What Drives Your Drivers: An In-Depth Look At Lyft And Uber Drivers

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ABSTRACT
Lyft and Uber are two of the most well-known, on-demand ride-service providers in the current landscape of shared mobility. As monthly ridership for these two services grow, researchers are left wondering about the individuals giving the rides: the drivers. This paper shifts the focus from on-demand, ride-sharing passengers to the drivers – a topic to which little attention has been paid. In August 2015, Kelley Blue Book provided a dataset from its nationwide survey of U.S. residents aged 18 to 64 that collected information on shared mobility awareness and usage, personal vehicle ownership, aspirations for future vehicle ownership, and attitudes and opinions on shared mobility and personal vehicle ownership. We estimate an ordinal logit to understand the willingness to be a driver for an on-demand ride sharing service. We find that the individuals who report higher VMT and that have more children are more willing to drive for the service. Older women with higher incomes are among the least likely to desire driving for these services. We introduce attitudinal factors and find that those who believe "Ride-sharing is better than vehicle ownership" are more willing to drive for these services. Furthermore, vehicle ownership is positively correlated with the desire to drive for on-demand ride services – owning a vehicle makes it possible for an individual to drive. The next step of this research is to develop a new survey that over samples ride-sharing drivers to better understand who is driving for these services, rather than who is willing to drive for them.

Keywords: On-Demand Ride Services, Shared mobility, Uber/Lyft drivers, Ordinal Logit

1. INTRODUCTION

Lyft and Uber are two of the most well-known, on-demand ride service providers in the current landscape of shared mobility. As of October 2016, Uber had 40 million monthly riders worldwide and that number appears to be growing (Kokalitcheva, 2016). While monthly ridership increases, driver retention remains low at roughly 4%. This means that about 96% of Uber drivers leave the company within a year of their start date (McGee, 2017).

With more than 40 million monthly riders, many ride service researchers have focused their research on the rider (Clewlow, Mishra, & Laberteaux, 2017; Rayle, Shaheen, Chan, Dai, & Cervero, 2014). Some research focuses on driver safety (Feeney, 2015) and other research on driver wages (Berger & Frey, 2017; Henao & Marshall, 2017). To date, there is very little research on driver characteristics. Two fundamental questions on driver characteristics are: What types of individuals want to drive for on-demand ride sharing companies such as Lyft or Uber? And what motivates an individual to drive for one or both of these companies? With the majority of research being done on Lyft/Uber riders, we have little information about the drivers; this paper attempts to fill that gap by providing an in-depth analysis of potential and current drivers. The everchanging dynamics of these services give researchers very little time to understand not only its riders but also drivers. As a result, research on drivers is relatively sparse. Uncovering driver characteristics can help transportation planners understand the changing dynamics of roadway users. Similarly, knowing the people that are driving for these services will allow vehicle manufacturers to tailor their vehicles to meet the needs and demands of drivers.

The automotive research company Kelley Blue Book provided our sample, which came from a nationwide survey of U.S. residents aged 18 to 64. The sample collected information on shared mobility awareness and usage, personal vehicle ownership, aspirations for future vehicle ownership, and attitudes and opinions on shared mobility and vehicle ownership. We estimate an ordinal logit model to understand the willingness to drive for an on-demand ride sharing service (e.g. Lyft/Uber). We find that vehicle ownership plays a significant role in estimating the willingness to drive for an on-demand ride sharing service; those who own a vehicle are more likely to drive than those who do not own a vehicle. Additionally, individuals who have strong and positive attitudes towards ride-sharing services are more likely to drive.

This paper is organized as follows: the following (second) section provides a review of relevant literature. The third section discusses the data used in this analysis and provides summary statistics of respondents in the sample. The fourth section discusses the methodology used. The fifth section presents the modeling results. The final (sixth) section presents conclusions and discusses the next steps of the project.

1. LITERATURE REVIEW

This literature review is split into two parts. It begins by reviewing on-demand shared mobility user characteristics, as well as providing a definition for on-demand shared mobility. The second part discusses taxi driver characteristics, which parallel on-demand ride sharing driver traits.

1.1 On-Demand Shared Mobility

Since 2010, on-demand ride sharing companies have provided rides to tens of millions of users (Goodin, Ginger; Moran, 2016; Kokalitcheva, 2016). They have only continued to grow in popularity, notoriety, and in name. These companies pair passengers with drivers through a smartphone application (app) installed on the phones of both parties: the passenger requests a ride in the app and the request is sent to a driver. If the driver denies the request, the request is sent to another driver. This process continues until the request is approved, and then the driver that accepts the request picks up, transports, and then drops off the passenger. The cashless operation is brokered by the company; fares, and in some cases tips, are collected through the app and paid to drivers accordingly. On-demand ride sharing has many different names: Transportation Network Companies (TNCs), on-demand ride sourcing, ride-hauling, ride-booking, ride-matching, and app-based ride sharing. This paper will use the term "on-demand ride sharing" to describe services such as Lyft and Uber.

Recently, attention has been given to user characteristics of these services. There have been several studies that explicitly focus on, or paid a great deal of attention to, on-demand ride sharing users and service usage (Clewlow et al., 2017; Rayle et al., 2014; Smith, 2016). In 2016, the five on-demand ride sharing companies licensed in New York City provided 133 million rides (Schaller, 2017). In fall 2016, on-demand ride sharing companies picked up 87% as many rides as yellow taxis (Schaller, 2017). According to a Pew Research Center survey conducted between November and December 2015, roughly 15% of Americans have used on-demand ride sharing apps (Smith, 2016). At a more disaggregate level, the Pew Report finds that about 21% of urbanites, 15% of suburbanites, and 3% of rural-dwellers have used on-demand ride sharing services (Smith, 2016). Using a survey of respondents from seven metropolitan areas in the U.S. administered in fall 2015, Clewlow et al. (2017) found adoption rates between 15% and 29% for individuals residing in suburban and urban neighborhoods, respectively (Clewlow et al., 2017). They also reported the adoption rate of on-demand ride sharing by generation (Clewlow et al., 2017). About 40% of those in Generation Y (adults born between the years 1977 and 1995) had downloaded and used one of the apps, compared to only 3% of those in the silent generation (adults born between the years 1925 and 1942) (Clewlow et al., 2017). A similar study of Millennials in California (those born between the years 1981 and 1997) found that on-demand ride share adopters are more likely to be students and employed and less likely to have children in the household (Alemi, Circella, Handy, & Mokhtarian, 2017). In general, on-demand ride sharing adopters tend to be younger and have higher levels of education compared to non-adopters (Alemi et al., 2017; Clewlow et al., 2017; Rayle et al., 2014).

1.2 Driver Characteristics

Services such as Lyft and Uber serve as matchmakers: matching drivers to riders and vice versa. The quickly changing landscape of these service drivers has made it difficult to research and publish studies in a timely manner; however, one study has succeeded. Using a survey of 601 Uber drivers weighted to the entire Uber driver population by average work hours and hourly earnings, Hall and Krueger (2015) were able to describe Uber driver characteristics and socio-demographic traits, and to compare these traits and characteristics to the population of all workers in the United States and to taxi drivers and chauffeurs (Hall & Krueger, 2015). Roughly 30% of Uber drivers are aged 30 to 39, which is a distinctly higher percentage than taxi drivers (19.9%) for the same age group (Hall & Krueger, 2015). Uber drivers have higher education levels than taxi drivers and chauffeurs – in fact, 47.7% of Uber drivers received a college or advanced degree whereas only 18.9% of taxi drivers and chauffeurs achieved the same. Furthermore, only 41.1% of workers (according to the American Community Survey) have received college or advanced degrees, meaning that Uber drivers in general are more educated than workers (Hall & Krueger, 2015). In terms of gender, compared to the overall population of workers in the United States, there are far fewer females – only 14% of Uber drivers are female (Hall & Krueger, 2015). Fewer Uber drivers are married than workers, but more have children at home (Hall & Krueger, 2015). Surprisingly, about 7% of Uber drivers are veterans, compared to 5.2% of all workers (Hall & Krueger, 2015). Although Hall and Krueger (2015) have provided the socio-demographic traits of Uber drivers, their report makes no mention of driver attitudes or feelings about vehicle ownership and ride sharing (Hall & Krueger, 2015). Furthermore, the report has no specific data about the drivers' past experiences with Uber as riders, something that the authors believe leads many individuals to become drivers (Hall & Krueger, 2015).

Based on the Hall and Krueger (2015) study, it appears that there are similarities between Lyft/Uber passengers and Uber drivers (Hall & Krueger, 2015). Both drivers and riders are younger and more educated (Alemi et al., 2017; Clewlow et al., 2017; Hall & Krueger, 2015; Rayle et al., 2014; Smith, 2016). This study hopes to further close the gap in research connecting drivers and passengers and to provide a deeper insight into likely drivers for these services.

2. EMPIRICAL CONTEXT

This study is based on data from an extensive online survey commissioned by Kelley Blue Book, an automotive research company based in Irvine, California, to study the motivations behind shared mobility usage, in addition to opinions and behaviors about current and future transportation. The survey collected information on respondents' involvement in ride sharing and vehicle sharing and how those factors affect other choices relating to shared mobility decisions and the intention to purchase a vehicle. The survey was administered in an online format, from August 3 to 9, 2015 to U.S. residents aged 18 to 64.

The final unweighted sample has 1,916 respondents. The average respondent in the dataset is 37 years old, female, Caucasian, married, has no children, and has a household income of approximately $62,500. Table 1 presents descriptive statistics for the sample population.

It should be noted that the descriptive statistics presented in Table 1 are not entirely representative of the US population. The surveyors over sampled Millennials (18-34 year olds in 2015) and under sampled Generation X/Baby Boomers (35-64 year olds in 2015). This over sampling allowed us to key into the group of individuals that heavily rely on shared mobility services. In terms of gender and ethnicity, males were slightly under sampled (47.8% vs. 50%) and ethnicity/race had similar over and under sampling.

This national survey collected data on awareness and used of a wide variety of services, including the burgeoning "pooling" offshoots. Respondents were asked about potential pricing schemes, such as their preferences for new shared mobility subscription services, barriers to using these services (if they did not already use them), interest in becoming a driver for ride-sharing, etc.

TABLE 1 Descriptive statistics (unweighted)

Characteristic (sample size)	**N (%)**	**Characteristic (sample size)**	**N (%)**
Gender (1916)		**Household income (1916)**	
Male	908 (47.4)	Less than $25,000	357 (18.6)
		$25,000 to $30,000	135 (7.05)
Age (1916)		$30,000 to $50,000	380 (19.8)
18 to 24	502 (26.2)	$50,000 to $75,000	359 (18.7)
25 to 34	508 (26.5)	$75,000 to $100,000	269 (14.0)
35 to 41	210 (11.0)	$100,000 to $125,000	117 (6.11)
42 to 50	255 (13.3)	$125,000 to $150,000	72 (3.76)
51 to 64	441 (23.0)	$150,000 to $200,000	68 (3.55)
		More than $200,000	42 (2.19)
		Prefer not to answer	117 (6.11)
Education level (1916)		**Characteristic (sample size)**	**Sample mean**
Some grade/high school	49 (2.56)		
High school/GED	341 (17.8)	Number of operational personal vehicles (1569)	1.18
Some college/technical school	531 (27.7)		
Associate’s degree	220 (11.5)		
Bachelor’s degree	530 (27.7)		
Graduate degree (e.g. MS, PhD, etc.)	202 (10.5)		
Professional degree (e.g. JD, MD, etc.)	31 (1.62)		
Prefer not to answer	12 (0.63)		
Employment (1916)			
Employed full-time	835 (43.6)		
Employed part-time	289 (15.1)		
Student	198 (10.3)		
Homemaker	219 (11.4)		
Other	31 (1.62)		
Unemployed	203 (10.6)		

The questionnaire consisted of 8 sections that collected information on:

A. Socio-demographic information (introduction): This section collected information from respondents and their children (where applicable) about their age, gender, ethnicity, marital status, parental obligations, child information, household location, and neighborhood type.
B. Vehicle ownership: This section collected information about vehicle ownership, including the number of vehicles in the household, general vehicle characteristics, and the respondent’s future vehicle purchase timeline.

C. Travel attitudes: The section asked the respondents to provide their beliefs and opinions about driving, personal transportation, and vehicle ownership.
D. Ride sharing and vehicle sharing information: This section collected information about the familiarity and usage of ride sharing and vehicle sharing services. The respondents were asked about each stage of ride sharing and vehicle sharing familiarity: a) had they heard of the service?; b) is the service available in their area?; c) had they used the service?; d) how they first heard about the service?; e) which specific service was available in their area?; and f) when did they first use the service? Ffor those who reported that they had never used any service, respondents were asked about their willingness to try the service.
E. Ride sharing attitudes: This section collected information about ride sharing attitudes by using several likert-scale type questions. In addition to the likert-scale questions, this section presented respondents with questions about different pricing schemes for ride sharing services, what transportation modes would ride sharing replace, and a 4-point likert-scale description of vehicle ownership vs. ride sharing.
F. Vehicle sharing attitudes: This section collected similar information to the previous section but within the context of vehicle sharing.
G. Future transportation: This section asked questions about the respondent's future travel intentions. Specifically, the survey asked about the situations in which respondents would use a certain mode of transportation. Furthermore, for those who indicated that they had not used ride sharing or vehicle sharing, attention was paid to what would encourage them to use these services in the future.
H. Socio-demographics (conclusions): The final section collected information about shared economy usage (e.g., AirBnB, VRBO, Couchsurfing, etc.), in addition to employment status, daily VMT, home parking availability, number of people in the household, level of education, and annual household income.

3. METHODOLOGY

Understanding the drive to drive for on-demand ride sharing services can be explained by several factors, including attitudes, socio-demographic characteristics, and personal travel choices. The Kelley Blue Book report (Hall & Krueger, 2015) focused only on driver socio-demographics and did not discuss a relationship between driving and personal attitudes. We aim to bridge this gap by looking to explore the relationship between the desire to drive for an on-demand ride sharing service and an individual's attitude towards vehicle ownership and ride sharing itself.

In the Kelley Blue Book survey, respondents were asked about the likelihood of them driving and their current driver status for on-demand ride sharing services. Figure 1 below presents the histogram of their responses.

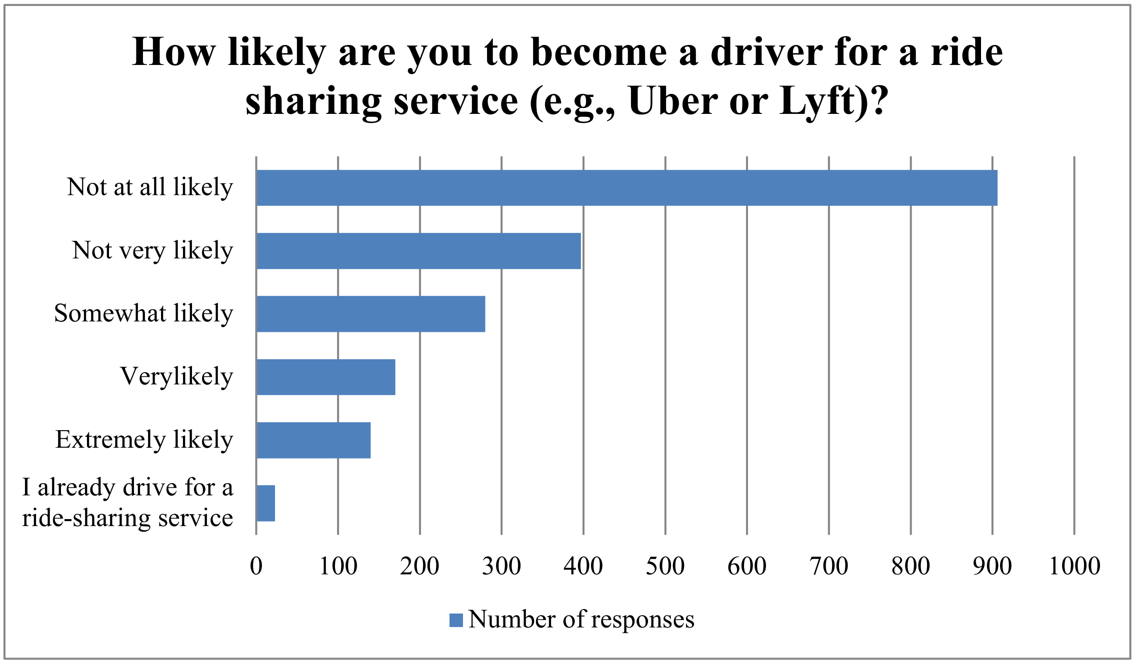

FIGURE 1 Histogram of responses.

While an overwhelmingly large number of respondents (N=1,303) indicated that they are "not very likely" or "not at all likely" to drive for an on-demand ride sharing service, the remaining respondents (N=613) indicated some willingness to drive for an on-demand ride sharing service. In fact, 23 respondents answered that they already drove for such a service; however, no information about the service for which they drove was collected.

As part of this modeling effort, we included several explanatory variables. The final version of the model includes 12 explanatory variables that were selected based on the literature as well as the inclusion of several factors extracted through a two-stage factor analysis. These variables are can be categorized into three groups: socio-demographic characteristics, personal travel, and attitudes.

We include several socio-demographic variables as explanatory variables in our model. We control for age using the age variable. We are also able to control for the number of children in the household. Being a parent or having to look after children means that work and other activities need to be flexible – driving for a service such as Lyft can provide the flexibility needed while allowing parents or guardians to make some (extra) income. We also control for the impact of gender and household income; we expect that with higher household income, the desire to drive for an on-demand ride sharing service would be low.

We also control for personal travel in the model. In general, we hypothesize that variables that are positively associated with travel will lead to a willingness to drive for Uber. Self-reported daily vehicle miles traveled (VMT), the availability of parking at home, and the number of shared mobility services that are used are considered personal travel variables. In this instance, the number of shared mobility services used serves as a proxy for the level of interaction with shared mobility in general. As an individual's experience and interaction with shared mobility increases, it becomes more likely that the individual wants to drive for a service. This reflects a desire to become more integrated into the shared mobility environment. The availability of parking at home could persuade or dissuade an individual from driving; while it may not be the first thought that comes to mind, having parking is almost necessary when it comes to vehicle ownership, and as a result, having the ability to drive for a service. In terms of daily VMT, individuals who drive more may enjoy the act of driving and therefore would like to drive for a service.

We also use attitudinal factors derived from likert-type statements in the survey. Using a two-stage factor analysis, six factors were extracted from 22 variables. Both factor analyses used a maximum likelihood factoring method with an oblique rotation. The first factoring stage included variables related specifically to vehicle ownership attitudes. The second stage focused on variables related to ride sharing attitudes. Our final model incorporates five of the six factors. The description of those factors is as follows:

a. Ride sharing factor – Pro-ride sharing: Individuals who score high on this factor tended to agree with statements such as “Ride sharing is better than using a taxi or renting a vehicle”, “Ride sharing is safe”, and “Using smartphone applications is a great way to request a ride”.
b. Ride sharing factor – Single item: This factor was a single item, meaning that respondents who “score high” on this factor strongly agreed with the statement “Ride -sharing is better than owning or leasing a vehicle for me”.
c. Vehicle ownership factor – Pro-vehicle ownership: Individuals who score high on this factor tended to agree with statements such as “Owning a vehicle is a smart investment” and “Owning/leasing a vehicle gives you a sense of freedom and independence”.
d. Vehicle ownership factor – Doesn’t need to own a vehicle: Individuals who score high on this factor tended to agree with statements such as “Having transportation is necessary but owning a vehicle is not” and “Owning/leasing a vehicle is too expensive”.
e. Vehicle ownership factor – Adventurer/multi-tasker: Respondents who score high on this two-variable factor agreed with the statements, “If I could, I’d prefer to drive a variety of vehicles rather than always drive the same one” and “I like the ability to multi-task while in a vehicle”.

Studies suggest that using a linear regression model is appropriate when a “variable has four or more [ordinal] categories,” (Bentler & Chou, 1987). For this study, we use an ordinal logit model to estimate the willingness of an individual to drive for an on-demand ride sharing service such as Lyft or Uber. Our dependent variable, “Willingness to drive”, was condensed into 3 levels for this analysis: Not likely to drive, somewhat likely to drive, and likely to drive. The first level, not likely to drive, includes 1,303 responses, which constitutes approximately 68% of respondents. The second level, somewhat likely to drive, consists of 280 responses, and the final level, likely to drive, included 333 responses. Table 2, below, presents some descriptive statistics for the variables tested to model the willingness to drive, including the mean, median, and standard deviation in age, income, number of children, and VMT for each willingness level. Furthermore, it includes some count information for categorical variables, such as level of education and gender. The average age of the individuals who indicated that they were likely to drive for a ride sharing service is approximately 33 years old with a standard deviation of 10.34 years. Furthermore, those with children indicate a higher willingness to drive than those without. The wealthiest individuals in our sample also indicated that they are likely to drive for an on-demand ride sharing service.

TABLE 2 Sample descriptives of dependent variable

		Willingness to drive level		
		Not likely to drive	Somewhat likely to drive	Likely to drive
Age	Mean	38.86	33.67	32.77
	Median	36	31	31
	Standard Deviation	14.47	12.18	10.34
Income	Mean	$60,547.78	$61,511.19	$71,364.35
	Median	$45,000.00	$62,500.00	$62,500.00
	Standard Deviation	$45,133.18	$45,087.84	$48,427.53
Number of Children	Mean	0.56	0.70	0.98
	Median	0	0	1
	Standard Deviation	0.99	1.12	1.12
VMT	Mean	16.83	19.51	24.23
	Median	8	15	15
	Standard Deviation	18.51	19.20	21.85
RS Factor - Pro-ride sharing	Mean	-0.17	0.16	0.55
	Median	-0.12	0.24	0.56
	Standard Deviation	0.93	0.79	0.81
RS Factor - Ride sharing is better than vehicle ownership	Mean	-0.25	0.27	0.73
	Median	-0.29	0.36	0.86
	Standard Deviation	0.74	0.69	0.67
Vehicle ownership factor – Pro-vehicle ownership	Mean	-0.04	0.02	0.13
	Median	0.02	0.06	0.18
	Standard Deviation	0.83	0.81	0.89
Vehicle ownership factor – Doesn’t need to own a vehicle	Mean	-0.06	0.02	0.21
	Median	-0.10	0.13	0.26
	Standard Deviation	0.78	0.71	0.78
Vehicle ownership factor – Adventurer/multi-tasker	Mean	-0.17	0.18	0.50
	Median	-0.17	0.15	0.60
	Standard Deviation	0.69	0.62	0.78
Gender (Row %)	Female	74.70%	12.00%	13.29%
	Male	60.57%	17.51%	21.92%
Education level (Row %)	Some grade/high school	57.14%	16.33%	26.53%
	High school/GED	74.19%	12.02%	13.78%
	Some college -tech school	71.56%	14.31%	14.12%
	Associate’s degree	70.91%	12.27%	16.82%
	Bachelor’s degree	63.58%	16.04%	20.38%
	Graduate degree (e.g. MS, PhD, etc.)	62.87%	17.82%	19.31%
	Professional degree (e.g. JD, MD, etc.)	48.39%	12.90%	38.71%
	Prefer not to answer	58.33%	25.00%	16.67%

4. RESULTS

4.1 Ordinal Logit Model

For this analysis, we use an ordinal logit model on the unweighted sample. While other studies suggest that multinomial logit (MNL) models provide a deeper, more thorough understanding of the dependent variable (Anowar, Yasmin, Eluru, & Miranda-moreno, 2014; Bhat & Pulugurta, 1998; Potoglou & Susilo, 2005), the authors believe that treating this variable as nominal would violate the ordinal relationship of the variable. Moreover, we risked an IIA violation since MNL treats the response variable as purely nominal variables. While there are risks with an ordinal logit model, we employed a parallel lines test to check that the slope parameters stayed the same for all response outcomes and that it is only intercepts (labeled "cut" in Table 3) that change. Since the parallel lines test assumption was met (i.e. the parameter estimates do not change based on the response level, only the intercepts change), we confidently employ an ordinal logit model to model the willingness to drive for an on-demand ride sharing service. The goodness of fit, R-squared, metric is 0.223, meaning that the variables in the model explain approximately 22.3% of the variance in the willingness to drive. Most studies that have investigated on-demand ride sharing usage report only descriptive statistics (Clewlow et al., 2017; Rayle et al., 2014). The parameters of the ordinal logit model estimated for this study are presented in Table 3 below.

TABLE 3 Parameter estimates for ordinal logit model

Term	Estimate	Std Error	Chi Square	Prob>ChiSq
Cut 1 [Not likely to drive]	0.524	0.177	8.73	0.0031
Cut 2 [Somewhat likely to drive]	1.674	0.183	83.68	<.0001
Age	0.029	0.005	39.32	<.0001
VMT	-0.008	0.003	8.95	0.0028
Number of Children	-0.216	0.054	16.19	<.0001
Female	0.221	0.057	15.23	<.0001
Vehicle Ownership Factor – Pro-vehicle ownership	0.194	0.090	4.66	0.0309
Vehicle Ownership Factor – Adventurer/multi-tasker	-0.699	0.104	45.07	<.0001
Doesn't own a vehicle (Indicator)	0.405	0.081	25.04	<.0001
RS Factor – Pro-ride sharing	-0.303	0.073	17.07	<.0001
RS Factor – Ride sharing is better than vehicle ownership	-1.217	0.087	195.19	<.0001

Number of observations	1916
R-Squared	0.223

As shown in Table 3, as the age parameter increases, the willingness to drive for on-demand ride sharing services decreases. Older individuals are not as familiar with these services, perhaps because they have white collar jobs that would make driving appear less beneficial than it would to a person in his or her 20s or 30s. Similar to the finds from (Hall & Krueger, 2015), we observe that women are less likely to drive for on-demand ride sharing services. Women, compared to men, may feel more uncomfortable or vulnerable driving or being alone with strangers in their vehicle. As VMT and the number of children at home increase, the willingness to drive for on-demand ride sharing increases. Having children living in your home and being a parent means finding employment that is flexible and will work with your schedule: driving for a service such as Lyft or Uber provides that flexibility needed in that environment. Those who drive more, on average, are more willing to drive for an on-demand ride sharing service – perhaps it is their increased mobility that leads them towards providing similar levels of mobility to others. Or perhaps it could be that they see their routine driving as a pathway to making some extra money. Vehicle ownership plays a role as well. More specifically, those who do not own a vehicle are less willing to drive for services such as Lyft or Uber. It should be noted that when this survey was administered in 2015, the vehicle renting options for potential drivers were not as plentiful as today, which likely results in vehicle ownership playing less of a role today than it would have in August 2015.

Understanding the willingness to drive for these services is aided by understanding attitudes. For instance, those who score highly on the pro-ride sharing factors are more likely to want to drive for Lyft. More specifically, individuals who scored highly on the factor "Ride sharing is better than vehicle ownership" expressed a higher willingness to drive for on-demand ride sharing programs. Surprisingly, identifying positively with statements that encourage vehicle ownership, such as "Owning/leasing a vehicle gives you a sense of freedom and independence", is negatively correlated with the willingness to drive for Uber or Lyft. Those who own a vehicle are more willing to drive for on-demand ride sharing services; it could be that those who do not own a vehicle, may not want to own a vehicle and are therefore less likely to drive for on-demand ride sharing services. Those who are more adventurous are more willing to drive for Lyft; the socialness, newness, and excitement could be within their comfort zone and make driving more appealing.

4.2 Previous Experience with On-Demand Ride Sharing Services

Previous experiences with an on-demand ride sharing service can greatly impact an individual's attitudes, opinions, and continuing use of the service. Figure 2 presents a graphical cross-tabulation of the respondents' shared mobility knowledge and their willingness to drive. Shared mobility knowledge is divided into three levels: the respondent had never heard of these services prior to the survey, the respondent had heard of these services but have never used them, and the respondent had used these services (alone, with friends, etc.). Most respondents fell into the second category, having heard of the services but never used them, followed by use of the services. The number within the bar represents the number of respondents who fall in that category. For instance, there are 69 respondents who have never heard of on-demand ride sharing, but indicated they are likely to drive for a service.

The Pearson chi-square value for the contingency table/graph is 355.109, meaning that the willingness to drive is different between the different levels of shared mobility knowledge. In general, most respondents reported that they were not likely to drive for a ride sharing service. As shown in Figure 2, those who have previous experience with on demand ride sharing make up more than 60% of those who indicated that they are likely to drive for ride sharing. Surprisingly, those who have no experience or knowledge of ride sharing indicated at a higher rate than individuals who have heard of it but not used it that they are likely to drive. While the survey tool collects information about how respondents were made aware of these services, it did not collect information on how the information was presented to them: positive press, bad press, negative word of mouth, etc. It could be that some respondents with no firsthand experience with these services have already decided against using the services and will not engage with them in any way.

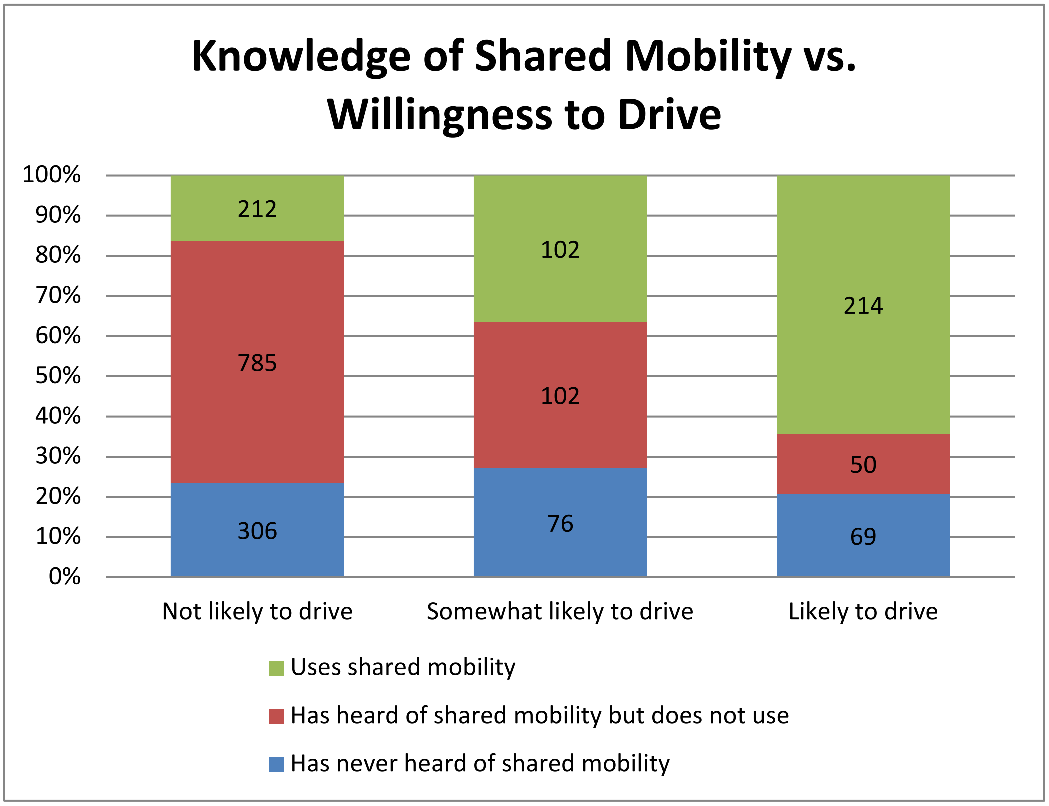

FIGURE 2 Knowledge of Shared Mobility vs. Willingness to Drive.

4.3 Motivations to Drive for an On-Demand Ride Sharing Service

In this subsection, we discuss the motivations to drive for an on-demand ride sharing service. Respondents that answered at least "somewhat likely" to the question "How likely are you to become a driver for a ride sharing service," were given a follow up question that asked about *why* they were interested in driving for these services. Figure 3 presents the graphical depiction of their responses.

The motivations for driving can differ from person to person and Figure 3, to some degree, represents those differences. While not all motivations are accounted for, and reasons undoubtedly exist that were not presented to the respondents, this list includes many of the critical motivations that the on-demand ride sharing companies would, themselves, highlight as reasons to drive. As shown in Figure 3, most respondents that answered this question said that their interest in driving for an on-demand ride sharing service is due to a desire to earn money, regardless of their willingness level. Enjoying the act of driving and meeting new people were overwhelmingly picked by those who indicated they were "likely to drive". Additionally, offsetting the cost of purchasing or leasing a vehicle, in general, is also a popular motivation. When looking at the specific reasons (e.g., offsetting the cost of buying a new car, buying a more expensive car, etc.) it could seem like purchasing or leasing a vehicle? is a less popular motivation – in some cases, individuals are interested in going from 0-car ownership to 1-car ownership, in other cases, individuals want to go from an economy vehicle to a more luxurious vehicle. Many services promote driving as a way to offset the costs of owning a vehicle and even provide vehicle leases for those who do not own a vehicle (Kieler, 2016).

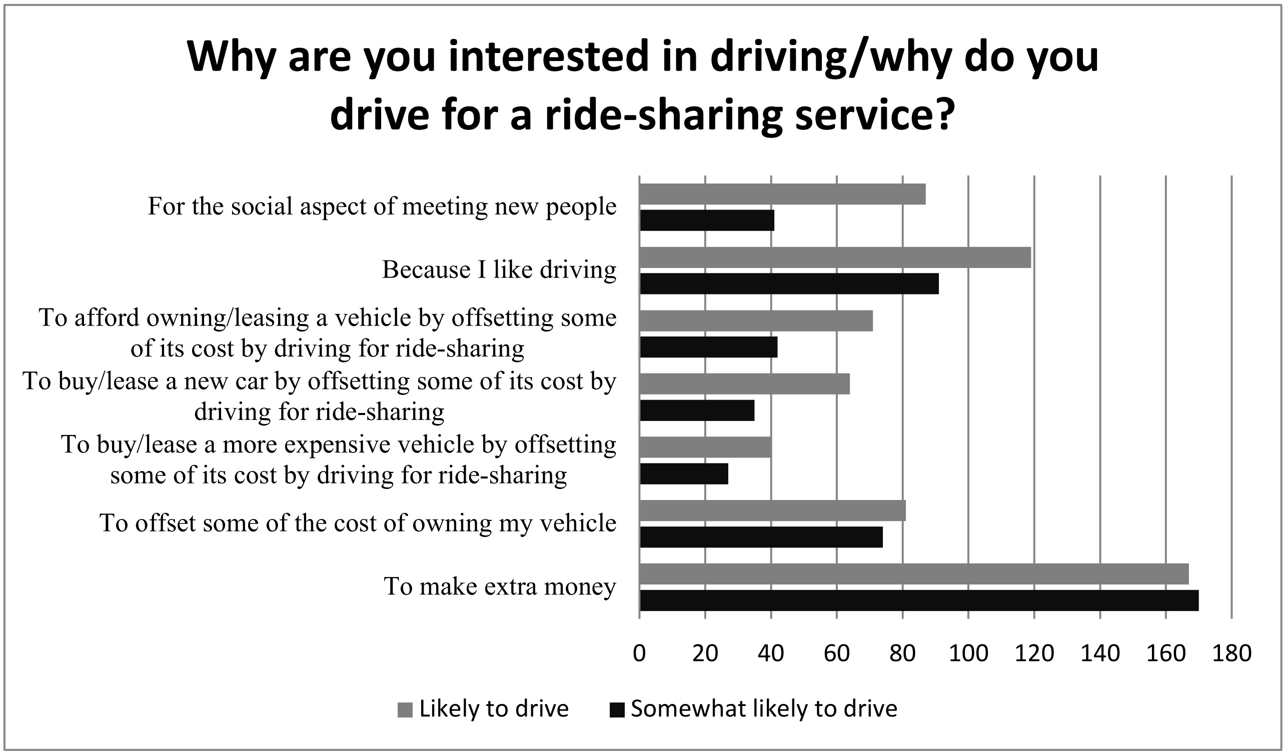

FIGURE 3 Answers to "Why are you interested in driving for a ride-sharing service".

5. DISCUSSION

For this study, we investigated the factors that influence an individual's willingness to drive for an on-demand ride sharing service, the relationship between on-demand ride sharing knowledge and willingness to drive, as well as the motivations for driving, using data collected by the automotive research company Kelley Blue Book in August 2015. As discussed in the literature, most studies have focused on the on-demand ride sharing user. There has been an omission, for the most part, on the drivers. The work discussed in this paper hopes to close that gap.

Using an ordinal logit model, we found that age, number of children, vehicle ownership, gender, and attitudes all play an important role in estimating the willingness to drive for an on-demand ride sharing service. More specifically, those who have positive attitudes towards ride sharing and vehicle ownership are more willing to drive for these services. Furthermore, personality traits also have an impact; those who are more adventurous or engage in multi-tasking are more willing to drive for Lyft. These individuals may enjoy meeting new people, driving to new places – wherever the ride takes them. While we are the first study to incorporate attitudes, we found that our socio-demographic results were consistent with (Hall & Krueger, 2015). More specifically, those interested in becoming on-demand ride sharing drivers are less likely to be female and younger than those who are not interested.

The contingency table presented in Figure 2 showed that the willingness to drive for shared mobility differs based on an individual's knowledge of shared mobility. The most surprising outcome is that those who had no knowledge of these services prior to the questionnaire appeared to be more willing to drive than those who had heard of the service but not used it; in this case knowledge deterred some individuals from wanting to drive. Those who indicated a willingness to drive were asked about the motivations behind that decision depicted by Figure 3. Earning extra money appears to be the most popular motivation for driving for an on-demand ride sharing service, followed by liking to drive.

The results of this modeling effort could be of interest to on-demand ride sharing services in terms of driver recruitment. The two most well-known companies, Uber and Lyft, already provide fiscal incentives to encourage driver enrollment; however, instead of wide-scale public campaigns (e.g., billboard advertisements or social media advertisements), these companies could target individuals with certain socio-demographic characteristic traits, ridership qualities, and vehicle ownership status. The results of this paper are unable to comment on retention rate, but if the ride-sharing companies were to track the socio-demographic characteristics and attitudes of their drivers, they may be able to better target drivers that will have higher retention rates and lessen driver turnover.

6. CONCLUSIONS AND LIMITATIONS

The ordinal logit discussed in this paper highlighted the factors that impact an individual's willingness to drive for an on-demand ride sharing service. Previous studies relied solely on socio-demographic traits (Hall & Krueger, 2015), but this study shows that attitudinal factors also have a significant impact. Most notably, the belief that ride sharing is better than vehicle ownership provides a strong indication that an individual is interested in driving for an on-demand ride sharing service; however, this does not lessen the impact of age, sex, or vehicle ownership – it merely provides more explanatory power to a topic that is under-researched. Those who indicate a willingness to drive for on-demand ride services are overwhelmingly motivated by the opportunity to make extra money.

The everchanging nature of these services means that having new data is essential to understanding behavior. While the findings in this paper represent the groundwork to understanding who will drive for these services, the driver population continues to grow and change. For instance, Uber's leasing pilot program was not introduced until August 2015, and was introduced mostly in the California market (Uber, 2015). At the time of the study, most respondents were likely unaware of the leasing program and their willingness to drive for these services could have changed because of the program. Moreover, as noted in McGee (2017), the ride sharing service driver retention rate remains low, and respondents that indicated a willingness to drive in 2015 may have different attitudes towards driving today, or may even have become drivers (McGee, 2017). Furthermore, we want to better understand the motivations for driving. While many respondents indicated that the money earned would be used to offset the cost of maintaining their vehicle or even purchasing a new/more expensive one, without real driver data, we cannot be certain that their stated preference will match their behavior. Therefore, the next phase of this research will be to conduct an intercept survey of drivers in Northern California sometime in early 2018 to update the data and gain deeper insight into vehicle ownership, the effectiveness of vehicle leasing programs, and the motivations for drivers to continue driving.

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