

On Investigating the Potential Effects of Private Autonomous Vehicle Use on Home/Work Relocations and Commute Times

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ABSTRACT

The current study is motivated by the need to better understand the potential impacts that vehicular automation may have on individual decisions of residential and work relocation in a future autonomous vehicle (AV) scenario. The study employs a multivariate approach to model five behavioral dimensions simultaneously: (1) technology-savviness (TS) propensity, (2) interest in productive use of travel time (IPTT) propensity, (3) interest in work relocation, (4) interest in residential relocation, and (5) tolerance to an increase in commute travel time. Data from a web-based survey of commuters in 2017 in the Dallas-Fort Worth Metropolitan Area (DFW) is employed. The results show that both TS and IPTT, as well as demographic variables, impact relocation decisions when individuals have a private AV available for their commute. Importantly, there is considerable heterogeneity across individuals in the willingness to relocate and/or accept longer commute times in an AV future. As such, our model results may be used to inform inputs to land use and travel demand models in an AV future. Also, our results suggest that the magnitude of value of travel time savings (VTTS) decrease considered in many earlier AV impact simulation studies may be much higher than reality. Relative to 50% and even 100% VTTS decreases assumed in many studies, our results suggest a much more modest 30% or so overall decrease in VTTS because of the ability to commute in a privately-owned AV. Finally, our results do predict a rather substantial extent of urban sprawl due to AVs, potentially up to a 68% increase in the horizontal spread of cities such as Dallas-Fort Worth, unless proactive planning and policies are implemented to avert such consequences of AVs.

Keywords: Autonomous vehicles; Willingness to move; Travel behavior; Travel demand; Value of travel time savings.

1 INTRODUCTION

One of the main transportation research challenges of the current decade is to understand and estimate the potential changes that self-driving vehicular technology may bring to transportation systems, individual behavior, and urban form. While fully automated vehicles (AVs) have the potential to enhance transportation supply and operations by allowing better traffic coordination and reduced roadway crashes, their impacts on the demand for travel and on the built environment are rather complex (see Milakis *et al.*, 2017; Duarte and Ratti, 2018; Lavieri and Bhat, 2019a). One consequence of automation that is central to many of these potential impacts is the dissociation between the use of automobiles and the need to drive, that is, the increased “passengerization” of automobile travel, as discussed by Mokhtarian (2018).

Concept-AVs are being advertised by manufacturers as “new living areas” and “new alternatives to flights” (see Audi, 2019; Volvo, 2019), since the removal of the steering wheel will allow a complete re-design of the interior of vehicles with the objective of improving comfort levels and facilitating the meaningful use of the time traveling (from sleeping to socializing to working). Such changes are likely to reduce the disutility commonly attributed to time spent traveling, which could potentially influence individuals’ mode choices, increase their propensity to travel (number and/or distance of trips) and attenuate the perceived inconvenience of congestion.

A decrease in travel time disutility is already observed by recent studies on the impacts of multitasking on travel choices. For instance, based on revealed preference data, Malokin *et al.*, (2017) found that the ability to multitask contributes to lower values of travel time savings (VTTS) among Californian millennial commuters. The same authors also observed that public transport modes would have their mode share decreased (by around 1.5 percentage points) if individuals did not have the option to use laptops/tablets while commuting. This result also led the authors to infer that, in a hypothetical AV scenario, the solo-auto mode can have an increase in share of a similar magnitude due to the added multitasking possibility (Malokin *et al.*, 2019). Similarly, Lavieri and Bhat (2019b) observed that the interest in using travel time productively currently contributes to the use of ride-hailing services (revealed choice) and reduces perceived VTTS under hypothetical AV scenarios (stated choice). Also based on stated choice data, de Almeida Correia *et al.* (2019) identified that in-vehicle work activities have greater potential to reduce VTTS than in-vehicle leisure activities.

While available research on the effects of multitasking on value of travel time is predominantly focused on a mode choice setting, changes in in-vehicle time use can also impact out-of-vehicle time use (see, for example, Pudāne *et al.*, 2018) and, consequently, influence other transportation related decisions, such as activity locations. In particular, if longer commute distances and times are tolerated, individuals may expand their job search areas or choose to relocate to more affordable or isolated areas. Such actions may not only result in increased distances traveled but could also contribute to urban sprawl. Considering that suburbanization is again on the rise in the United States (U.S.) (see Frey, 2018), automation could trigger an

acceleration of this process and a surge in potentially more unsustainable patterns of energy and resources consumption (Ewing and Hamidi, 2015).

The current study is motivated by the need to better understand the potential impacts that vehicular automation may have on individual decisions that can result in urban sprawl. Specifically, we examine individual preferences toward residential and work relocation in a future AV scenario taking into consideration people's technology-savviness and interest in the productive use of travel time, two important elements for in-vehicle multitasking that can influence time sensitivity and work/home location choices (in the rest of this paper, the term AV will be used to refer to privately owned AVs and AV use will refer to the use of privately owned AVs). In doing so, we use a multivariate approach to model five behavioral dimensions simultaneously: (1) technology-savviness propensity, (2) interest in productive use of travel time (IPTT) propensity, (3) interest in residential relocation, (4) interest in work relocation, and (5) tolerance to an increase in commute travel time. Different relationships between the five dependent variables are tested and lifecycle, lifestyle, and built environment characteristics are used as explanatory variables. The model is estimated using data obtained through a web-based survey of commuters in the Dallas-Fort Worth Metropolitan Area (DFW). Using the model, we arrive at informed guesstimates of the VTTS decrease that may be expected due to AV use for the commute, as well as a first quantification of the extent of urban sprawl that may be engendered by AVs.

The DFW area is one of the fastest growing regions in the U.S. and covers a 13-county area in northern Texas. The population of the DFW metro region is about 7.4 million, accounting for 27 percent of the state of Texas' total population (Hegar, 2019). And, over time, a higher percentage of this population is living at the urban edges as opposed to in the central parts, a trend reflected in the highest percentage of population increases (approximately 18%-26% increase in ten years) occurring in four counties to the north and east of the metropolitan center (U.S. Census, 2019). This urban sprawl is already having an impact on travel patterns, with the average one-way commute time in the DFW area being 27 minutes, two minutes higher than both the U.S. and State of Texas averages (Data USA, 2017). As importantly, an increasing percentage of individuals have a "super commute" of over 90 minutes (rising 17%, from 1.75% in 2010 to 2.05% in 2017) (U.S. Census, 2017). In this sense, vehicular automation could contribute to an already worrisome scenario of urban sprawl and commute lengths in DFW.

The remainder of this paper is organized as follows. The next section presents a literature overview of the current discussions and investigations related to the potential impacts of automation on the built environment and on urban sprawl. Section 3 introduces the analytic framework, explains the data sources, survey instrument, sample characteristics and modeling methodology. Section 4 presents the model estimation results and goodness of fit measures. Section 5 discusses how the model results may be used to inform land use-transportation forecasting systems in an AV future, and also derives first-estimates of the potential VTTS decrease and urban sprawl that may be engendered in an AV future. The final section concludes the paper with a summary, limitations, and future research directions.

2 LITERATURE OVERVIEW

The adoption of AVs and its implications for transportation and society have been the focus of extensive research in the past few years. From willingness to pay for automation, to preferences between AV ownership and sharing, to changes in vehicle miles traveled (VMT), to reductions in parking requirements, the growing literature has investigated multiple hypotheses for the automated future (see for example, Bansal *et al.*, 2016; Childress *et al.*, 2015; Daziano *et al.*, 2017; Kröger *et al.*, 2019; Lavieri *et al.*, 2017; Levin *et al.*, 2017; Zhang *et al.*, 2015; Zhang *et al.*, 2018). Recent efforts have also produced reviews and discussion studies that compile and compare analyses to identify common trends as well as research gaps and policy implications (see for example, Becker and Axhausen, 2017; Milakis *et al.*, 2017; Duarte and Ratti, 2018; Fraedrich *et al.*, 2019; Hawkins and Habib, 2019; Soteropoulos *et al.*, 2019). But, as acknowledged in many of these reviews, most studies attempting to understand AV effects on travel behavior and land-use are based on simulations and modeling using *a priori* assumptions related to VTTS decreases or capacity increases. There is no attempt in many of these studies to examine whether, for example, the ability to multi-task and work productively in a driverless environment within the context of a private vehicle (as we know it) will lead to the magnitude of VTTS decreases assumed, an issue pointedly also noted recently by Singleton (2019) (many earlier studies assume 50% or even more drop in VTTS due to AVs). Besides, almost all such modeling studies completely ignore variations in VTTS across a heterogeneous population. Also, probably due to their long-term nature, impacts of automation on commute distance, residential relocation, and urban sprawl have been presented as a motivation in many empirical analyses and have also been discussed by most of the review studies, but have not served as the main focus of empirical analyses. Indeed, to the authors' knowledge, only two studies have been dedicated to investigating the residential relocation problem in future AV scenarios -- Zhang and Guhathakurta (2018) and Carrese *et al.* (2019).

Zhang and Guhathakurta (2018) integrated a residential location model with a shared AV (SAV) simulation model to investigate home relocation decisions based on individuals' current preferences toward residential location attributes and real estate development patterns in Atlanta (GA, U.S.). The authors tested multiple scenarios (all considering that trips are served by SAV fleets) that in some instances involved VTTS reductions due to hands-off travel. Even though residential relocation to less dense areas resulted in higher waiting times for SAVs, the authors observed residential relocations that increased commuting distances in all scenarios, even when VTTS reductions were not considered. On the other hand, Carrese *et al.* (2019) administered a small-scale survey ($n=200$) in Rome, Italy, to examine individuals' willingness to relocate, their acceptable distance of relocation (compared to the current residential location), and the influence of AV availability on the relocation decision. They identified that residential dissonance was higher among individuals living in central areas and that these groups were willing to move farther distances, confirming that AVs may induce suburbanization.

Based on distinct approaches, the two studies discussed above provide preliminary insights into the impacts of automation on commute distances and residential relocation, supporting the hypothesis that AVs can potentially lead to urban sprawl. However, the first study, like many

earlier modeling and simulation studies, is based on multiple strong assumptions (for example, low travel cost per mile, assumed VTTS reduction, and no changes in activity-travel patterns or congestion) and does not elicit actual preferences and interest from individuals, while the second survey-based study employs a small sample supplemented with an exploratory aggregate-level analysis. In this context, the current paper contributes to the literature by examining individual-level preferences and behaviors related to residential/work relocations and the resulting commute, using a relatively large scale stated-preference survey of 1607 commuters in the DFW area. The paper then uses the results to arrive at empirical estimates of VTTS decreases for the commute due to AVs as well as an aggregate quantification of urban sprawl due to AVs.

3 METHODOLOGY

3.1 The Survey

The data used for the analysis in this paper was obtained through a web-based survey developed and administered by the authors in the fall of 2017. The distribution was achieved through mailing lists held by multiple entities (local transportation planning organizations, universities, private transportation sector companies, non-profit organizations, and online social media) resulting in a convenience sample. The survey was implemented in the Dallas-Fort Worth (DFW) metroplex and was limited to commuters (individuals who had their primary work place outside their homes).

The survey collected data on individual demographics, household characteristics, and commute/travel characteristics. The individual demographics data included age, gender, race, education level attained, employment type (full time, part time, self-employed), and household income. The household characteristics data included number of members of the household, number of workers, location of household (downtown vs. suburb), and whether the respondent is a homeowner. Commute/travel characteristics included whether the respondent telecommuted, vehicle ownership, and daily commute time.

In addition to the individual demographics, household characteristics, and commute/travel information, the survey also collected information on people's technology use, as well as interest in using travel time more productively. Finally, the survey included stated choice questions involving responses related to home/work relocations and commute time sensitivity in response to owning a self-driving vehicle. The specific questions were as follows: "Consider a scenario in which you own a self-driving vehicle and you don't need to spend your commute time paying attention to traffic anymore. Would you consider moving farther from your work location? Would you consider changing your work location? How much longer would you be willing to commute to/from work?" For ease in presentation, we will refer to these choice outcomes collected in the survey as "move home", "move work", and "increase commute time", respectively. These three outcomes represent the main outcomes of interest in the current study.

Before the stated choice experiments, respondents were presented with the definition of autonomous vehicles, as "Self-driving vehicles, also sometimes referred to as *autonomous cars* or *driverless cars*, are capable of responding to the environment and navigating without a human driver in the vehicle controlling the vehicle. In the following questions, whenever you read the

term *self-driving vehicle*, imagine a car with no steering wheel that operates like a personal chauffeur”. Respondents also were provided the option to watch a 90-second educational animation video about how AV-technology works and how the user experience might be.

3.2 Analytic Framework and Data Description

The analytic framework is focused on understanding how AVs may impact residential and work locations, as well as commute times, while explicitly considering individual-level variables (individual demographics, household characteristics, and commute/travel information) as well as technology-savviness (or tech-savviness for short) and interest in the productive use of travel time (IPTT) (the latter two variables are of interest in this study because they directly impact travel time sensitivity). Tech-savviness and IPTT are latent (unobserved) stochastic psychological constructs that are modeled as functions of individual characteristics. Any effects of these latent stochastic constructs on two or more of the three main outcomes of interest in this study (move home, move work, and increase commute travel time, in response to having an AV) generates unobserved correlation among the three main outcomes, through a common stochastic term embedded in each latent construct. At the same time, for reasons discussed below Equation (3) in Section 3.2.1, we consider tech-savviness and IPTT as co-endogenous with the main outcomes (that is, we allow correlations between the latent constructs and the three main outcomes of interest). Figure 1 provides a diagrammatic representation of the framework, based on Bhat’s Generalized Heterogeneous Data Model (GHDM) (Bhat, 2015a). The components are discussed below.

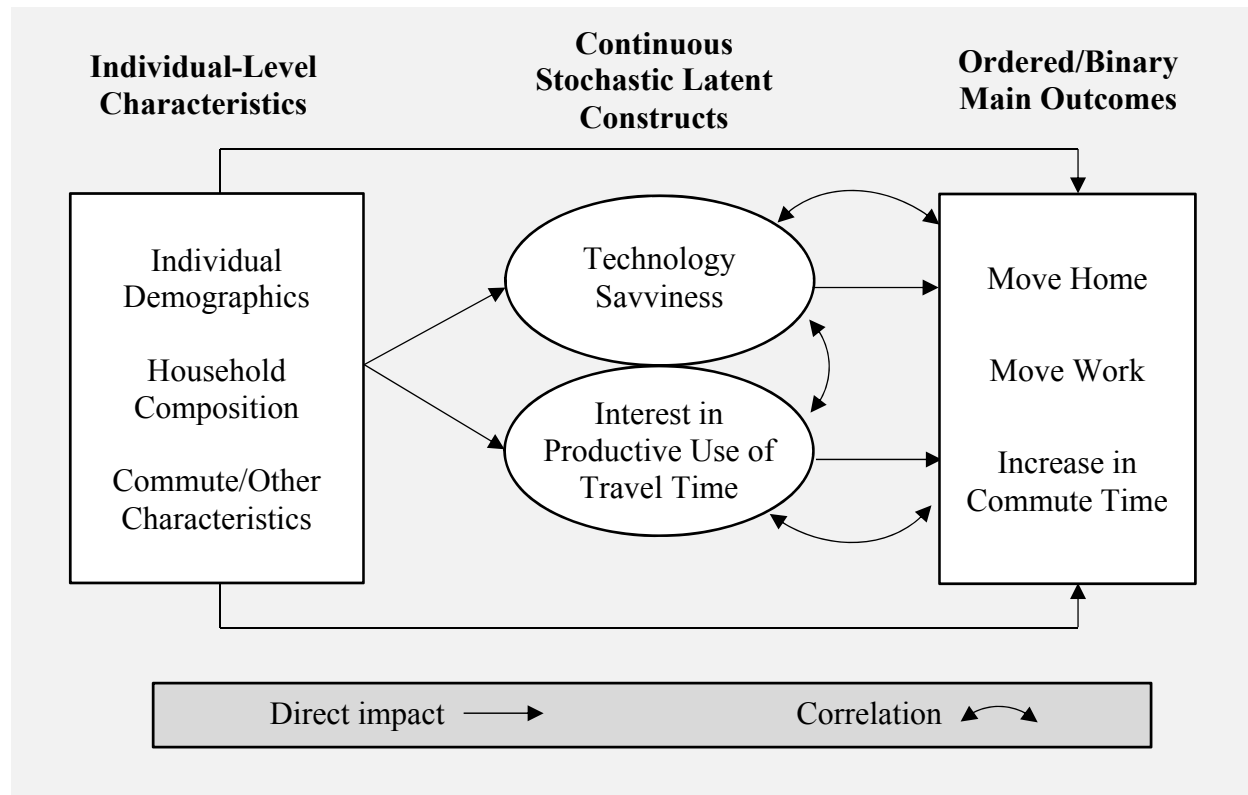


Figure 1. Model Framework

3.2.1. Stochastic Latent Constructs

In the structural equations model component of the framework, individual-level characteristics (left side of Figure 1) are used to explain the two stochastic latent constructs representing tech-savviness and IPTT. The first latent construct, tech-savviness, represents the individual's familiarity and affinity with technology, in our case, information and communication technologies (ICTs). Tech-savviness is important in our framework because the ability to use the time released by not having to drive may be predicated on how tech-savvy an individual is. For example, Astroza *et al.* (2017) indicate that tech-savviness has a significant and positive impact on not only smartphone ownership, but also the intensity of use of smartphone apps to obtain travel information, as well as the intensity of use of social media and websites (accessible via smartphone, tablet, or computer).

The second latent construct, IPTT, captures the general attitude toward the use of travel time productively. This is a dimension different from tech-savviness, in the sense that tech-savviness may be viewed as a measure of the ability to pursue ICT-based use of travel time, while IPTT refers to the actual desire to do so (and may involve activities that do not require ICT use). We can draw a parallel with the Theory of Planned Behavior (Ajzen, 1991) where IPTT represents the general attitude towards the behavior, while tech-savviness represents the perceived behavioral control (at least in terms of spending the in-vehicle time using ICTs). Thus, individuals who are tech-savvy may not necessarily be keen on using travel time productively. Indeed, according to Singleton (2019), the most common multi-tasking activities during travel (and when not driving) do not appear to be what would be traditionally labeled as being productive and are more about passing time/coping with the commute boredom (including activities such as thinking/daydreaming, viewing scenery or watching people, and listening to music). Thus, we believe it is important to consider IPTT separately from tech-savviness.

Of course, by definition, the two stochastic latent constructs; tech-savviness and IPTT; are not directly observed. However, several indicators of these variables have been collected in our survey. The first latent construct, tech-savviness, has five indicators, each measured on the same five-point Likert scale of (1) Does not describe me at all, (2) Describes me slightly, (3) Describes me moderately well, (4) Describes me very well, and (5) Describes me extremely well. The indicators for tech-savviness are:

- I frequently use online banking service.
- I frequently purchase products online.
- Every day, I spend at least some time on online social media.
- Learning how to use new smartphone apps is easy for me.
- I do most of my work on a computer or tablet.

Table 1 provides descriptive statistics of these indicators. In general, the convenience sample we collected is relatively tech-savvy, with close to 90% effectively describing themselves as frequent users of online banking service and purchasing products online (see the percentages in the “Describes me very well” and “Describes me extremely well” columns). Between 75% and 80%

of the respondents assert that the statements “learning how to use smartphone apps is easy for me” and “I do most of my work on a computer/tablet” describes them very or extremely well. A lower percentage (about 61%) indicate that the statement “Every day, I spend at least some time on online social media” describes them very well or extremely well. The second latent construct, interest in productive use of travel time (IPTT), has two indicators, each measured on the following five-point Likert scale: (1) Strongly disagree, (2) Somewhat disagree, (3) Neither agree or disagree, (4) Somewhat agree, and (5) Strongly agree. The indicators for IPTT are:

- Self-driving vehicles are appealing because they will allow me to use my travel time more effectively.
- I would not mind having a longer commute if I could use my commute time productively.

Table 1 also presents descriptive statistics for the two indicators above. 61% of the sample shows positive interest in the possibility of using travel time more effectively in AVs. A lower percentage, close to 55%, describe themselves as interested in commuting longer if they could be more productive during their commute. The generally lower percentage of individuals who appear to be interested in using travel time productively relative to those who consider themselves tech-savvy adds further credibility and support for considering tech-savviness and IPTT as separate psychological/attitudinal/self-description variables.

Table 1. Distribution of Attitudinal Indicators

Indicators of...	Attitudinal Indicator	Response Category					Total
		Does not describe me at all	Describes me slightly well	Describes me moderately well	Describes me very well	Describes me extremely well	
		Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	
Technology Savviness	I frequently use online banking services	39 (2.4)*	55 (3.4)	103 (6.4)	300 (18.7)	1110 (69.1)	1607(100.0)
	I frequently purchase products online	20 (1.2)	117 (7.3)	239 (14.9)	379 (23.6)	852 (53.0)	1607(100.0)
	Every day, I spend at least some time on online social media	258 (16.1)	160 (10.0)	210 (13.1)	273 (17.0)	706 (43.9)	1607(100.0)
	Learning how to use new smartphone apps is easy for me	40 (2.5)	88 (5.5)	268 (16.7)	436 (27.1)	775 (48.2)	1607(100.0)
	I do most of my work on a computer	73 (4.5)	92 (5.7)	158 (9.8)	286 (17.8)	998 (62.1)	1607(100.0)
Indicators of...	Attitudinal Indicator	Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly Agree	Total
		Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	
Interest in Productive Use of Time (IPTT)	Self-driving vehicles are appealing because they will allow me to use my travel time more effectively	216 (13.4)**	134 (8.3)	277 (17.2)	505 (31.4)	475 (29.6)	1607 (100.0)
	I would not mind having a longer commute if I could use my commute time productively	209 (13.0)	266 (16.6)	265 (16.5)	626 (39.0)	241 (15.0)	1607 (100.0)

* Row Percentage $(39/1607) \times 100$ rounded to 2.4%

** Row Percentage $(216/1607) \times 100$ rounded to 13.4%

In the current paper, and unlike earlier applications of the GHDM model (see Astroza *et al.*, 2017; Lavieri *et al.*, 2017; Lavieri and Bhat, 2019a,b), we do not consider all the indicator variables for each latent construct as separate endogenous variables. Rather, we reduce the suite of indicators for each construct to a single continuous latent construct “factor”. To do so, we use traditional confirmatory factor analysis procedures using the indicators mentioned above. In particular, let $\boldsymbol{w}_{z_l^*}$ be a vector of indicators for the unobserved latent construct z_l^* for an individual (we suppress the index for individual in this presentation). Then, to ensure that all the indicators for each latent construct are on an equal footing, we normalize the vector to obtain

$$\boldsymbol{\tau}_{z_l^*} = \frac{\boldsymbol{w}_{z_l^*} - \boldsymbol{\mu}_{z_l^*}}{\boldsymbol{\sigma}_{z_l^*}}, \quad (1)$$

where $\boldsymbol{\mu}_{z_l^*}$ is the sample mean vector of the indicators and $\boldsymbol{\sigma}_{z_l^*}$ is the sample standard deviation vector. Then, the factor analysis proceeds by writing $\boldsymbol{\tau}_{z_l^*} = \boldsymbol{R}_{z_l^*} z_l^* + \boldsymbol{\mathcal{G}}_{z_l^*}$, where $\boldsymbol{R}_{z_l^*}$ is a vector of the z_l^* factor’s (latent construct’s) loadings on each of its indicators, and $\boldsymbol{\mathcal{G}}_{z_l^*}$ is a vector of error terms to recognize that the indicator vector $\boldsymbol{w}_{z_l^*}$ (and, equivalently, $\boldsymbol{\tau}_{z_l^*}$) is obtained only for a sample of the population. The loading vector $\boldsymbol{R}_{z_l^*}$ is essentially estimated by capturing as much of the variance-covariance of the original $\boldsymbol{\tau}_{z_l^*}$ elements through the variance-covariance of the loading vector $\boldsymbol{R}_{z_l^*}$ (Mueller and Hancock, 2001, for a discussion). In doing so, the elements of the $\boldsymbol{\mathcal{G}}_{z_l^*}$ vector are assumed independent of z_l^* , and the scale of the factor z_l^* itself is normalized to standard deviation of one with a mean value of zero (this is an innocuous normalization).

Once the loading vector $\boldsymbol{R}_{z_l^*}$ is estimated for each latent construct, the single continuous indicator value for each of the latent constructs is computed as $c_{z_l^*} = (\hat{\boldsymbol{R}}_{z_l^*}^{-1})' \boldsymbol{\tau}_{z_l^*}$. Of course, these are point values for a particular sample, and are considered as manifestations of the underlying stochastic latent construct z_l^* . That is, we write $c_{z_l^*} = z_l^*$ in our econometric model, and then write z_l^* itself as a linear function of covariates:

$$z_l^* = \boldsymbol{\alpha}_l' \boldsymbol{w} + \eta_l, \quad (2)$$

where \boldsymbol{w} is a $(D \times 1)$ vector of observed covariates (excluding a constant), $\boldsymbol{\alpha}_l$ is a corresponding $(D \times 1)$ vector of coefficients, and η_l is a standard normally distributed random error term. For future use, we also define the $(L \times D)$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \dots, \boldsymbol{\alpha}_L)'$, and the $(L \times 1)$ vectors $\boldsymbol{z}^* = (z_1^*, z_2^*, \dots, z_L^*)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3, \dots, \eta_L)'$. In our empirical case, $L=2$. In matrix form, we may write Equation (1) as:

$$\mathbf{z}^* = \boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}. \quad (3)$$

We consider a multivariate normal correlation structure for $\boldsymbol{\eta}$ to accommodate interactions among the unobserved latent variables: $\boldsymbol{\eta} \sim MVN_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is $(L \times L)$ correlation matrix.

The reduction of the many different indicators for each latent construct into a single continuous factor value not only facilitates estimation, but also serves another important purpose. By writing the single continuous factor for each construct as $c_{z_i} = z_i^* = \boldsymbol{\alpha}'_i \boldsymbol{w} + \eta_i$, we are able to easily consider the latent constructs themselves as being potentially endogenous to the main outcome variables by allowing correlation effects between the error terms η_i and the error terms in the main outcome equations. This feature is particularly relevant because our main outcome variables involve residential and work location choices, which are influenced by multiple lifecycle and lifestyle factors (such as the presence and age of children in the household or the desire to be engaged in natural surroundings, see for example, Bhat, 2015b) that are unobserved in our model (variables not measured in the survey) and that may also influence people’s level of tech-savviness and interest in multitasking while traveling. For example, tech-savvy individuals are commonly associated with being able to handle digital disruptions well, but also being very time-conscious and not dealing too well with general life disruptions (because of constant digital stimulations; see McFarlane, 2010; Sarwar and Soomro, 2013). Thus, tech-savvy individuals may intrinsically be less inclined to move their home farther from their work place and spend time dealing with a life disruption, leading to a negative correlation between tech-savviness and “move home”. Separately, though, tech-savviness is also likely to positively and directly impact the inclination to move homes farther from the workplace because of the ability to use gadgets in AVs while also attempting to act on any residential dissonance. If the intrinsic disinclination to move homes among tech-savvy individuals (due to the error correlation) is ignored, this may temper the “true” positive direct effect of tech-savviness on inclination to move homes due to AVs.^{1,2} Finally, by modeling the single continuous factors as well as all the main outcomes jointly, we also efficiently estimate the structural equation model matrix elements $\boldsymbol{\alpha}$ from information on the constructed continuous factors as well as the main outcomes. For future use, we stack the L continuous factors into an $(L \times 1)$ vector $\boldsymbol{c} = (c_{z_1}, c_{z_2}, \dots, c_{z_L})'$, so that $\boldsymbol{c} = \mathbf{z}^*$.

3.2.2. Exogenous Variables

In this study, as already discussed, we consider individual-level characteristics as exogenous variables to explain the two latent constructs as well as the three main outcomes. Table 2 presents

¹ Note that the “move home” question explicitly indicated “moving farther from your work location”.

² Also note that two of the attitudinal indicators used to draw the IPTT latent construct imply trade-offs between commute or travel time and productive use of travel time. Thus, there is the potential for endogeneity between the outcome “commute time increase” and these IPTT indicators, which reinforces the need to test for unobserved error correlations between the latent construct formed from the IPTT indicators and the outcomes of interest.

the distribution and descriptive statistics of the individual demographics, household characteristics, and transportation-related characteristics of the respondents. To provide a sense of the characteristics of our sample, we compare, whenever possible, sample descriptives with the commuter population in the DFW area, as characterized by the U.S. Census Bureau (2018a,b).

Table 2 shows that men comprise 58.4% of our sample, which is a slight over-representation relative to the Census statistic on men in the DFW commuter population (which is 54.0%). Individuals aged 45 to 64 are also over-represented (53.2% compared to 35.8%), as are non-Hispanic Whites (75.0% relative to 51.0% from the Census). Additionally, there is a skew in our sample toward those who are employed full-time (81.6% versus 60.8%) and hold an undergraduate or graduate degree (75.5% compared to 33.7%). The Census data provides household income and household composition statistics only for all households, and not selectively for only those households with at least one employed individual. So, we are unable to compare our sample descriptives on these variables with those from the Census. However, the sample descriptives do appear to be skewed toward individuals from higher income households and multi-worker households. As for other household characteristics, we observe that most respondents live in suburban neighborhoods (65.1%), are home owners (73.0%) and own at least one vehicle per employed household member (85.3%). About a fifth of respondents telecommute at least on a weekly basis. Finally, compared to the DFW commute time average from 2012 (27 minutes, Data USA, 2017), the current sample presents a skew toward longer commutes, with the average being 33.53 minutes.

Clearly, the sample is not representative of the DFW commuter population along many dimensions. The divergence between our sample and the DFW commuter population may be attributable to many factors. For example, the main topic of the survey was self-driving vehicles, which may be of more interest to highly educated and high-income individuals who travel long distances for their commute. In addition, the survey was conducted strictly through an online platform and the largest mailing list used in the distribution was of toll-road users, who are likely to be individuals who travel long distances and are high-income. But, while the overall descriptive statistics of the dependent variables cannot be generalized to the DFW population, there is no reason to believe that the individual level relationships estimated from disaggregate models developed in this paper are not applicable to the larger population. At the very least, the relationships should provide important insights on the fundamental relationship between work/residence locations and commute travel behavior in an autonomous vehicle future (that does not currently exist at all) and socio-demographic/lifestyle characteristics.

Table 2. Sample Distribution of Exogenous Variables: Socio-Demographic and Household Related Characteristics

Variable	Count	%	Variable	Count	%
<i>Individual Demographics</i>			<i>Household Characteristics</i>		
Gender			Household annual income		
Female	668	41.6	Under \$49,999	184	11.4
Male	939	58.4	\$50,000-\$99,999	443	27.6
Age			\$100,000-\$149,999	496	30.9
18 to 34	261	16.2	\$150,000-\$199,999	269	16.7
35 to 44	360	22.4	\$200,000 or more	215	13.4
45 to 54	432	26.9	Household composition		
55 to 64	423	26.3	Single person household	191	11.9
65 or more	131	8.2	Single worker multi-person household	265	16.5
Ethnicity			Multi-worker household	1151	71.6
Non-Hispanic White	1205	75.0	Residential location		
Non-Hispanic Black	102	6.3	Central or Downtown area	375	23.3
Hispanic	109	6.8	Suburban area	1046	65.1
Asian/Pacific Islander	101	6.3	Small Town or Rural area	186	11.6
Other	90	5.6	Residence ownership		
Employment type			Homeowner	1173	73.0
Full-time employee	1312	81.6	Not a homeowner	434	27.0
Part-time employee	138	8.6	Vehicle availability		
Self-employed	157	9.8	< 1 vehicle per worker	236	14.7
Education			≥ 1 vehicle per worker	1371	85.3
Completed high-school	238	14.8	<i>Commute/other Characteristics</i>		
Completed technical school/associate degree	154	9.6	Telecommuting status		
Completed undergraduate degree	724	45.0	< 1 per week	1295	80.6
Completed graduate degree	491	30.6	≥ 1 per week	312	19.4
			Commute time (minutes)		
			Average	33.53	Std. Dev
			Time	20.6	

3.2.3. Main Outcome Variables

As already discussed, the three main outcomes in the model are move home, move work, and increase commute time. Specifically, presented with an AV future, respondents are asked to make location and commute choices (stated choices). When asked whether they would consider moving their home farther from their workplace (a binary response of “yes” or “no”), about 33% of respondents indicated in the affirmative. The corresponding percentage (again as a binary choice) for whether they would move their workplace is 34%. The acceptance of longer commutes was measured in five ordinal categories: (1) not a single minute more, (2) up to 10 minutes more, (3) 10-20 minutes more, (4) 20-30 minutes more, and (5) > 30 minutes more; and around 70% of the respondents stated that they would be willing to commute up to 10 minutes more or even longer in a hands-free driving situation (with a non-negligible percentage of 17.7% willing to commute even longer than 20 minutes). The cross-tabulation of the three outcomes is provided in Table 3. The distribution of the “move home” and “move work” responses (see the first row, last column of the table) shows that about a fifth of the sample is in the “yes-yes” category, and that more than half respond in the “no-no” category (see the penultimate row, last column of the table). As expected, those who express the desire to move their place of residence and work (the “yes-yes” category) are also the most accepting of commute time increases, while those who do not express any interest in home/work relocations (the “no-no” category) are the least accepting of commute time increases. Interestingly, even in this last “no-no” category, over half of the respondents indicate that they would be willing to accept a higher commute time. Between the segments of respondents who would be interested in moving only home or only work, individuals willing to move only home tend to be more willing to accept increases in commuting time. This result suggests greater geographic dissonance in terms of residential location choice than work location choice and reinforces the notion that AVs may indeed facilitate residential sprawl.³ Further, this result emphasizes the importance of understanding differences between residential and work location choices and the distinct ways in which these preferences interact with the acceptance of longer commutes due to hands-free driving. For example, the decision to move home may be related to the desire to pursue non-work activities (or subjective feelings, such as an affinity for more space) or to lower one’s cost of living. Similarly, the decision to move work may be guided by the desire to pursue better career opportunities or to take advantage of a more desirable work environment.

³ The reduced acceptance of a commute increase for job relocation purposes may also be influenced by the fact that the spatial distribution of jobs tends to be less dispersed than that of housing and/or that the market for specialized jobs for our highly educated sample is particularly concentrated; see Balbontin and Hensher, 2018.

Table 3. Increase in Commute Time Distribution by Location Choice

Move Home	Move Work	Increase in Commute Time					Total
		Not a single minute more	up to 10 minutes	10 to 20 minutes	20 to 30 minutes	> 30 minutes	
Yes	Yes	4 (1.1%) [†]	54 (15.4%)	135 (38.6%)	88 (27.5%)	69 (17.4%)	350 (21.8%) [‡]
Yes	No	11 (6.2%)	45 (25.3%)	72 (40.4%)	29 (16.3%)	21 (11.8%)	178 (11.1%)
No	Yes	53 (27.0%)	79 (40.3%)	46 (23.5%)	15 (7.6%)	3 (1.6%)	196 (12.2%)
No	No	417 (47.2%)	290 (32.8%)	116 (13.1%)	43 (4.9%)	17 (2.0%)	883 (54.9%)
Total		485 (30.2%) [§]	468 (29.1%)	369 (23.0%)	175 (10.9%)	110 (6.8%)	1607 (100%)

[†] Row-percentage $(4/350) \times 100$ rounded to 1.1%.

[‡] Column percentage $(350/1607) \times 100$ rounded to 57.7%.

[§] Row percentage $(485/1607) \times 100$ rounded to 30.2%.

3.2.4. Framework for Jointly Modeling Continuous and Ordered Outcomes

In this study, we jointly model five outcomes: two continuous outcomes (representing the two latent stochastic factors of interest) and three ordinal outcomes.⁴ The important point here is that the continuous variables are used as determinants of the ordinal outcomes but are also considered endogenous to capture any unobserved correlations that jointly impact the latent constructs and the three main ordinal outcomes. In addition, a recursive structure of influence of the actual ordinal outcomes is estimable among the three ordinal outcomes.⁵ Econometrically speaking, from a pure estimation standpoint, the methodology in this paper is a special case of the GHDM model proposed by Bhat (2015a). But, conceptually and structurally speaking, there is an important difference. In particular, unlike in Bhat's discussion of the GHDM model and its many applications thus far, we expressly consider the latent stochastic constructs as being endogenous to the main ordinal outcomes. This is because we write the continuous factor vector (developed through the factor analysis approach discussed earlier in Section 3.2.1) as $c = z^*$ in the measurement equation model, and consider c as endogenous, while also using c as impacting the three main outcomes.

To complete the measurement equation model, and continuing to suppress the index for individuals, define i as the index for each ordinal outcome ($i = 1, 2, \dots, I$; in the current study, $I = 3$). Let the number of categories for each ordinal outcome i be K_i (*i.e.*, the categories of ordinal

⁴ Two of the three ordered outcomes are, in reality, binary outcomes. Their formulations are, however, econometrically identical to that of ordinal variables with only two categories each.

⁵ In joint limited-dependent variables systems in which one or more dependent variables are not observed on a continuous scale, such as the joint system considered in this paper that has ordinal as well as continuous dependent variables, the structural effects of one variable on another can only be in a single direction. See Maddala (1983) and Bhat (2015a) for a more detailed explanation. It is critical to note that, regardless of which directionality of structural effects among the endogenous variables is specified (or even if no relationships are specified), the system is a joint bundled system because of the correlation in unobserved factors impacting the underlying propensities.

outcome i are indexed by k and belong in $\{1, 2, \dots, K_i\}$; for the two binary outcomes corresponding to “move home” and move work”, $K_i=2$). Following the usual ordered response framework notation, it is possible to write the latent propensity (y_i^*) for each ordinal outcome as a function of relevant covariates and relate this latent propensity to the observed frequency outcome (y_i) through threshold bounds (see McKelvey and Zavoina,1975):

$$y_i^* = \beta_i' \mathbf{x} + \mathbf{d}_i' \mathbf{z}^* + \varepsilon_i, \quad y_i = k \text{ if } \theta_i^{k-1} < y_i^* < \theta_i^k \quad (k = 1, 2, 3, \dots, K_i), \quad (4)$$

where \mathbf{x} is an $(A \times 1)$ -vector of covariates (not including a constant, but including individual-level characteristics and possibly the observed ordinal values of other endogenous variables in a recursive fashion, as discussed earlier), β_i is a corresponding $(A \times 1)$ -vector of coefficients to be estimated (some of the elements of β_i will be zero), ε_i is a standard normal error term (assumed to be identical and independently distributed across individuals), \mathbf{d}_i is an $(L \times 1)$ vector of latent variable loadings on the i^{th} ordinal outcome, and θ_i^k is the upper bound threshold for frequency category k of ordinal outcome i ($\theta_i^0 < \theta_i^1 < \theta_i^2 < \dots < \theta_i^{K_i}$; $\theta_i^0 = -\infty$, $\theta_i^{K_i} = +\infty$ for each ordinal outcome i). For later use, let $\theta_i = (\theta_i^1, \theta_i^2, \theta_i^3, \dots, \theta_i^{K_i-1})'$ be a $[(K_i - 1) \times 1]$ vector of stacked thresholds for ordinal outcome i , and let $\theta = (\theta_1', \theta_2', \dots, \theta_I')$ be a stacked vector of the thresholds of all ordinal outcomes. Stack the I underlying variables y_i^* into an $(I \times 1)$ vector \mathbf{y}^* , and the error terms ε_i into another $(I \times 1)$ vector $\boldsymbol{\varepsilon}$. Define $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_I)$ [$(A \times I)$ matrix] and $\mathbf{d} = (\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_I)$ [$(L \times I)$ matrix], and let the correlation matrix of $\boldsymbol{\varepsilon}$ be $\boldsymbol{\Upsilon}$ (so, $\boldsymbol{\varepsilon} \sim MVN_I[\mathbf{0}_I, \boldsymbol{\Upsilon}]$); Finally, define $\theta_{low} = (\theta_1^{y_1-1}, \theta_2^{y_2-1}, \dots, \theta_I^{y_I-1})'$ as a $(I \times 1)$ vector containing the stacked lower thresholds for the decision-maker, and $\theta_{up} = (\theta_1^{y_1}, \theta_2^{y_2}, \dots, \theta_I^{y_I})'$ as a $(I \times 1)$ vector containing the stacked upper thresholds for the decision-maker. Then, in matrix form, the measurement equation for the main outcomes may be written as:

$$\mathbf{y}^* = \boldsymbol{\beta}' \mathbf{x} + \mathbf{d}' \mathbf{z}^* + \boldsymbol{\varepsilon}, \quad \theta_{low} < \mathbf{y}^* < \theta_{up}. \quad (5)$$

To proceed further, we may write the structural (SEM) and the measurement (MEM) components of the joint model as follows:

$$\mathbf{z}^* = \boldsymbol{\alpha} \mathbf{w} + \boldsymbol{\eta} \quad (\text{SEM component}), \quad (6)$$

$$\mathbf{c} = \mathbf{z}^* \quad (\text{MEM component}), \quad (7)$$

$$\mathbf{y}^* = \boldsymbol{\beta}' \mathbf{x} + \mathbf{d}' \mathbf{z}^* + \boldsymbol{\varepsilon} \quad (\text{MEM component}), \quad (8)$$

$$\text{with } Cov \begin{pmatrix} \boldsymbol{\eta} \\ \boldsymbol{\varepsilon} \end{pmatrix} = \boldsymbol{\Psi} = \begin{bmatrix} \boldsymbol{\Gamma} & \boldsymbol{\Omega} \\ \boldsymbol{\Omega}' & \boldsymbol{\Upsilon} \end{bmatrix} \quad (E \times E \text{ matrix}), \quad E = L + I.$$

$\boldsymbol{\Omega}$ in the equation above represents the $(L \times I)$ correlation elements between the $\boldsymbol{\eta}$ and $\boldsymbol{\varepsilon}$ error elements (this recognizes the endogeneity of the latent constructs in the system). To develop the reduced form equations, replace the right side of the SEM component into the MEM components to obtain the following system:

$$\mathbf{c} = \alpha\mathbf{w} + \boldsymbol{\eta} \quad (9)$$

$$\mathbf{y}^* = \boldsymbol{\beta}'\mathbf{x} + \mathbf{d}'(\alpha\mathbf{w} + \boldsymbol{\eta}) + \varepsilon = \boldsymbol{\beta}'\mathbf{x} + \mathbf{d}'\alpha\mathbf{w} + \mathbf{d}'\boldsymbol{\eta} + \varepsilon \quad (10)$$

Now, consider the $[(E \times 1)]$ vector $\mathbf{s} = \begin{pmatrix} \mathbf{c} \\ \mathbf{y}^* \end{pmatrix}$. Let $\mathbf{g} = (\mathbf{d}', \mathbf{IDEN}_I)'$, an $(E \times I)$ -matrix. Define

$$\mathbf{B} = \begin{bmatrix} \mathbf{B}_c \\ \mathbf{B}_{y^*} \end{bmatrix} = \begin{bmatrix} \alpha\mathbf{w} \\ \boldsymbol{\beta}\mathbf{x} + \mathbf{d}'\alpha\mathbf{w} \end{bmatrix} \text{ and } \boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_c & \boldsymbol{\Sigma}_{cy^*} \\ \boldsymbol{\Sigma}'_{cy^*} & \boldsymbol{\Sigma}_{y^*} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Gamma} & \boldsymbol{\Omega} + \boldsymbol{\Gamma}\mathbf{d}' \\ \boldsymbol{\Omega}' + \mathbf{d}\boldsymbol{\Gamma}' & \mathbf{g}'\boldsymbol{\Psi}\mathbf{g} \end{bmatrix}. \quad (11)$$

Then $\mathbf{s} \sim \text{MVN}_E(\mathbf{B}, \boldsymbol{\Sigma})$. Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = [\text{Vech}(\boldsymbol{\alpha}), \text{Vech}(\boldsymbol{\Gamma}), \text{Vech}(\boldsymbol{\beta}), \text{Vech}(\mathbf{d}), \text{Vech}(\boldsymbol{\Omega}), \text{Vech}(\boldsymbol{\Upsilon}), \boldsymbol{\theta}]$, where the operator "Vech(.)" vectorizes all the non-zero unique elements of the matrix/vector on which it operates.

Using the marginal-conditional partitioning of a multivariate normal distribution, the likelihood function may be written as:

$$\begin{aligned} L(\boldsymbol{\delta}) &= f_L(\mathbf{c} | \mathbf{B}_c, \boldsymbol{\Sigma}_c) \times \Pr[\boldsymbol{\theta}_{low} < (\mathbf{y}^* | \mathbf{c}) < \boldsymbol{\theta}_{up}] , \\ &= f_L(\mathbf{c} | \mathbf{B}_c, \boldsymbol{\Sigma}_c) \times \int_{D_r} f_I(\mathbf{r} | \tilde{\mathbf{B}}_{y^*}, \tilde{\boldsymbol{\Sigma}}_{y^*}) d\mathbf{r}, \end{aligned} \quad (12)$$

where the integration domain $D_r = \{\mathbf{r} : \boldsymbol{\theta}_{low} \leq \mathbf{r} \leq \boldsymbol{\theta}_{up}\}$ is simply the multivariate region of the elements of the $(\mathbf{y}^* | \mathbf{c})$ vector determined by the observed ordinal outcomes. $f_L(\mathbf{c} | \mathbf{B}_c, \boldsymbol{\Sigma}_c)$ is the MVN density function of dimension L with a mean of \mathbf{B}_c and a covariance of $\boldsymbol{\Sigma}_c$, and evaluated at \mathbf{c} , and $f_I(\mathbf{r} | \tilde{\mathbf{B}}_{y^*}, \tilde{\boldsymbol{\Sigma}}_{y^*})$ is the MVN density function of dimension I with a mean of $\tilde{\mathbf{B}}_{y^*} = \mathbf{B}_{y^*} + \boldsymbol{\Sigma}'_{cy^*} \boldsymbol{\Sigma}_c^{-1} (\mathbf{c} - \mathbf{B}_c)$ and a covariance of $\tilde{\boldsymbol{\Sigma}}_{y^*} = \boldsymbol{\Sigma}_{y^*} - \boldsymbol{\Sigma}'_{cy^*} \boldsymbol{\Sigma}_c^{-1} \boldsymbol{\Sigma}_{cy^*}$ and evaluated at \mathbf{r} . The dimension of the integration in Equation (12) depends on I . But, regardless of the value of I , one can use a composite marginal likelihood (CML) approach to develop a surrogate likelihood function and maximize this CML function to obtain a consistent estimator (see Bhat and Dubey, 2014; Bhat, 2015a,b).

4 MODEL RESULTS

The final model specification was obtained based on a systematic process of testing alternative combinations of explanatory variables and eliminating statistically insignificant ones. Also, for continuous variables such as respondent current commute time, a number of functional forms were tested, including linear form and a dummy variable categorization. In the final model specification, not all the variables included are statistically significant at a 95% confidence level, but some of these were retained as they provided intuitive interpretations and insights. Important also to note is that, as indicated in Section 3.2.4, only a recursive structure of influence of the actual ordinal outcomes is estimable among the three ordinal outcomes. In our specifications, we systematically

tried all possible combinations of recursive effects among the three outcomes, and settled on the combination that provided the best data fit.

In the next section, the latent constructs' loadings on the attitudinal indicators obtained in the confirmatory factor analysis are presented followed by the results of the SEM component. The subsequent sections discuss the correlations between the five dependent variables, and the effects of individual demographics, household characteristics, commute/other characteristics, and the latent constructs on the three main outcomes of interest (move home, move work, and increase in commute time).

4.1 Latent Constructs

The standardized factor loadings obtained in the confirmatory factor analysis conducted to generate the two continuous latent constructs are presented in Table 4. As expected, the loading of each indicator on its corresponding latent construct is positive. Interestingly, the best indicators for tech-savviness correspond to the ease of learning how to use smart phone apps and online banking/product purchase, and relatively less to do with spending time online for social purposes and conducting work using a computer/tablet. Overall, the magnitudes of the loadings in our factor analysis are acceptable as most of them are above 0.5 (Hair *et al.*, 2013).

Table 4. Loadings of Latent Variables on Indicators

Attitudinal Indicators	Loadings of Indicators on Latent Constructs			
	Technology Savviness		Interest in Productive use of Travel Time (IPTT)	
	Coefficient	t-stat	Coefficient	t-stat
Learning how to use new smartphone apps is easy for me	0.643	29.373		
I frequently use online banking services	0.614	28.141		
I frequently purchase products online	0.693	33.051		
Every day, I spend at least some time on online social media	0.440	17.452		
I do most of my work on a computer or tablet	0.374	14.222		
Self-driving vehicles are appealing because they will allow me to use my travel time more effectively			0.669	46.010
I would not mind having a longer commute if I could use my commute time productively			0.570	18.443

The effects of the socio-economic and household characteristics on the latent constructs of tech-savviness and IPTT are presented in Table 5. While there is no difference between men and women in the level of self-described tech-savviness, women, in general, are less interested in the productive use of travel time. This result may be a consequence of a mismatch between the nature

of time scarcity faced by women (especially mothers) and the nature of activities that can be conducted inside a vehicle (for example, child-care and household responsibilities and chores may need physical presence time at home that cannot be substituted by time in a vehicle; see Craig and Mullan, 2010, for a comprehensive analysis of work-family time commitment by gender). Also, the literature on travel-based multitasking suggests that men and women engage in different types of activities while traveling (Keseru and Macharis, 2018). While women are more likely to engage in time-passing, interaction with others, and social activities (conversing with other passengers, engaging in personal calls, and accessing online social media), men are more prone to pursue individual activities and work-related activities (Russell *et al.*, 2011; Berliner *et al.*, 2015; Guo *et al.*, 2015). Thus, there may be both a combination of the types of activities women typically pursue (that cannot be undertaken very well within a vehicle) as well as intrinsic differences in how men and women would like to spend their commute travel time.

The effects of age in Table 5 indicate that younger individuals (those between 18 to 34 years of age) show the most familiarity with ICT use and the greatest interest in being productive when commuting. These results are consistent with the common knowledge that millennials are digital natives and use ICT devices more frequently (and for more diverse purposes) while traveling than their older peers (Russell *et al.*, 2011; Malokin *et al.*, 2017; Keseru and Macharis, 2018). Those who identify themselves as Non-Hispanic Whites self-describe themselves (through indicators) as having lower levels of tech-savviness than their peers. This is an interesting result that deserves further probing in future studies. One possible reason may be that our latent construct of tech-savviness confounds “true” tech-savviness with privacy-sensitivity/security consciousness (because some indicators of tech-savviness include the use of on-line banking and product purchases online), and earlier studies have suggested that non-Hispanic Whites may be more privacy and security conscious than their peers (see Lavieri and Bhat, 2019b). In terms of employment arrangement, compared to full-time employees and self-employed individuals, part-time workers have the lowest levels of tech-savviness and IPTT. This result is consistent with the findings by Lavieri *et al.*, 2018 who show that part-time employees and those who are not in managerial and professional jobs have reduced digital accessibility (tech-savviness) and limited flexibility to conduct work outside their main work location. Finally, as expected and also observed by Lavieri *et al.*, 2018 and Lavieri and Bhat, 2019a, income has a positive association with tech-savviness and IPTT.

Table 5. Determinants of Latent Variables

Variables (base category)	Structural Equations Model Component Results			
	Technology Savviness		Interest in Productive use of Travel Time (IPTT)	
	Coefficient	t-stat	Coefficient	t-stat
<i>Socio-Demographic Characteristics</i>				
Gender (male)				
Female	---		-0.126	-2.885
Age (45 or older)				
18 to 34	0.506	6.477	0.192	2.892
35 to 44	0.402	6.473	0.147	2.544
Race (other ethnicities)				
Non-Hispanic White	-0.143	-4.094	---	
Employment Type (full-time employee or self-employed)				
Part-time employee	-0.524	-6.761	---	
<i>Household Characteristics</i>				
Household income (< \$200k)				
≥ \$200,000	0.23	2.969	0.19	2.493

“---” not statistically significant at 95% confidence level and removed from specification.

4.2 Correlations between Outcomes

Before presenting the effects of the exogenous variables and the latent constructs on the three main outcomes of interest, we discuss the estimated correlation coefficients. Our modeling framework allowed for correlations between the two latent constructs, cross-correlations between the latent constructs and the three ordered outcomes, as well as endogenous recursive effects between the ordered outcomes (the latter being “true” effects after accommodating for spurious associative effects through the correlations in the error terms). The endogenous recursive effects displayed strong magnitude and significance (as presented in Table 6 and discussed in the following sections) capturing, together with the exogenous variables, most of the association between the outcomes. But, by way of correlations, we found only two correlations to be statistically significant. Both latent constructs are positively correlated (coefficient 0.177 and t-stat 7.289), indicating that unobserved factors that contribute to the level of tech-savviness of individuals also contribute to their level of IPTT. A general proclivity toward time efficiency is probably behind this effect, as both online activities and productive use of travel time allow individuals to optimize time use. A negative correlation is observed between tech-savviness and the intention to move home (coefficient -0.216 and t-stat -2.987), which, as discussed earlier, may be attributed to tech-savvy individuals also intrinsically less inclined to move because of the life disruption.

4.3 Effect of Explanatory Variables

4.3.1. Endogenous Variable Effects

The direct effects of the endogenous latent constructs and the exogenous variables on the three outcomes of move home, move work, and commute time increase in an AV future are presented in Table 6. To be precise, the effects in Table 6 provide the impact of variables on the propensity to move home, move work, and accept increased commute time.

As expected, among the endogenous effects, individuals with high tech-savviness and high IPTT show a higher desire to move home in an AV future relative to their peers. While tech-savvy individuals may have some traits that make them less inclined to move (captured by the error correlation effect discussed in the previous paragraph), the use of in-vehicle time for non-driving activities appears to make it easier for tech-savvy individuals to act upon any residential dissonance they have through relocation, as also observed by Carrese *et al.*, 2019. Interestingly though, tech-savviness by itself does not impact the inclination to move work or be accepting of longer commute times, presumably because, as also observed by Singleton (2019), tech-savviness by itself may not always translate to the use of smart gadgets during travel. However, IPTT has a strong positive effect on both work relocation propensity as well as higher commute time acceptance, reinforcing the notion that those who believe that their commutes can be made more productive, and are desirous of having this happen, are more open to considering work arrangements that may offer other benefits to them (even if farther away from home). It is also interesting to note the strong positive effect of the “move home” propensity on the other two outcomes, suggesting that once a person moves home, she or he would be more likely to consider new work arrangements and incur a higher commute time to perhaps increase market potential after a disruption in the commute pattern anyway. Finally, under the category of endogenous effects, the propensity to accept higher commute times has a direct positive influence on work relocation, again suggesting that those who are willing to accept longer commutes without driving themselves also are prepared to expand their job location expanse to potentially search for better work opportunities and conditions.

Table 6. Results of Move Home, Move Work, and Commute Time Increase Choice Models

Exogenous Variables (base category)	Move Home*		Move Work*		Commute Increase*	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Endogenous Effects						
Technology savviness	0.379	5.059	---	---	---	---
Interest in productive use of time	0.421	14.508	0.147	6.828	0.402	27.596
Move home (no)						
Yes	n/a	---	0.964	21.995	1.232	36.154
Commute Increase (not a single minute)						
Up to 10 minutes	n/a	---	0.325	6.263	n/a	---
10 to 20 minutes	n/a	---	0.505	8.583	n/a	---
More than 20 minutes	n/a	---	0.653	9.872	n/a	---
Individual Demographics						
Gender (male)						
Female	-0.096	-2.734	---	---	-0.096	-3.324
Age (45 or older)						
18 to 34	0.148	2.546	0.159	3.250	---	---
35 to 44	---	---	0.118	2.628	---	---
Employment Type (full-time or part-time)						
Self-employed	0.212	3.467	---	---	---	---
Education (< undergraduate degree)						
Undergraduate degree	0.215	3.330	0.199	2.837	---	---
Graduate degree	0.099	2.204	0.096	2.072	---	---
Household Characteristics						
Income (< \$250,000)						
≥ \$250,000	-0.247	-3.561	-0.228	-2.840	---	---
Composition (multi-worker household)						
Single worker multi-person household	---	---	-0.145	-2.809	---	---
Single person household	---	---	---	---	-0.194	-4.130
Residential Location (central or rural area)						
Located in suburbs	0.191	5.042	0.137	3.497	---	---
Residence Ownership (not a home owner)						
Home owner	-0.368	-8.940	---	---	-0.115	-3.534
Vehicle Availability (≥ 1 vehicle per worker)						
Less than 1 vehicle per worker	---	---	---	---	0.074	1.857
Commute/Other Characteristics						
Telecommuting Status (< once a week)						
≥ Once a week	0.081	1.768	0.079	1.712	---	---
Commute Time (< 30 minutes)						
≥ 30 minute commute	---	---	---	---	-0.191	-6.665
Uncomfortable reading in a moving vehicle (no)						
Yes	---	---	---	---	-0.173	-5.960

* The constant value in the case of “move home” was 0.469; the constant value for the “move work” was 1.350; and the threshold values for the “commute increase” dimension were -0.625, 0.411, 1.341, and 2.043.

** “---” not statistically significant at 95% confidence level and removed from specification.

4.3.2. Individual Demographic Effects

In terms of individual characteristics, women appear more reluctant to move home locations and incur longer commute times. This may reflect general resistance to change in the living situation among women relative to men. According to Croson and Gneezy (2009), there may be three explanations for this gender reluctance to change. The first is based on the notion of “risk as feelings” (see also Loewenstein *et al.*, 2001), which states that our instinctive and intuitive emotions dominate reasoned approaches when faced with risk (in our case, a change constitutes a risk). Further, since women experience feelings of nervousness and fear more than men in anticipation of negative outcomes, the net result may be a heightened averseness to change among women. The second is based on the notion of confidence; men tend to be more overconfident in uncertain situations, which perhaps translates to more openness to change in men than women. The third explanation is tied to the notion of believed appropriate response; that is, men tend to view a change as a challenge to be experienced, while women tend to view change (and situations they perceive as “risky” in general) as threats that must be avoided (McDaniel and Zuckerman, 2003; Meier-Pesti and Penz, 2008). In addition to a general resistance to change, women (particularly mothers) may also be reluctant to incur longer commute distances because of a felt need to be close to home to pursue household-related errands and be available to handle any exigency situations with children (Lavasani *et al.*, 2017). Note that being a female has both a direct effect (as just discussed) as well as an indirect negative effect through the IPTT variable, reinforcing the notion that women have greater space-time constraints (possibly due to family-related responsibilities) and thus productive use of travel may be ineffective in reducing their time scarcity.

Young adults (less than 35 years of age) show an increased inclination to move their home/work locations (compared to those over the age of 35) in an AV future. This result corroborates findings by Zhang *et al.* (2018) who observe that those under the age of 40 are the most likely to move residences to take advantage of more affordable property values and what they view as better living conditions. Further, this population segment typically changes jobs more often compared to middle and older aged populations (Lu and Gursoy, 2016; Bureau of Labor Statistics, 2018), a tendency that seems to get accentuated when they do not have to drive. Similarly, self-employed individuals and those with higher education levels also appear to be more open to moving homes and/or work places, perhaps a reflection of their work arrangement stability (in the case of self-employed individuals) or confidence in their market potential. Finally, those with an undergraduate degree are more open to relocate than those less educated, which may simply be a reflection of undergraduate degree holders being able to explore their market potential and careers more so than the less educated. Interestingly, it appears that those with a graduate degree, while still more likely to move than those with less than an undergraduate degree, are more reluctant to relocate compared to those with an undergraduate degree. This is possibly because graduate degree holders are already in job and housing locations that they like, and have less incentive to move.

4.3.3. Household Characteristics

Several household-related variables present statistically significant effects on the main outcomes. Individuals in households with very high incomes (over \$250,000 per year) show a negative propensity for residential and work relocation, again potentially a reflection of lower residential and work dissonance because they already live and work in desirable locations. Household composition also influences work relocation intention and willingness to accept longer commutes. Specifically, single workers living in multi-member households have the lowest intention to change work locations, probably due to obligations of financial responsibility and a need for stability within their respective households, while single individuals are most averse to longer commutes. Suburban dwellers (relative to those who live in central or rural areas) show stronger intentions to relocate their homes and work locations, suggesting higher home and work dissonance among suburban dwellers relative to other areas. This result is particularly worrisome, as it suggests further sprawl of those who are already suburbanized. On the other hand, those who own their residences are less likely (than those who rent their homes) to change their home locations and accept longer commutes, which is expected considering the financial implications of a home relocation for home owners (Lee and Waddell, 2010). Also, home ownership may be associated with certain lifecycle variables (such as having children) that were not captured in our survey and that make longer commute times burdensome (because, for example, child-care activities cannot be undertaken virtually from a vehicle). Finally, within the category of household variables, individuals living in a vehicle-scarce household (less than one vehicle per worker) are associated with a higher tolerance to commute time increases if an AV is available to chauffeur them to work.

4.3.4 Commute/Other Characteristics

Individuals who telecommute at least once a week express a higher propensity (relative to those who telecommute less often or never telecommute) for residential and work relocation in the presence of an AV. This result may be a first evidence that an AV's chauffeuring capabilities may trigger or compound the residential sprawling effects of telecommuting. Our results also suggest that a 30-minute commute time appears to be a threshold point beyond which individuals are rather unwilling to accept too much more of longer commutes. Finally, as expected, those who are uncomfortable reading inside a vehicle are less likely to accept increases in commute time due to hands-free driving.

4.4 Model Goodness of Fit

The performance of the joint model may be compared with that of a restricted model (say RES) that does not consider latent constructs (and consequently also ignores any type of dependency between the ordered outcomes). In the latter model, to put things in as equal a footing as possible in terms of observed variable effects, we include the determinants of the latent constructs as explanatory variables, while maintaining the recursivity in the dimensions as obtained from our final joint model.

The two models may be compared using the composite likelihood information criterion (CLIC) (Varin and Vidoni, 2005). The CLIC takes the following form:

$$\log L_{CML}^*(\hat{\theta}) = \log L_{CML}(\hat{\theta}) - \text{tr}[\hat{\mathbf{J}}(\hat{\theta})\hat{\mathbf{H}}(\hat{\theta})^{-1}] \quad (13)$$

The model providing a higher value of CLIC is preferred. In addition to the comparison using the CLIC values, an informal predictive non-nested likelihood ratio test may be used to compare the models. Using the parameter values at the joint model convergence, the predictive log-likelihood value $L(\hat{\theta})$ of the two models were evaluated. The adjusted likelihood ratio index of each model was computed with respect to the log-likelihood with only the constants and threshold values (in the case of the ordered response “increase commute time” variable):

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\theta}) - M}{L(c)} \quad (14)$$

where $L(\hat{\theta})$ and $L(c)$ are the predictive log-likelihood functions at convergence and at constants/thresholds, respectively, and M is the number of parameters (excluding the constants and the thresholds) estimated in the model. If the difference in the indices is $(\bar{\rho}_2^2 - \bar{\rho}_1^2) = \tau$, then the probability that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_2 - M_1)]^{0.5}\}$, with a small value for the probability of chance occurrence suggesting that the difference is statistically significant and the model with the higher value for the adjusted likelihood ratio index is preferred.

We also evaluate the data fit of the two models intuitively and informally at both the disaggregate and aggregate levels. To do so, we consider the three main outcomes (move home, move work, and commute increase) and compute the marginal multivariate predictions for these three dimensions jointly. At the disaggregate level, for the joint model, we estimate the probability of the observed multivariate outcome for each individual using Equation (10), with $\mathbf{y}^* = (y_1^*, y_2^*, y_3^*)'$. This vector has a mean of $\mathbf{B}_{\mathbf{y}^*}$ and variance-covariance matrix $\Sigma_{\mathbf{y}^*}$, with the same notations as earlier. Then, one can compute the multivariate probability for different combinations using a trivariate dimensional integral. For example, the probability that an individual is inclined to move home, is inclined to move work, and willing to accept a longer commute in ordinal category k may be written as:

$$P(y_1 = 1, y_2 = 1, y_3 = k) = \int_{y_1=0}^{\infty} \int_{y_2=0}^{\infty} \int_{y_3=\theta_1^{k-1}}^{\theta_1^k} f_3(\mathbf{y}^* | \mathbf{B}_{\mathbf{y}^*}, \Sigma_{\mathbf{y}^*}) d\mathbf{y}^*. \quad (15)$$

Other probabilities may be similarly computed at the individual level. Then, we compute an average (across individuals) probability of correct prediction at this three-variate level. Similar disaggregate measures are computed for the RES model. At the aggregate level, we design a heuristic diagnostic check of model fit by computing the predicted aggregate share of individuals for combinations of the three dimensions. For ease in presentation, we convert the “commute increase” dimension also into just two categories of up to 10 minutes and more than 10 minutes.

This reduces the number of combinations of the three dimensions to eight. The predicted shares for each of these eight multivariate outcomes is computed for all the two models and compared to the actual shares, and the absolute percentage error (APE) statistic is computed.

The results of our disaggregate data fit evaluation are provided in Table 7a. The CLIC values in Table 7a clearly favor the joint model over the independent model. The same result is obtained when comparing the predictive likelihood values at convergence. The average probability of correct prediction at the three-variate level is 0.1628 for our joint model, relative to 0.1381 for the RES model. The predictive adjusted likelihood ratio indices, and the corresponding informal non-nested likelihood ratio statistics are also presented in Table 7a. The probability that the adjusted likelihood ratio index difference between the joint model and the RES model could have occurred by chance is literally zero (see the last row of Table 7a).

Table 7a. Disaggregate Data Fit Measures

Summary Statistics	Model	
	Joint Model	RES Model
Composite Marginal log-likelihood value at convergence	-11828.923	-12252.751
Composite Likelihood Information Criterion (CLIC)	-11919.022	-12330.885
Predictive log-likelihood at convergence	-8143.756	-8368.316
Average probability of correct prediction	0.1628	0.1381
Constants only predictive log-likelihood at convergence (with constants and thresholds)	-8992.194	
Number of parameters	43	37
Predictive adjusted likelihood ratio index	0.090	0.065
Informal non-nested adjusted likelihood ratio test: Joint model versus RES model	$\Phi [-20.76] \ll 0.001$	

At the aggregate level, the eight combinations at the three-variate level are identified in Table 7b. For each of these combinations, the shares predicted by the joint model are generally better to the RES model. Overall, across all the combinations, the weighted average (weighted by the share of each combination) is 23.2% for the joint model, compared to 48.6% for the RES model (see the last row of Table 7b). Overall, the aggregate fit measures in Table 7b reinforce the disaggregate level results in Table 7a.

Table 7b. Aggregate Data Fit Measures

Alternative			Observed Share	Joint Model		RES Model	
Move Home	Move Work	Increase Commute Time		Predicted Share	APE*	Predicted Share	APE*
Yes	Yes	<10 mins.	0.036	0.062	72.2	0.053	47.2
		≥10 mins.	0.182	0.159	12.6	0.025	86.3
	No	<10 mins.	0.035	0.059	68.5	0.195	457.1
		≥10 mins.	0.076	0.089	17.1	0.087	14.5
No	Yes	<10 mins.	0.082	0.101	23.2	0.093	13.4
		≥10 mins.	0.040	0.063	57.5	0.040	0.0
	No	<10 mins.	0.439	0.346	21.2	0.353	19.6
		≥10 mins.	0.110	0.121	10.0	0.154	40.0
Weighted average across all combinations				23.2		48.6	

*APE: Absolute Percentage Error

5 INPUT FOR LAND USE-TRAVEL DEMAND MODELS

Most earlier studies attempting to examine the potential effects of AVs make strong assumptions regarding important parameters in travel demand modeling. Rather than make such strong assumptions, the model developed in this paper can serve the purpose of providing important information based on a more informed investigation of potential user behaviors in an AV future. In fact, the model in this paper can be absorbed into an agent-based integrated land-use and travel evolution model, such as the Comprehensive Econometric Microsimulator for Socio-Economics, Land-use, and Transportation System (CEMSELTS; see Guo *et al.* 2005). In particular, in CEMSELTS and many other such land-use and travel models, the home and work locations (the latter if an individual works) are critical “backbone nodes” that form the central “corridor” for activity-travel episodes of individuals, in addition to defining the commute. The home location is usually considered as the base location for individuals, the place that most people start their activities from each day and the place that most people come back to at the end of the day. The work location is the most commonly visited location for most employed individuals during the work week, and forms the base location for any mid-day activities. Besides, many non-work activities that are chained with the commute are undertaken off the home-work commute path. Thus, the home and work locations can act as facilitators or suppressors of out-of-home activity pursuits of individuals, based on the relative spatial location of the home/work vis-à-vis activity opportunity locations (see, for example, Bhat and Koppelman, 1993; Pinjari and Bhat, 2011). In turn, the residential and work location choices of households, at an aggregate level, impact the built environment as transport, land use, and urban form change in response to where people live and may want to work. This bidirectional and dynamic interaction between where people choose

to live and want to work and how the built environment evolves is at the heart of integrated land-use and transportation modeling (Hawkins and Habib, 2019).

In the above context, every individual in a base synthetic population may be taken through the model developed in this paper to predict her/his future decisions regarding home and work location choices.⁶ The approach to do this should recognize the unobserved covariance among the choices (engendered by the latent stochastic constructs of tech-savviness and IPTT), as well as accommodate the recursive sequence of effects among the endogenous variables themselves. In a microsimulation setting where a synthetic population is generated (see, for example, Guo and Bhat, 2007), this is very easy to do by using expressions similar to Equation (15) to determine the probabilities of all combinations of move home, move work, and the ordinal commute time variable. Then, these probabilities may be translated to a unique deterministic combination decision for each individual in synthetic population in the usual way (see, for example, Lavieri and Bhat, 2019a) for further downstream use in the land use-transportation simulator. In the current paper, just to demonstrate this process, we compute the probabilities for all multivariate combinations for each individual in the survey sample. Then, once the multivariate probabilities are computed, we marginalize these probabilities to develop the bivariate probabilities of each combination of yes/no of “move home” and “move work”. From the multivariate and bivariate probabilities, we compute the probability of each ordinal category of “increase commute time” for each of the four combinations of “move home” and “move work” using Bayes’ rule. For example, the expression for the “yes” to “move home” and “yes” to “move work” combination for ordinal category k for “increase commute time” would simply be:

$$P(y_3 = k | y_1 = 1, y_2 = 1) = \frac{P(y_1 = 1, y_2 = 1, y_3 = k)}{P(y_1 = 1, y_2 = 1)} = \frac{P(y_1 = 1, y_2 = 1, y_3 = k)}{\sum_{k=1}^K P(y_1 = 1, y_2 = 1, y_3 = k)} \quad (16)$$

Once these conditional probabilities are evaluated for each individual in the survey sample, we then compute an individualized cardinal value for “increase commute time” (for each move home and move work combination) by assigning the following cardinal values to each ordinal category: (a) not even a minute more (=0 minutes), (b) up to 10 minutes (=5 minutes), (c) 10-20 minutes (=15 minutes), (d) 20-30 minutes (=25 minutes), and (e) >30 minutes (35 minutes). To obtain an

⁶ An important note is in order here. Due to the way the survey was conducted, the analysis is individual-based, not household-based. On the other hand, one could legitimately argue that the home location decision is a household-level decision. In fact, Khan *et al.* (2012) argue that even employment and work location decisions should be viewed as a household-level decision as individuals in the household consider what is best for not only themselves individually, but also the household as a single unit. Until a time when some of the AV questions are sought in large-scale household travel surveys, one way to proceed is to define an individual from each household as the “householder” (based on, for example, the Census definition of a householder), implement our model for that householder, and maintain the future choices for the household to be consistent with the predictions from our model for the householder. Of course, an additional caveat here is that our model focuses on whether an individual would consider relocating home/work, and not whether she/he would actually do so. In retrospect, our question should probably have been more pointed and asked “will you relocate” rather than “would you consider relocating”. Of course, on the other hand, all of these responses are but stated responses and need to be viewed with a certain grain of salt anyway. But such responses still provide us better information than simply imposing random choices on individuals.

expected value of commute time increase (in minutes) specific to each move home and move work combination, we average the individual values across all individuals in the survey sample.

The results are provided in the first numeric column of Table 8. As expected, the commute time increase across individuals who choose to relocate residential and work locations in the presence of AVs (=17.4 minutes) is higher than the expected commute time increase across individuals who choose not to relocate their residential and/or work locations (=5.9 minutes). The second numeric column of Table 8 translates the commute time increases to corresponding percentage increases in the presence of AVs, for each home-work relocation combination. Specifically, the percentage commute time increase is computed at an individual level for each home-work relocation combination, and these individual level percentages are averaged to obtain the expected percentage commute time increase for each relocation combination. The results show that individuals who choose to relocate both home and work, on average, show a willingness to tolerate a commute time increase of up to 83.8%, relative to an average of only 29.7% amongst those who do not relocate home and do not relocate work. The averages for relocation either only at the home end or the work end fall in-between.

The above set of results can be “turned on its head” to obtain an informed and personalized valuation for the percentage decrease in VTTS due to AVs rather than using a single random number for the percentage VTTS decrease applied across the board to all individuals. After all, being tolerant of additional commute time is equivalent to a decrease in commute VTTS. That is, being tolerant of an $x\%$ increase in commute time may be equated to an $x\%$ decrease in commute VTTS. In addition, the percentage VTTS decrease as estimated from our study corresponding to the “no home relocation” and “no work relocation” case may be compared to the VTTS decreases assumed in most earlier simulation studies that do not focus on home/work location changes, but on travel behavior changes such as trip generation, mode choice, activity location choice, and route choice decisions. The two last columns of Table 8 provide the expected values of commute time increase and the corresponding percentage VTTS decreases regrouped by no relocation of any kind versus relocation in work and/or home. The percentage VTTS decrease corresponding to the no home and no work relocation is of the order of 30% (as also indicated earlier). This is way below the 50% or even the 100% decrease in VTTS for private car AVs assumed in many earlier activity-travel simulation studies, and raises the importance of studying user behavior much more carefully before plunging into mechanical simulations or having extensive review papers of the results of such simulations.

Table 8: Estimates of VTTS Decrease and Extent of Sprawl Due to AVs

Move Home/Move Work	Results for all home/work relocation combinations		Results grouped by whether the individual relocates home/work or not (%)	
	Expected Value of Commute Time Increase (min)	Expected Value of VTTS Decrease (%)	Expected Value of Commute Time Increase (min)	Expected Value of VTTS Decrease (%)
Yes, Yes	17.4	83.8%	13.9	67.7%
Yes, No	14.9	72.4%		
No, Yes	8.3	40.8%		
No, No	5.9	29.7%	5.9	29.7%

Another useful insight from the final column of Table 8 is the extent of potential urban sprawl that may be caused by AVs. When averaged across all individuals in the sample, the predicted commute time increase conditional on relocation at one or both of the home/work ends is 13.9 minutes and the corresponding percentage commute time increase is 67.7%. Thus, the upper range of sprawl due to AVs may be reasoned to be of the order of 68%. We characterize this as an “upper range” because, as discussed in footnote 6 on page 27, the survey question focused on whether an individual would consider relocating, rather than actually relocating. Also, this estimate of percentage sprawl increase is based on time, not distance; however, given that the survey is of individuals who all drive to work, the equivalence of a time percentage increase to that of a distance percentage increase may not be very unreasonable. Also, an argument may be made that commute time increases among those who move work and/or home do not necessarily translate to urban sprawl. For instance, it may be that a person working in a suburban fringe area of the metropolitan area may move farther away from the workplace by changing residences from a suburban location to the urban core, leading to an urban compaction rather than urban sprawl. That is, the direction of relocation of home/work can matter. However, in the Dallas area, the work locations continue to be dominantly concentrated in the urban core, even if new employment centers have sprung up outside the traditional urban core (Liu *et al.*, 2019). On the other hand, net internal household migration data from the U.S. Census⁷ clearly shows a move of residences from the urban core to suburban areas at the fringes of the Dallas metropolitan area (see also Frey, 2018, who notes a similar trend across metropolitan areas in the country). Assuming this pattern of relatively fixed work locations in the urban core and substantial residential relocations from the urban core to the

⁷ <https://flowmapper.geo.census.gov/map.html> (Accessed: 11 November 2019)

suburban fringes continues, it is not unreasonable to view commute travel time increases as primarily being associated with urban sprawl. Overall, notwithstanding the caveats just mentioned, this estimated impact of AVs on sprawl is indeed rather substantial, and suggests that cities may expand horizontally by up to about 68% of their current size. This is of substantial concern due to VMT impacts as well as the concomitant air quality, greenhouse gas, and energy dependence impacts (Stone, 2008; Ewing and Hamidi, 2015). Indeed, it may be that money disincentive policies to discourage individuals from substantially increasing their commute distances/times will need to be considered in an AV future. Also, along with urban sprawl and increases in VMT, increased congestion can lead to environmental impacts as commuters who were once interested in switching routes as they became more congested are willing to stay on a route that has slowdowns (due to tolerating an increase in commute times). To mitigate this potential impact, policy makers should understand the potential effects of AV chauffeuring and promote the use of shared rides and other measures that can reduce the number of vehicles on the roadway, while still allowing commuters to be productive during their journeys.

6 DISCUSSION AND CONCLUSIONS

The field of transportation research has seen multiple studies that tout the potential operational and safety gains brought forth by AVs. Many of these studies are based on simulations, and make some substantial assumptions of user behavior and infrastructure capacity increases, without much basis for those assumptions in the first place. Further, there have been review/synthesis studies that attempt to assimilate and integrate the findings of individual simulation studies. Unfortunately, there is only limited value in even these synthesis studies, given the assumptions of the individual studies. While some of the individual studies do use a scenario approach to recognize the wide bandwidth of possible user behavior responses, it still remains an open question whether the wide bandwidth sufficiently captures behavior in an AV future.

This study attempts to more fundamentally consider human behavior responses in an AV future in the context of residential location, work location, and commute choices. The intent is to provide some (or at least better) guidance for developing inputs to land use and travel demand models to predict activity-travel patterns in an AV future as well as provide insights for proactive land use/transportation policy making. The experimental design is based on a hypothetical scenario where individuals have a self-driving vehicle available for their commutes and no longer need to spend time playing the role of the “driver”. The model includes three main outcomes of interest - the binary choice of whether an individual would consider (or not) moving home, the binary choice of whether an individual would consider (or not) moving work, and the amount of additional travel time they would be willing to tolerate. These three choice dimensions are modeled as functions of individual demographics, household and commute characteristics, as well as two latent constructs representing technology-savviness and interest in productive use of travel time. Sample values for these two constructs are constructed using confirmatory factor analysis, and then used as continuous co-endogenous variables (but recognizing that the constructed values are but point values for a particular individual, and that there would be variation around this

constructed value in the population). The constructs reflect the ability and interest in multi-tasking, and the multivariate model considers the effects of these constructs on the main outcomes after controlling for associative error correlation effects.

The results from our model reveal that individuals with high levels of interest in the productive use of travel time (compared to those with low levels) are more willing to relocate their residences and workplaces, and tolerate larger commute time increases than their peers. An intriguing result is that greater familiarity and frequency of use of ICTs (represented by technology savviness) impacts home relocation intentions, but does not show a direct effect on the tolerance for work relocation or longer commutes. In this sense, it becomes clear that the desire (motivation) to use time productively plays a more important role in increasing commute time tolerance than the ability to conduct ICT-based activities in a vehicle. In terms of sociodemographic groups, individuals between 18 and 34 years (the so-called “millennials”) show a strong tendency for both home and work relocations as well as commute time increases. This proclivity is explained not only by their higher interest in the productive use of travel time and higher levels of tech-savviness, but also by direct lifecycle effects. This result has particularly worrisome impacts considering that this generation has become the majority of the U.S. labor force (Fry, 2018). While those aged 18 to 34 were identified as the segment most likely to relocate and increase commute times, women appear to be less likely to relocate home, and increase commute times, as well as have lower levels of IPTT. This is perhaps because of a combination of the types of activities women typically perform based on societal expectations and norms (such as child-care activities) that cannot be pursued very well within a vehicle, as well as because of intrinsic differences in how men and women would like to spend their commute travel time. In an ironic twist, this may further increase the asymmetry in work/career opportunities between men and women, because men may become more open to considering new work opportunities in the marketplace even if that implies much longer commutes, while women continue to be confined to jobs with short commutes.

Our results indicate more likely home/work relocations among suburban dwellers (relative to those who live in central or rural areas), suggesting further sprawl of those who are already suburbanized. Also, individuals living in a vehicle-scarce household (less than one vehicle per worker) are associated with a higher tolerance to commute time increases if an AV is available to chauffeur them to work. This is an important outcome as this population could also benefit from, and may be open to, using transit options in an AV future. Although a number of other household and individual variables also influence commute times, our results indicate that a 30-minute commute time appears to be a threshold point beyond which individuals are rather unwilling to accept too much more of longer commutes.

Overall, our results provide many important insights. First, there is considerable heterogeneity among individuals in their willingness to relocate and/or accept longer commute times in an AV future. Our model results may be used to inform inputs to land use and travel demand models in an AV future by predicting individual attributes related to home and work locations. Second, our results suggest that the VTTS decreases considered in many earlier simulation studies to model travel impacts of an AV future may be much more dramatic than what

would be reality. While there are definitely limitations in the way we have come up with estimates of VTTS decreases, our estimates are based on actual surveys of potential user behavior rather than random values assumed in scenarios. Relative to 50% and even 100% VTTS decreases assumed in many studies, our results suggest a much more modest 30% or so overall decrease in VTTS because of the ability to commute in an AV. Third, our results do predict a rather substantial extent of urban sprawl due to AVs, to the effect of potentially up to a 68% increase in the spread of cities such as Dallas-Fort Worth. This would have substantial societal implications, ranging from increased congestion and air pollution to impacts in housing markets, as different segments of the population choose to move further from their work locations and increase their commute times. Proactive planning and policies are likely to be needed to avert such unintended consequences of AVs.

Of course, as with any other study, this study also has its limitations. First, the survey is not representative of the DFW metropolitan area, and the survey excludes non-commuters. To strengthen the insights into relocation choices, and commute increases, future studies should aim to capture individuals representing both commuters and non-commuters within a single household. Including non-commuters is important as they influence both the residential relocation decisions and have impacts on commutes of those who do work within the household. Second, this study uses stated preference data gathered through an online survey. The main disadvantage of using stated preference data, as discussed by Wardman (1988), is that commuters' actual behaviors may not follow how they respond to the questions contained within the survey. Of course, until AVs become available to the public, stated preference studies constitute the only approach to predict activity-travel patterns and design proactive policies to reduce unintended consequences. But it may be possible to increase the realism of stated preference responses through more realistic visualizations of an AV future in virtual reality settings. Third, specific questions pertaining to multitasking were limited or absent from the survey. Future studies and surveys should include questions capturing the nature of commuters' multitasking activities and behaviors, to examine the rich interplay in the relationships among activity-travel behaviors undertaken within an AV, home/work relocations, and activity-travel behaviors pursued outside an AV. Fourth, the questions used in the modeling effort did not incorporate considerations related to the costs of owning, maintaining, and operating AVs, which may have led some respondents to believe that the costs associated with owning AVs are similar to that associated with owning regular vehicles, thus influencing their tolerances for commute time increases.

In closing, and notwithstanding the limitations just identified, it is the hope that this research will encourage additional research pursuits investigating fundamental user behavior in an AV future, including studies that evaluate how individuals' "travel time budget" might change with the advent of AVs. It is the view of the authors that undue attention has been placed on predicting travel impacts in relatively mechanical agent-based/other simulation models, at the expense of undertaking research on basic user behavior considerations.

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