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

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Abstract

Ride-hailing services have grown 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 because of 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 important 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 uses repeated cross-sectional data collected in 2015 and 2017 in the Puget Sound region to analyze the differential effects 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 binary probit-ordered probit model is estimated on the pooled dataset 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.

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 use has posted impressive gains over time. Ride-hailing services provide on-demand mobility and are often viewed in the realm of Mobility on Demand (MoD) where individuals purchase mobility on demand by the trip as opposed to owning and using their own private vehicle. The two largest providers of on-demand mobility in the United States, 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. 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 for by users through the convenience of a smartphone app (*1*).

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 several metropolitan area travel surveys (e.g., San Diego, Sacramento, Phoenix) in the United States, have indicated mode shares of less than 1% for ride-hailing services (*2*). While ride-hailing

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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 for transit and traditional taxi services (*3*), 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 (*3*) 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 use; growth in the use of these services has important implications for future transit investment, 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 neither readily available nor 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 might possibly have helped in the development of robust forecasts of ride-hailing mode usage. Ride-hailing service companies are understandably reluctant to share ridership data (for reasons of privacy and business competitiveness). 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 only 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 into 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 U.S. 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 therefore 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 toward ride-hailing modes and a 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 effect on the traditional taxi industry, particularly in places such as New York City, has had very significant economic and personal effects (*4, 5*); 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 because of 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 simultaneously control for variations in respondent characteristics across different surveys when examining changes in behavior over time.

The rest of the paper is organized as follows. The nest section 2 a brief literature review, focusing on demand for ride-hailing services and the general evolution of new technologies in the market. We then present the data description, followed by a detailed presentation of the modeling framework, behavioral considerations, and econometric methodology. Model estimation results are then described followed by concluding remarks and directions for future research.

Literature Review

Because of 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 ride-hailing is used), and the potential vehicle miles of travel (VMT) implications of ride-hailing modes (e.g., because of 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 therefore provide little behavioral insight into 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 relation to the true uptake in ride-hailing services.

In relation to 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 (*1, 6–9*). 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 of one or more of their household vehicles because of the availability of ride-hailing services. More recently, several studies have been conducted using survey data collected in the State of California, with a particular focus on millennials (*10–12*). The California survey incorporates a panel component aimed at capturing 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 dataset 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 (*13*) analyzed data collected from a sample of commuters in the Dallas-Fort Worth area to identify the psycho-social influencers that motivate the 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). Therefore, a few studies have explored alternative data sources to better understand ride-hailing usage patterns. For example, Kooti et al. (*14*) 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 their 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. (*15*) 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) constituted approximately 37% and 50% of ride-hailing drivers' miles driven and travel time, respectively (*15–17*). Dias et al. (*16*) 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. (*18*) explored the RideAustin trip data to analyze the energy implications of ride-hailing; they estimated that empty trips between servicing rides accounted for 26% of total ride-hailing VMT and the net effect of ride-hailing on energy use is a 41% to 90% increase compared with baseline, pre-TNC, personal travel.

The studies mentioned above provide rich insights into the nature of ride-hailing trips and empty VMT. The reader is also referred to Tirachini (*19*) for a more exhaustive review of ride-hailing studies, both in the U.S. and internationally. However, to our knowledge, no study has explored the temporal behavioral dynamics of ride-hailing use. Of course, the study of changes in traveler behavior over time relates to considerations of the temporal stability (or not) of behaviors, which has been examined extensively within the broad context of temporal transferability of travel demand models (see (*20*) for an exhaustive review of such temporal transferability studies). Some other studies examine travel behavior variability without necessarily tying to transferability, including Marchetti (*21*), Meyer (*22*), Wu et al. (*23*), Miller and Shalaby (*24*), Sharaby and Shiftan (*25*), Zhao et al. (*26*), and Abenoza et al. (*27*). But none of these studies examines the relatively new phenomenon of travel behavior changes over time in relation to ride-hailing use. In an attempt to address the issue of how ride-hailing affects user behavior, Young et al. (*28*) focused on the twenty business trips made to Columbus, Ohio by one single individual, splitting the trips into two groups according to what the individual used as the primary mode of transportation: rental car or ride-hailing service. In their study, the authors analyze the individual's business expense reports, which contain data on the individual's vehicle miles traveled, their cost of transportation, and their daily work routines. While the analysis presented by Young et al. (*28*) focuses on how this one single individual changed travel behaviors when using ride-hailing services (compared with when the individual used car rental services), it does not provide any information on the temporal change in ride-hailing use. Furthermore, as noted by the authors, the study's focus on one single individual's business trips limits how generalizable the results may be. In comparison, the study we present in this paper uses multi-year cross-sectional data with a significantly larger sample size and focuses explicitly on the temporal change in ride-hailing use.

While studies on the temporal evolution of ride-hailing behavior at the individual level have not been undertaken thus far, the growth in ride-hailing usage is well documented in relation to aggregate trends (*3*). 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 (*3*). Other anecdotal information also points to the dramatic growth in ride-hailing services: it took Uber six years to serve its first billion rides and just six more months to serve its second billion (*29, 30*).

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 several theoretical paradigms and models that intend to explain the adoption and use of (new) technologies over time. Ride-hailing companies have been expending considerable resources to enhance adoption and use of the technology by implementing strategies, partnerships, service amenities, and incentives. Both Uber and Lyft have introduced monthly subscription services that avoid the need for pay-per-trip; the companies are partnering with transit agencies to complement transit services; and they are partnering with employers to provide special pricing and rider programs for employees (*31, 32*). As the ride-hailing product is continuously enhanced, population socio-demographics evolve, and attitudes toward 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 to 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 uses 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.

Data

Ride-hailing services were introduced in the Puget Sound region in 2011 (*33*). In this study, ride-hailing use is analyzed by pooling data from the 2015 and 2017 Puget Sound Regional Household Travel Surveys conducted by the Puget Sound Regional Council (*34, 35*). The data collection process, the assembly of the pooled data, and the data sample characteristics are described in this section of the paper.

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 socioeconomic, 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; and
- 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 toward autonomous vehicles; and preferences in relation to 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), email, telephone calls, and Facebook ads (the Facebook ads were only used in 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 response 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 (a small pilot smartphone app retrieval was also trialed in 2015, but these households are not included in the publicly available 2015 data). 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-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 in specific geographic areas, 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 because of 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 [*8*], Lavieri and Bhat [*13*], and Alemi et al. [*10*]), 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.

Descriptive Statistics

In this study, we only used the first and third sections of the survey (i.e., we did not use the second section, which constituted the travel diary portion of the survey). The survey datasets from 2015 and 2017 were reconciled (with respect to variable definitions and coding) and then merged to produce a pooled dataset 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 dataset included 8,542 observations, of which 3,800 belonged to the 2015 survey and 4,742 to the 2017

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

	Sample			PSR		Sample			PSR
Variables	2015	2017	Total	2017	Variables	2015	2017	Total	2017
Gender					Household size				
Male	45.8%	49.1%	47.6%	50.0%	1 person	23.1%	24.2%	23.7%	27.4%
Female	54.2%	50.9%	52.4%	50.0%	2 people	45.2%	49.5%	47.6%	35.0%
Age					3 or more people	31.7%	26.3%	28.7%	37.6%
18–24[a]	5.2%	6.6%	6.0%	8.6%	Education				
25–34	18.9%	32.2%	26.3%	20.6%	Less than high school	1.9%	1.3%	1.6%	8.4%
35–44	16.6%	21.4%	19.3%	18.1%	High school graduate	9.1%	5.5%	7.1%	21.8%
45–54	15.8%	12.7%	14.1%	18.0%	Vocational/technical training	3.7%	2.3%	2.9%	na
55–64	20.2%	12.4%	15.9%	16.9%	Some college	15.3%	10.6%	12.7%	33.6%
65–74	15.2%	10.3%	12.5%	10.7%	Associates degree	6.8%	5.7%	6.2%	
75–84	6.4%	3.7%	4.9%	4.8%	Bachelor's degree	36.4%	41.7%	39.3%	23.3%
85 or older	1.7%	0.7%	1.0%	2.3%	Graduate/post-graduate degree	26.8%	32.9%	30.2%	12.9%
Has a smartphone[b]					Employment				
No	29.4%	9.8%	18.5%	22.4%	Employed full-time (paid)	46.5%	57.8%	52.8%	74.1%
Yes	70.6%	90.2%	81.5%	77.6%	Employed part-time (paid)	9.1%	8.0%	8.5%	
Has a valid driver's license					Self-employed	6.6%	6.5%	6.5%	
No	7.7%	7.1%	7.3%	na	Unpaid volunteer or intern	1.2%	0.8%	1.0%	
Yes	92.3%	92.9%	92.7%	na	Homemaker	5.9%	5.1%	5.5%	25.9%
Household vehicle ownership					Retired	23.8%	13.9%	18.3%	
0 vehicles	9.5%	12.5%	11.2%	7.5%	Not currently employed	6.9%	7.9%	7.4%	
1 vehicle	34.4%	43.5%	39.5%	31.1%	Frequency of ride-hailing				
2 vehicles	38.6%	33.7%	35.9%	38.2%	Never	87.1%	51.8%	67.5%	na
3 or more vehicles	17.5%	10.3%	13.4%	23.2%	Less than 1 day per month	5.3%	19.0%	12.9%	na
Household income					1–3 days per month	4.8%	18.8%	12.6%	na
Under $25,000	11.4%	9.4%	10.3%	14.9%	1 day per week	1.8%	5.2%	3.7%	na
$25,000–$49,999	18.3%	13.7%	15.8%	18.3%	2–4 days per week	0.7%	4.4%	2.8%	na
$50,000–$74,999	15.7%	15.1%	15.3%	17.4%	5 days per week	0.1%	0.6%	0.4%	na
$75,000–$99,999	16.0%	14.2%	15.0%	13.8%	6–7 days per week	0.2%	0.2%	0.1%	na
$100,000 or more	38.6%	47.6%	43.6%	35.6%					
Observations (n)	3,800	4,742	8,542	na	Observations (%)	44.5%	55.5%	100.0%	na

Note: PSR = puget sound region; PSRC = Puget Sound Regional Council; na = not applicable.
[a]This row does not contain individuals aged 18 and 19 for the "PSR 2017" column. This is because of minor data incompatibility issues between the PSRC surveys and the census data.
[b]The smartphone ownership data in the "Sample" columns refer to individual-level smartphone ownership. However, the "PSR 2017" column refers to household-level smartphone ownership.

survey. Descriptive statistics for these samples of individuals can be found in Table 1, which also contains data from the entire Puget Sound region, according to the 2017 American Community Survey (*36*).

Some of the differences between the two surveys are worth noting. The 2017 dataset 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 between 25 and 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 percentage of individuals who responded to the 2015 survey did not have the technology required to use the on-demand mobility services.

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 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 vehicle 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

Table 2. Cross-Tabulation of Smartphone Ownership and Frequency of Ride-Hailing ($n = 8{,}542$)

		Owns a smartphone								
		2015			2017			Total		
	Frequency of ride-hailing	Yes	No	Total	Yes	No	Total	Yes	No	Total
Number of observations	Never	2,207	1,104	3,311	2,036	418	2,454	4,243	1,522	5,765
	Less than 1 day per month	196	7	203	877	22	899	1,073	29	1,102
	1–3 times per month	179	4	183	878	15	893	1,057	19	1,076
	1 day per week	67	1	68	242	3	245	309	4	313
	2–4 days per week	27	0	27	206	3	209	233	3	236
	5 days per week	3	0	3	27	1	28	30	1	31
	6–7 days per week	5	0	5	13	1	14	18	1	19
	Total	2,684	1,116	3,800	4,279	463	4,742	6,963	1,579	8,542
Column-wise percentages	Never	82.2%	98.9%	87.2%	47.6%	90.4%	51.7%	61.0%	96.3%	67.4%
	Less than 1 day per month	7.3%	0.6%	5.3%	20.5%	4.8%	19.0%	15.4%	1.8%	12.9%
	1–3 times per month	6.7%	0.4%	4.8%	20.5%	3.2%	18.8%	15.2%	1.2%	12.6%
	1 day per week	2.5%	0.1%	1.8%	5.7%	0.6%	5.2%	4.4%	0.3%	3.7%
	2–4 days per week	1.0%	0.0%	0.7%	4.8%	0.6%	4.4%	3.3%	0.2%	2.8%
	5 days per week	0.1%	0.0%	0.1%	0.6%	0.2%	0.6%	0.4%	0.1%	0.4%
	6–7 days per week	0.2%	0.0%	0.1%	0.3%	0.2%	0.3%	0.3%	0.1%	0.2%
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Column-wise percentages	Never	66.7%	33.3%	100.0%	83.0%	17.0%	100.0%	73.6%	26.4%	100.0%
	Less than 1 day per month	96.6%	3.4%	100.0%	97.6%	2.4%	100.0%	97.4%	2.6%	100.0%
	1–3 times per month	97.8%	2.2%	100.0%	98.3%	1.7%	100.0%	98.2%	1.8%	100.0%
	1 day per week	98.5%	1.5%	100.0%	98.8%	1.2%	100.0%	98.7%	1.3%	100.0%
	2–4 days per week	100.0%	0.0%	100.0%	98.6%	1.4%	100.0%	98.7%	1.3%	100.0%
	5 days per week	100.0%	0.0%	100.0%	96.4%	3.6%	100.0%	96.8%	3.2%	100.0%
	6–7 days per week	100.0%	0.0%	100.0%	92.9%	7.1%	100.0%	94.7%	5.3%	100.0%
	Total	70.6%	29.4%	100.0%	90.2%	9.8%	100.0%	81.5%	18.5%	100.0%

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 living in households with 2 or fewer people and a decrease in the share of respondents living in households with 3 or more people. The shift in income levels is also in line with differences 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. Furthermore, 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 residents and vehicles and are more likely to own a smartphone (compared with 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. It is commonly thought that smartphone ownership has a deterministic relationship with access to ride-hailing (i.e., if an individual does not have a smartphone, their frequency of ride-hailing will be "Never"). However, the data in Table 2 reveal that this is not entirely true. While smartphone ownership does seem to be associated with higher frequencies of ride-hailing use, there are still individuals in the sample who do not own smartphones and who still use ride-hailing services. This is likely because individuals without smartphones can gain access to ride-hailing services through friends, co-workers and family members (e.g., traveling in a ride-hailing vehicle that was hailed by someone else).

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 because of several 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.

Methodology

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 because of respondent's characteristics and the passage of time, the modeling approach teases out any potential confounding effects because of sampling differences between the years and isolates effects of respondent characteristics from the "true" change over time.

The third factor—the "true" change over time—may have three causes. 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 (*37, 38*). 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.

Motivation for Modeling Structure

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 that had higher incomes and that were more educated and younger than those in 2015. If the differences between 2015 and 2017 respondents can be completely attributed to such observed variables (that is, observed heterogeneity in the two pools of respondents) 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 (we will refer to this as unobserved heterogeneity in the two pools of 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 affects ride-hailing use. However, it is conceivable that there are several other such factors or combinations of factors that are unobserved and affect ride-hailing usage (*13*).

The Model

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. The first dependent binary outcome in the model, y_{q1}, corresponds to whether an individual q belongs to the 2017 dataset ($y_{q1} = 1$) or the 2015 dataset ($y_{q1} = 0$), with a latent propensity of belonging to the 2017 dataset (denoted by y^*_{q1}) mapping to the observed outcome, y_{q1}, in the usual binary choice framework:

$$y^*_{q1} = \boldsymbol{\beta}'_1 \mathbf{x}_{q1} + \varepsilon_{q1}, \qquad y_{q1} = \begin{cases} 0 & if \quad y^*_{q1} \leq 0 \\ 1 & if \quad y^*_{q1} > 0 \end{cases} \tag{1}$$

where

the vector $\mathbf{x}_{q1}$ represents a set of observed exogenous individual-level (demographic and other) variables,

the corresponding vector of coefficients $\boldsymbol{\beta}_1$ captures the differences in observed individual characteristics between the pools of respondents in 2017 and 2015, and

the error term ε_{q1} in this binary dependent variable equation captures differences in unobserved characteristics between 2017 respondents and 2015 respondents (as indicated in the previous section, one of the reasons for this difference may be attributed to the 2017 pool comprising a higher share of individuals who are very tech-savvy, 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 (the five aggregated frequency categories are: "Never," "Less than 1 day per month," "1–3 days per month," "1 day per week," and "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). When modeling this second outcome, in the usual framework of an ordered-response equation, we consider an underlying continuous propensity (y^*_{q2}) for ride-hailing that gets mapped onto the observed ordinal category of the frequency of ride-hailing, y_{q2}, through a set a thresholds ψ_n ($n = 1,2,3,\ldots,N;\ N = 5$ in our analysis) to be estimated. For usual identification purposes, we set $\psi_0 = -\infty$ and $\psi_N = \infty$. The form of this second equation is as follows:

$$y^*_{q2} = \boldsymbol{\beta}_2'\mathbf{x}_{q2} + \delta y_{q1} + (\boldsymbol{\gamma}'\mathbf{z}_{q2})y_{q1} + \varepsilon_{q2},$$
$$y_{q2} = n \ \text{ if } \psi_{n-1} < y^*_{q2} < \psi_n,\ \psi_0 = -\infty,\ \psi_N = \infty \qquad (2)$$

As can be observed from above, the underlying propensity y^*_{q2} is specified to be a linear function of three components: (a) observed individual socio-demographics and other characteristics (represented by the $\mathbf{x}_{q2}$ vector) and whose effects are captured by the corresponding $\boldsymbol{\beta}_2$ vector; (b) a 2017 dummy variable shifter term capturing intrinsic differences in ride-hailing propensity between 2017 respondents and 2015 respondents, captured by the δy_{q1} term; and (c) individual demographics interacted with the 2017 dummy variable to accommodate for the difference in ride-hailing propensity across socio-demographic groups between the two years, captured by the $(\boldsymbol{\gamma}'\mathbf{z}_{q2})y_{q1}$ ($\boldsymbol{\gamma}$ is a coefficient vector to be estimated on an exogenous vector $\mathbf{z}_{q2}$, which need not necessarily comprise the same elements as $\mathbf{x}_{q2}$). The underlying continuous propensity is also specified to be stochastic through an error term, ε_{q2}, that captures the influence of unobserved characteristics on the propensity of ride-hailing. Our simultaneous equations model allows this error term to be correlated with the error term ε_{q1} in the first binary equation. As alluded to earlier, this correlation captures unobserved individual factors that make an individual more likely to be represented in the 2017 pool relative to the 2015 pool as well as make an individual have a higher propensity for ride-hailing (such an unobserved individual effect, for example, may be tech-savviness).

In summary, with this two-equation joint framework, the coefficient vector $\boldsymbol{\beta}_2$ in Equation 2 on individual demographics represents the vector of "true" effects of demographics on ride-hailing propensity in 2015. The 2017 dummy variable shifter term δ captures the "true" evolutionary difference in ride-hailing propensity for a base demographic group not appearing in interaction terms of the 2017 dummy variable with individual exogenous variables. Lastly, the interaction terms of the 2017 dummy variable with individual exogenous variables, $\boldsymbol{\gamma}'\mathbf{z}_{q2}$, essentially capture heterogeneity (across demographic groups) in the "true" evolutionary shifts in ride-hailing propensity between 2015 and 2017. All these effects are "cleansed" and "true" effects because we recognize associative effects because of the correlation in unobserved factors between the first binary and second ordinal equations. Our approach 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 rather unique application of this framework to control for unobserved factors across surveys. Note that, for estimation, we assume that each of the error terms ε_{q1} and ε_{q2} are standard normally distributed. The model is a classic switching ordered-response model system. We refer the reader to Greene and Hensher (*39*) for estimation details, which is relatively straightforward using the maximum likelihood inference approach.

Computing Average Treatment Effects

After estimating the model, it is possible to analyze each variable's ATE, that is, the direct effects 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 during estimation to obtain "true" variable effects on the "frequency of ride-hailing" ordinal outcome and, therefore, the ATE effects from the first binary equation 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; and
(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; and
- 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 from the global 2015 dataset. Using Equation 3, we 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.

Model Results

Model estimation results are presented in Table 3. The first equation in the joint model primarily serves as a mechanism for controlling sample selection. This is labeled as "Outcome 1" in Table 3, and the results for this equation are provided in the first numeric column of Table 3. Overall, the model coefficients for this equation reflect the results from our 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 because of observed characteristics at play. By specifying and estimating a simultaneous equations model that accommodates error correlation, we also account for possible *unobserved* sample-selection effects as well. The correlation coefficient between the two error terms is 0.431 (with a t-statistic of 8.598), indicating the clear presence of sample selection. This clearly shows 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 affect propensity to participate in the 2017 version of the survey and

Table 3. Joint Model Estimation Results

			Outcome 2: frequency of ride-hailing			
	Outcome 1: belongs to 2017		Base (2015)		Interactions (2017)	
Parameter	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Gender (base: Male)	na	na	na	na	na	na
Female	−0.081	−2.935	na	na	na	na
Age (base: 18–34 years)	na	na	na	na	na	na
35–44 years	−0.114	−2.768	−0.421	−7.171	0.158	2.418
45–54 years	−0.286	−8.379	−0.803	−12.591		
55–64 years			−1.073	−15.505		
65 years or older			−1.375	−10.799	0.525	3.786
Has a smartphone (base: No)	na	na	na	na	na	na
Yes	0.693	17.068	1.039	15.495	na	na
Has valid driver's license (base: No)	na	na	na	na	na	na
Yes	na	na	0.104	1.809	na	na
Household vehicle ownership (base: No vehicles)	na	na	na	na	na	na
1 vehicle	−0.174	−3.551	−0.463	−9.896	na	na
2 or more vehicles	−0.521	−10.312	−0.981	−13.676	0.176	2.542
Household income (base: Under $50,000)	na	na	na	na	na	na
$50,000–$99,999	0.105	2.614	0.273	3.558	−0.203	−2.294
$100,000 or more	0.237	5.807	0.598	7.828	−0.231	−2.619
Household size (base: Single-person household)	na	na	na	na	na	na
Multi-person household	na	na	−0.279	−3.712	0.179	2.066
Education (base: Does not have a bachelor's degree)	na	na	na	na	na	na
Has a bachelor's degree or higher	0.147	4.536	0.406	6.423	−0.172	−2.384
Employment (base: Unemployed)	na	na	na	na	na	na
Employed part-time	na	na	na	na	0.193	2.899
Employed full-time	na	na	0.322	8.528	na	na
Self-employed	na	na			na	na
Year (base: 2015)	Coef.	t-stat	Coef.		t-stat	
2017	na	na	na		na	
Thresholds	Coef.	t-stat	Coef.		t-stat	
Threshold 1	0.132	2.142	1.009		11.403	
Threshold 2	na	na	1.528		17.443	
Threshold 3	na	na	2.27		25.89	
Threshold 4	na	na	2.676		30.052	

Note: na = not applicable. Number of observations: 8,542. Number of parameters: 35. Null log-likelihood (only thresholds): –15,831. Independent log-likelihood (no correlation): –12,588. Full log-likelihood: –12,558. Likelihood ratio: Full versus Null (*p*-value): 6,546 (0.000). Likelihood ratio: Full versus Independent (*p*-value): 60 (0.000). Pseudo Rho Squared: 0.207. Adjusted Pseudo Rho Squared: 0.205.

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).

In the rest of this section, and because it is the primary outcome of interest, the focus of our discussion is on the results for the frequency of ride-hailing.

Joint Model Estimation Results

The second numeric column of Table 3 provides the results for the frequency of ride-hailing use. The coefficients presented provide the effect of variables on the underlying latent propensity for ride-hailing use. 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 3 refers to the effects of the explanatory variables on an individual's underlying propensity to use ride-hailing in 2015, while the "Interaction (2017)" column represents the changes of those effects from 2015 to 2017. As may be noted from Table 3, the latter column involves only interaction effects of the dummy variable with demographics, with the dummy variable (the second component in Equation 2 in Section 4.1 by itself not appearing as a separate variable). This was because, based on our empirical analysis, the dominant effect of being in the 2017 pool (relative to the 2015 pool of respondents) on the underlying ride-hailing propensity use was captured through variations across demographic groups, not as a generic shifter in the underlying propensity across the two years.

There is a noteworthy overarching result: the effects 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. (*6*), Dias et al. (*1*), Lavieri et al. (*8*), Kooti et al. (*14*), Vinayak et al. (*9*), Alemi et al. (*10*), and Lavieri and Bhat (*13*). The extensive use of interactions complicates the interpretation of the results for the 2017 year from Table 3. Therefore, we leave the discussion of the temporal behavioral dynamics to later, where we directly analyze the effects of each variable on individuals' actual number of ride-hailing trips per month. But one important observation from the interaction effects is this. Whenever a variable appears in both the base (2015) effect column as well as the interaction (2017) effect column for the "frequency of ride-hailing" outcome variable, the signs of the coefficients are reversed between the two columns, and the magnitude of the coefficients in the interaction (2017) column is lower than that of the base (2015) effect column. This has a clear implication that the differences that exist across demographics in 2015 in the context of ride-hailing frequency are being substantially tempered in 2017. That is, over time, between the two years, there appears to be much less heterogeneity in the population in the use of ride-hailing. We return to this point later.

The improvement in model fit gained by using a joint approach is also discernible from the likelihood ratios displayed at the bottom of Table 3 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 –12,558, –12,588, 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 into 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 is 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.

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 ATEs, it is possible to obtain a clearer picture of the changes in ride-hailing trip frequency for different demographic groups. Table 4 presents the results of the ATE calculations. Four sets of results are presented in Table 4: "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. Note that these findings constitute "true" treatment effects after controlling for any sample-selection effects—both because of observed and unobserved attributes.

- *Across Demographics within 2015*: Those aged 35–44 years made, on average, 0.905 fewer ride-hailing trips per month (compared with those 18–34 years) in 2015.
- *Across Demographics within 2017*: Those aged 35–44 years made, on average, 0.943 fewer ride-hailing trips per month (compared with those aged 18–34 years) in 2017.
- *Across Demographics from 2015 to 2017*: Those aged 35–44 years in 2017 made, on average, 0.915 fewer ride-hailing trips per month than those aged 18–34 years in 2015.
- *Within Demographics from 2015 to 2017*: Those aged 35–44 years in 2017 made, on average, 0.010 fewer ride-hailing trips per month than individuals aged 35–44 years in 2015.

Table 4. Average Treatment Effects of Variables on Ride-Hailing Trips per Month

	Across demographics						Within demographics	
	Within 2015		Within 2017		From 2015 to 2017		From 2015 to 2017	
Parameter	ATE	*t*-stat	ATE	*t*-stat	ATE	*t*-stat	ATE	*t*-stat
Gender								
Male (base)	na	na	na	na	na	na	0.031	0.904
Female	na	na	na	na	0.031	0.904	0.031	0.904
Age								
18–34 years (base)	na	na	na	na	na	na	0.028	0.580
35–44 years	−0.905	−49.447	−0.943	−33.238	−0.915	−29.061	−0.010	−0.335
45–54 years	−1.296	−73.367	−1.342	−51.655	−1.313	−42.145	−0.017	−0.916
55–64 years	−1.503	−81.365	−1.548	−51.807	−1.519	−55.561	−0.016	−1.260
65 years or older	−1.631	−82.335	−1.322	−62.202	−1.294	−36.074	0.338	15.165
Has a smartphone								
No (base)	na	na	na	na	na	na	−0.005	−0.615
Yes	0.813	30.449	0.868	137.848	0.863	71.617	0.050	1.400
Has valid driver's license								
No (base)	na	na	na	na	na	na	0.017	0.585
Yes	0.207	12.875	0.222	12.985	0.239	5.655	0.033	0.958
Household vehicle ownership								
No vehicles (base)	na	na	na	na	na	na	0.101	1.217
1 vehicle	−0.803	−16.838	−0.864	−37.089	−0.763	−7.682	0.040	0.733
2 or more vehicles	−1.366	−17.699	−1.410	−90.076	−1.309	−15.247	0.057	4.405
Household income								
Under $50,000 (base)	na	na	na	na	na	na	0.174	8.352
$50,000–$99,999	0.168	6.430	0.075	10.110	0.249	12.253	0.081	1.853
$100,000 or more	0.747	30.451	0.475	42.951	0.649	42.084	−0.098	−2.715
Household size								
Single-person household (base)	na	na	na	na	na	na	−0.398	−28.398
Multi-person household	−0.610	−20.273	−0.049	−3.167	−0.447	−21.199	0.163	3.813
Education								
No bachelor's degree (base)	na	na	na	na	na	na	0.137	6.968
Bachelor's degree or higher	0.518	36.998	0.398	32.721	0.535	17.758	0.017	0.444
Employment								
Unemployed (base)	na	na	na	na	na	na	0.010	0.390
Employed part-time	na	na	0.234	17.607	0.244	8.008	0.244	8.008
Employed full-time	0.379	31.133	0.405	74.920	0.415	15.559	0.036	0.972
Self-employed	0.379	31.133	0.405	74.920	0.415	15.559	0.036	0.972

Note: na = not applicable; ATE = average treatment effect; t-stat = t-statistic.

Gender did not play a significant role in influencing frequency of ride-hailing. This could be an indication that ride-hailing companies in the Puget Sound region have successfully addressed concerns about personal safety for women (for example, a service called Safr caters exclusively to female riders and employs exclusively female drivers).

Several studies have previously documented that older age groups are associated with a lower level of ride-hailing use (e.g., *1, 6, 14*). But our findings show a reduction in age-related differences over time. It is also interesting that the isolated effect of the passage of time (as observed in the column labeled "Within demographics - From 2015 to 2017" in Table 4) is strongest for the oldest demographic segment of those over 65 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 the marketing efforts of ride-hailing companies. The results here suggest that the effects of age softening when it comes to adoption and use of ride-hailing use over time.

Smartphone ownership is significantly associated with ride-hailing adoption and usage. In 2015, individuals who owned a smartphone made, on average, 0.812 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 7% (to 0.868 trips per month). As expected, individuals without smartphones were the least affected group (in relation to 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 0.050 trips per month (on average). As smartphone ownership increases, ride-hailing service use is also likely to increase. The Pew Research Center (*40*) reports that, between 2015 and 2017, smartphone market penetration increased from 67% to 72% in the United States.

The effect of having a driver's license 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 with those who do not) made about 0.2 more ride-hailing trips per month in both 2015 and 2017.

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 with zero-vehicle households) made an average of 1.366 fewer ride-hailing trips per month. In 2017, this difference increased modestly to 1.410 trips per month. In the last column, it can be observed that all car-ownership levels increased ride-hailing use, but the increase is greatest for zero-vehicle households and smallest for one-vehicle households.

Another variable—arguably the most important one from an equity and environmental justice standpoint—worthy of discussion is household income. Similar to Kooti et al. (*14*), Dias et al. (*1*), and Alemi et al. (*10*), it is found that higher income levels were associated with higher frequencies of ride-hailing in both 2015 and 2017. However, the differences between income groups faded significantly (although some differences clearly remain). In 2015, individuals in households with income between \$50k and \$99k reported, on average, 0.168 more ride-hailing trips per month than those in households earning under \$50k. The corresponding value for the highest income group (\$100k or more) is 0.747. In 2017, the differences reduced quite dramatically; those in the household income segment of between \$50k and \$99k showed almost the same level of usage as the lowest income group (under \$50k), while the highest income group (\$100k or over) showed a more modest 0.475 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.

A dampening of differences in ride-hailing use is exhibited in the effects of household size (structure). In 2015, individuals in multi-person households made about 0.610 fewer trips per month than singe persons. In 2017, that difference reduced to a mere 0.049 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 modes (including micro-mobility options, such as e-scooters), whereas individuals in multi-person households may gravitate more toward 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.

Higher levels of education are associated with higher ride-hailing trip rates in both years, and the passage of time from 2015 to 2017 seems to have 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 2017 is approximately 27% smaller than what it was in 2015. Furthermore, individuals without bachelor's degrees seem to have increased their frequency of ride-hailing over time while their more educated counterparts have not.

Employment is another variable where differences appear to have softened over time. In 2015, employed individuals (full-time and self-employed) engaged in about 0.379 more ride-hailing trips per month than unemployed or part-time employed individuals. In 2017, this difference increased to about 0.405 for full-time employed individuals relative to unemployed individuals. However, part-time employed individuals increased their usage 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, did 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. 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 the 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 trips 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.

Conclusion

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 could 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 binary probit-ordered probit model, in which the first dependent 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 ATEs of different variables on ride-hailing frequency.

The results show that several demographic variables play a significant role in determining the 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, between 2015 and 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. Several 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 influences (e.g., family, friends, and co-workers) are 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 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 because of ride-hailing vehicles clogging roadways.

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 in 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.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: F.F. Dias, T. Kim, C.R. Bhat, R.M. Pendyala, W.H.K. Lam, A.R. Pinjari, K.K. Srinivasan, G. Ramadurai; data collection: PSRC; analysis and interpretation of results: F.F. Dias, T. Kim, C.R. Bhat, R.M. Pendyala, W.H.K. Lam, A.R. Pinjari, K.K. Srinivasan, G. Ramadurai; draft manuscript preparation: F.F. Dias, T. Kim, C.R. Bhat, R.M. Pendyala, W.H.K. Lam, A.R. Pinjari, K.K. Srinivasan, G. Ramadurai. All authors reviewed the results and approved the final version of the manuscript.

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