

## **Modeling the Evolution of Ride-Hailing Adoption and Usage: A Case Study of the Puget Sound Region**

### **Felipe F. Dias**

The University of Texas at Austin  
Department of Civil, Architectural and Environmental Engineering  
301 E. Dean Keeton St. Stop C1761, Austin, TX 78712, USA  
Tel: +1-512-471-4535  
Email: [fdias@utexas.edu](mailto:fdias@utexas.edu)

### **Taehooie Kim**

Arizona State University  
School of Sustainable Engineering and the Built Environment  
660 S. College Avenue, Tempe, AZ 85287-3005, USA  
Tel: +1-480-727-3613;  
Email: [taehooie.kim@asu.edu](mailto:taehooie.kim@asu.edu)

### **Chandra R. Bhat** (corresponding author)

The University of Texas at Austin  
Department of Civil, Architectural and Environmental Engineering  
301 E. Dean Keeton St. Stop C1761, Austin, TX 78712, USA  
Tel: +1-512-471-4535  
Email: [bhat@mail.utexas.edu](mailto:bhat@mail.utexas.edu)  
and  
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

### **Ram M. Pendyala**

Arizona State University  
School of Sustainable Engineering and the Built Environment  
660 S. College Avenue, Tempe, AZ 85287-3005, USA  
Tel: +1-480-727-4587  
Email: [ram.pendyala@asu.edu](mailto:ram.pendyala@asu.edu)

### **William H.K. Lam**

The Hong Kong Polytechnic University  
Department of Civil and Environmental Engineering  
9/F, Block Z, 181 Chatham Road South, Hung Hom, Kowloon, Hong Kong  
Tel: +852-2766-6045  
Email: [william.lam@polyu.edu.hk](mailto:william.lam@polyu.edu.hk)

(the list of authors continues on next page)

**Abdul R. Pinjari**

Indian Institute of Science

Department of Civil Engineering

Centre for infrastructure, Sustainable Transportation and Urban Planning (CiSTUP)

SID Complex, IISc Campus, Bengaluru - 560012, Karnataka, India

Tel: +91-80-2293-2043

Email: [abdul@iisc.ac.in](mailto:abdul@iisc.ac.in)

**Karthik K. Srinivasan**

Indian Institute of Technology Madras

Department of Civil Engineering

BSB 235, IIT Madras, Chennai 600036, India

Tel: +91-44-2257-4282

Email: [karthikks@iitm.ac.in](mailto:karthikks@iitm.ac.in)

**Gitakrishnan Ramadurai**

Indian Institute of Technology Madras

Department of Civil Engineering

BSB 229, IIT Madras, Chennai 600036, India

Tel: +91-44-2257-4298

Email: [gitakrishnan@iitm.ac.in](mailto:gitakrishnan@iitm.ac.in)

## **ABSTRACT**

Ride-hailing services have experienced dramatic growth in cities around the world. There are, however, few studies and even fewer publicly available data sources that provide a basis to understand and quantify changes in ride-hailing usage over time. Ride-hailing use may change over time due to socio-demographic shifts, economic and technological changes, and service attribute enhancements, as well as changes in unobserved attributes such as attitudes and perceptions, lifestyle preferences, technology savviness, and social influences. It is critical to quantify the effects of these different forces on ride-hailing frequency so that robust forecasts of ride-hailing use can be developed. This paper utilizes repeated cross-sectional data collected in 2015 and 2017 in the Puget Sound region to analyze the differential impacts of socio-demographic variables on the evolution of ride-hailing adoption and usage. By doing so, the study is able to isolate and quantify the pure effect of the passage of time on adoption of ride-hailing services. A joint bivariate-ordered probit model is estimated on the pooled data set to explicitly account for sample selection differences between the 2015 and 2017 surveys that may affect estimates of ride-hailing adoption in the two years. Model estimation results are used to compute average treatment effects of different variables on ride-hailing usage over time. It is found that the effects of most demographic variables on individuals' propensity to use ride-hailing are softening over time, leading to reduced differences in ride-hailing use among market segments. This suggests that there is a "democratization" of ride-hailing services over time.

## **KEY WORDS**

Ride-hailing, e-hailing, mobility as a service, bivariate ordered probit model, travel forecasting, evolutionary dynamics in behavior, market adoption, mobility-as-a-service, MaaS

## 1 INTRODUCTION

Ride-hailing services, also referred to as Transportation Network Companies (TNC), have experienced a surge in usage over the past several years. Although they have been around for less than a decade, their usage has posted impressive gains over time. Ride-hailing services provide on-demand mobility, and are often viewed in the realm of Mobility-as-a-Service (MaaS) where individuals purchase mobility by the trip on-demand as opposed to owning and using their own private vehicle. The two largest providers of on-demand mobility in the United States, namely, Uber and Lyft, have both experienced growth in usage and recently went public with stock offerings that have essentially valued the companies in the tens of billions of dollars. Just last year, Uber reported serving its ten billionth ride (Uber, 2018). The growth in usage is not surprising; these services offer reliable, lower cost (than traditional taxi), on-demand, and door-to-door transportation that can be requested (hailed), tracked, and paid by users through the convenience of a smartphone app (Dias et al, 2017).

Despite the dramatic growth in the demand for and usage of ride-hailing services, the fact remains that these services command only a very modest mode share. Most recent travel surveys, including the 2017 National Household Travel Survey and a number of metropolitan area travel surveys (*e.g.*, San Diego, Sacramento, Phoenix) in the United States, indicate mode shares of under one percent for ride-hailing services (RSG, Inc., 2018). While ride-hailing services may have shifted some travel away from the personal automobile, particularly in a few dense urban markets, they have generally served as a substitute to transit and traditional taxi services (Schaller, 2018), both of which are traditional means of transportation with very low mode shares to begin with. As such, until the ride-hailing mode truly begins making inroads into the personal vehicle share of daily travel, the ride-hailing mode share is likely to remain modest. Nevertheless, the growth in ride-hailing usage in absolute numbers has been substantial (Schaller, 2018) and is likely to continue in the near future as the services evolve and make their offerings more appealing.

Planning efforts in metropolitan areas around the world need to account for the (likely) continued growth in ride-hailing service usage; growth in the use of these services has important implications for future transit investments, parking capacity needs, curbside management, safety, and vehicle miles of travel. Metropolitan Planning Organizations (MPOs) would be able to plan future transportation investments in a way that accounts for the potential growth in ride-hailing service usage. However, forecasts of ride-hailing usage are not readily available and not easy to develop. Unfortunately, there is a dearth of data on usage of ride-hailing services over time (except for some very aggregate statistics) that could have possibly helped in the development of robust forecasts of ride-hailing mode usage. Ride-hailing service companies are understandably reluctant to share ridership data (due to privacy and business competitiveness reasons). As a result, transportation professionals and researchers have generally relied on secondary data sources and conducted their own surveys to quantify and model ride-hailing mode use/choice. These research efforts (reviewed in the next section) have provided valuable insights into ride-hailing service usage patterns and market penetration, but have not provided much information on the *evolution* of ride-hailing mode use *over time*. Surveys are largely cross-sectional in nature and provide information about traveler behavior and values at one point in time.

The gap in knowledge about the *evolutionary dynamics* of ride-hailing mode use is precisely what this paper attempts to address. The objective of this paper is to use repeated cross-sectional data collected in the same region to develop a model of the change in ride-hailing mode use over time. The model is developed and specified such that the effects of different contributing

factors can be isolated and quantified, thus providing deep insights on the “true” change in the adoption and use of ride-hailing services over time. There are a variety of forces that may contribute to changes in ride-hailing use over time. Prior research has shown that younger individuals are more likely to adopt and use these services. As millennials and Generation Z individuals comprise the largest segments of the US population, it is plausible to expect higher levels of ride-hailing mode use as they come of age and favor the use of shared modes as opposed to private (vehicle) ownership. At the same time, the population of the United States is aging; as older individuals find it increasingly difficult to drive on their own, their adoption of ride-hailing services may grow over time (especially as they become increasingly comfortable with technology). In other words, there are socio-demographic forces that may contribute to changes in ride-hailing mode use. Second, changes in economic conditions may bring about changes in ride-hailing mode use. As real incomes rise, purchasing power grows, and ride costs remain the same (or even decrease), the adoption of ride-hailing services may change (grow). The affordability of the services is likely to be a key factor in the adoption and level of use of ride-hailing modes, and hence economic considerations are critical in developing any forecast of ride-hailing demand. Finally, there may be a “true” change in the willingness to adopt and use ride-hailing services over time as they become increasingly commonplace and well-established. In other words, even after controlling for all built environment, socio-economic and demographic forces at play, there may be a change in ride-hailing usage that is attributable to shifts in attitudes towards ride-hailing modes and willingness to adopt transportation innovations. This study presents a model that distinguishes and quantifies the effects of these three main sources of change in people’s adoption and use of ride-hailing modes.

Being able to forecast change in ride-hailing adoption and use over time is also critical to policy development so that interventions can be put in place to avoid unintended consequences. Indeed, the impact on the traditional taxi industry, particularly in places such as New York City, has had very significant economic and personal effects (The New York Times, 2017 and 2019); if the growth in ride-hailing usage had been foreseen sufficiently in advance, perhaps policies and interventions could have been put in place to proactively manage the transition and reduce harm to those who relied on the traditional taxi industry for their livelihood. The same can be said about traditional transit services; as metropolitan areas grapple with the future of transit, an ability to forecast changes in ride-hailing use over time would enable agencies to plan future transit investments and service adjustments more strategically (and in ways that would have ride-hailing services complement, rather than substitute, the use of transit).

To conduct the analysis of evolutionary behavioral dynamics in ride-hailing use, data from the Puget Sound region is used in this study. The Puget Sound Regional Council (PSRC) conducted regional household travel surveys in both 2015 and 2017, thus providing valuable travel behavior and mode use information at two points in time. There was no attempt to obtain responses from the same set of households across the two years; thus the PSRC surveys constitute a repeated cross-sectional approach to data collection, not a panel-based approach. Because this is a repeated cross-sectional survey, the changes in ride-hailing use observed over time (between the two surveys) may also be due to different sample selection mechanisms at play (more on this later). We control for such sample selection in the current paper by applying the traditional econometric sample-selection framework in a rather unique way to the case of simultaneously controlling for variations in respondent characteristics across different surveys when examining changes in behavior over time.

The rest of the paper is organized as follows. Section 2 offers a brief literature review, focusing on demand for ride-hailing services and the general evolution of new technologies in the market. Section 3 presents the data description, while Section 4 offers a detailed presentation of the modeling framework, behavioral considerations, and econometric methodology. Model estimation results are described in Section 5 and concluding remarks and directions for future research are furnished in Section 6.

## 2 LITERATURE REVIEW

Due to the ever-growing presence and usage of ride-hailing services in metropolitan areas around the country, many studies have been devoted to understanding and characterizing this phenomenon. Much of this prior research has aimed to understand the characteristics of ride-hailing users (who uses the service), the characteristics of ride-hailing trips (how, why, when, and where is ride-hailing used), and the potential vehicle miles of travel (VMT) implications of ride-hailing modes (*e.g.*, due to empty or deadheading trips). These studies have shed considerable light on the nature of ride-hailing mode usage; however, the studies are based on cross-sectional data and hence provide little behavioral insights on the evolution or growth of ride-hailing usage over time. There are aggregate studies of overall growth in ride-hailing usage (numbers of rides over time), but such time series analyses provide little in the way of behavioral insights in terms of the true uptake in ride-hailing services.

In terms of behavioral survey-based studies, initial work has reported that ride-hailing users are generally younger, more educated, live in urban areas, earn higher incomes, and own fewer cars than the general population (Rayle *et al.*, 2016, Clewlow and Mishra, 2017, Dias *et al.*, 2017, Lavieri *et al.*, 2017, and Vinayak *et al.*, 2018). These studies also reveal that the main reasons users choose to use ride-hailing services are to avoid driving while intoxicated and to avoid parking-related issues. Furthermore, about 9% of respondents claimed to have disposed one or more of their household vehicles due to the availability of ride-hailing services. More recently, a number of studies have been conducted using survey data collected in the State of California, with a particular focus on millennials (Alemi *et al.*, 2018; Alemi *et al.*, 2019; Circella *et al.*, 2018). The California survey incorporates a panel component with a view to capture behavioral dynamics over time. While the panel nature of the survey has not been fully exploited yet, studies conducted to date using the California Millennials Survey data set have shown that older millennials who are employed and have higher levels of education are more frequent users of ride-hailing services than other categories of millennials. In yet another recent survey-based study, Lavieri and Bhat (2019) analyzed data collected from a sample of commuters in the Dallas-Fort Worth area to identify the psycho-social influencers that motivate use of ride-hailing services. They found that individuals with stronger pro-environmental, technology-embracing, and variety-seeking attitudes are more likely to use ride-hailing services. In particular, they observed that attitudinal factors are important to consider, in addition to individual socio-demographics.

Although survey-based research has shed light on ride-hailing users and their characteristics, it is naturally limited by the nature of the survey, sample selection issues, response biases, and other usual concerns associated with sample surveys (especially when seeking to study rare behaviors). Hence, a few studies have explored alternative data sources to better understand ride-hailing usage patterns. For example, Kooti *et al.* (2017) partnered with Yahoo to gather the receipts sent by Uber to riders' email addresses after a trip was completed. This gave the

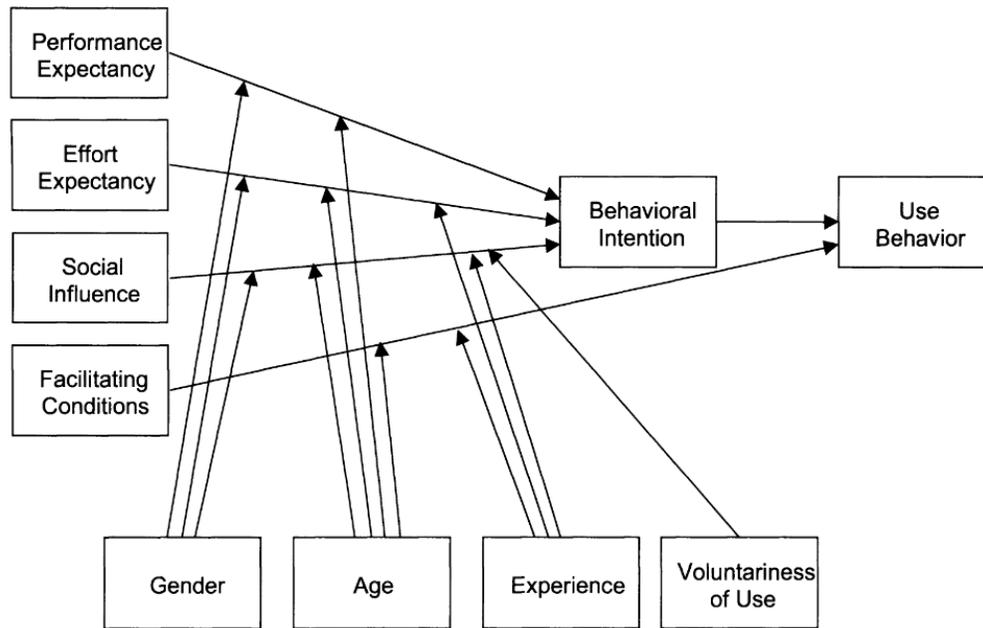
researchers access to trip-level information for approximately 59 million rides. The authors then coupled the data mined from the receipts with Yahoo's own database on users' demographics. They showed that the average active Uber rider is a female individual in her mid-20s with an above-average income. They were also able to draw insights into ride-hailing usage by Uber's different tiers of service, finding that the more affluent riders are more likely to use the more expensive tiers, such as Uber Black.

Another stream of research has attempted to mine actual trip data that is becoming increasingly available as ride-hailing companies begin to share and publish anonymized trip-level data. In 2017, RideAustin, a ride-hailing company in Austin, Texas, shared about a year's worth of trip-level ride data, encompassing 1.5 million trips between June 2016 and April 2017. Using this data, Lavieri *et al.* (2018) found that there was a positive spatial correlation component to ride-hailing trip generation, suggesting the existence of a spill-over effect (*i.e.*, areas with high ride-hailing trip generation levels increased their neighbors' trip generation rates). Studies using this data also suggested that in some cases, ride-hailing might act as a substitute to public transit and that deadheading (*i.e.*, driving without a passenger) constitutes approximately 37% and 50% of ride-hailing drivers' miles driven and travel time, respectively (Lavieri *et al.*, 2018; Dias *et al.* 2019; and Komanduri *et al.*, 2018). Dias *et al.* (2019) fused secondary land use and census data to the RideAustin data to draw inferences about the characteristics of frequent ride-hailing users and ride-hailing trip purposes. Wenzel *et al.* (2019) explored the RideAustin trip data to analyze energy implications of ride-hailing; they estimated that empty trips between servicing rides accounts for 26% of total ride-hailing VMT and the net effect of ride-hailing on energy use is a 41–90% increase compared to baseline, pre-TNC, personal travel.

While the studies mentioned above provide rich insights on the nature of ride-hailing trips and empty VMT, studies that explore the growth or behavioral dynamics of ride-hailing use are few and far between. The growth in ride-hailing usage is well documented in terms of aggregate trends (Schaller, 2018). Ride-hailing services have experienced dramatic growth in the past several years, with the total number of rides now exceeding total local bus ridership across the country (Schaller, 2018). Other anecdotal information also points to the dramatic growth in ride-hailing services: it took Uber six years to serve its first billionth ride and just six more months to serve its second billionth (Uber, 2015; Fortune, 2016).

The dramatic growth in ride-hailing ridership suggests that there are critical evolutionary dynamics at play that need to be better understood and quantified so that planning agencies can forecast growth in usage of this mode over time and develop long-range transportation plans and investments accounting for such growth. There are a number of theoretical paradigms and models that intend to explain adoption and use of (new) technologies over time. A popular behavioral paradigm in this realm is the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh *et al.* (2003). The theory, depicted in Figure 1, has been used to explain technology adoption in a number of applications including, but not limited to, potential adoption of self-driving vehicles (Zmud *et al.*, 2016). The framework draws a distinction between the *intention to use* and the *actual use* of a technology, implying that the actual use of a technology must be preceded by an intention to do so. The paradigm identifies four key constructs as moderating an individual's intent to use and actual adoption of new technology. The first is called *performance expectancy*, which refers to the degree to which an individual believes a technology or system will yield benefits. The second is *effort expectancy*, which captures the level of effort (or ease) needed to use a technology or system. The third is *social influence*, which reflects the

level of peer influence that an individual perceives in the context of adopting a new system. The fourth is *facilitating conditions*, which accounts for the degree to which an individual perceives the presence of a supporting organizational and technical infrastructure that enables system adoption and use. These four constructs are, in turn, moderated and influenced by such observable variables as gender, age, experience with technology use, and voluntariness of system use (which captures the degree to which system use is voluntary or mandatory). Figure 1 depicts how the different variables moderate the influence of various constructs on intention to use and actual usage of a new system.



**Figure 1 Framework for Unified Theory of Acceptance and Use of Technology**  
**Source: Venkatesh et al. (2003)**

Ride-hailing companies have been expending considerable resources to enhance adoption and use of the technology by implementing strategies, partnerships, service amenities, and incentives that would advance all four constructs that influence behavioral intention and actual usage. Both Uber and Lyft have introduced monthly subscription services that avoid the need to pay-per-trip; the companies are partnering with transit agencies to complement transit services; and the companies are partnering with employers to provide special pricing and rider programs for employees (Uber, 2018; Lyft; 2018). Essentially, the ride-hailing companies are attempting to improve *facilitating conditions*, reduce *effort expectancy*, enhance *performance expectancy*, and engender *social influence*. As the ride-hailing product is continuously enhanced, population socio-demographics evolve, and attitudes towards ride-hailing services change, the adoption and usage of these services is likely to progress over time. However, there is virtually no research to date that provides insights on the contribution of different factors to the evolution of ride-hailing usage, and this study aims to fill this critical gap with a view to inform forecasts of future ride-hailing use. This study utilizes data from the Puget Sound region that is available at two time points, 2015 and 2017, to model behavioral dynamics and quantify the *true* evolution (over time) in the adoption and use of ride-hailing services while explicitly controlling for changes in other factors.

### 3 DATA

Ride-hailing services were introduced in the Puget Sound region in 2011 (Uber, 2011). In this study, ride-hailing usage is analyzed by pooling data from the 2015 and 2017 Puget Sound Regional Household Travel Surveys conducted by the Puget Sound Regional Council (PSRC, 2015 and 2018). The data collection process, the assembly of the pooled data, and the data sample characteristics are described in this section of the paper.

#### 3.1 Survey Data Collection Process

In both 2015 and 2017, the Puget Sound Regional Household Travel Survey (hereafter, the survey) was comprised of three main sections.

- Section I: Pre-travel diary information: designed to collect general household- and individual-socio-economic, demographic, and related information
- Section II: Travel diary: designed to collect information on individuals' actual trip making patterns by recording all trips undertaken by each individual in the household
- Section III: Post-travel diary information: designed to collect additional individual-specific attitudinal and mode usage and preference information (*e.g.*, frequency of use of alternative travel modes, including ride-hailing services; attitudes towards autonomous vehicles; and preferences regarding ridesharing)

As noted earlier, the survey did not constitute a panel-based approach, and therefore there was no effort to track the same households across survey years. The PSRC used a household address-based sampling frame with a geographically stratified sampling approach. Using this approach, invitations requesting participation in the study were sent out to numerous households through postcards (*i.e.*, physical mail), e-mail, telephone calls and Facebook ads (the Facebook ads were exclusive to the 2017 effort). Those who agreed could choose to fill out Section I of the survey either through an online platform named rSurvey, or by telephone – where a telephone attendant solicited information from the respondent and actually used the rSurvey platform to enter the respondent's information. The distinction between these two modes of responses was not available in the publicly available datasets, making this an unobserved preference.

In 2015, Section II of the survey (the travel diary section) had to be completed using the same survey instrument as chosen by the respondent in Section I. In 2017, however, some of the users were allowed to complete this section of the survey using a smartphone app named rMove<sup>1</sup>. The app could (passively) track GPS locations and periodically remind the respondents to activate the app and provide all secondary travel diary data during the travel survey days. The choice between rSurvey or rMove for the travel diary portion of the survey was offered using the following protocol: during each week of the 2017 data collection process, the first 140 households in which all adults reported owning rMove-compatible smartphones were given the option to use the smartphone app for an additional \$15 incentive per person, while that week's remaining households were automatically assigned to complete their travel diaries using rSurvey, the online survey tool.

Once respondents completed the travel diary portion of the survey, they were led to Section III, where they were asked to provide their frequencies of use of certain modes (including ride-

---

<sup>1</sup> A small pilot smartphone app retrieval was also trialed in 2015, but these households are not included in the publicly available 2015 data.

hailing services), their workplace/school locations, and other individual-specific information about attitudes and preferences. Section III adopted the same survey instrument as that chosen by the respondent in Section I of the survey.

Besides the slight differences in the data collection methods described above, there were also notable differences in the financial incentives offered in each survey year. In both years, households were offered a \$10 incentive in the form of an Amazon or Starbucks gift card if they completed the survey. In 2017, however, there were some additional incentives: first, to boost low response rates seen in specific geographic areas<sup>2</sup>, some households qualified to receive an extra \$10 incentive; second, as mentioned earlier, households that opted to use the rMove smartphone app for recording travel data were offered an additional incentive of \$15 per person.

These changes in the data collection process between the two years could lead to samples that are not directly comparable due to sample selection processes at play. For example, it is quite possible that the 2017 data collection effort yielded a sample of more tech-savvy individuals because some respondents were allowed to use a smartphone app to record their trip diary information. Since tech-savvy individuals are more likely to use ride-hailing services (as documented by Lavieri *et al.*, 2017; Lavieri and Bhat, 2019; and Alemi *et al.*, 2018), it is possible that this unobserved variable (*i.e.*, tech-savviness) may be responsible for a part of the increase in ride-hailing use between 2015 and 2017 respondents. If this effect is not adequately controlled, then erroneous estimates of the change (over time) in the “true” willingness to adopt and use ride-hailing services may be obtained.

### 3.2 Descriptive statistics

In this study, the first and third sections of the survey are used; the second section, which constitutes the travel diary portion of the survey, is not used in this study. The survey data sets from 2015 and 2017 were reconciled (with respect to variable definitions and coding) and then merged to produce a pooled data set of respondents with the year of their response explicitly coded in the data. After some cleaning of the data to remove records with missing information on key variables, the final pooled data set included 8,542 observations, of which 3,800 belonged to the 2015 survey while the remaining 4,742 belonged to the 2017 survey. Descriptive statistics for these samples of individuals can be found in Table 1.

Some of the differences between the two surveys are worth noting. The 2017 data set is more evenly split between male and female respondents. The 2017 data seems to skew significantly younger with more than half of its sample aged 25-44 years; the same age group only accounts for little more than one-third of the 2015 sample. In 2015, nearly 30% of the sample did not own a smartphone; in 2017, just under 10% of the sample did not own a smartphone – suggesting that the 2017 sample is likely to be more tech-savvy, on average, than the 2015 sample. Also, given that ride-hailing services require the use of a smartphone app, a larger percent of individuals who responded to the 2015 survey do not have the technology required to use the on-demand mobility services.

---

<sup>2</sup> According to the PSRC (2018), these included households outside of King County and households that belonged to the following urban villages (UVs) in Seattle: Belltown, Greater Duwamish, Northgate, Pike/Pine, Pioneer Square, South Lake Union, Upper Queen Anne, and Uptown. The City of Seattle defines UVs as “areas where conditions can best support increased density needed to house and employ the city’s newest residents.”

**Table 1 Socio-Economic and Demographic Characteristics of Puget Sound Travel Survey Sample (n = 8,542)**

Variables	2015	2017	Total	Variables	2015	2017	Total
<b>Gender</b>				<b>Education</b>			
Male	45.8%	49.1%	47.6%	Less than high school	1.9%	1.3%	1.6%
Female	54.2%	50.9%	52.4%	High school graduate	9.1%	5.5%	7.1%
<b>Age</b>				Some college	15.3%	10.6%	12.7%
18-24	5.2%	6.6%	6.0%	Vocational/technical training	3.7%	2.3%	2.9%
25-34	18.9%	32.2%	26.3%	Associates degree	6.8%	5.7%	6.2%
35-44	16.6%	21.4%	19.3%	Bachelor's degree	36.4%	41.7%	39.3%
45-54	15.8%	12.7%	14.1%	Graduate/post-graduate degree	26.8%	32.9%	30.2%
55-64	20.2%	12.4%	15.9%	<b>Employment</b>			
65-74	15.2%	10.3%	12.5%	Employed full-time (paid)	46.5%	57.8%	52.8%
75-84	6.4%	3.7%	4.9%	Employed part-time (paid)	9.1%	8.0%	8.5%
85 or older	1.7%	0.7%	1.0%	Self-employed	6.6%	6.5%	6.5%
<b>Has a smartphone</b>				Unpaid volunteer or intern	1.2%	0.8%	1.0%
Yes	70.6%	90.2%	81.5%	Homemaker	5.9%	5.1%	5.5%
No	29.4%	9.8%	18.5%	Retired	23.8%	13.9%	18.3%
<b>Has a valid driver's license</b>				Not currently employed	6.9%	7.9%	7.4%
Yes	92.3%	92.9%	92.7%	<b>Frequency of ride-hailing</b>			
No	7.7%	7.1%	7.3%	Never	87.1%	51.8%	67.5%
<b>Vehicles in household</b>				Less than 1 day per month	5.3%	19.0%	12.9%
0 vehicles	9.5%	12.5%	11.2%	1-3 days per month	4.8%	18.8%	12.6%
1 vehicle	34.4%	43.5%	39.5%	1 day per week	1.8%	5.2%	3.7%
2 vehicles	38.6%	33.7%	35.9%	2-4 days per week	0.7%	4.4%	2.8%
3 or more vehicles	17.5%	10.3%	13.4%	5 days per week	0.1%	0.6%	0.4%
<b>Household income</b>				6-7 days per week	0.2%	0.2%	0.1%
Under \$25,000	11.4%	9.4%	10.3%	<b>Household size</b>			
\$25,000-\$49,999	18.3%	13.7%	15.8%	1 person	23.1%	24.2%	23.7%
\$50,000-\$74,999	15.7%	15.1%	15.3%	2 people	45.2%	49.5%	47.6%
\$75,000-\$99,999	16.0%	14.2%	15.0%	3 or more people	31.7%	26.3%	28.7%
\$100,000 or more	38.6%	47.6%	43.6%	<b>Observations (%)</b>			
<b>Observations (n)</b>	3,800	4,742	8,542		44.5%	55.5%	100.0%

In both years, the split between individuals with and without driver's licenses was very similar, with a little more than 92% of respondents having driver's licenses. Curiously, even though the split of driver's license ownership remained mostly unchanged, there was a significant change in vehicle ownership. In 2015, only 9.5% of respondents had no vehicles in their households, while 17.5% of them resided in households with three or more vehicles. In 2017, however, the share of individuals in zero-vehicle households was 12.5% while the share of individuals in households with three or more vehicles stood at just 10.3%. Although vehicle ownership and income are often positively correlated with one another, the opposite appears true in this sample; the 2017 sample exhibits lower levels of vehicle ownership, but skews significantly richer: respondents who live in households that earn \$100,000 or more per year increased from 38.6% in 2015 to 47.6% in 2017. The vehicle ownership shift may be related to household size, at least to some degree: between the two years, there was an increase in the share of respondents who live in households with 2 or fewer people and a decrease in the share of respondents who live in households with 3 or more people. The shift in income levels is also in line with differences seen in education and employment. Individuals in the 2017 data are more educated, with almost three-

quarters having a bachelor's degree or higher; in the 2015 sample, just about two-thirds of the sample have attained this level of education. Further, between 2015 and 2017, there is a significant increase in full-time employment (from 46.5% in 2015 to 57.8% in 2017) and a significant decrease in retired respondents (from 23.8% in 2015 to 13.9% in 2017). In summary, the 2017 data is comprised of richer employed individuals who reside in households with fewer vehicles and are more likely to own a smartphone (compared to the 2015 data).

Finally, when it comes to frequency of use of ride-hailing, there is a clear increase. The "Never Use" category changes from approximately 87% in 2015 to just about 52% in 2017, while virtually all other frequency categories more than doubled, with the exception of the "6-7 days per week" category, which remained the same at a very small share. These statistics show that there is a substantial change in ride-hailing service usage between the two survey years. The change in ride-hailing frequency and usage between the two survey years is likely to be due to a number of factors, including growing popularity of the service, changes in sample composition, and socio-demographic shifts. It is very plausible that there is a genuine or "true" increase in the adoption of ride-hailing services, independent of other phenomena (socio-economic shifts and changes in ride-hailing service attributes); it is the goal of this study to quantify that increase in ride-hailing adoption so that forecasts can be developed based on market adoption trends.

#### **4 METHODOLOGY**

This section presents the modeling methodology and the approach to computing average treatment effects (ATEs) for quantifying the influence of various factors on ride-hailing service adoption and use. As discussed in the sample description section, respondents in 2017 were generally from households with higher income, more educated, and younger than those in 2015. If the differences between 2015 and 2017 respondents can be completely attributed to such observed variables in the surveys, and if there were no other substantial environmental changes between 2015 and 2017, then the "true" change in ride-hailing use may be teased out by combining data from both 2015 and 2017 and estimating a single equation model of ride-hailing use (including a dummy variable for 2017, as well as interactions of this dummy variable with demographics to accommodate observed heterogeneity in the change across demographic groups). However, this approach is not appropriate if there are unobserved individual/household/environment characteristics (that is, characteristics that are not observed in the survey) that influence ride-hailing use and intrinsically differentiate the pools of 2017 and 2015 respondents. As indicated earlier, for example, the 2017 survey allowed the use of a smartphone app for entering travel diary information. This may have triggered a higher response from tech-savvy individuals in 2017. This unobserved variable (tech-savviness) may contribute, at least in part, to the differences in ride-hailing use between the 2015 and 2017 survey years. If this self-selection effect is not adequately controlled, then the single equation model would yield an inflated estimate on the 2017 dummy variable, as well as inconsistent estimates of the 2017 dummy variable interactions with other demographic variables, leading to inflated estimates of the "true" change in willingness to adopt and use ride-hailing. Similarly, the 2017 survey was accompanied by a Facebook ad drive, which could also have contributed to an intrinsically more tech-savvy sample in 2017. This discussion considered tech-savviness as an example to motivate controlling for potential unobserved factors that render 2017 respondents different from 2015 respondents in a manner that impacts ride-hailing use. However, it is conceivable that there are a number of other such factors or combinations of factors that are unobserved and affect ride-hailing usage (Lavieri and Bhat, 2019).

#### 4.1 Motivation and Model

In this study, changes in ride-hailing frequencies over time are considered to be driven by three main factors: (a) economic changes (*i.e.*, changes in living expenses, inflation, true purchasing power, technology pricing), (b) changes in population socio-economic and demographic characteristics, and (c) the “true” intrinsic change in the willingness to adopt and use ride-hailing services. For this analysis, it is assumed that there are no significant economic changes in the Puget Sound Region between 2015 and 2017, given the short time span between the two surveys. Further, to accurately quantify changes in ride-hailing due to respondent’s characteristics and the passage of time, the modeling approach teases out any potential confounding effects due to sampling differences between the years and isolates effects of respondent characteristics from the “true” change over time.

For this analysis, three main causes behind the third factor – the “true” change over time – are considered. The first cause is related to marketing strategies employed by ride-hailing companies. As companies such as Uber and Lyft try to increase their client bases, they use marketing strategies to make their product more known to an ever-growing segment of the population. The second cause is related to service expansion and enhancement in ride-hailing. In the Puget Sound Region, one important service change that happened between the two survey years was the launch of pooled ride-hailing services, where ride-hailing users were offered a discount for sharing a ride with other passengers who had similar pick-up and drop-off locations (Uber, 2016; Lyft, 2016). The third and last reason behind this “true” change in ride-hailing behavior is the increased familiarity and comfort people might feel as these services become increasingly commonplace. The analysis presented in this paper cannot tease out the independent effects of each one of these three factors: they are all captured together as a composite “true” effect of the passage of time.

As noted in Section 3.1 and in Table 1, the two data collection efforts yielded ride-hailing frequencies that were far from identical as well as key differences in several other observed demographic characteristics. To control for observed and unobserved changes between survey years, the evolution of ride-hailing usage is modeled using a joint binary probit-ordered probit model. This model is actually equivalent to a bivariate ordered probit model, where one of the two dependent outcomes has only two possible categories. Therefore, the methodology presented in this section is that of a simple bivariate ordered probit model. The first dependent outcome in the model corresponds to whether or not an observation belonged to the 2017 dataset. The coefficients in this first equation reflect the influence of observed characteristics on the probability of responding to the survey in a given year, while the error term captures the influence of unobserved characteristics (*e.g.*, maybe tech-savvy individuals were more likely to respond in 2017 given the potential to use a smartphone app for the trip diary section). The second dependent outcome is the individuals' frequency of ride-hailing, aggregated to five categories from the original seven-category variable depicted in Table 1<sup>3</sup>. When modeling this second outcome, individuals' socio-demographic variables are interacted with the 2017 dummy variable to capture the differential changes in ride-hailing frequencies across different socio-demographic groups over the years, while the error term accounts for the influence of unobserved characteristics on the frequency of

---

<sup>3</sup> The five aggregated frequency categories are: "Never", "Less than 1 day per month", "1-3 days per month", "1 day per week", "2 or more days per week". This was done because the number of individuals who reported using ride-hailing services 5 days per week and 6-7 days per week were too few to retain them separately.

ride-hailing. Our simultaneous equations model allows the error term in the frequency equation to be correlated with the error term of the sample selection equation. In summary, with this two-equation joint framework, the coefficients in the second equation capture the “true” change of the impacts of demographic variables on the frequency of ride-hailing while the correlation term across the errors in the two equations captures the effect of common unobserved variables. This is a rather novel, simple and elegant way of using a sample-selection framework to simultaneously control for variations in respondent characteristics across different surveys, while estimating “true” changes in behavior over time. While earlier applications of the sample-selection model have generally controlled for unobserved factors in examining inter-relationships among variables within the *same* survey, the current study is a unique application of this framework to control for unobserved factors *across* surveys.

The UTAUT framework presented in Figure 1 posits that, in general, individual-specific characteristics such as age and gender do not directly impact adoption of a new technology – rather, these characteristics moderate the influence of constructs such as “intention to use” and “effort expectancy” on the adoption and use of new systems. In the current paper, however, the data does not allow for the development and identification of such constructs; therefore, the analysis is constrained to modeling the influence of demographic variables on the evolution of adoption and use of ride-hailing services over time.

#### 4.2 Computing Average Treatment Effects (ATEs)

After estimating the model, it is possible to analyze each variable's average treatment effect (ATE), *i.e.*, the direct impacts of the exogenous variables on the frequency of ride-hailing use. Note that only ATEs for the “frequency of ride-hailing” outcome are presented in this paper, since that constitutes the main outcome of interest. The “belongs to 2017” sample-selection outcome is simply used to control for unobserved effects, and therefore its ATEs are not directly relevant to the question of interest.

To obtain the desired order-of-magnitude effects, cardinal values are assigned to each of the ordinal levels of ride-hailing. The cardinal value assignments corresponding to different frequency levels in the model are as follows:

- (1) “Never” = 0 trips per month,
- (2) “Less than 1 day per month” = 0.333 trips per month,
- (3) “1-3 days per month” = 2 trips per month,
- (4) “1 day per week” = 4 trips per month,
- (5) “2 or more days per week” = 16 trips per month.

With these assignments, and using the notation  $c_k$  for the cardinal value assignment corresponding to frequency level  $k$ , the marginal expected value of the frequency of ride-hailing for individual  $q$  ( $\tilde{y}_q$ ) is:

$$E(\tilde{y}_q) = \sum_{k=1}^K c_k \times Pr(y_q = k) \quad (3)$$

where  $Pr(y_q = k)$  is the probability that individual  $q$  falls into frequency category  $k$  and is calculated using the estimated coefficients of the model. Using this equation, it is possible to compute the aggregate-level ATEs of exogenous variables.

In the current analysis, four types of ATEs are calculated:

- Across demographics within 2015
- Across demographics within 2017
- Across demographics from 2015 to 2017
- Within demographics from 2015 to 2017

Furthermore, all of the exogenous variables are discrete variables, including binary variables such as education level and driver’s license ownership, and multinomial (*i.e.*, categorical) variables such as employment and age. Calculations are illustrated here for the “Across demographics within 2015” effects case using smartphone ownership (where “No” is the base) as the influential variable of interest. The same approach applies to the three other cases. First, take the original dataset and assign zeros to the 2017 dummy variable and all of the 2017 interaction dummy variables. This essentially forces all observations to belong to 2015. This is called the global 2015 dataset. Then the global 2015 dataset is modified by assigning a value of “0” for the “Smartphone Ownership – Yes” dummy variable. This forces all observations in the dataset to *not* own smartphones. All other exogenous variables are kept at their original values as seen in the global 2015 dataset. Using Equation 3, compute the average of the expected frequency of ride-hailing across the entire sample and label the resulting value as BASE\_15. Subsequently, a similar procedure is undertaken with one key difference: the global 2015 dataset is modified to set the value of the “Smartphone Ownership – Yes” dummy variable for each individual equal to one, effectively forcing all individuals in the dataset to own smartphones. The average expected frequency of ride-hailing is computed for this new sample and the resulting value is labeled SPHNY\_15. It is now possible to obtain an aggregate-level ATE of the “Smartphone Ownership – Yes” dummy variable for 2015 by computing the difference between the BASE\_15 and SPHNY\_15 values. Finally, the mean and standard errors of the aggregate-level ATEs are computed across 1,000 bootstrap draws taken from the estimated sampling distributions of the model’s parameters.

## 5 MODEL RESULTS

The first equation in the joint model primarily serves as a mechanism for controlling sample selection. Overall, the model coefficients for this equation reflect what was seen in the descriptive statistics. The sample in 2017 tended to be comprised of individuals in higher income, lower vehicle ownership households. They tended to be younger, have a higher education, and own a smartphone relative to the 2015 sample. Thus, it can be concluded that there is sample selection due to observed characteristics at play. By specifying and estimating a simultaneous equations model that accommodates error correlation, it is possible to account for *unobserved* sample selection effects as well. Because it is the primary outcome of interest, the remainder of this section is devoted to presenting results for the frequency of ride-hailing.

### 5.1 Joint Model Estimation Results

Model estimation results are presented in Table 2. The behavioral dynamics (*i.e.*, the change from 2015 to 2017) associated with the passage of time are reflected in the joint model through the use of a dummy variable which indicates whether or not the observation belonged to the 2017 dataset and by interacting this dummy variable with all other explanatory variables. Therefore, the “Base (2015)” column in Table 2 refers to the effects of the explanatory variables on the individual’s

underlying propensity to use ride-hailing in 2015, while the “Interaction (2017)” column represents the changes of those impacts from 2015 to 2017.

There are two noteworthy overarching results: first, there is a general increase in ride-hailing frequencies from 2015 to 2017; second, the impacts of most demographic variables change from 2015 to 2017, either reducing or intensifying differences in ride-hailing engagement for various demographic segments. In other words, the model results suggest that there is an evolution in the adoption and use of the technology, with the degree of evolution varying across demographic groups.

Model estimation results show that higher ride-hailing trip rates in the 2015 base year are associated with younger, wealthier, more educated and employed individuals who own driver’s licenses, own smartphones, and live in single person households with fewer vehicles. These findings corroborate the results from many prior studies, including for example, Rayle *et al.* (2016), Dias *et al.* (2017), Lavieri *et al.* (2017), Kooti *et al.* (2017), Vinayak *et al.* (2018), Alemi *et al.* (2018) and Lavieri and Bhat (2019). The extensive use of interactions complicates the interpretation of the results from Table 2. Therefore, we leave the discussion of the temporal behavioral dynamics to Section **Error! Reference source not found.**, where we directly analyze the impacts of each variable on individuals’ actual number of ride-hailing trips per month.

The error correlation term is positive and significant. This suggests that there are unobserved attributes that both contribute to an individual participating in the 2017 survey and using ride-hailing services. As mentioned throughout this paper, tech-savvy individuals who are comfortable using smartphone apps are more likely to use ride-hailing services. Such individuals may have had a greater propensity to participate in the 2017 version of the survey when a smartphone app (*rMove*) could be used to record travel diary information in the second stage of the survey (such an option was not available in the 2015 version of the survey). Other unobserved attributes that may simultaneously impact propensity to participate in the 2017 version of the survey and adopt and use ride-hailing services include residential location choice preferences, lifestyle preferences (*e.g.*, desire for active mode use), and variety-seeking proclivities. The significant error correlation also serves as a justification for the adoption of a simultaneous equations model that accounts for sample selection; this ensures that estimates of coefficients in the ride-hailing frequency equation are consistent (yielding estimates of changes in ride-hailing adoption over time that are not artificially inflated).

The improvement in model fit gained by using a joint approach is also discernible from the likelihood ratios displayed at the bottom of Table 2 where the log-likelihoods are furnished for three models: the joint model, the independent model (correlation term fixed at zero) and the null model (only constants/thresholds). The log-likelihoods for these three models are, respectively -12,591, -12,621, and -15,831. The joint model yields an improved log-likelihood value and the likelihood ratio tests show that the joint model is indeed statistically superior to both the null model and the independent model.

For further insights on the goodness-of-fit of the joint model, several aggregate and disaggregate measures of goodness-of-fit were examined. The joint model was found to correctly predict the joint outcomes of about 29% of the observations in the dataset, which is quite high considering that there are a total of 10 combinations of outcomes. Furthermore, a comparison of true and predicted aggregate shares that belong to each combination of outcomes showed that the performance of the joint model is superior to that of the independent model (that ignores error

correlation). The mean absolute percentage error (MAPE) for the joint model is lower than that for the independent model.

## 5.2 Quantifying Effects

The procedure outlined in Section 4.2 is applied to estimate the effects of different variables on the evolution of ride-hailing usage over time. By calculating average treatment effects (ATEs), it is possible to obtain a clearer picture of the changes in ride-hailing trip frequency for different demographic groups. Table 3 presents the results of the ATE calculations. Four sets of results are presented in Table 3: “Across demographics within 2015”, “Across demographics within 2017”, “Across demographics from 2015 to 2017”, and “Within demographics from 2015 to 2017”. These four phenomena may be explained as follows, using the results for the “Age 35-54 years” variable as an illustration:

- *Across Demographics within 2015*: Those aged 35-54 years make, on average, 1.012 fewer ride-hailing trips per month (compared to those 18-34 years) in 2015.
- *Across Demographics within 2017*: Those aged 35-54 years make, on average, 0.747 fewer ride-hailing trips per month (compared to those aged 18-34 years) in 2017.
- *Across Demographics from 2015 to 2017*: Those aged 35-54 years in 2017 make, on average, 0.826 fewer ride-hailing trips per month than those aged 18-34 years in 2015.
- *Within Demographics from 2015 to 2017*: Those aged 35-54 years in 2017 make, on average, 0.186 more ride-hailing trips per month than individuals aged 35-54 years in 2015.

An examination of the effects noted above suggests that the differences between age groups are dampening over time; the difference in ride-hailing frequency between individuals aged 18-34 years and individuals aged 35-54 years is decreasing with the passage of time. The third effect listed above depicts the evolution of the difference between different age groups over time. Lastly, the fourth effect suggests that individuals aged 35-54 years have, in general, increased their use of ride-hailing services over time. Note that these findings constitute true treatment effects after controlling for any sample selection effects – both due to observed and unobserved attributes.

**Table 2 Joint Model Estimation Results**

Parameter	Outcome 1: Belongs to 2017		Outcome 2: Frequency of Ride-Hailing			
			Base (2015)		Interactions (2017)	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
<b>Household income</b> (base: Under \$50,000)						
\$50,000-\$99,999	0.106	2.648	0.267	3.486	-0.197	-2.230
\$100,000 or more	0.242	5.913	0.599	7.915	-0.229	-2.618
<b>Vehicle ownership</b> (base: No vehicles)						
1 vehicle	-0.173	-3.535	-0.467	-9.997		
2 or more vehicles	-0.525	-10.363	-0.991	-13.798	0.168	2.413
<b>Household structure</b> (base: Single-person household)						
Multi-person household			-0.264	-3.508	0.179	2.065
<b>Sex</b> (base: Male)						
Female	-0.081	-2.957				
<b>Age</b> (base: 18-34 years)						
35-54 years	-0.189	-5.339	-0.561	-9.771	0.162	2.362
55 years or older	-0.279	-7.464	-1.198	-14.835	0.339	3.716
<b>Education</b> (base: Does not have a bachelor's degree)						
Has a bachelor's degree or higher	0.153	4.745	0.415	6.633	-0.164	-2.290
<b>Has valid driver's license</b> (base: No)						
Yes			0.108	1.879		
<b>Has a smartphone</b> (base: No)						
Yes	0.704	17.034	1.068	15.925		
<b>Employment</b> (base: Unemployed)						
Employed part time					0.196	2.975
Self-employed or employed full time			0.323	8.734		
<b>Year</b> (base: 2015)	<b>Coef.</b>	<b>t-stat</b>	<b>Coef.</b>		<b>t-stat</b>	
2017						
<b>Thresholds</b>	<b>Coef.</b>	<b>t-stat</b>	<b>Coef.</b>		<b>t-stat</b>	
Threshold 1	0.147	2.390	1.061		12.078	
Threshold 2			1.578		18.140	
Threshold 3			2.318		26.619	
Threshold 4			2.723		30.732	
<b>Correlations</b>	<b>Coef.</b>			<b>t-stat</b>		
Correlation between error terms	0.426			8.480		

Number of observations: 8,542  
 Number of parameters: 30  
 Null Log-likelihood (only thresholds): -15,831  
 Indep Log-likelihood (no correlation): -12,621  
 Full Log-likelihood (joint model): -12,591  
 Likelihood Ratio: Full vs. Null (p-value): 6,480 (0.000)  
 Likelihood Ratio: Full vs. Indep. (p-value): 58 (0.000)  
 Pseudo Rho Squared: 0.205  
 Adjusted Pseudo Rho Squared: 0.203

A number of studies have previously documented that older age groups are associated with a lower level of ride-hailing use (e.g., Rayle *et al.*, 2016; Kooti *et al.*, 2017; and Dias *et al.*, 2017). But the findings of this study clearly show a reduction in age differences over time. Individuals aged 55 years and older also follow a pattern similar to that depicted by the 35-54-year-old group. It is also seen that the isolated effect of the passage of time (as seen in the column labeled “Within Demogs - From 2015 to 2017” in Table 3) is strongest for the oldest demographic segment of 55+ years old. This shows that older individuals are increasingly embracing technology and discovering the convenience afforded by ride-hailing services. They may also be responding to marketing efforts of ride-hailing companies. The UTAUT framework indicates that age moderates the effect of *social influence*, *effort expectancy* and *performance expectancy* on the intention to use new technology. The results here suggest that the moderating effects of age on *social influence*, *effort expectancy* and *performance expectancy* are softening when it comes to adoption and use of ride-hailing use over time.

Gender did not play a significant role in influencing frequency of ride-hailing within any of the two years, but gender does come into play across time: between 2015 and 2017, women engaged in 0.083 more ride-hailing trips per month, on average. This could be an indication that women are finding this mode of transportation increasingly convenient and hesitation to use the mode due to concerns about personal safety may be dampening over time. Ride-hailing companies have made targeted efforts to enhance rider safety, particularly for women (for example, a service called Safr caters exclusively to female riders and employs exclusively female drivers). According to the UTAUT framework, gender moderates the intention to use new technology through the constructs of *social influence*, *effort expectancy* and *performance expectancy*. The results in this paper suggest that, for the specific case of ride-hailing, gender does not have a significant moderating effect on *social influence*, *effort expectancy* and *performance expectancy*.

Smartphone ownership is significantly associated with ride-hailing adoption and usage. In 2015, individuals who owned a smartphone made, on average, 0.838 more trips per month than those who did not. That effect intensified in 2017, as the difference between those with and without smartphones increased by about 15% (to 0.95 trips per month). As expected, individuals without smartphones were the least affected group (in terms of ride-hailing use per month). As ride-hailing services can only be accessed through the use of a smartphone app, it is to be expected that the segment of the population without smartphones would show virtually no change in ride-hailing use (i.e., they are unlikely to use the services at all in both time points). However, the segment that owns smartphones shows an increase in ride-hailing trip frequency of 0.114 trips per month (on average). As smartphone ownership increases, ride-hailing service use is also likely to increase. The Pew Research Center (2019) reports that, between 2015 and 2017, smartphone market penetration increased from 67% to 72% in the United States. In the context of the UTAUT framework, smartphone ownership is likely to improve *facilitating conditions*, significantly reducing the barrier to use ride-hailing services.

**Table 3 Average Treatment Effects (ATEs) of Variables on Ride-hailing Trips per Month**

Variable	Across Demographics						Within Demogs	
	Within 2015		Within 2017		From 2015 to 2017		From 2015 to 2017	
	ATE	t-stat	ATE	t-stat	ATE	t-stat	ATE	t-stat
<b>Household income</b>								
Under \$50,000 (base)							0.267	10.365
\$50,000-\$99,999	0.155	6.297	-0.018	-1.146	0.249	16.092	0.094	2.628
\$100,000 or more	0.725	34.059	0.408	22.562	0.675	48.382	-0.050	-1.730
<b>Vehicle ownership</b>								
No vehicles (base)							0.186	2.733
1 vehicle	-0.783	-17.412	-0.885	-31.611	-0.699	-8.110	0.084	1.896
2 or more vehicles	-1.331	-18.404	-1.411	-56.534	-1.225	-15.242	0.106	8.926
<b>Household structure</b>								
Single-person household (base)							-0.217	-12.577
Multi-person household	-0.560	-18.870	-0.169	-14.475	-0.386	-19.506	0.174	5.175
<b>Sex</b>								
Male (base)							0.083	2.803
Female					0.083	2.803	0.083	2.803
<b>Age</b>								
18-34 years (base)							-0.079	-2.107
35-54 years	-1.012	-63.410	-0.747	-61.748	-0.826	-25.503	0.186	6.779
55 years or older	-1.450	-68.967	-1.166	-113.978	-1.245	-37.206	0.205	12.270
<b>Education</b>								
No bachelor's degree (base)							0.115	11.835
Bachelor's degree or higher	0.457	26.985	0.434	26.923	0.549	24.278	0.092	2.548
<b>Has valid driver's license</b>								
No (base)							0.070	2.603
Yes	0.100	7.720	0.114	9.519	0.183	7.148	0.084	2.828
<b>Has a smartphone</b>								
No (base)							0.001	0.133
Yes	0.838	44.795	0.950	113.084	0.951	64.705	0.114	3.565
<b>Employment</b>								
Unemployed (base)							0.033	1.526
Emp. part time			0.322	17.875	0.354	10.752	0.354	10.752
Emp. full time / self-employed	0.454	56.796	0.510	39.044	0.543	16.643	0.089	2.763
<b>Global ATE from 2015 to 2017</b>	<b>ATE</b>				<b>t-stat</b>			
	0.083				2.803			

Higher education levels are associated with higher ride-hailing trip rates in both years, and the passage of time from 2015 to 2017 does not seem to have appreciably dampened the difference between those who have a college degree and those who do not. The difference between people with and without bachelor's degrees in 2015 is very similar to that in 2017. Indeed, the increase in ride-hailing trip frequency between 2015 and 2017 for each of the two groups is very similar (0.115 versus 0.092). Employment is one of the few variables where differences appear to have intensified over time. In 2015, employed individuals (full time and self-employed) engaged in about 0.45 more ride-hailing trips per month than unemployed or part-time employed individuals. In 2017, this difference increased to about 0.51 for full-time employed individuals relative to unemployed individuals. However, part-time employed individuals increased usage in transitioning from 2015

to 2017, thus narrowing the gap between full- and part-time employed individuals with respect to ride-hailing usage. Unemployed individuals, on the other hand, do not show an appreciable uptake in ride-hailing frequency; unemployed individuals have lower incomes, are likely to be older and retired, and may not have the need to use ride-hailing services when compared with their employed counterparts. The UTAUT framework does not explicitly identify employment as a key factor, but it is likely that part-time employed individuals find ride-hailing services to be convenient, reliable, efficient, and affordable for their short work trips (an independent analysis of 2017 National Household Travel Survey data shows that part-time employed individuals have commute distances considerably shorter than full-time employed individuals, rendering ride-hailing trip costs more affordable) when compared with other alternative modes such as public transit and non-motorized modes. Employees may also share information about these services among one another. Thus, employment appears to be associated with higher levels of *social influence* (coworkers influencing one another), *effort expectancy*, and *performance expectancy* – although enhancements in *facilitating conditions* are likely contributing to the increased adoption as well.

Consistent with expectations, individuals in zero-car households use ride-hailing services more frequently than individuals in households with vehicles. The difference in ride-hailing use between households with and without vehicles intensifies over time. In 2015, individuals in households with two or more vehicles (compared to zero-vehicle households) made an average of 1.33 fewer ride-hailing trips per month. In 2017, this difference increased modestly to 1.4 trips per month. In the last column, it can be seen that all car-ownership levels increased ride-hailing use, but the increase is greatest for zero-vehicle households and smallest for one-vehicle households. In the context of UTAUT, it appears that possessing fewer (or no) vehicles increases the *facilitating conditions* to use ride-hailing.

The effect of driver's license holding is rather interesting. Although one might expect those without a driver's license to use ride-hailing services to a greater degree, the opposite is true. Individuals who have a driver's license (when compared to those who do not) make about 0.1 more ride-hailing trips per month in both 2015 and 2017. It is likely that this variable is actually capturing the effect of an individual's preference for being transported in regular cars (as opposed to using transit, biking or walking); when the individual with a license does not have access to his or her own vehicle, then the preference is to use a private vehicle service such as traditional taxi or ride-hailing service as opposed to alternative modes of transportation. From a UTAUT perspective, it appears that having a driver's license increases users' *performance expectancy*.

A dampening of differences in ride-hailing use is seen in the effects of household size (structure). In 2015, individuals in multi-person households made about 0.56 fewer trips per month than single persons. In 2017, that difference reduced to a mere 0.169 trips per month. The last column shows that individuals in multi-person households increased their ride-hailing use between 2015 and 2017, while single persons actually reduced their use of the mode. It appears that single persons may be more amenable to trying other alternative modes (including micro-mobility options, such as e-scooters), whereas individuals in multi-person households may gravitate more towards ride-hailing services as an alternative to driving their own vehicle. It appears that ride-hailing companies have been able to successfully narrow the gap in ride-hailing behaviors between single- and multi-person households, most likely through an improvement of *facilitating conditions*.

The last variable – and most important from an equity and environmental justice standpoint – worthy of discussion is household income. Similar to Kooti *et al.* (2017), Dias *et al.* (2017), and

Alemi *et al.* (2018), it is found that higher income levels are associated with higher frequencies of ride-hailing in both 2015 and 2017. However, the differences between income groups have faded significantly (although some differences clearly remain). In 2015, individuals in households with income \$50k-\$99k reported, on average, 0.155 more ride-hailing trips per month than those in households making under \$50k. The corresponding value for the highest income group (\$100k or more) is 0.725. In 2017, the differences reduced quite dramatically; those in the household income segment of \$50k-\$99k showed virtually the same level of usage as the lowest income group (under \$50k), while the highest income group (\$100k or over) showed a more modest 0.408 more ride-hailing trips per month. An examination of the last column shows the trend very clearly; those in the base category of \$50k or lower showed the greatest increase in ride-hailing use from 2015 to 2017. Those in the highest income group did not show any appreciable change in ride-hailing frequency, while those in the middle income group had a modest increase in ride-hailing use. Overall, the differences among income groups appear to be dampening over time. There seems to be a “democratization” of ride-hailing across income segments over time. From a transportation equity point of view, this is a positive development as it demonstrates that the new mode of service is increasingly accessible to those in lower economic strata of society. Classifying this effect in terms of the UTAUT, it appears that reduced *effort expectancy*, increased *social influence*, and increased *facilitating conditions* are bringing about greater adoption among lower income groups.

## 6 CONCLUSIONS

This paper presents an investigation of the evolution of ride-hailing service adoption and usage over time. The main sources of changes in users’ adoption of ride-hailing services are conceptualized as falling into three categories: (a) economic and technological changes (*i.e.*, changes in living expenses, inflation, true purchasing power, and technology), (b) changes in socio-economic and demographic characteristics, and (c) the “true” change in the willingness to adopt and use ride-hailing services as they become more commonplace and well-established. Although there is a plethora of prior research dedicated to understanding ride-hailing usage within a cross-sectional survey context (at one point in time), there is virtually no prior research that examines evolutionary dynamics in ride-hailing use. Understanding evolutionary dynamics is critical to developing forecasts of ride-hailing use over time, that can in turn be used to inform long-range transportation investments and planning processes.

This issue is tackled in this study using pooled data from the Puget Sound Regional Council’s 2015 and 2017 travel surveys. The study employs a novel application of the traditional sample-selection framework to capture the unobserved effects induced by changes in the sampling procedures across survey years. The proposed application amounts to estimating a joint bivariate ordered response model, in which the first dependent binary variable corresponds to whether or not an observation belonged to the 2017 survey, and the second dependent variable corresponds to an individual’s ride-hailing frequency (in the past 30 days). The model renders it possible to capture and separate the true effects of demographics and the passage of time on individuals’ frequency of use of ride-hailing services while controlling for differences in sampling procedures across survey years. The joint model is used to calculate the average treatment effects (ATEs) of different variables on ride-hailing frequency.

The results show that several demographic variables play a significant role in determining frequency of ride-hailing usage. This is no surprise and is consistent with results reported in earlier

research. More frequent ride-hailing users tend to be younger, employed, more educated, have higher incomes, own smartphones, have driver's licenses, own fewer vehicles, and live alone. The novel contribution of this study lies in the finding that the passage of time generally softens (reduces) differences between demographic groups. For example, in transitioning from 2015 to 2017, it was found that the true differences in ride-hailing use between high- and low-income individuals became less pronounced, as did the differences across age groups. The differences between market segments are not stable over time, and it appears that technology diffusion effects are at play – contributing to a narrowing of the gap in ride-hailing use between market segments. A number of factors may contribute to this dampening – ride-hailing services have marketed and improved their service offerings, individuals are becoming increasingly comfortable with technology and new disruptive modes of transportation, and social influence (*e.g.*, family, friends, and co-workers) is motivating individuals to adopt and use the service. Unobserved attributes may also be contributing to the dampening of differences; as individuals become increasingly tech-savvy, environmentally sensitive, and active in their lifestyle choices and preferences, there is likely to be an uptake in ride-hailing use. This “democratization” is evidence of technology diffusion stemming from greater accessibility of services to a wider cross-section of the population. Ride-hailing companies should continue to market and enhance services and price structures (*e.g.*, monthly subscription services) so that all segments of the population can take advantage of this modal option – contributing to reduced transportation inequity. Transit agencies should partner with ride-hailing companies to enhance *facilitating conditions* and lower *effort expectancy* associated with the use of transit; and consider adopting some of the marketing strategies of ride-hailing companies to attract riders. It appears that ride-hailing services can play an important role in promoting transportation equity and environmental justice; the challenge remains, however, in mitigating unintended consequences such as empty vehicle miles and traffic congestion due to ride-hailing vehicles clogging roadways.

Overall, after controlling for all demographics and potential sampling issues, the aggregate true increase in ride-hailing frequency that is due exclusively to the passage of time is of the order of +0.1 ride-hailing trip per month per person. This number might appear small compared to the dramatic growth ride-hailing companies have experienced in recent years. However, the large growth in ride-hailing usage represents a composite effect of many contributing factors; ride-hailing companies are constantly expanding service to an ever-growing number of cities, socio-economic and demographic characteristics are changing, people are embracing technology in ever-increasing numbers, and service attributes of ride-hailing transport are becoming increasingly appealing. The +0.1 figure represents the *pure* effect of passage of time, assuming all other variables and factors are held *constant*. This figure explains why ride-hailing has remained modest in mode share.

This study offers a basis for transportation planning agencies to develop robust forecasts of ride-hailing use over time. Current models may be able to account for changes in ride-hailing use that stem from changes in socio-demographic characteristics of the population and changes in service attributes (*e.g.*, reliability, waiting time, and price) – primarily through segmented mode choice models. However, current transportation forecasting models are woefully inadequate in being able to account for the “passage of time” effect. As time progresses, technology adoption evolves as attitudes and perceptions change, social influences inspire new users, and new services become more commonplace and well-established. Accounting for this effect is critical to developing forecasts of ride-hailing use; and more importantly, forecasts should account for the differential uptake of ride-hailing services among various demographic groups (with the passage

of time). The model presented in this paper accommodates such heterogeneity in the effects of different demographic variables on the evolution of ride-hailing usage.

The main limitation of the current study is inability to account for individual-specific factors over time. The data and methods used in this paper do not consider the behavior of the same individuals over time. Instead, two cross sectional datasets from the same region are pooled. Future studies should explore the use of truly longitudinal (*i.e.*, panel) data and modeling approaches to analyze evolutionary dynamics in behavior. Another of the paper's key limitations is the underlying assumption that the general economic and technological environment was constant between 2015 and 2017. It is probably safe to make the assumption that the economic and technological changes in the Puget Sound Region are small enough to be ignored between 2015 and 2017. Future research should seek to develop new methods that could account for these effects as well. It would also be interesting to explore dynamics over more than a two-year time span, to see when and whether the effects of the passage of time plateau and reach saturation (or continue unabated for many years). Finally, it would be of value to explore evolutionary dynamics in other regions of the world to assess geographic and cultural variability in uptake of ride-hailing services.

## ACKNOWLEDGEMENTS

This research was partially supported by the Data-Supported Transportation Operations and Planning (D-STOP) Center and the Center for Teaching Old Models New Tricks (TOMNET), both of which are Tier 1 University Transportation Centers sponsored by the US Department of Transportation. The work described in this paper was also supported by a research grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (No. PolyU 152095/17E), and by the Ministry of Human Resource Development (MHRD) of the Government of India through its Scheme for Promotion of Academic and Research Collaboration (SPARC) program. The authors are grateful to Lisa Macias for her help in formatting this document.

## REFERENCES

- Alemi, F., G. Circella, S. Handy, and P. Mokhtarian. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society*, Vol. 13, 2018: 88-104.
- Alemi, F., Circella, G., Mokhtarian, P.L., and Handy, S.L. What drives the use of ridehailing in California? Ordered probit models of the usage frequency of Uber and Lyft. *Transportation Research Part C*, Vol. 102, 2019: 233-248.
- Circella, G., Lee, Y., & Alemi, F. Exploring the Relationships Among Travel Multimodality, Driving Behavior, Use of Ridehailing and Energy Consumption. *UC Davis: National Center for Sustainable Transportation*. Available at: <https://escholarship.org/uc/item/31v7z2vf>. Accessed on July 20, 2019.
- Clewlow, R.R., and G.S. Mishra. Disruptive transportation: The adoption, utilization, and impacts of ride-hailing in the United States. *University of California, Davis, Institute of Transportation Studies, Davis, CA, Research Report UCD-ITS-RR-17-07*. October 2017.
- Dias, F.F., P.S. Lavieri, V.M. Garikapati, S. Astroza, R.M. Pendyala, and C.R. Bhat. A Behavioral Choice Model of the Use of Car-sharing and Ride-sourcing Services. *Transportation*, 2017. 44(6): p1307-1323.

- Dias, F.F., P.S. Lavieri, T. Kim, C.R. Bhat, and R.M. Pendyala, 2019. Fusing multiple sources of data to understand ride-hailing use. *Transportation Research Record: Journal of the Transportation Research Board*, 2673(6), 214-224.
- Fortune. *Uber completes 2 Billion Rides*. Jul 2016. Available at: <http://fortune.com/2016/07/18/uber-two-billion-rides/>. Accessed on Jan 15, 2019.
- Komanduri, A., Wafa, Z., Prousaloglou, K. and Jacobs, S., 2018. *Assessing the impact of app-based ride share systems in an urban context: Findings from Austin*. *Transportation Research Record*, 2672(7), pp.34-46.
- Kooti, F., M. Grbovic, L.M. Aiello, N. Djuric, V. Radosavljevic, and K. Lerman. Analyzing Uber's Ride-sharing Economy. *Proceedings of the 26th International Conference on World Wide Web Companion*, 2017, pp. 574-582. International World Wide Web Conferences Steering Committee.
- Lavieri, P.S., V.M. Garikapati, C.R. Bhat, R.M. Pendyala, S. Astroza, and F.F. Dias. Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies. *Transportation Research Record: Journal of the Transportation Research Board*, 2017. Vol. 2665(1): p1-10.
- Lavieri, P.S., F.F. Dias, N.R. Juri, J. Kuhr, and C.R. Bhat. A Model of Ridesourcing Demand Generation and Distribution. *Transportation Research Record: Journal of the Transportation Research Board*, 2018. Vol 2672(46). pp 31-40.
- Lavieri, P.S. and Bhat, C.R., 2019. Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. *Transportation Research Part C: Emerging Technologies*, 105, pp.100-125.
- Lyft. *Lyft Line is now in Seattle!* Apr 2016. Available at: <https://blog.lyft.com/posts/lyft-line-seattle>. Accessed on Jun 19, 2019.
- Lyft. *New! Subscribe and Save with the All-Access Plan*. Oct 2018. Available at: <https://blog.lyft.com/posts/subscribe-and-save-with-the-all-access-plan/>. Accessed on Jan 15, 2019.
- Pew Research Center. *Mobile Fact Sheet*, Jun 2019. Available at: <https://www.pewinternet.org/fact-sheet/mobile/>. Accessed on Jun 19, 2019.
- PSRC. *Puget Sound Regional Travel Study – Report: 2015 Household Travel Survey*, 2015. Available at: <https://www.psrc.org/sites/default/files/2015-household-survey-tech-report.pdf>. Accessed Jan 15, 2019.
- PSRC. *2017 Puget Sound Regional Travel Study*, 2018. Available at: <https://www.psrc.org/sites/default/files/psrc2017-final-report.pdf>. Accessed Jan 15, 2019.
- Rayle, L., D. Dai, N. Chan, R. Cervero, S. Shaheen. Just a Better Taxi? A Survey-based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco. *Transport Policy*, 2016. 45: 168-178.
- RSG, Inc. *San Diego Regional Transportation Study – Volume 1: Technical Report*. Submitted to San Diego Association of Governments, San Diego, CA, 2018. Available at [https://www.sandag.org/uploads/publicationid/publicationid\\_2145\\_23025.pdf](https://www.sandag.org/uploads/publicationid/publicationid_2145_23025.pdf). Accessed on July 20, 2019.
- Schaller, B. *The New Automobility: Lyft, Uber and the Future of American Cities*. Schaller Consulting, Brooklyn, New York. 2018. Available at <http://www.schallerconsult.com/rideservices/automobility.pdf>. Accessed on July 20, 2019.

- The New York Times. *Taxi Medallions, Once a Safe Investment, Now Drag Owners Into Debt*. Sep 2017. Available at: <https://www.nytimes.com/2017/09/10/nyregion/new-york-taxi-medallions-uber.html?module=inline>. Accessed on Jun 19, 2019.
- The New York Times. *'They Were Conned': How Reckless Loans Devastated a Generation of Taxi Drivers*. May, 2019. Available at: <https://www.nytimes.com/2019/05/19/nyregion/nyc-taxis-medallions-suicides.html>. Accessed on Jun 19, 2019.
- Uber. *You Are Now Free To Move About Seattle*. Aug 2011. Available at: <https://web.archive.org/web/20110924021549/http://blog.uber.com/2011/08/12/you-are-now-free-to-move-about-seattle/>. Accessed on Jun 19, 2019.
- Uber. *One in a billion*. Dec 2015. Available at: <https://www.uber.com/newsroom/one-in-a-billion/>. Accessed on Jan 15, 2019.
- Uber. *uberPool is now available across town*. Apr 2016. Available at: <https://www.uber.com/blog/seattle/uberpool-in-seattle/>. Accessed on Jun 19, 2019.
- Uber. *10 Billion*. Jul 2018. Available at: <https://www.uber.com/newsroom/10-billion/>. Accessed on Jan 15, 2019.
- Uber. *Introducing Ride Pass: A new way to plan your day (and budget) with Uber*. Oct 2018. Available at: <https://www.uber.com/newsroom/ride-pass/>. Accessed on Jan 15, 2019.
- Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D., 2003. User acceptance of information technology: Toward a unified view. *MIS quarterly*, pp.425-478.
- Vinayak, P., Dias, F.F., Astroza, S., Bhat, C.R., Pendyala, R.M. and Garikapati, V.M. Accounting for multi-dimensional dependencies among decision-makers within a generalized model framework: An application to understanding shared mobility service usage levels. *Transport Policy*, 72, 2018: 129-137.
- Wenzel, T., Rames, C., Kontou, E. and Henao, A., 2019. Travel and energy implications of ridesourcing service in Austin, Texas. *Transportation Research Part D: Transport and Environment*, 70, pp.18-34.
- Zmud, J., Sener, I.N. and Wagner, J., 2016. Self-driving vehicles: Determinants of adoption and conditions of usage. *Transportation Research Record*, 2565(1), pp.57-64.