology is a critical factor in fostering new opportunities for the existing transportation system by shifting it from private mobility type to a service-use kind (Krueger et al., 2016). The findings mean that for most users, shared mobility will be the ultimate preference and will be based on Shared Autonomous vehicles (SAV). Despite the impact the SAV advancement will have on the producers, most scholars are adamant that its effect on the behavior of the customer, congestion, environment, and urban form is still unknown (Stocker and Shaheen, 2018). Also, there is no adequate literature to suggest how the technology is likely to affect the preferences of the users since no large-scale production of the SAV exists today, especially in the public domain.

To understand preferences of the autonomous vehicle consumers and how their behaviors will change, Vosooghi et al. (2017), have developed a new simulation-based approach which predicts the impact of the automated drive system on the passengers' comfort and trust on the system (Vosooghi et al. (2017). Becker and Axhausen (2017)

refute the claims raised in the previous paragraph by suggesting that models do not only focus on the behavioral experiments but also its characteristics and perceptions (Bonnefon et al., 2016 and Becker and Axhausen, 2017). For instance, the level of awareness of the autonomous vehicles and willingness to pay for them. On the other hand, Steck et al. (2018) associated the preference of autonomous vehicle users to the value of travel time usage. Steck et al. (2018), who uses the mixed logit model approach, found that clients' preference for the autonomous vehicle was influenced by in-vehicle travel time and cost play (Steck et al., 2018). The same studies suggest that demographic information, such as age, income, and gender, did not influence the modal split between current cars and the self-driving ones. The study by Steck et al. (2018) also investigates the preference level for both privately-owned autonomous cars and SAV which led to the conclusion that using the latter will reduce the value of travel time services by up to 10 percent of the commuting time and hence, it is a factor that can be considered when addressing the preferences of the AV consumers. The research also elaborates on the expected benefits of the use of autonomous vehicle for public transportation.

A similar study to the one executed by Steck et al. (2018) is conducted by Liu et al. (2017) using agent-based simulation to investigate four probable fare levels through a stochastic process and how it affects preference level of any user (Liu et al., 2017). However, in this study, the authors compare the modal split between conventional vehicles and SAVs. For both studies i.e. Steck et al (2018) and Liu et al. (2017), travel and waiting time, as well as cost are considered to have a strong bearing on the user's preferences compared to the characteristics that are specific to an individual.

Haboucha et al. (2017) who developed a model to investigate the long-term choice for AVs, postulate that cost does not play a significant role in affecting what the travelers prefer despite being an important variable (Haboucha et al., 2017). In fact, according to the study, 25 percent of the users would refuse to use these vehicles even if it was provided to them completely free (Haboucha et al., 2017). At the same time, the researchers identified individual-related attributes, such as age, educational background, income level, and gender affected the user's preferences.

Bansal et al. (2016) arrive at the same conclusion as the authors above by asserting that age and gender supersede the other demographical characteristics in shaping the consumers' perception of the autonomous vehicles (Bansal et al., 2016). The preference of self-driving vehicles by younger generation can be attributed to the fact that they find it safer and less time consuming, but the older group believe that the current cars are more reliable than AVs and will continue as such for sometimes (Bansal et al., 2016). All the variables discussed are not the only factors that affect a user's preference since privacy is considered a high priority. According to Schoettle and Sivak (2015), data security and privacy are significant in determining the choice of the user, especially whether to use or not to use the autonomous vehicles (Schoettle and Sivak, 2015). To address this concern, Bonnefon et al. (2016) as well as Goodall (2017) in the survey of ethical dilemmas that may arise due to the inadequate security suggests that majority of the respondents requested to be involved in the programming of the vehicles. The probability that their involvement will shape their perception will most likely also affect their preferences of the cars to the current ones.

Bansal and Kockelman (2017) conducted a study to establish the adoption of AVs under different pricing models - $1, $3 and $2 per 1.61 kilometers (Bansal and Kockelman, 2017). Analysis using the univariate Ordered Probit (OP) model indicated that the respondents with past accidents had positive correlation with the willingness to pay for automatic cars i.e. people involved in accidents were more likely to buy automated vehicles (Bansal and Kockelman, 2017). Among other analysis, they found that 45.8% of the respondents were interested in installing automatic brakes for emergency breaking, while 22.8% were not interested. 19.5% of the respondents were confident that the AVs could operate independently, while 49% believed that the AVs could reliably operate (Bansal and Kockelman, 2017). Only 33.33% showed confidence in using the AVs in taking children to school (Bansal and Kockelman, 2017).

The study by Barua et al. (2015) revealed that only 25% of the consumers generally preferred using the autonomous vehicles for transport. However, 52% of the respondents indicated that they would prefer the use of AVs, by the year 2024 (Barua et al., 2015). 71% of the respondents showed interest in using the vehicles due to reduced emissions, while 73% preferred the vehicles due to fuel efficiency and 54% trusted that the vehicles could effectively pick and drop the passengers at the designated points (Barua et al., 2015). 73% of the respondents indicated that the adoption of AVs depends on the security of the vehicles, while 72% cited the security of the drive system as the main barrier to the adoption of the AVs (Barua et al., 2015). A research similar to this was conducted by Nordhoff et al. (2017) to establish the levels of preference of autonomous vehicles within particular populations from

Australia, UK, Switzerland, France, US and Germany. The study considered demographic aspects such as age, gender and awareness of technology. 44.8% of the respondents preferred daily use of AVs due to convenience and 43.5% indicated that AVs would be generally more useful than the conventional vehicles (Nordhoff et al., 2017). 43.6% of the respondents trusted the AV's ability to pick and drop passengers, and to maneuver through traffic.

Lustgarten and Le Vine (2018) analyzed the preference of consumers for the AVs as per the identified features of the vehicles (Lustgarten and Le Vine, 2018). Demographic factors such as the location of residence, income and marital status were considered. The sample constituted individuals between 15 and 90 years, and 31% had children at home while 68% of the were not living with any children. 9% of the respondents asserted that the safety of AVs depends on the level of traffic congestion, while 48% suggested a reduction of the clearance distance between an AV and other car in the front (Lustgarten and Le Vine, 2018). Studies conducted by Menon on the perception of consumers on the adoption of AVs considered demographic factors such as levels of education, age, gender, and levels of income (44). However, 20% of the respondents were not conversant with AVs at the time of research (Menon 44). The respondents indicated that the principle advantages of the AVs are improved safety on the roads, more use of the time of travelling since the vehicle occupants can be involved in other activities and less stress during driving.

The research by Menon et al. (2016) further indicated that 28.44% of the respondents were greatly concerned about the safety of the AVs, while 51.77% were moderately concerned (Menon et al., 2016). Although, factors that were considered in the safety of

the AVs were not indicated in the research. 45.71% of the respondents were moderately concerned about the performance of AVs in heavy traffic, while 35.74% were extremely concerned (Menon et al., 2016). Pettigrew et al. (2019) conducted a study on the consumer perception of AVs in Australia and established that 57% of the respondents had very little information regarding AVs (Pettigrew et al., 2019). 14% of the respondents did not support the idea of the adoption of AVs due to the associated dangers such as software crashes and inability to recognize objects that cross the highway so suddenly and only 16% of the respondent supported the idea of adopting the AVs (Pettigrew et al., 2019). Previous research provides information on the levels of preference of AVs in different parts of the world, but there is no literature on how the preference in the opinions of consumers will change when taxi, ridehailing and autonomous vehicles have the same price and waiting time. Also, previous research lacks in the understanding of different demographic segments and their propensity for children to ride AV unsupervised. This research takes a deeper insight into these preferences.

3. Methodology

3.1. Data Collection

This chapter explains the methodology that was used in this study. The data was acquired from a survey which involved a qualitative design to explore and describe the factors influencing customers' preferences for mobility on demand services. This was a stated preference (SP) study which was conducted through the web-based Qualtrics platform. The survey was distributed among a continuous panel provided by Survey Sampling International (SSI, a professional survey firm) in October-November 2017.

In the survey, the respondents were asked about sociodemographic, travel characteristics, and opinions regarding the use of autonomous vehicles for different purposes and different circumstances. Any person who was a driver for the MoD services or was younger than 18 years was not considered eligible for the analysis. Also, those who completed the survey within 10 minutes or less were also eliminated. After checking for errors and validation of data, a total of 2489 observations were used for the analyzing the models.

3.2.Models

3.2.1. Random Parameter Logit Models

The use of random parameter models permeates the variation of values across a given population in line with a pre-specified distribution; thus, where a parameter depicts significant variation across observations, it means that each set of observation is characterized by its own parameter (Greene, 2000). In RP models, therefore, the parameters within observed variables undergo random variations as opposed to fixed. Further, the variations embedded on each parameter affirm that the unobserved utility linked to any alternative has linear relationship over time for every case of decision-maker (Train, 2009). The linear relationship is included into the estimation deriving from panel observations of repetitive choices for each individual (Greene, 2000). For instance, at the time where an individual 'i' acquires utility from alternative 'j', in a given choice situation 't', it follows that utility $U_{ijt} = \beta_i x_{ijt} + \varepsilon_{ijt}$ given equals as iid extreme value in a given time. The actual logit formula:

$$L_{im}(\beta) = \prod_{t=1}^{T} \left[\frac{e^{\beta_i' x_{imt^t}}}{\sum_j e^{\beta_i' x_{ijt}}} \right]$$

Further, the unconditional probability serves as the integral of the product identified over all the values of β such that:

$$P_{im} = \int L_{im}(\beta) f(\beta) d\beta$$

The other analysis is on the potential distributions related to the random coefficients. The notable matter is that random coefficients such as the ones generated in this study have pre-specified varying distributions which include normal, uniform, lognormal and triangular. For instance, in the case of normal distribution, it is likely to have a segment of the sample reporting negative parameters while others generating positive parameters; whereas the proportion of every part of the group empirically measured by the mean and dispersion trends of the distribution (Train, 2009). On the other hand, the lognormal distribution remains useful in the event the coefficient shows to have similar sign for each circumstance; the limitation to this is that it leads to creation of a thicker right tail. According to Hensher et al. (2005) it was noted that in a random parameters model, not any of the generated distributions produces desirable outcomes notwithstanding that a normal distribution within the random parameters serves as the most frequent assumption. However, in the application to the present study, the researcher held that belief that the random coefficients can be fitted in either of the sign for varying individuals in the sampled population. In fact, for this study,the application involving the random coefficients was manifested in different signs within the surveyed population. The present research relied on cross-sectional data and the panel progression required addressing systematic group effects.

In addition, mixed logit models have been used in this dissertation to capture flexible as well as adoptable econometric procedure for different discrete choice model that derives from a randomly created utility maximisation (McFadden and Train, 2000). The model also helps to overcome the limitations associated with standard multinomial logit since it permeates the adoption of random taste variation, linearity of unobserved factors, and patterns of unrestricted substitution (Train, 2009). In addition, mixed logit does not involve the assumptions related to independent as well as identically distributed error terms and the behavioural trends of the participants. According to Hensher et al. (2005) the stochastic component of utility in mixed logit consists of two parts: one of the parts is where there is correlated trends in the alternatives; then, second consideration is the presence of heteroskedastic patterns evident in both individual and alternative specific constants within the model.

3.2.2. Multinomial Logit Model

One of the simplest approaches is to elect one of the response categories to be considered as a baseline then undertaking calculations of log-odds for the rest of the categories in relation to the baseline; then proceed to let the log-odds to serve as a linear function of the regressors or predictors (Borooah, 2002).

$$\eta_{ij} = \frac{\log \pi_{ij}}{\pi_{ij}} = \alpha_j + x_i' \beta_j$$

In the model α_j serves as the constant while β_j being the vector within the regression coefficients. The approach is suitable where there is unordered categories. In addition, it is also applicable where the dependent variables serve as nominal with over two

levels and it consists of a predictive analysis used to depict the relationship across one nominal dependent variable versus two or more independent variables (Train, 2009). The multinomial logistic regression was applied to predict the categorical conditions in the dependent variable against the independent variables identified in the socio-demographic factors of age, household income, gender, and education level of the sample. The independent variables were both dichotomous and continuous. For instance, gender was a categorical whereas age and household income were continuous variables. The multinomial logit model relied on maximum likelihood estimation to administer evaluation on the relationship of the variables.

According to Train (2000) the strengths of using a multinomial logit model is that it does not consider assumptions for linearity, normality, and or homoscedasticity condition to be fulfilled contrary to a discriminant functional analysis that requires such assumptions to be met. However, the model has assumptions that need to be fulfilled such as: independence within the dependent variable whereby it requires that the choice or association/membership in one category does not depict any relationship to the membership or choice in a different category (this could be a dependent variable). In such a context, the Hausman-McFadden test may be used to check for the violation of the above assumption.

4. Data

Table 2.1 summarizes statistics of the explanatory variables used in all the models of this study. In the sample, the proportion of males is 31% and the average age of the respondents is 36.2 years. The survey oversampled the female population. The independent variable, education was divided into six different categories and the

average education of the sample is a associates or technical degree. The average income in the sample is $81,853 which is in congruent to the population average salary i.e. $81,346.

Key summary statistics of the response variables is shown in Table 2.2. The results indicate that only around 20% of the sample prefer to send their child in AV unsupervised without a driver's license. Among the different options, given the wait time and price were same, 13% of the respondents choose taxi, 57% choose ridehailing, 18% choose autonomous vehicles and only 12% were indifferent between the given options. Also, 72% of the population acknowledge that the price of automated uber trip should be cheaper as there is no human labour to compensate for, followed by compromise to safety (37%). Among reasons for higher cost of automated uber trips, 13% of the sample believe that it should be higher as the cost of technology is costly.

Table 2. 1 Key explanatory Variables

Explanatory Variables	**N**	**Mean**	**Min.**	**Max.**
Male indicator	2489	0.3149	0	1
Age (in years)	2489	36.2	18	69
Education level	2489	4.216	1	6
Household Income (US$)	2489	81853	5000	900000

Table 2. 2 Key response variables

Response variables (indicators)	**N**	**Mean**	**SD**
Model 1			
Respondents who prefer to let a child of age 8 without a driver's license ride on an AV for trips up to 3 miles	2489	0.206	0.404
Model 2			
Preference for taxi	2489	0.13	0.333
Preference for ridehailing	2489	0.57	0.494
Preference for autonomous vehicles	2489	0.18	0.384
Indifferent between the above three options	2489	0.12	0.322

Model 3			
Preference for higher cost of automated uber trips	1810	0.15	0.35
Model 4			
Preference for No Human Labor to Compensate	1810	0.72	0.446
Model 5			
Preference for Compromise to Safety	1810	0.37	0.482
Model 6			
Preference for Responsibility of Eventual Problems	1810	0.02	0.143
Model 7			
Preference for Higher Cost of Technology	1810	0.13	0.332
Model 8			
Preference for Safety of Automated Uber Trips	1810	0.04	0.187

5. Results and Discussions

5.1. Preference to let a child of age 8 without a driver's license ride on an AV for trips up to 3 miles

Table 2.3 shows the parameter estimates of the binary logistic regression model that explains the association between individuals' sociodemographic characteristics and their stated response to let a child – at least of age 8 without a driver's license – ride on an AV for trips up to 3 miles (the base category is: to not let a child, at least of age 8 without a driver's license, ride on an AV for trips up to 3 miles). As the dependent variable is binary (yes/no), a binary logistic regression chosen as an appropriate method for analysis. We hypothesize the sociodemographic explain differences in the responses. The independent variables for this model thus were: a) Age of the respondents, b) Gender of the respondents, c) Household income, and (d) The number of children in the household. Also, to test for heterogeneity in the parameters, the coefficients of age and gender variables were assumed to be independent normally distributed as the standard deviation for the other independent variables were insignificant.

The results show that there is a positive association between household income and the stated intention to let a child of 8 years and without a driver's license, ride in an AV alone. This means that higher income people are more likely to allow their children in an AV unsupervised, as compared to the lower income group. For the next covariate, age, we find a negative association between age and the preference to let a child ride AV. In fact, for a marginal increase in age, the odds of allowing a child ride in an AV decreases by 0.98. One reason for this might be that younger people are more well versed with the technological advancements and believe in them to let the child drive alone. Previous research has also shown that younger people are more likely to adopt these technological advancements as compared to older people. Being a male is associated positively with the likelihood of allowing a child without driver's license to ride an AV for up to 3 miles. Precisely, being a male increases the odds of allowing the child to ride AV unsupervised by a factor of 2.10 as compared to that of females. Previous research shows that males are more likely to adapt to the technological advancements as compared to females.

Table 2. 3 Binary Logistics Parameter estimates with Random Parameters (Model 1)

Explanatory Variables	**Estimate**	**Std. Error**	**z-value**	**Odds Ratio**
Children Count	9.296e-02	5.915e-02	1.572	1.097
Household Income	3.025e-06	8.798e-07	3.438	1.000
Age (Mean)	-1.644e-02	6.978e-03	-2.356	0.983
Male Indicator (Mean)	7.441e-01	1.364e-01	5.456	2.104
Age (Standard Deviation)	7.296e-03	1.568e-02	0.465	1.007
Male Indicator (Standard Deviation)	2.667e-01	8.271e-01	0.322	1.305

N	2489			
Loglikelihood	-1210			

Note: "Preference to not let a child of age 8 without a driver's license ride on an AV for trips up to 3 miles" is the base category

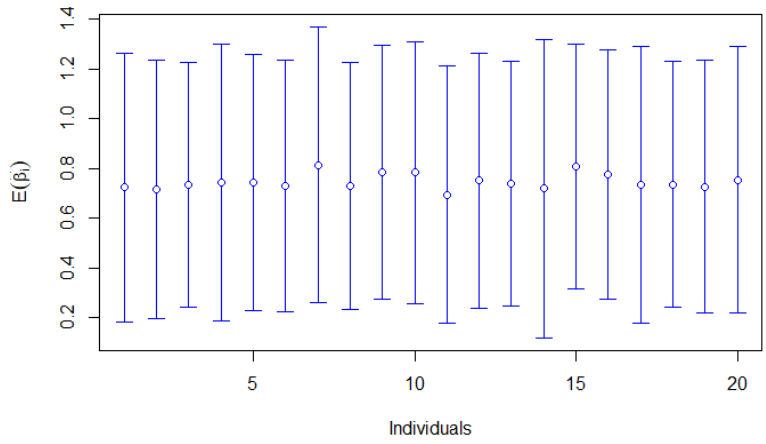

Figure 2. 1 95% Probability Intervals for Male Indicator

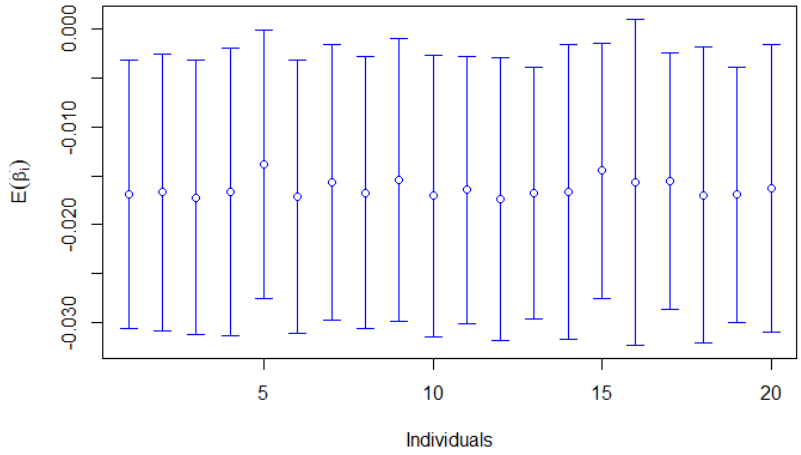

Figure 2. 2 95% Probability Intervals for Age

5.2. Preference for Taxi, Ride-hailing or Autonomous Vehicles given same wait time and price

Table 2.4 shows the parameter estimates and the relative risk ratios of the multinomial logistic regression model that explains the relationship between socio-demographics and respondents' preferences of choosing either a regular taxi, a ridehailing service such as Uber or Lyft, a self-driving taxi with a mobile application, or being indifferent

between the alternatives if the wait time and the price of each of the option was the same. The independent variables for this model are: 1) Age of the respondent; 2) Education level of the respondent; c) Gender of the respondent and; d) Household income. The analysis of the estimates that follows sets regular taxis as basis for the comparisons.

The results indicate that the preference to ridehailing decreases with increased age. The relative risk ratio indicates that with a marginal increase in age, the odds of choosing ridehailing services decrease by a factor of 0.97 to the original odds. The same can be seen between the preference of self-driving taxi and regular taxi. Again, we see from the estimates that older people are more likely to choose regular taxi than a self-driving taxi with a mobile application. Haboucha et al. (2017) had similar findings and concluded that the adopters of AVs are likely to be students, the young, and people who are more educated (Haboucha et al., 2017). The next parameter, associated with education of the respondents, shows that the more educated respondents are more likely to use regular taxi than ridehailing services. However, more educated people are more likely to choose self-driving taxi than they are to choose regular taxi. The odds of using self-driving taxi increases by small percentage of 0.3.

Moreover, males in the sample are less likely to use ridehailing services but are more likely to use a self-driving taxi. As a matter of fact, the relative risk ratio for males for self-driving taxi is 1.356 which means that for males as compared to females, the propensity to use self-driving taxi is 35% higher. The estimates for household income show that the higher income group are more likely to use ridehailing hailing services

than the lower income group. They are also more likely to use self-driving taxi. However, for individuals with a higher income, the increment effect is 0% which indicates that this variable would not cause much variation to any of the preferences. High income earners, residents of urban areas and those who had experienced accident with conventional vehicles showed a higher willingness to pay for the AVs (Bansal and Kockelman, 2017).

Table 2. 4 Multinomial Logistic Parameters Estimates (Model 2)

Explanatory Variables	**Estimate**	**Std. Error**	**z-value**	**Relative Risks Ratio**
Ridehailing				
Age	-3.2584e-02	4.8877e-03	-6.6667	0.967
Education	-1.2232e-01	4.9598e-02	-2.4663	0.884
Male Indicator	-2.6591e-01	1.3651e-01	-1.9479	0.766
Household Income	4.0438e-06	1.3199e-06	3.0638	1.00
Self-Driving Taxi				
Age	-4.5437e-02	6.1047e-03	-7.4430	0.955
Education	3.4657e-03	5.8890e-02	0.0589	1.003
Male Indicator	3.0493e-01	1.5817e-01	1.9279	1.356
Household Income	4.4517e-06	1.4907e-06	2.9863	1.00
No Preference				
Age	-1.2288e-02	6.2706e-03	-1.9596	0.987
Education	-1.0420e-01	6.3430e-02	-1.6427	0.901
Male Indicator	-7.3242e-02	1.7524e-01	-0.4179	0.929
Household Income	4.3990e-06	1.5917e-06	2.7637	1.00
N	2489			
Loglikelihood	-2744.8			
Pseudo R-square	0.0205			

Note: “Preference to use regular taxi service” is the base category

5.3. Preference for Higher Cost of an Automated Uber Trip

Table 2.5 shows the parameter estimates of a binomial logistic regression model, which explains the association between individuals' sociodemographic characteristics and their stated willingness to pay a higher price of an automated Uber trip as compared to an Uber operated by human drivers (base category: lower price of an automated Uber trip).

As seen from the estimates, there is a negative association between age and higher price of an automated Uber trip. This indicates that the propensity to willing to pay more for an automated Uber trip decreases with the increase in age. Precisely, a marginal increase in age decreases the odds of a higher willingness to pay for an automated uber trip by 0.97. As for the next regressor, the results show that being a male is associated negatively with a higher willingness to pay for an automated Uber trip. This is an interesting finding, as it was seen in the previous results that even though males are more likely to choose a self-driving taxi, their propensity for a higher WTP for the self-driving vehicle is lower. The results also depict that with the increase in household income, the likelihood of being willing to pay a higher price for an automated Uber trip decreases whereas as the education level increases, the likelihood to pay higher prices for automated Uber trip increases. One plausible reason for this positive association could be that more educated individuals are more likely to understand the technological advancements that goes into an automated vehicle and hence are aware that the cost could be higher. A study by Krueger et al. (2016) indicated that autonomous vehicles are more attractive to a younger generation than

the older ones and that their preferences are considerably sensitive to the service variables.

Table 2. 5 Binary Logistic Regression Estimates (Model 3)

Explanatory Variables	**Estimate**	**Std. Error**	**z-value**	**Odds Ratio**
Age	-3.001e-02	6.512e-03	-4.608	0.970
Male indicator	-6.947e-02	7.928e-02	-0.876	0.932
Household Income	-3.213e-06	1.482e-06	-2.168	0.999
Education level indicator	9.197e-03	5.132e-02	0.179	1.00
N	1810			

Note: "Preference for the willingness to pay lower cost of an automated uber trip" is the base category

5.4. Preference for Reasons of Lower Cost of an Automated Uber Trip

Table 2.6 shows the results of three different binary logistic regression models. The first model explains the association between socio-demographics with the preference for lower price of an automated Uber trip because there is no human labor to compensate. We find that there is a positive association between male and the preference for a lower price because there is no human labor to compensate. Even though this estimate is statistically significant, the odds ratio indicates that there would be a 0% incremental effect and thus, the predictor males does not cause much variation to the preferences. The education level indicator is also associated positively with the preference for lower price of the automated uber trips because there is no labor to compensate. Specifically, the results show that the being highly educated increases the odds of preferring lower prices for the absence of human labor by 9%.

The next model is also a binary logistic regression model which studies the association between socio-demographics with the preference for a lower price of an automated uber trip because travelling in an automated trip is a compromise to safety. The results indicate that the age, male indicator and household income are negatively associated with the preference for lower price of the automated trip as safety is compromised. Also, individuals with higher education level are more likely to prefer a lower price for an automated uber trip to compromise for their own safety.

The final model, also a binary logistic regression model, studies the propensity of the different socio-demographic with the preference for lower rates of an automated uber trip due to the responsibility of the eventual problems with automated vehicles. The result shows that older people and individuals with higher education are less likely to prefer lower rates owing to the responsibility of eventual problems. However, males as compared to females and higher income households as compared to the lower income households, are more likely to prefer less cost owing to the responsibilities for the eventual problems.

Table 2. 6 Binary Logistic Regression Estimates (Model 4, 5, 6)

Explanatory Variables	**Estimate**	**Std. Error**	**z-value**	**Odds Ratio**
Preference for No Human Labor to Compensate (Model 4)				
Age	1.500e-02	4.812e-03	3.117	1.01
Male indicator	6.706e-03	5.451e-02	0.123	1.00
Household Income	5.641e-06	1.207e-06	4.673	1.00
Education level indicator	9.504e-02	4.096e-02	2.320	1.09
Preference for Compromise to Safety (Model 5)				
Age	-4.512e-03	4.261e-03	-1.059	0.995
Male indicator	-3.268e-02	5.163e-02	-0.633	0.967

Household Income	-2.061e-06	1.039e-06	-1.984	0.999
Education level indicator	3.898e-03	3.794e-02	0.103	1.003
Preference for Responsibility of Eventual Problems (Model 6)				
Age	-1.859e-02	1.565e-02	-1.188	0.981
Male indicator	9.382e-02	1.150e-01	0.816	1.09
Household Income	4.628e-06	3.367e-06	1.374	1.00
Education level indicator	-1.035e-01	1.289e-01	-0.803	0.90
N	1810			

Note: "No preference for no human labor to compensate" is the base category for model 4. "No preference for compromise to safety" is the base category for model 5 and "no preference for responsibility of eventual problems" is the base category for model 6.

5.5. Preference for Reasons of Higher Cost of an Automated Uber Trip

Table 2.7 depicts the results of two binary logistic regression models which explains the preference of the users for a higher cost of an automated uber trip owing to the understanding that automated uber trips might have the cost of technology associated with it and the safety in the automated uber cars would be more than the one which is driven by human drivers.

In the first model, which shows the association between demographic and the preference for a higher cost of an automated uber trip because of the cost of technology, the results indicate that as the age increases, the likelihood of preferring higher cost decreases. As compared to females, males are less likely to prefer the higher cost of automated uber trip for the cost of technology and similarly, as compared to the lower household income individuals, the higher income individuals are less likely to preference the higher cost for technology. However, individuals with

higher education level are more likely to prefer higher cost for an automated trip due to the cost of technology and their odds of choosing this increase by a factor of 1.05. The second model presents the estimates for the preference of higher price of an automated uber trip because of the increased safety of the trip and its association with the socio-demographics. The older individuals and higher household income individuals are less likely to prefer higher price for an automated uber trip owing to the safety of the trips. However, as compared to females, males are more likely to prefer a higher price due to the safety factor of an automated trip. Similarly, individuals with higher education level are also more likely to prefer higher price for an automated uber trip owing to the safety of automated trip as compared to the individuals with lower education level.

Table 2. 7 Binary Logistic Regression Estimates (Model 7, 8)

Explanatory Variables	**Estimate**	**Std. Error**	**z-value**	**Odds Ratio**
Preference for Higher Cost of Technology (Model 7)				
Age	-2.731e-02	6.961e-03	-3.924	0.973
Male indicator	-9.508e-02	9.317e-02	-1.021	0.909
Household Income	-3.318e-06	1.588e-06	-2.089	0.999
Education level indicator	5.087e-02	5.544e-02	0.918	1.05
Preference for Safety of Automated Uber Trips (Model 8)				
Age	-5.369e-02	1.475e-02	-3.640	0.947
Male indicator	5.701e-03	1.168e-01	0.049	1.005
Household Income	-7.559e-07	2.765e-06	-0.273	0.99
Education level indicator	5.609e-02	9.924e-02	0.565	1.057
N	1810			

Note: “No preference for higher cost of technology” is the base category for model 7. “No preference for safety of automated uber trips” is the base category for model8.

6. Conclusion

The study aimed to discern the preferences of autonomous vehicle users using random parameter logit model and multinomial logit model. In both the models, the focus was to establish how the socio-demographic is going to impact the "consumer behavior" for autonomous vehicles.

For the first model, the study focused on whether autonomous vehicle users have their preferences influenced by the reality of automated vehicles running safely and reliably on all roadways, such that a child of age 8, without a driver's license may be allowed to travel alone for trips covering 3 miles away from home. The results confirmed that males and individuals with higher household income have incremental effects on the preference of letting a child ride an automated trip but for age, a decreasing significant effect was confirmed by the negative beta coefficient. The findings are in tandem with Zmud et al. (2016) who noted on the importance of safety and its significant role in influencing preferences for using autonomous vehicles. However, the study by Anania et al. (2018) cited that majority of the parents were not willing to let their children use autonomous buses in going to school. The study concluded that the parents felt unsafe with the automated vehicles. It was also found that children who had relatively older parents were more unwilling to let their child ride on an automated bus which helps in explaining the results of this study in that age depicted negative effects towards preference for autonomous vehicle usage, mostly because of safety issues. Later, a proposal has been presented to examine further perceptions on preferences of AV among different generations such as Generation X, Millennials, and Generation Z. The approval seen in the results in terms of gender and household income on the

preference for AV due to safety and children involvement may be re-confirmed by Krueger et al. (2016) who noted that safety improvements influences choice of the model.

The next set of modelling presented outcomes on the preferred option among regular taxi, ride-hailing services and autonomous taxis, where price and waiting time remained the same. The regression outcomes confirmed that age is negatively associated with ridehailing and self-driving cars as compared to regular taxi. The gender indicator had a positive relationship with self-driving cars i.e. males were more likely than females to prefer self-driving car than regular taxi if the price and wait time were the same. Higher household income individuals were more likely to choose either ridehailing or self-driving cars as compared to the regular taxi but without causing much incremental effects as the odds ratio was 1.00. The aspect of age having negative significant effects on preference for autonomous vehicle usage aligns to previous researches. The study by Krueger et al (2016) has important bearing to this research in the sense that they noted that autonomous vehicles have more appeal to the younger generation compared to the older ones; this is an essential establishment and re-echoes the intention of this study to delve into more research regarding the preference for autonomous vehicles across different age groups. The negative effects on age can also be affirmed by the findings by Krueger et al (2016) who noted that different age groups show differing preferences for AV. For the next models, the findings indicated that on different occasions autonomous vehicle users regard the cost of an automated Uber trip as important when compared to that of a human driver. One

limitation with the study is that it only shows the correlation, but the causation needs to be determined. Further studies can focus on causation effects.

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