ICT's Impacts on Ride-hailing Use and Individual Travel

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Abstract

Previous studies have explored the relationships between an individual's use of information and communication technology (ICT) and their travel. However, these studies often focus on one specific type of travel and have not considered new forms of mobility, such as ride-hailing, that are enabled by greater ICT penetration. This paper focuses on how ICT use impacts an individual's self-reported travel behavior—including total number of trips, personal miles traveled (PMT), and vehicle miles traveled (VMT) in a typical travel day—and ride-hailing use in the past month. Specifically, we investigate whether substitution or complementarity dominates the relationships between ICT use and an individual's net travel; how ICT impacts individual ride-hailing adoption and frequency of use; and how ride-hailing use is associated with an individual's overall travel behavior. Using data from the 2017 U.S. National Household Travel Survey (NHTS), we estimate a structural equation model that includes a robust set of individual, household, built environment, and travel characteristics, frequency of ICT use, and a hurdle model (two-part regression) of the adoption and frequency of ride-hailing use. Results reveal that greater ICT is not significantly related to the total number of trips that an individual takes, but it does significantly predict higher PMT and VMT. Greater ICT use is positively and substantively correlated with whether or not the individual has used ride-hailing in the past 30 days, but has no significant relationship with the frequency of ride-hailing use with this bounded outcome being controlled for. We further find that an individual's ride-hailing use has a small negative correlation with their PMT and VMT after controlling for other common factors. Our results indicate the importance of future research examining the mechanisms by which ICT use increases the distance individuals travel and the role that new ICT-enabled modes, such as ride-hailing, play in changing these mechanisms at both the individual and system levels.

Keywords: ICT; ride-hailing use; individual travel; hurdle model

1. Introduction

As information and communications technology (ICT)—including the Internet, wireless networks, computers, and cell phones—becomes ever more prevalent in the U.S., a growing body of research has explored its impacts on travel. Understanding the impact of ICT use on travel is complicated by the fact that ICT use can be measured in different ways, and its impacts on travel behavior can be explored from multiple perspectives (system, household, or individual). In this paper, we adopt a measure of ICT use derived from an individual's frequency of Internet use via three different devices: smartphone, tablet, and personal computer. We then explore how this measure of ICT use predicts an individual's travel behavior across all types of trips.

At the individual-level, theory suggests that ICT use can interact with travel through multiple mechanisms (Salomon, 2000; 1986; Mokhtarian, 2002; 1990):

1. *Substitution*: the need for individual travel is reduced by ICT use, as some location-based activities are substituted by ICT-based counterparts (e.g., telecommuting),
2. *Complementarity/generation*: ICT inspires new location-based activities, new forms of mobility, or improves productive use of travel time. By reducing barriers to travel or creating new reasons or means to travel, complementarity increases individual travel,
3. *Modification*: ICT does not affect the amount that an individual travels, but alters existing travel behaviors in different ways through trip timing, trip chaining, activity sequencing, choice of travel mode, etc., and
4. *Neutrality*: ICT leads to no change in travel.

And while significant work has explored each of these mechanisms for specific types of trips or specific (mainly metropolitan) populations, few studies have explored the cumulative impacts of these mechanisms in the United States. In this paper, we consider the net impact of ICT use on all of an individual's travel—including the number of trips made and person- and vehicle- miles traveled—for a representative sample of the entire U.S. population using data from the 2017 National Household Travel Survey (NHTS). This allows us to determine whether substitution or complementarity is the dominating relationship between ICT use and individual travel; in other words, whether greater ICT use predicts more or less individual travel.

In addition, we explore how ICT use interacts with an individual's use of new ride-hailing services provided by a Transport Network Company like Uber or Lyft.[1] Compared to other forms of travel, ride-hailing relies most heavily on an individual's access to ICT since smartphone applications are the primary mechanism by which individuals are exposed to and access these transport services. Therefore, this paper includes specific investigation into ride-hailing use when exploring the impacts of ICT use on individual travel.

This paper focuses on how ICT use impacts an individual's travel behavior, in general, and ride-hailing use, in particular. Using a structural equation modeling approach, we investigate three interrelated research questions: (1) Does substitution or complementarity dominate the relationships between ICT use and an individual's overall travel? (2) How does ICT use impact individual ride-hailing adoption and frequency of use? (3) How is ride-hailing use associated

[1] This paper does not distinguish between private ride-hailing services like UberX or Lyft Classic and pooled ride-hailing services like UberPOOL and Lyft Shared.

with an individual's overall travel behavior, after controlling for ICT use and other common factors?

The rest of the paper is organized as follows. Section 2 reviews previous studies on ICT use and travel behavior, with a focus on individual-level impacts. Section 3 describes the data used in this study and the analytic approach. Section 4 presents and discusses the modeling results in order of our three research questions. We conclude with Section 5, which summarizes our findings, discusses their potential policy implications, and lays out directions for future research.

2. Literature review

2.1 ICT and individual travel

At the individual-level, theory suggests that ICT use can interact with travel through multiple mechanism: substitution (leading to a decrease in travel), complementarity (leading to an increase in travel), or modification or neutrality (leading to no change in overall travel) (Salomon, 2000; 1986; Mokhtarian, 2002; 1990). Of these mechanisms, substitution and complementarity have received the greatest attention in the literature, with many studies empirically demonstrating the presence of substitution, complementarity, or both in the relationship between specific types of ICT use and specific types of trips, such as telecommuting, teleshopping, or teleleisure. In this study, we complement existing literature by conducting an empirical study looking at how frequency of ICT use across various platforms (smartphone, tablet, and computer) relates to an individual's total travel for a dataset representative of the entire U.S. population.

2.1.1 Substitution

Substitution stems from the fact that ICT offers alternative means of conducting activities. Replacing location-based activities with remote activities may eliminate the trips needed for an individual to engage in that activity (Nie et al., 2002; Salomon and Mokhtarian, 2008; Mokhtarian and Tal, 2013). For example, telecommuting enables working at home or other alternative workplaces, teleshopping provides alternatives to shopping without visiting a store, and teleleisure enables people to conduct leisure activities or meet with friends without traveling. Studies have confirmed that, under certain conditions, telecommuting and teleshopping can substitute for an individual's travel, resulting in lower personal vehicle-miles traveled.

When it comes to impacts of telecommuting and teleshopping on personal travel, many studies have found a negative correlation between telecommuting/teleshopping and vehicle miles traveled (VMT). Analysis of data from the California Pilot Telecommuting Project demonstrates a 20% reduction in travel for telecommuters over a 3-day period, a reduction of more than 40 personal vehicle-miles traveled on an average telecommuting day, and a 75% and 60% reduction of trips during morning-peak and evening-peak hours, respectively (Goulias and Pendyala, 1991; Pendyala et al., 1991; Kitamura et al., 1990). Using a subset of these same data, Koenig et al. (1996) found that, on a commuting day, telecommuters reduce their commute travel by 27% and VMT by 77%, and their non-commute VMT also decreased by 5.3 miles. Based on data from the Puget Sound Demonstration Project Henderson and Mokhtarian (1996) measured a reduction of 53.7% (or 34 miles) in VMT for telecommuters. In another study using data from the U.S. and the Netherlands, Mokhtarian et al. (1995) found that telecommuting resulted in reductions of 36.1 person-miles travelled and of 26.3 vehicle-miles traveled. Others, such as Mokhtarian

(1991), De Graaff (2004) and De Graaff and Rietveld (2007), also conclude that telecommuting does result in a weak substitution of travel at the individual level.

Studies on other applications of ICT also reveal the substitution of personal travel. For example, Luley et al. (2002) and Lenz (2003) found that e-shopping resulted in reduced frequency of total trips and shopping trips. Lyons et al. (2008) provide the evidence of ICT as a substitute for travel considering both teleworking and e-shopping; using an ordered regression model, Sasaki and Nishii (2010) find that when the number of telecommunication increases, the trip duration decreases, indicating a substitution effect between telecommunication and travel demand.

2.1.2 Complementarity

While substitution suggests that ICT use may reduce the need for personal travel, ICT use may also stimulate travel demand through the generation of new reasons or ways to travel. This complementarity has been demonstrated in several studies regarding telecommuting, teleshopping, or teleleisure.

When it comes to telecommuting, some studies have found that people who used home computer for work had greater daily travel distances, suggesting potential for complementarity rather than substitution when considering an individual's travel beyond their work-based trips (Hjorthol, 2002). Mokhtarian (1991) suggested that an individual who uses telecommuting may travel less for work, but their overall travel may increase if the multi-purpose trips previously chained with his/her commuting trip is divided into several single-purpose trips (Mokhtarian, 1991). Others find that ICT and virtual meetings fail to achieve the claimed benefits of reducing travel (Arnfalk and Kogg, 2003) and that greater ICT use is associated with more long-distance journeys due to the increase in distant contacts enabled by teleconferencing technologies and services (Larsen et al., 2007).

For teleshopping, the majority of studies suggest that complementarity may outweigh substitution. Gould et al. (1998) found that working women tend to spend the time saved by e-shopping on other out-of-home activities and generate more trips. Others have found that online shoppers make more shopping trips than those who do not shop online (Farag et al., 2007). In fact, online shopping may generate additional shopping trips at the individual level (Casas et al., 2001) partially because, in addition to shopping online, people may use ICT to search for a product or check its availability before traveling to buy it (Douma et al., 2003).

Other studies provide the conceptual framework (Mokhtarian et al., 2006) and initial empirical evidence for complementarity in teleleisure. Senbil and Kitamura (2003) find that greater use of cellular and home telephones is associated with more leisure-related travel. Wang and Law (2007) conclude that ICT use generates additional time that can be used for recreational activities and their associated travel. And other studies indicate that ICT may lead to activity fragmentation that requires individuals to reallocate time for leisure activities and travel (Ben-Elia et al., 2014; Lenz and Nobis, 2007).

2.1.3 The coexistence of substitution and complementarity

In all likelihood, substitution and complementarity coexist and interact differently for different types of trips or different ICT technologies. A comprehensive review of about 100 studies of the impacts of ICT on personal activities and travel behavior, found that substitution is more prevalent for telecommuting, while complementarity is more common for teleshopping and teleleisure (Andreev et al., 2010). Viswanathan and Goulias (2001) and Lee-Gosselin and

Miranda-Moreno (2009) demonstrated that Internet access/use was negatively associated with daily travel times and trip levels (suggesting substitution), while mobile technology is positively associated with travel and activity (suggesting complementarity). Srinivasan and Reddy Athuru (2004) demonstrate that ICT use (particularly Internet use) both substitutes and complements the total number of trips an individual makes using data from the 2000 Bay Area Travel Survey. Using data from the 2001 NHTS for the Baltimore metropolitan area, Zhang et al. (2007) estimate the impacts of ICT on VMT, total daily trips, and daily walking trips, finding the simultaneous existence of substitution and complementarity, with complementarity as the dominant mechanism.

2.2 Ride-hailing as a new, ICT-enabled mode

This study is the first to incorporate ride-hailing into the discussion of ICT and individual travel behavior. We explore how greater ICT use predicts not only ride-hailing adoption, but also frequency of ride-hailing use once the service is adopted. Additionally, among the studies that examine the associations between ride-hailing use and individual travel, this study is the first to control for use of ICT and individual travel characteristics (i.e. the percentage of trips accompanied by others, whether the individual is flexible about time) as control variables in the model, which have long been recognized as factors influencing ride-hailing use and travel behaviors.

2.2.1 ICT and ride-hailing use

Since ICT provides the technological foundation for ride-hailing services, it is likely that a positive relationship exists between ICT use and ride-hailing use. Initial studies noted that the demographics of the most frequent users or ride-hailing—younger, better-educated, higher-income, and urban individuals (Schaller, 2018; Clewlow and Mishra, 2017; Rayle et al., 2016; Smith, 2016)—generally match the profiles of ICT users (Poushter, 2017). This has sparked discussion about how unequal access to ICT and the requisite skills to use it, normally referred to as the "digital divide," could impact the use of ride-hailing services (Jin et al., 2018).

A few studies have demonstrated that there is a positive relationship between ICT and ride-hailing use for selected groups of people and geographic areas within the U.S. Alemi et al. (2018a, 2018b) found that Californian millennials who actively use social media (i.e., Facebook) and frequently use smartphones to assist their daily travel decision-making are more likely to use ride-hailing. Lavieri and Bhat (2019) revealed that 'technology savviness' is positively correlated with ride-hailing adoption. However, there is still a lack of empirical evidence on the relationship between an individual's level of ICT use and the frequency with which they use ride-hailing that appropriately accounts for the two-step decision-making process of ride-hailing adoption and then frequency of use.

2.2.2 Ride-hailing use and individual travel

Regarding the relationship between an individual's ride-hailing use and their overall travel, existing literature has found both positive and negative correlations. Ride-hailing users appear to own fewer vehicles and travel with more companions (via ride-sharing or ride-splitting), both of which might be associated with less individual (vehicle) travel (Rayle et al., 2016; Jacobson and King, 2009). However, ride-hailing users may also travel more because of the convenience brought about by this new ICT-enabled mode (i.e. induced demand). In fact, while surveys across U.S. cities indicate that most ride-hailing trips substitute trips by other modes, there is evidence that 3-22% of ride-hailing trips would not have been made if ride-hailing had not been available (Lavieri and Bhat, 2019; NYCDOT, 2018; Gehrke et al., 2018; Clewlow and Mishra, 2017; Henao, 2017; Rayle et al., 2016). It is also important to note that other factors, such as the built environment, individual attitudes, and vehicle ownership, may be related to both an individual's ride-hailing use and their overall travel, playing a role in the relationship between the two as common contributors.

2.3 ICT use, ride-hailing use, and household or system-wide travel

It is important to note that ICT use can have impacts at the household or system level that are beyond the scope of this individual-level study. For example, telecommuting may lead to increases in household travel if this enables other members of the household to use the telecommuter's vehicle (Salomon, 2000). In fact, while moderate reductions in personal travel are consistently observed as a result of telecommuting, the net result of telecommuting on household travel is much smaller, with multiple studies finding almost negligible reductions (Ory and Mokhtarian, 2006; Collantes and Mokhtarian, 2003; Choo et al., 2002; 2005; Mokhtarian, 1998). Similarly for teleshopping (or e-commerce), the reduction in individual's VMT traveling to and from stores may be counterbalanced by an increase in VMT traveled by delivery trucks fulfilling growing order volumes on increasingly tight time-tables (Furtado and Martinez, 2019).

Similarly, ride-hailing use can have impacts at the system level not captured by the individual travel outcomes that are the focus of this study. An individual's travel does not account for the deadheading and cruising of ride-hailing drivers in order to pick them up, which can leads to even more VMT than without ride-hailing (Henao and Marshall, 2018; Anderson, 2014).

3. Data and Methods

3.1 Survey Sample

This study uses data from 2017 U.S. National Household Travel Survey (NHTS).[2] The survey collects self-reported travel information (such as trip start and end time, travel distance, travel purpose, travel mode, number of companions) for all trips taken within a single assigned travel day (24-hour period) by all household members aged 16 or older. The survey was conducted from March 31, 2016 through May 8, 2017, and the assigned travel day was during April 19, 2016 and April 25, 2017. The raw data contain in total 923,572 trips of 264,234 individuals in 129,696 household. Our analysis is conducted at the individual level, so from the raw sample size of 264,234 individuals, we remove 91,155 observations with 'NA' values on our key model variables, leaving us with a final sample size 173,079 individuals for our model estimation.

3.2 Data

The NHTS asks individuals to report the frequency with which they accessed the Internet via three different devices—smartphone, tablet, and personal computer—in the last 30 days before the travel day. We use these three items to estimate a measure of ICT use.

From the self-reported travel diaries in the NHTS, we extract three key measures of individual travel: total number of trips conducted by the respondent on the travel day, personal miles travelled (PMT), and vehicle miles travelled (VMT). PMT and VMT are measured for all trips

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[2] U.S. Department of Transportation, Federal Highway Administration, 2017 National Household Travel Survey. URL: http://nhts.ornl.gov. These data are collected from a stratified random sample of U.S. households in all 50 states and the District of Columbia.

the individual makes on all modes in the given travel day, including ride-hailing. In addition to these general indicators of individual travel, 2017 is the first year in which the NHTS asked about the use of ride-hailing. Respondents were asked 'how many times did you use the ride-hailing apps in the past 30 days'. Assuming that individuals who use the ride-hailing app take a ride-hailing trip[3], we derive two measures from this non-negative count variable: a binary indicator of whether or not the individual has used the app in the past 30 days and, if so, the frequency of its use.

The survey also collects information on household and respondent socio-economic and demographic characteristics, general characteristics of the individual's travel, as well as geospatial information that can be used to characterize the built environment around a respondent's home:

- *Individual socio-demographics* available in the dataset include race (white or non-white), age, gender (male or female), education level, and employment status;
- *Household structure and socio-economic status* are measured by household income, household vehicle ownership, and the number of adults and children in the household;
- *General characteristics of the individual's travel* include the percentage of trips on the travel day that the respondent takes with a companion and whether the respondent reports being flexible about their activity and travel time (0/1)
- *Built environment characteristics* are also provided by the NHTS data, classified based on the household's residential location. We include a binary indicator of whether or not the individual lives in an urban area as defined by the U.S. Census as well as a measure of the population density of the census tract.

Finally, we also include a variable indicating the maturity of the ride-hailing market in each respondent's Metropolitan Statistical Area (MSA). The first year in which one of Uber or Lyft entered the market is recorded from publicly available information on the company's websites and then a continuous indicator of the years since that first entrance (relative to 2017) is calculated.

Table 1 presents all variables used in this study and their descriptive statistics for this final sample, and Appendix A presents the proportion of each category of the variables.

[3] We use the 'ride-hailing app usage' as a proxy for the 'ride-hailing trips'. Although in occasional cases an individual may use a ride-hailing app but not take a ride-hailing trip, in most cases a person who reports using the ride-hailing app likely ordered and took the ride-hailing trip. Therefore, this proxy is reasonable and has been adopted by several other studies looking at ride-hailing use using this same NHTS data (Batbold and Bin-Nun, 2019; Conway et al., 2018; Schaller, 2018).

Table 1. Descriptive statistics

Category	Variable	Description	Mean	Std.dev	Min	Max
ICT use	PC	Frequency of internet use via PC (4 = daily; 3 = a few times a week; 2 = a few times a month; 1 = a few times a year; 0 = never)	3.44	1.16	0	4
	Smartphone	Frequency of internet use via smartphone (4 = daily; 3 = a few times a week; 2 = a few times a month; 1 = a few times a year; 0 = never)	3.14	1.55	0	4
	Tablet	Frequency of internet use via tablet (4 = daily; 3 = a few times a week; 2 = a few times a month; 1 = a few times a year; 0 = never)	2.10	1.72	0	4
Individual travel	Trip number	Total number of trips by each respondent on the travel day	3.73	2.80	0	50
	PMT	Total travel distance (in 100 miles) by each respondent on the travel day	0.32	0.49	0	9.44
	VMT	Vehicle miles travelled (in 100 miles) by each respondent on the travel day	0.24	0.41	0	8.5
Ride-hailing use	Ride-hailing adoption	Have used ride-hailing app in the past 30 days (0/1)	0.08	0.27	0	1
	Ride-hailing use	Frequency of ride-hailing app use in the past 30 days	0.33	1.78	0	90
Individual socio-demographics	White	Race (1 = white; 0 = non-white)	0.84	0.37	0	1
	Age	Age (years)	53.19	17.59	16	92
	Male	Gender (1 = male; 0 = female)	0.47	0.50	0	1
	Educational attainment	Highest education level (5 = graduate/professional; 4 = bachelor; 3 = some college or associates degree; 2 = high school or GED; 1 = less than high school)	3.44	1.15	1	5
	Employed	Whether the respondent is employed (1 = employed; 0 = unemployed)	0.57	0.50	0	1
Household structure and socio-economic status	Income	Household annual income (in $10,000)	8.57	6.38	0.5	25
	Number of vehicles	Number of vehicles owned by the household	2.20	1.23	0	12
	Number of adults	Number of adults in the household	2.00	0.80	1	10
	Number of children	Number of children in the household	0.42	0.87	0	8
Individual travel characteristics	Accompanied trips	Percentage of trips being accompanied by someone else	0.34	0.41	0	1
	Flexible time	Whether the respondent is flexible about time (1 = yes; 0 = no)	0.27	0.45	0	1
Built environment	Urban	Whether the respondent live in urban area (1 = yes; 0 = no)	0.77	0.42	0	1
	Population density	population density of the census tract (1000 persons per square mile)	3.38	4.91	0.05	30
	Years since TNC entry	Number of years since a ride-hailing service (Uber or Lyft) entered the MSA (relative to 2017)	1.34	1.90	0	8

3.3 Analytic Approach

In this study, we consider the impact of ICT use on an individual's travel behavior—including total number of trips, total distance traveled, and vehicle miles traveled in a typical travel day—as well as the frequency of ride-hailing use in the past month. The total number of trips and the frequency of ride-hailing use are both non-negative, integer-valued count variables, but are treated as continuous numeric variables in the model.

We first use confirmatory factor analysis (CFA) to estimate a latent measure of ICT use based on self-reported frequency of Internet use via personal computer, tablet, and smartphone devices. Each of these three indicators is ordinal (see Table 1), so the CFA was estimated using a probit link function. Next, we run a structural equation model (SEM) that simultaneously estimates the latent factor of ICT use and uses it to predict multiple travel behavior outcomes, controlling for individual socio-demographics, household structure, travel characteristics, and built environment characteristics (see Figure 1).

When it comes to predicting ride-hailing use, we employ a hurdle model (or two-part regression) that more accurately captures the two-step decision-making processes confronted by individuals, who choose whether or not to use ride-hailing services and then how frequently to use them. The hurdle model consists of two parts: one model that determines whether the hurdle of ride-hailing adoption (more than zero trips in the past 30 days) is cleared and a second model that determines the frequency of ride-hailing use conditional on having adopted the service (Mullahy, 1986; Cragg, 1971). The hurdle model is incorporated into our structural equation model following Muthén, Muthén, and Asparouhov (2016, pg 288-290). We define a binary indicator, $u_{i,}$ that represents whether or not individual i has used ride-hailing in the past 30 days (number of trips greater than 0). We estimate a probit regression model for a binary outcome u_i (Equation 1) and a linear regression on the zero-censored number of ridehailing trips (Equation 2). Following typical practice and because it results in a better model log-likelihood value, the positive continuous outcome is log-transformed:

$$P(u_i = 1|x_i) = \Phi(\gamma_0 + \gamma_1 x_i), \qquad (1)$$

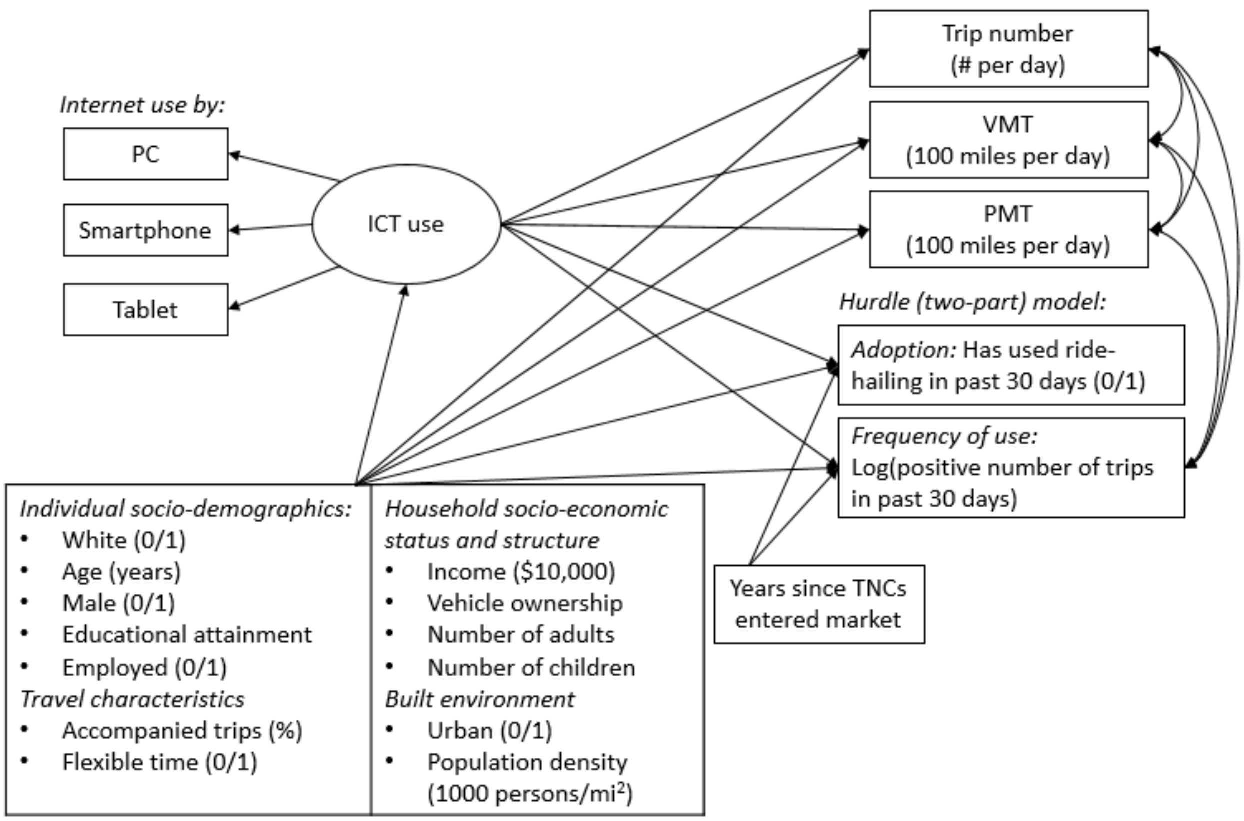
where Φ is the cumulative distribution function of *N(0, 1)*

$$\log(y_{i|u_i=1}) = \beta_0 + \beta_1 x_i + \varepsilon_i, \text{ where } \varepsilon_i \sim N(0, V) \text{ after the log transformation} \qquad (2)$$

Both the CFA and SEM models were estimated using maximum likelihood with robust standard errors (MLR) estimation in Mplus version 8.1 (Muthén and Muthén, 2017). Since the NHTS data includes information on multiple individuals from the same household, standard errors were clustered by household ID.

There are a few key benefits to adopting this SEM approach. First, it allows for the estimation of multiple regressions with correlated outcomes in the same model. This model specification explicitly accounts for the fact that individual travel behavior and ride-hailing use are related to one another (rather than treating them as independent outcomes in separate models). The results allow for direct comparison of the magnitude of coefficients across multiple outcomes; for example, allowing us to explore how strongly ICT use predicts trip number versus PMT and VMT versus ride-hailing use. Second, the SEM accounts for measurement error in our latent construct of ICT use when using it as a predictor of travel behavior. Third, simultaneously estimating ICT use as a latent factor based on multiple observed indicators also serves as weak instrumentation to control for potential endogeneity between ICT use and travel behavior (Guevara and Ben-Akiva, 2010).

Figure 1. Path diagram for the SEM



4. Results and Discussions

4.1 Confirmatory Factor Analysis: Latent Measure of ICT Use

Our analysis begins with the estimation of a measure of ICT use based on self-reported frequency of Internet use via personal computer, tablet, and smartphone. Estimated factor loadings are provided in Table 2, while full estimation results including probit thresholds along with input code can be found at https://github.com/jcmoody6/ict-nhts-2017.

Table 2. Estimated factor loadings for the ICT use confirmatory factor analysis

Item	*b*	*S.E.*	*p*	*β*	*pseudo-R^2*
PC	1.000^x	--	--	0.542	0.294
Smartphone	2.626	0.084	.000***	0.861	0.742
Tablet	1.229	0.020	.000***	0.621	0.386

Note: ^{x} = fixed parameter; -- = not applicable; *b* = unstandardized coefficient; S.E. = standard error; p = p-value for two-tailed t-test against b = 0; *β* = fully standardized coefficient. Statistical significance is indicated as p-value: * < 0.1, ** < 0.05, *** < .01. Overall goodness of fit cannot be determined because the model is perfectly identified (has zero degrees of freedom).

While ideally we would like to see that our latent measure of ICT use explains the majority of the variance in each of our ordinal items (indicated by a standardized factor loading greater than 0.70 and an R^2 greater than 0.5), we find that each of our standardized factor loadings are above generally cited empirical cutoff such as 0.4 or 0.5 (Kline, 2016). Comparing the magnitudes of the standardized factor loadings, we find that our ICT factor loads strongest on Internet use via smartphone, followed by tablet, and then personal computer. This is unsurprising given that smartphones are the fastest growing way to access the Internet (Cisco, 2016; Napoli and Obar, 2015). Lella (2016) finds that smartphone applications account for 50% of all time people spend on digital media in the U.S. There is even a substantial population in the U.S. who rely exclusively on smartphones to access the Internet (Smith, 2017; Tsetsi and Rains, 2017).

While not a focus area of this paper, we note that our exploration of ICT use (dominated by smartphone use) fits into a larger discussion about the digital divide in the U.S. (Selwyn, 2004). Poushter (2017) estimated that around 23% of the U.S. population still did not have access to a smartphone, similar to numbers published by the Pew Research Center (Smith, 2016). In the 2017 NHTS data, 18% of respondents report never having used a smartphone to access the Internet (Appendix A). Furthermore, a multivariate regression of ICT use on the socio-demographics, household structure, travel characteristics, and built environment variables included in this study (Appendix B) provides initial insights into what factors contribute most to ICT use (or lack thereof). We find that higher income, higher education, and younger age are significantly predictive of greater ICT use and that these coefficients are substantial after controlling for the other factors. This suggests that the elderly, those with lower incomes, and lower educational attainment use ICT less, potentially indicative of worse access.

4.2 Structural Equation Model: Predicting Travel Behavior and Ride-hailing Use

In this section, we present and discuss the results of the SEM predicting individual travel and ride-hailing use using ICT, individual socio-demographics, household structure and socio-economic status, as well as characteristics of travel and the built environment (see Figure 1). Goodness of fit indices are not available for the model in the current software package. For ease of discussion, results from the model are broken up into multiple tables in the subsections below. Complete model input and output files are available at https://github.com/jcmoody6/ict-nhts-2017.

4.2.1 Individual Travel

First, we consider the overall travel of the individuals in our sample, including the total number of trips, person-miles traveled (PMT) and vehicle-miles traveled (VMT) in a single travel day (see Table 3). We find that our models and its collection of individual socio-demographics, household structure and socio-economic status, and traveler and built environment variables explain only a small portion of the overall observed variance in individual travel, with R^2 values for total number of trips = 0.116, PMT = 0.091, and VMT = 0.069. These values are typical for disaggregate models of travel behavior, but they also indicate that many other factors not included in our model contribute to an individual's travel, including the activities in which they engage, the time spent on them, how they are distributed in space (i.e., land use patterns), and the transportation infrastructure and services available (Van Wee et al., 2013; Wang and Law, 2007; Choo and Mokharian, 2007).

Table 3. SEM results for linear regression of individual travel outcomes on ICT use and other predictors

Outcome	**Predictor**	***b***	***S.E.***	***p***	***β***
Number of trips in a typical travel day	White (0/1)	0.204	0.019	.000***	0.027
	Age (years)	0.004	0.001	.000***	0.023
	Male (0/1)	-0.062	0.012	.000***	-0.011
	Educational attainment	0.242	0.007	.000***	0.100
	Employed (0/1)	0.440	0.017	.000***	0.078
	Household income ($10,000)	0.000	0.002	.787	0.001
	Number of vehicles	0.100	0.008	.000***	0.044
	Number of adults	-0.408	0.011	.000***	-0.116
	Number of children	0.081	0.009	.000***	0.025
	Accompanied trips (%)	1.857	0.016	.000***	0.275
	Flexible time (0/1)	0.298	0.017	.000***	0.047
	Urban (0/1)	0.268	0.018	.000***	0.040
	Population density (1000 people/mi^2)	0.007	0.002	.000***	0.012
	ICT	0.010	0.021	.632	0.003
	R^2	0.116	0.002	.000***	--
PMT (100 mi)	White (0/1)	-0.001	0.003	.757	-0.001
	Age (years)	0.000	0.000	.011**	0.009
	Male (0/1)	0.041	0.002	.000***	0.042
	Educational attainment	0.016	0.001	.000***	0.039
	Employed (0/1)	0.093	0.003	.000***	0.094
	Household income ($10,000)	0.001	0.000	.000***	0.020
	Number of vehicles	0.031	0.001	.000***	0.079
	Number of adults	-0.043	0.002	.000***	-0.071
	Number of children	-0.012	0.002	.000***	-0.022
	Accompanied trips (%)	0.272	0.004	.000***	0.232
	Flexible time (0/1)	0.020	0.003	.000***	0.018
	Urban (0/1)	-0.075	0.004	.000***	-0.065
	Population density (1000 people/mi^2)	-0.005	0.000	.000***	-0.052
	ICT	0.027	0.004	.000***	0.042
	R^2	0.091	0.001	.000***	--
VMT (100 mi)	White (0/1)	-0.002	0.003	.407	-0.002
	Age (years)	0.001	0.000	.000***	0.029
	Male (0/1)	0.075	0.002	.000***	0.091
	Educational attainment	0.019	0.001	.000***	0.054
	Employed (0/1)	0.099	0.002	.000***	0.121
	Household income ($10,000)	0.000	0.000	.116	-0.005
	Number of vehicles	0.029	0.001	.000***	0.087
	Number of adults	-0.046	0.001	.000***	-0.090
	Number of children	0.003	0.001	.036**	0.006
	Accompanied trips (%)	0.086	0.003	.000***	0.088
	Flexible time (0/1)	0.018	0.003	.000***	0.020
	Urban (0/1)	-0.058	0.003	.000***	-0.060
	Population density (1000 people/mi^2)	-0.006	0.000	.000***	-0.068
	ICT	0.034	0.003	.000***	0.063
	R^2	0.069	0.001	.000***	--

First we consider the estimated relations between socio-demographics and an individual's travel behavior. Here our model results generally agree with established literature. We find that white individuals conduct slightly more trips per day, but their PMT and VMT are not significantly different from other racial groups. Age is positively predictive of trip number, PMT, and VMT, indicating that older individuals tend to travel a little more than younger individuals. When it comes to gender, male respondents on average take fewer trips than female respondents, but tend to travel longer distances with those trips. Results also reveal that respondents with higher education levels and who are employed tend to travel more, including more trips and greater PMT and VMT.

Regarding household socio-economic status and structure, we find that household income is not significantly predictive of total number of trips nor of VMT, but has a minor positive relationship with PMT. The greater the number of vehicles owned by the household, the more trips and greater distance (both PMT and VMT) the individual travels. Furthermore, individuals in household with greater numbers of adults tend to take significantly fewer trips and travel shorter distances. In fact, for each additional adult in the household, daily trip numbers decrease by 0.408, PMT decreases by 4.3 miles, and VMT decreases by 4.6 miles on average. This result suggests that when household trips are divided up among more adults, it leads to less travel at the individual level. Finally, individuals in households with more children tend to take more trips, have marginally greater VMT, but less PMT. A potentially related finding is that individuals who travel with companions (such as children or other dependents) for a greater percentage of their trips make significantly more trips and travel greater distances in terms of both PMT and VMT.

Considering characteristics of the built environment, we find that respondents living in urban areas tend to take more trips, but travel shorter distances (by both PMT and VMT). Even after controlling for whether or not the respondent lives in an urban area, population density of their home location remains significantly predictive of greater number of trips, and shorter travel distances.

Finally, when it comes to the relationship between ICT use and individual travel, we find that ICT use does not significantly predict the total number of trips that an individual takes in a day, but it does significantly and positively predict PMT ($b = 0.027$, $S.E. = 0.004$, $p < .001$, $\beta = 0.042$) and VMT ($b = 0.034$, $S.E. = 0.003$, $p < .001$, $\beta = 0.063$). Our results show that individuals in the U.S. who use ICT more also exhibit greater daily person- and vehicle-miles traveled. Our model suggests that, at the individual-level, ICT's complementarity and substitution cancel out when it comes to the total number of trips, but that complementarity outweighs substitution when it comes to distance traveled.

These findings provide important nuance to previous studies on the relationship between ICT use and travel behavior. While some studies have suggested that ICT use can induce more travel by increasing the number of activities an individual engages in, especially for social (Mokhtarian et al., 2006; Harvey and Taylor, 2000) and shopping trips (Cao, 2012; Weltevreden et al., 2009; Farag et al., 2007; Casas et al., 2001), our study demonstrates that across all types of individual travel, there is no significant change in number of trips with increasing ICT use.

Despite similar numbers of trips, respondents with greater ICT use do appear to travel further on average. This may be because ICT helps reduce both real and perceived disutility of travel time by enabling multitasking and improving availability of travel information (Salomon and Mokhtarian, 2008; Lyons et al., 2008; Avineri and Prashker, 2006; Mokhtarian and Salomon, 2001). In other words, ICT can help make time spent traveling less 'costly,' encouraging people to travel longer. Another potential explanation is that ICT encourages more decentralized land use patterns or fragmentation of activities, which could increase travel distances (Ben-Elia et al., 2014; Lenz and Nobis, 2007; Ory and Mokhtarian, 2006; Mokhtarian et al., 2004; Couclelis, 2004). However, the mechanisms underlying empirical associations between fragmentation and increased travel have yet to be fully explored in the literature. Finally, while the model's simultaneous estimation of ICT use as a latent factor based on multiple observed indicators serves as weak instrumentation to control for potential endogeneity between ICT use and travel behavior, we cannot rule out the possibility that the small, positive correlation observed is attributable to variables, such as social influence or attitudes, not adequately captured by the controls in our model.

4.2.2 Ride-hailing Use

Next we consider the SEM results of our hurdle (two-part) model predicting ride-hailing. Table 4 presents probit regression results predicting a binary indicator of whether or not the individual has used a ride-hailing application in the past month (*adoption*) and linear regression results predicting the zero-censored, log-transformed number of ride-hailing trips in the past 30 days (*frequency*; treated as continuous). Overall, we find that our model is much better at predicting an individual's adoption of ride-hailing (pseudo-R^2 for the binary indicator = 0.410) than it is at predicting frequency of use (R^2 = 0.074).

When it comes to the relations between socio-demographic characteristics of the individual and ride-hailing use, our model results find that younger and more highly educated individuals are more likely to adopt ridehailing and use it more frequently. This finding is consistent with previous studies of national (Conway et al., 2018; Schaller, 2018) and metropolitan samples (Smith, 2016; Rayle et al., 2016; Clewlow and Mishra, 2017; Henao, 2017; Gehrke et al., 2018). In addition, we find that male respondents are more likely to adopt ride-hailing, and take approximately one more ride-hailing trips per month than equivalent female respondents. This result matches previous studies that show men are more likely to use ride-hailing and are somewhat more frequent users than women nationally (Schaller, 2018; Conway et al., 2018). But results are more mixed at the metropolitan level; for example, men were found to be more likely to be ridehailing users in studies of Denver (Henao, 2017) and San Francisco (Rayle et al., 2016), but women were found to be more likely to be ride-hailing users in studies of other cities like Boston (Gehrke et al., 2018; Clewlow and Mishra, 2017). Finally, considering employment, we find that our model contradicts previous studies that have found that being employed is predictive of greater likelihood and frequency of ride-hailing use nationally (Conway et al., 2018) and in Seattle (Dias et al., 2017). Our model estimates that being employed is negatively predictive of whether or not an individual has used ride-hailing while it is not significantly predictive of the frequency of use once adoption is taken into account. This discrepancy with previous studies may be due to our more robust set of covariates and use of a hurdle model to capture the two-step decision-making processes of ride-hailing adoption and frequency of use.

Table 4. SEM results using hurdle (two-part) model to predict ride-hailing use

Outcome	Predictor	*b*	*S.E.*	*p*	*β*
Have used ride-hailing app in the past 30 days (0/1)	White (0/1)	0.022	0.015	.145	0.006
	Age (years)	-0.021	0.000	.000***	-0.279
	Male (0/1)	0.094	0.010	.000***	0.036
	Educational attainment	0.119	0.006	.000***	0.105
	Employed (0/1)	-0.043	0.015	.005***	-0.016
	Household income ($10,000)	0.027	0.001	.000***	0.133
	Number of vehicles	-0.107	0.008	.000***	-0.101
	Number of adults	-0.182	0.013	.000***	-0.111
	Number of children	-0.205	0.008	.000***	-0.138
	Accompanied trips (%)	0.058	0.014	.000***	0.018
	Flexible time (0/1)	0.210	0.013	.000***	0.072
	Urban (0/1)	0.253	0.020	.000***	0.081
	Population density (1000 people/mi^2)	0.044	0.001	.000***	0.164
	Years since TNC entry	0.006	0.003	.068*	0.008
	ICT	0.511	0.023	.000***	0.296
	pseudo-R^2	0.410	0.006	.000***	--
Frequency of ride-hailing use in the past 30 days (zero-censored; log-transformed)	White (0/1)	0.005	0.019	.782	0.002
	Age (years)	-0.008	0.001	.000***	-0.179
	Male (0/1)	0.062	0.013	.000***	0.037
	Educational attainment	-0.033	0.009	.000***	-0.046
	Employed (0/1)	-0.030	0.022	.170	-0.018
	Household income ($10,000)	0.015	0.002	.000***	0.116
	Number of vehicles	-0.082	0.010	.000***	-0.121
	Number of adults	-0.014	0.016	.376	-0.013
	Number of children	-0.085	0.010	.000***	-0.090
	Accompanied trips (%)	-0.019	0.018	.303	-0.009
	Flexible time (0/1)	0.070	0.016	.000***	0.038
	Urban (0/1)	-0.031	0.033	.354	-0.015
	Population density (1000 people/mi^2)	0.020	0.001	.000***	0.117
	Years since TNC entry	0.004	0.004	.282	0.009
	ICT	0.025	0.033	.447	0.022
	R^2	0.074	0.006	.000***	--

Considering the socio-economic status of the individual's household, we find that having a higher household income is significantly predictive of greater likelihood of having used ride-hailing in the past month and of greater frequency of use. This result differs from other studies employing multivariate modeling approaches, particularly Conway et al. (2018) who used the same NHTS dataset and found that higher income individuals are more likely to have used ride-hailing, but "for those who use ride-hailing, low-income and high-income people tend to use it with about the same frequency." Other studies in specific metropolitan regions have found conflicting results: in Seattle, having a lower income was significantly predictive of greater frequency of ride-hailing use (Dias et al., 2017), while in Dallas, being from a household with very high income (above, $200,000 dollars per year) was predictive of greater frequency of ride-hailing use (Lavieri and Bhat, 2019). We also find that household vehicle ownership is negatively predictive of having used ride-hailing as well as the frequency of its use. In fact, having an additional vehicle in the household predicts 0.9 fewer ride-hailing trips per month.

This result again corroborates other studies that have shown that not owning a car or owning fewer cars is highly related to ride-hailing use nationally (Schaller, 2018; Conway et al., 2018) and in multiple metropolitan areas including San Francisco (Rayle et al., 2016), Boston (Gehrke et al., 2018), Seattle (Dias et al., 2017), and Dallas (Lavieri and Bhat, 2019).

Regarding household structure, the number of adults and children in the household are both negatively correlated with adoption of ride-hailing services. Again, these findings parallel those from Conway et al. (2018), who found that being from a smaller household with fewer children predictive of greater likelihood of having used ride-hailing. In addition, households with more children took significantly fewer ride-hailing trips in the past month, even after controlling for service adoption.

When it comes to the built environment, our model generally agrees with established knowledge that individuals in urban and more densely populated areas are more likely to adopt ride-hailing (e.g., Conway et al., 2018; Schaller, 2018). In addition, the longer that ride-hailing services have been available in the market, the more likely an individual is to have used it in the past 30 days. However, after controlling for whether or not an individual has used ride-hailing, the maturity of the ride-hailing market is not significantly predictive of frequency of ride-hailing use. In other words, once ride-hailing is adopted, the market maturity does not appear to have much impact on how often it is used. Even after controlling for whether or not the individual has used a ride-hailing service, we find that population density remains positively and strongly predictive of frequency of ride-hailing use. In fact, an increment in population density of 6,000 people per square mile (equivalent to changing from Philadelphia, PA to San Francisco, CA) predicts 6.12 additional ride-hailing trips per month holding all other variables constant. However, there is significant potential for omitted variable bias here because it is likely that population density is highly correlated with attributes of service quality of ride-hailing that are not captured in the model. This is because greater population density also implies an improved ability of the ride-hailing algorithms to efficiently match passengers and vehicles, reducing waiting times.

Our model expands on other studies by including variables indicating whether the respondent is flexible about the times at which they travel and how often he/she travels with a companion. We find that time flexibility is positively and significantly predictive of both having used ride-hailing and frequency of ride-hailing use. We find that traveling with a companion is positively predictive of having used ride-hailing, but does not significantly predict frequency of use.

Finally, we consider the relations between ICT use and ride-hailing use. We find that greater ICT use is positively, significantly, and substantively correlated with whether or not an individual has used a ride-hailing service in the past month ($b = 0.511$, $S.E. = 0.023$, $p < 0.001$, $\beta = 0.296$). Having controlled for whether or not the individual has used ride-hailing, ICT use is not significantly predictive of frequency of ride-hailing use ($b = 0.025$, $S.E. = 0.033$, $p = 0.447$, $\beta = 0.022$). This result indicates that, individuals who use ICT more (across various platforms) are more likely to adopt ride-hailing, but that ICT use is not related to the number of trips taken once the ride-hailing service is adopted. Our result build on previous studies that found that people who actively use social media and are more 'technology savvy' are more likely to use ride-hailing (Alemi et al., 2018a, 2018b; Lavieri and Bhat, 2019).

Furthermore, comparing the magnitudes of the standardized coefficients of ICT use on ride-hailing adoption and of ICT use on the other individual travel behavior outcomes, we find that ICT use is more strongly related to ride-hailing adoption than individual mobility in general.

This makes sense given the fact that ICT use (especially smartphone use) provides the primary platform by which individuals access ride-hailing services (via apps or over-the-phone booking). As a result, ICT use is more strongly predictive of ride-hailing adoption compared to other factors, and compared to its impact on other travel behaviors that do not directly rely on ICT.

4.2.3 Ride-hailing Use and Individual Travel Behavior

Finally, we consider the correlations among the residuals of our outcome variables in the model (standardized covariances, β, in Table 5). As expected, we find that individuals who take a greater number of trips are also likely to travel more miles, even after controlling for individual socio-demographics, household structure and socio-economic status, as well as characteristics of the built environment.

When it comes to an individual's ride-hailing frequency and the total number of trips that individual takes, we find that there is no significant correlation. This result parallels findings from surveys across U.S. cities that indicate that most ride-hailing trips substitute trips by other modes rather than representing additional trips, with induced demand representing only about 3% of ride-hailing trips in New York City (NYCDOT, 2018), 5% in Boston (Gehrke et al., 2018), 6% in Dallas (Lavieri and Bhat, 2019), 8% in San Francisco (Rayle et al., 2016), 12.2% in Denver (Henao, 2017), and 22% across seven major U.S. metropolitan areas (Clewlow and Mishra, 2017).

Table 5. Estimated covariances among residuals of the travel behavior outcomes in the SEM

		b	***S.E.***	***p***	***B***
PMT	VMT	0.146	0.002	.000***	0.803
Number of trips	PMT	0.308	0.004	.000***	0.253
	VMT	0.274	0.003	.000***	0.265
Frequency of ride-hailing use	Number of trips	-0.022	0.018	.230	-0.010
	PMT	-0.010	0.003	.001***	-0.027
	VMT	-0.012	0.002	.000***	-0.038

However, when it comes to an individual's ride-hailing frequency and their PMT and VMT, we find small, but significant negative correlation. This result suggests that, on average in the U.S., individuals who use ride-hailing more frequently have slightly lower person- and vehicle-miles traveled. This result holds even after controlling for ridehailing adoption; the maturity of the ride-hailing market; individual and household socio-demographics, including vehicle ownership; and characteristics of the built environment, such as urbanicity, population density. While it may be that higher rates of ride-sharing among ride-hailing users leads to lower PMT/VMT as has been postulated by previous studies (Rayle et al., 2016; Jacobson and King, 2009), it may also be that individuals who already travel fewer miles are more likely to take ride-hailing, which can be cheaper and more convenient for short trips. There is also the possibility that this negative correlation between ride-hailing frequency and PMT/VMT is capturing residual nonlinearity in the relationship of predictors (such as income) with PMT and VMT. Further research is needed to disentangle the potential bidirectional relationships between an individual's ride-hailing frequency and the total distance they travel.

Finally, it is important to remember that this study considers only the correlations among ride-hailing use and travel at the individual level. When it comes to the system-level impacts, issues such as the deadheading or cruising of ride-hailing drivers not considered in this study could lead to significantly more VMT.

5. Conclusions and Future Research

This paper examines how ICT use in the U.S. impacts an individual's travel behavior, in general, and ride-hailing use, in particular. Our study builds on previous research on the relationship between ICT use and individual travel by looking at all types of travel across a nationally representative sample of individuals. We find that ICT use does not significantly predict the total number of trips that an individual takes. This result might suggest that, when it comes to the total number of trips an individual takes, ICT's complementarity and substitution with travel cancel out. On the other hand, greater ICT use does predict greater individual PMT and VMT, indicating that complementarity outweighs substitution when it comes to distance traveled, even after controlling for the sociodemographic and other characteristics of the individuals who use ICT and travel more. Future research could examine what mechanisms encourage people who use ICT more to also travel longer, such as how ICT use makes time spent traveling less 'costly,' may contribute to decentralized land use patterns that could increase travel distance, or change individual activity patterns in other ways. While many potential mechanisms are theoretically possible (Mokhtarian, 2009), additional empirical work could help clarify which are significant and how they interact with one another and the many other factors that impact ICT use and travel behavior.

Furthermore, we find that ICT use is much more strongly related to ride-hailing adoption than to individual mobility in general. Adding to existing literature that has found that individuals who actively use social media and are more technologically savvy are more likely to use ride-hailing (Alemi et al., 2018a, 2018b; Lavieri and Bhat, 2019), we find that those who have greater ICT use across various platforms are more apt to adopt ride-hailing. However, having controlled for the adoption of ride-hailing services using a hurdle model, greater ICT use is not significantly predictive of frequency of use. This finding provides important nuance when including ride-hailing into the ongoing discussions of ICT's impacts on individual travel behaviors.

Finally, we investigate the correlations among individual travel and ride-hailing use, controlling for ICT use and other characteristics of the individual, household, and built environment. We find that ride-hailing use is negatively associated with PMT and VMT at the individual level. In other words, individuals who use ride-hailing more frequently have slightly lower person- and vehicle-miles traveled on average in the U.S. This finding is correlational (not causal) and at the individual-level (rather than system-level), but adds to the empirical evidence on the association between ride-hailing and individual travel behaviors.

There exist opportunities for future research to address some of the remaining limitations of this study. First, with appropriate data sources, future research could extend the individual-level analysis of this paper to consider the household and system level relationships among ICT use, ride-hailing, and individual travel. Such a study might reach different conclusions as it would need to account for the travel of ride-hailing drivers (including deadheading or cruising) in addition to the travel of individuals (or passengers). Second, as ride-hailing continues to establish itself in urban transportation systems, data collected over time could allow for examination of the time dynamics of the relationships discussed in this paper. Third, it could be interesting to examine how the use and design of travel-related smartphone apps (e.g., Google Maps) rather than general ICT use influence individual travel, including ride-hailing. Lastly, additional survey questions would be needed to disentangle the relationship between ICT and ride-hailing use for individuals who are already familiar with ride-hailing versus for individuals for whom ride-hailing is still a new transportation mode. Some of this research could utilize future waves of the NHTS data, especially if it continues to add more questions about ICT and ride-hailing use that differentiate by type of ICT and investigate familiarity with new modes of travel. However, other complementary datasets are likely necessary for research exploring impacts of ICT and ride-hailing use on travel behaviors at the system-level.

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References

Aguiléra, A., Guillot, C., & Rallet, A. (2012). Mobile ICTs and physical mobility: Review and research agenda. *Transportation Research Part A: Policy and Practice*, *46*(4), 664-672.

Alemi, F., Circella, G., Handy, S., & Mokhtarian, P. (2018a). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society*, *13*, 88-104.

Alemi, F., Circella, G., Mokhtarian, P., & Handy, S. (2018b). Exploring the latent constructs behind the use of ride-hailing in California. *Journal of choice modelling*, *29*, 47-62.

Anderson, D. N. (2014). "Not just a taxi"? For-profit ridesharing, driver strategies, and VMT. *Transportation*, *41*(5), 1099-1117.

Andreev, P., Salomon, I., & Pliskin, N. (2010). State of teleactivities. *Transportation Research Part C: Emerging Technologies*, *18*(1), 3-20.

Arnfalk, P., & Kogg, B. (2003). Service transformation—managing a shift from business travel to virtual meetings. *Journal of Cleaner Production*, *11*(8), 859-872.

Avineri, E., & Prashker, J. N. (2006). The impact of travel time information on travelers' learning under uncertainty. *Transportation*, *33*(4), 393-408.

Batbold, G., & A.Y. Bin-Nun. (2019). The Impact of Transportation Network Companies: Evidence from the 2017 National Household Transportation Survey. Presented at 98th Annual Meeting of the Transportation Research Board, Washington, D.C.

Ben-Elia, E., Alexander, B., Hubers, C., & Ettema, D. (2014). Activity fragmentation, ICT and travel: An exploratory Path Analysis of spatiotemporal interrelationships. *Transportation Research Part A*, *68*, 56–74.

Bhat, C. R., Sivakumar, A., & Axhausen, K. W. (2003). An analysis of the impact of information and communication technologies on non-maintenance shopping activities. *Transportation Research Part B: Methodological*, *37*(10), 857-881.

Cao, X. J. (2012). The relationships between e-shopping and store shopping in the shopping process of search goods. *Transportation Research Part A: Policy and Practice*, *46*(7), 993-1002.

Casas, J., Zmud, J., & Bricka, S. (2001, January). Impact of shopping via Internet on travel for shopping purposes. In *80th Annual Meeting of the Transportation Research Board, Washington, DC*.

Choo, S., Mokhtarian, P. L., & Salomon, I. (2002). *Impacts of home-based telecommuting on vehicle-miles traveled: a nationwide time series analysis*. Institute of Transportation Studies, University of California at Davis.

Choo, S., Mokhtarian, P. L., & Salomon, I. (2005). Does telecommuting reduce vehicle-miles traveled? An aggregate time series analysis for the US. *Transportation*, *32*(1), 37-64.

Choo, S., & Mokhtarian, P. L. (2007). Telecommunications and travel demand and supply: Aggregate structural equation models for the US. *Transportation Research Part A: Policy and Practice*, *41*(1), 4-18.

Cisco. (2016). Cisco visual networking index: Global mobile data traffic forecast update, 2015–2020. Retrieved from http://www.cisco.com/c/dam/m/en_in/innovation/enterprise/assets/ mobile-white-paper-c11-520862.pdf

Clewlow, R. R., & Mishra, G. S. (2017). 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*.

Collantes, G. O., & Mokhtarian, P. L. (2003). *Telecommuting and residential location: relationships with commute distance traveled for State of California workers*. Institute of Transportation Studies, University of California, Davis.

Conway, M., Salon, D., & King, D. (2018). Trends in Taxi Use and the Advent of Ride-hailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Science*, *2*(3), 79.

Couclelis, H. (2004). Pizza over the Internet: e-commerce, the fragmentation of activity and the tyranny of the region. *Entrepreneurship & Regional Development*, *16*(1), 41-54.

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica: Journal of the Econometric Society*, 829-844.

De Graaff, T. D. (2004). On the Substition and Complementarity between Telework and Travel: A Review and Application.

De Graaff, T., & Rietveld, P. (2007). Substitution between working at home and out-of-home: The role of ICT and commuting costs. *Transportation Research Part A: Policy and Practice*, *41*(2), 142-160.

Dias, F.F., P.S. Lavieri, V.M. Garikapati, S. Astroza, R.M. Pendayala, & C.R. Bhat. (2017). A behavioral choice model of the use of car-sharing and ride-sourcing services. *Transportation* 44(6): 1307-1323.

Douma, F., Wells, K., Horan, T., & Krizek, K. (2003, December). ICT and travel in the twin cities metropolitan area: enacted patterns between Internet use and working and shopping trips. In *TheProceedings of the 83rd Annual Meeting of the Transportation Research Board (CD-ROM) in Washington DC*.

Farag, S., Schwanen, T., Dijst, M., & Faber, J. (2007). Shopping online and/or in-store? A structural equation model of the relationships between e-shopping and in-store shopping. *Transportation Research Part A: Policy and Practice*, *41*(2), 125-141.

Furtado, Francisco and Luis Martinez (2019). Chapter 5. Disruptions in Freight Transport In *ITF Transport Outlook 2019,* pp 153-216. OECD Publishing: Paris, France. https://doi.org/10.1787/transp_outlook-en-2019-en

Gehrke, S.R. A. Felix, & T. Reardon. (2018). *Fare Choices: A Survey of Ride-Hailing*

Passengers in Metro Boston. Metropolitan Area Planning Council [MAPC].
Gould, J., Golob, T. F., & Barwise, P. (1998). Why do people drive to shop? Future travel and telecommunications tradeoffs. University of California, Irvine Institute of Transportation Studies: Irvine, CA. https://escholarship.org/uc/item/7rb0h6gd
Goulias, K. G., & Pendyala, R. M. (1991). Innovations in transportation: the case of telecommuting. Working Paper No. 72. University of California Transportation Center: Berkeley, CA. https://escholarship.org/content/qt3jj308dm/qt3jj308dm.pdf
Guevara, C., & Ben-Akiva, M. (2010), "Addressing Endogeneity in Discrete Choice Models: Assessing Control-Function and Latent-Variable Methods" In Hess, S. & Daly, A (ed) *Choice Modelling: The State-of-the-art and The State-of-practice*, pp. 353-370. Emerald Group Publishing Limited. https://doi.org/10.1108/9781849507738-016
Harvey, A. S., & Taylor, M. E. (2000). Activity settings and travel behaviour: A social contact perspective. *Transportation*, *27*(1), 53-73.
Henao, A. (2017). *Impacts of Ridesourcing-Lyft and Uber-on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior*. University of Colorado at Denver.
Henao, A., & Marshall, W. E. (2018). The impact of ride-hailing on vehicle miles traveled *Transportation*, 1-22.
Henderson, D. K., & Mokhtarian, P. L. (1996). Impacts of center-based telecommuting on travel and emissions: analysis of the Puget Sound Demonstration Project. *Transportation Research Part D: Transport and Environment*, *1*(1), 29-45.
Hjorthol, R. J. (2002). The relation between daily travel and use of the home computer. *Transportation Research Part A: Policy and Practice*, *36*(5), 437-452.
Jacobson, S. H., & King, D. M. (2009). Fuel saving and ridesharing in the US: Motivations, limitations, and opportunities. *Transportation Research Part D: Transport and Environment*, *14*(1), 14-21.
Jin, S. T., Kong, H., Wu, R., & Sui, D. Z. (2018). Ridesourcing, the sharing economy, and the future of cities. *Cities*, *76*, 96-104.
Kitamura, R., Goulias, K., & Pendyala, R. M. (1990). *Telecommuting and travel demand: an impact assessment for state of California telecommute pilot project participants* (No. UCD-TRG-RR-90-8).
Kline, R. (2016). *Principles and Practice of Structural Equation Modeling,* 4th Ed. New York, NY: Guilford Press.
Koenig, B. E., Henderson, D. K., & Mokhtarian, P. L. (1996). The travel and emissions impacts of telecommuting for the State of California Telecommuting Pilot Project. *Transportation Research Part C: Emerging Technologies*, *4*(1), 13-32.
Larsen, J., Urry, J., & Axhausen, K. W. (2007). Networks and tourism: Mobile social life. *Annals of Tourism Research*, *34*(1), 244-262.
Lavieri, P.S., & C.R. Bhat. (2019). Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. Presented at 98th Annual Meeting of the Transportation Research Board, Washington, D.C.
Lee-Gosselin, M., & Miranda-Moreno, L. F. (2009). What is different about urban activities of those with access to ICTs? Some early evidence from Québec, Canada. *Journal of Transport Geography*, *17*(2), 104-114.
Lella, A. (2016). Smartphone apps are now 50% of all U.S. digital media time spent. Retrieved from http://www.comscore.com/Insights/Blog/Smartphone-Apps-Are-Now-50-of-All-USDigital-Media-Time-Spent

Lenz, B. (2003). Will electronic commerce help to reduce traffic in agglomeration areas? *Transportation Research Record: Journal of the Transportation Research Board*, (1858), 39-46.

Lenz, B., & Nobis, C. (2007). The changing allocation of activities in space and time by the use of ICT—"Fragmentation" as a new concept and empirical results. *Transportation Research Part A: Policy and Practice*, *41*(2), 190-204.

Luley, T., Bitzer, W., & Lenz, B. (2002). Travel substitution by electronic commerce? A simulation model for the Stuttgart region. *Zeitschrift für Verkehrswissenschaft*, *73*, 133-155.

Lyons, G., Farag, S., & Haddad, H. (2008). The substitution of communications for travel? *The Implementation and Effectiveness of Transport Demand Management measures: An International Perspective*, 211-232.

Mokhtarian, P. L. (1990). A typology of relationships between telecommunications and transportation. *Transportation Research Part A: General*, *24*(3), 231-242.

Mokhtarian, P. L. (1991). Telecommuting and travel: state of the practice, state of the art. *Transportation*, *18*(4), 319-342.

Mokhtarian, P. L. (1998). A synthetic approach to estimating the impacts of telecommuting on travel. *Urban studies*, *35*(2), 215-241.

Mokhtarian, P. (2009). If telecommunication is such a good substitute for travel, why does congestion continue to get worse?. *Transportation Letters*, *1*(1), 1-17.

Mokhtarian, P. L. (2002). Telecommunications and travel: The case for complementarity. *Journal of Industrial Ecology*, *6*(2), 43-57.

Mokhtarian, P. L., Handy, S. L., & Salomon, I. (1995). Methodological issues in the estimation of the travel, energy, and air quality impacts of telecommuting. *Transportation Research Part A: Policy and Practice*, *29*(4), 283-302.

Mokhtarian, P. L., & Salomon, I. (2001). How derived is the demand for travel? Some conceptual and measurement considerations. *Transportation research part A: Policy and practice*, *35*(8), 695-719.

Mokhtarian, P. L., Salomon, I., & Handy, S. L. (2004). A taxonomy of leisure activities: the role of ICT. Research report. University of California, Davis: Institute of Transportation Studies

Mokhtarian, P. L., Salomon, I., & Handy, S. L. (2006). The impacts of ICT on leisure activities and travel: A conceptual exploration. *Transportation*, *33*(3), 263-289.

Mokhtarian, P. L., & Tal, G. (2013). Impacts of ICT on travel behavior: a tapestry of relationships. *The Sage handbook of transport studies*, 241-260.

Mullahy, J. (1986). Specification and testing of some modified count data models. *Journal of econometrics*, *33*(3), 341-365.

Muthén, L. K., & Muthén, B. O. (2017). *Mplus User's Guide: Statistical Analysis with Latent Variables*. Version 8. Los Angeles, CA: Muthén & Muthén.

Muthén, B. O., Muthén, L. K., & Asparouhov, T. (2016) *Regression and Mediation Analysis Using Mplus.*

New York City Department of Transportation [NYCDOT]. (2018). *NYC Mobility Report*.

Napoli, P. M., & Obar, J. A. (2015). The emerging Internet underclass: A critique of mobile Internet access. The Information Society, 30(5), 323–334. doi:10.1080/01972243.2014.944726

Nie, N. H., Hillygus, D. S., & Erbring, L. (2002). Internet use, interpersonal relations, and sociability. *The Internet in everyday life*, 215-243.

Ory, D. T., & Mokhtarian, P. L. (2006). Which came first, the telecommuting or the residential relocation? An empirical analysis of causality. *Urban Geography*, *27*(7), 590-609.
Pendyala, R. M., Goulias, K. G., & Kitamura, R. (1991). Impact of telecommuting on spatial and temporal patterns of household travel. *Transportation*, *18*(4), 383-409.
Poushter, J. (2017). Smartphones are common in advanced economies, but digital divides remain. *Washington, DC: Pew Research Centre*.
Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesharing services in San Francisco. *Transport Policy*, *45*, 168-178.
Salomon, I., (1986). Telecommunications and travel relations: a review. *Transportation Research Part A: Policy and Practice*, 20A (3), 223–238.
Salomon, I. (2000). Can telecommunications help solve transportation problems. *Handbook of Transportation Modelling Eds DA Hensher, KJ Button* (Pergamon Press, Oxford) *pp*, 449-462.
Salomon, I., & Mokhtarian, P. L. (2008). Can telecommunications help solve transportation problems? A decade later: Are the prospects any better. *The handbook of transport modeling*, 519-540.
Sasaki, K., & Nishii, K. (2010). Measurement of intention to travel: Considering the effect of telecommunications on trips. *Transportation Research Part C: Emerging Technologies*, *18*(1), 36-44.
Schaller, B. (2018). The New Automobility: Lyft, Uber and the Future of American Cities.
Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New media & society*, *6*(3), 341-362.
Senbil, M., & Kitamura, R. (2003, August). Simultaneous relationships between telecommunications and activities. In *International Conference on Travel Behaviour Research*.
Smith, A. (2016). Shared, collaborative and on demand: The new digital economy. *Pew Research Center*, *19*.
Smith, A. (2017). Record shares of Americans now own smartphones, have home broadband. Retrieved from http://www.pewresearch.org/fact-tank/2017/01/12/evolution-of-technology/
Srinivasan, K., & Reddy Athuru, S. (2004). Modeling interaction between internet communication and travel activities: Evidence from Bay Area, California, Travel Survey 2000. *Transportation Research Record: Journal of the Transportation Research Board*, (1894), 230-240.
Tsetsi, E., & Rains, S. A. (2017). Smartphone Internet access and use: Extending the digital divide and usage gap. *Mobile Media & Communication*, *5*(3), 239-255.
Van Wee, B., Geurs, K., & Chorus, C. (2013). Information, communication, travel behavior and accessibility. *Journal of Transport and Land Use*, *6*(3), 1-16.
Viswanathan, K., & Goulias, K. (2001). Travel behavior implications of information and communications technology in Puget Sound region. *Transportation Research Record: Journal of the Transportation Research Board*, (1752), 157-165.
Wang, D., & Law, F. Y. T. (2007). Impacts of Information and Communication Technologies (ICT) on time use and travel behavior: a structural equations analysis. *Transportation*, *34*(4), 513-527.

Weltevreden, J. W., & Rotem-Mindali, O. (2009). Mobility effects of B2C and C2C e-commerce in the Netherlands: A quantitative assessment. *Journal of Transport Geography*, *17*(2), 83-92.

Zhang, F., Clifton, K. J., & Shen, Q. (2007). Reexamining ICT impact on travel using the 2001 NHTS data for Baltimore Metropolitan Area. In *Societies and Cities in the Age of Instant Access* (pp. 153-166). Springer, Dordrecht.

Appendix A. Detailed descriptions of the variables

Variable	Unit level	Relevant question(s) in NHTS	Code/range	Proportion
trip number	Person	Count of person trips on travel day	0-50	-
PMT	Trip	Trip distance in miles on travel day, derived from route geometry returned	0-9621.053	-
VMT	Trip	Trip distance in miles for personally driven vehicle trips in travel day	0-5441.489	-
PC	Household	Frequency of desktop or laptop computer use to access the internet	4 = Daily	75.2%
			3 = A few times a week	10.9%
			2 = A few times a month	4.4%
			1 = A few times a year	2.1%
			0 = Never	7.4%
Smartphone	Household	Frequency of smartphone use to access the internet	4 = Daily	73.1%
			3 = A few times a week	5.4%
			2 = A few times a month	2.3%
			1 = A few times a year	1.2%
			0 = Never	18.0%
Tablet	Household	Frequency of tablet use to access the internet	4 = Daily	34.8%
			3 = A few times a week	14.9%
			2 = A few times a month	9.9%
			1 = A few times a year	5.8%
			0 = Never	34.5%
Ride-hailing usage	Person	Count of ride-hailing app usage in the past 30 days	0-99	-
White	Person	Race	1 = white	83.5%
			0 = other races	16.5%
Age	Person	age	5-92	-
Male	Person	gender	1 = male	46.5%
			0 = others	53.5%
Educational attainment	Person	Educational attainment	5 = graduate/professional degree	22.7%
			4 = bachelor's degree	25.3%
			3 = some college or associates degree	29.9%
			2 = high school graduate or GED	17.6%
			1 = less than a high school graduate	4.5%
Income	Household	Household income ($10,000)	0.5 = less than $10,000	3.9%

			1.25 = $10,000 - $14,999	3.9%
			2 = $15,000 - $24,999	7.2%
			3 = $25,000 - $34,999	8.4%
			4.25 = $35,000 - $49,999	11.6%
			6.25 = $50,000 - $74,999	18.1%
			8.75 = $75,000 - $99,999	14.6%
			11.25 = $100,000 - $124,999	11.8%
			13.75 = $125,000 - $149,999	6.7%
			17.5 = $150,000 - $199,999	6.7%
			25 = $200,000 or more	7.1%
Employed	Person	Working status	1 = Yes	56.7%
			0 = No	43.3%
Number of vehicles	Household	Count of household vehicles	0-12	-
Travel companion	Trip	Number of people on trip (excluding the respondent)	1 = 1 - 400	46.4%
			0: no companion	53.6%
Time flexibility	Person	Whether the respondent is flexible about time	1 = Yes	27.4%
			0 = No	72.6%
Number of adults	Household	Count of adults (at least 18 years old) in the household	1-10	-
Number of children	Household	Count of household members – number of adults	1-10	-
Live in urban	Household	Household's urban area by classification, based on home address and 2014 TIGER/Line Shapefile	1 = Urban	77.2%
			0 = Rural	22.8%
Population density	Household	Category of population density (persons per square mile) in the census tract of the household's home location	0.05 = 0 - 99	14.9%
			0.3 = 100 - 499	17.9%
			0.75 = 500 - 999	9.7%
			1.5 = 1000 - 1999	13.5%
			3 = 2000 - 3999	18.9%
			7 = 4000 - 9999	19.6%
			17 = 10000 - 24999	4.2%
			30 = 25000 - 999999	1.3%
TNC entering year	Household	Years since TNC has entered the census tract of the household's home location (until 2017)	0 = no TNC	62.5%
			1-6	37.5%

Appendix B. Regression of ICT use on individual socio-demographics, household socio-economic status and structure, travel characteristics, and built environment

Outcome	Predictor	*b*	S.E.	*p*	*β*
ICT use (factor)	White (0/1)	-0.058	0.007	.000***	-0.029
	Age (years)	-0.015	0.000	.000***	-0.359
	Male (0/1)	-0.046	0.003	.000***	-0.031
	Educational attainment	0.120	0.003	.000***	0.183
	Employed (0/1)	0.126	0.006	.000***	0.083
	Household income ($10,000)	0.039	0.001	.000***	0.331
	Number of vehicles	0.048	0.003	.000***	0.078
	Number of adults	0.045	0.005	.000***	0.047
	Number of children	0.037	0.004	.000***	0.043
	Accompanied trips (%)	0.072	0.006	.000***	0.040
	Flexible time (0/1)	0.096	0.006	.000***	0.057
	Urban (0/1)	0.128	0.007	.000***	0.071
	Population density (1000 people/mi^2)	0.000	0.001	.760	-0.001
	R^2	0.508	0.005	.000***	--