AUTONOMOUS VEHICLES, TRAVEL BEHAVIOR, AND URBAN STRUCTURE

A Dissertation

by

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ABSTRACT

The advent of autonomous vehicles presents both opportunities and challenges to planners who might see the potential of new technologies in supporting more compact cities but worry about the potential downsides of carbon-intensive development. However, cities struggle to anticipate and then plan for autonomous vehicles and the cities they will reshape. This is particularly true for smaller cities, which account for the majority of future population growth, but political power, technical knowledge, and planning capacity are often insufficient.

This study engages with the concern through an exploration of the social and spatial implications of autonomous vehicles, with a focus on small and medium-sized metropolitan areas. Specifically, I ask three questions. First, how might commuters behave and respond to autonomous vehicles? Second, what are the implications of engagement in in-vehicle activities in autonomous vehicles for time use, and might these implications further exacerbate inequality? Finally, if autonomous vehicles had been introduced to cities, what spatial changes would prevail?

This study addresses the research questions through a combination of analytical and research methods involving a large-scale stated experiment on the behavioral impacts of autonomous vehicles on commuters in small and medium-sized metropolitan areas and a counterfactual analysis to explore whether and to what extent the behavioral changes might lead to spatial changes of cities.

I find that the potential impact of autonomous vehicles on the value of travel time is modest, socially differentiated, and location specific. Suburban commuters have the largest reduction in perceived travel time costs, followed by their urban and rural counterparts. Also, it is not surprising to find that commuters envision themselves to engage in in-vehicle activities differently. Commuters who live in suburban areas with longer commuting trips are more likely to engage in in-vehicle activities, such as working and reading. This propensity does not differ by gender and, thus, I argue that while autonomous vehicles may improve overall activity participation, they will fail to close the gap in activity participation between men and women. The potential changes in travel behavior could ultimately lead to changes in urban spatial structure. I find that urban expansion rather than urban densification would have been the dominant effect if autonomous vehicles had been introduced to the cities.

The findings of this study contribute to the ongoing debate concerning whether autonomous vehicles will aggravate urban sprawl by demonstrating that autonomous vehicles tend to create an enabling environment for suburban living and will most likely lead to greater urban expansion.

DEDICATION

To my parents and Sharon.

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Undertaking the dissertation research has been extremely challenging but intellectually engaging. I am fortunate to work with leading scholars who agreed to be on my doctoral committee: Profs. Wei Li, Chanam Lee, Shannon Van Zandt, Rebekka Dudensing, and Kumares Sinha. I am most grateful for their feedback from the beginning to the end of this project. None of this would be possible without their unconditional and continuing support. I would like to express my special gratitude to my advisor Wei Li for years of support of my research and his positive energy when times were tough.

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This work was supervised by a dissertation committee consisting of Professors Wei Li [advisor], Chanam Lee, and Shannon Van Zandt of the Department of Landscape Architecture and Urban Planning, Professor Rebekka Dudensing of the Department of Agricultural Economics, and Professor Kumares Sinha of the Department of Civil Engineering at Purdue University.

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1. INTRODUCTION

1.1. The Emerging Future of Autonomous Vehicles

The advent of autonomous vehicles (AVs) might once again transform how people move and where people live. The feature that no driver is needed and the possibility of customized vehicle space will bring improvements of substantial magnitude in the comfort and productivity of commuting hours. Technological changes in urban mobility have strikingly improved how we transport goods, people, and ideas in the twentieth century. The potential disrupting effect of AVs on mobility and urban form presents a unique opportunity but also challenges to all levels of government to revisit the fundamental purposes of transportation and to refine urban development policy for better cities.

Most car manufacturers, as well as tech companies like Waymo (formerly Google's self-driving car project), are at various stages of research on and development of AVs to share the AV market. Uber, a ridesharing service company, has already launched its AV fleet in Pittsburgh and San Francisco. Governments in Europe, the United States, and Asia have quickly followed, and they expect that AVs can bring enormous benefits before long.

AVs are also known as "driverless," "self-driving," or "automated" vehicles. There are different levels of vehicle automation. Organizations such as SAE International and the National Highway Traffic Safety Administration (NHTSA) have categorized vehicle automation into different levels (see **Figure 1.1** below). Fully automated vehicles operate without direct driver input to control steering, acceleration, and braking. With

AVs, drivers are not expected to constantly monitor the roadway. Various models of AV operation and deployment have been suggested, mainly two categories: (1) private autonomous vehicles (AVs), denoting private use with or without private ownership, and (2) shared autonomous vehicles (SAVs), denoting shared use with or without private ownership. SAVs include carsharing (such as Zipcar https://www.zipcar.com/), ridesharing (such as Zimride https://zimride.com/), and on-demand services (such as Uber https://www.uber.com/). This research focuses on AVs and SAVs with full automation.

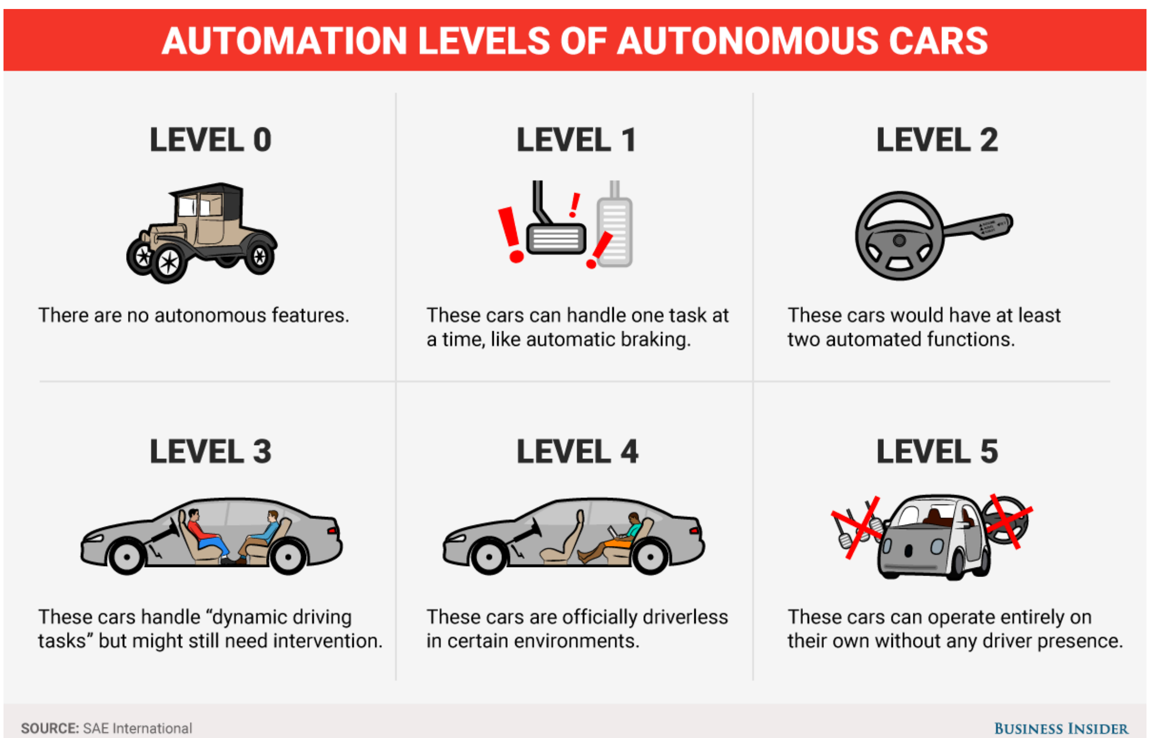

Figure 1.1 Automation levels of autonomous vehicles

Along with the development of AVs, other building blocks for improving and changing how services and infrastructure are provided include the sharing economy, the Internet of things, and artificial intelligence. The application of the new technologies goes far beyond the listed building blocks. The landscapes of future cities are expected to be dramatically different from how people, goods, information, and capital are connected and move today.

The significance of technological changes in urban mobility is only likely to increase, as the world becomes increasingly urban and warmer. The urgency of understanding technological changes in urban mobility is heightened by transportation and public health crises in cities, which are created by previously new transportation technologies and are presently haunting our quality of urban living. Planners now are better equipped to more critically assess the effect of new transportation technologies and no longer see technological changes as a silver bullet to address the urban issues, as AVs can be either a negative or positive disruption. AVs might support compact development, provide independent mobility, and allow more urban space for other purposes but can lead to more auto-dependent lifestyles, more sprawling cities, and declining public transportation systems. The indeterminate nature of the technologies characterizes the uncertainties of the autonomous futures.

1.2. A Focus on Smaller Communities

Technological changes in urban mobility are a collective attempt to make the world the way one wishes it to be. Although technologies are shared phenomena, the effects, such as benefits of the technologies, are differently experienced. Technological advancements can produce inequalities or exaggerate existing ones. Social and spatial changes driven by the introduction of autonomous vehicles will undoubtedly create winners and losers.

Cities are struggling to anticipate and plan for the new mobility technologies that will reshape their transportation systems and the built environment (Guerra, 2015; Yigitcanlar et al., 2019). This challenge is particularly true for smaller cities. These communities account for the majority of population growth in the United States (Frey, 2017), but their political power, technical knowledge, and planning capacity are generally less than what is available in larger urban areas. However, the smaller cities are largely “off the map” in urban studies and planning practices (Bell & Jayne, 2009); and autonomous vehicle studies are no exception.

This research examines the potential effects of autonomous vehicles on travel and urban spatial structure, with a focus on small and medium-sized metropolitan areas in the United States. First, I examine how autonomous vehicles might affect commuters’ travel behavior. Second, instead of considering how to prepare for autonomous vehicles, I ask, can autonomous vehicles fulfill the purpose of reducing the gap of activity participation between men and women? Finally, if autonomous vehicles had been introduced to cities, what spatial changes would prevail? In answering these questions, I aim to examine the socially uneven and spatially differentiated effects of whom and where they might benefit and lose from the development of autonomous vehicles.

Study I (Chapter 2)

In Study I, I explore the potential effect of autonomous vehicles on commuters’ valuation of travel time. In particular, I focus on the effect on auto commuters in small and medium-sized metropolitan areas, concerning the spatial variability across urban areas, suburbs, and rural areas. I design a stated choice experiment to elicit potential changes in auto commuters' valuation of travel time in autonomous vehicles and apply a mixed logit model to quantify the changes in the value of travel time if taking autonomous vehicles. I find that suburban commuters who drove in the reference trip have the largest reduction in their value of travel time, followed by their urban counterparts and rural counterparts.

Study II (Chapter 3)

In Study II, I examine the equity implications of individuals' potential in-vehicle activities in autonomous vehicles that might affect their daily activity participation, with a focus on gender. Drawing on space-time perspective and distributional justice theory, I first operationalize the '*midfare'* concept to measure the extent that individuals can translate in-vehicle activity opportunities into welfare and utility. Using the in-vehicle activities data, I first examine the socio-economic determinants of potential engagement with in-vehicle activities. Next, I assess the equity effects of in-vehicle activities across different social groups. The results confirm that in-vehicle activities can provide more opportunities for daily activity participation, but the distribution of the benefits is inequitable, as the gap in activity participation between men and women appears to persist.

Study III (Chapter 4)

In Study III, I begin with a spatial dynamic analysis of spatial changes in U.S. metropolitan areas over the last three decades, examining the interdependent relationship between transportation and urban expansion. Next, instead of predicting future urban expansion, I use counterfactual techniques to evaluate the effect of autonomous vehicles on urban expansion if they were introduced to cities in the past. I find the decentralization of employment and increased congestion have significantly encouraged urban expansion over the last three decades. Furthermore, I show that urban expansion rather than urban densification would be the dominant effect if autonomous vehicles had been introduced to the cities under all scenarios of reductions in transportation costs. I argue that autonomous vehicles are likely to have similar, or even larger, effects on future urban expansion than in the counterfactual past if they can be widely adopted.

2. WILL AUTONOMOUS VEHICLES CHANGE AUTO COMMUTERS' VALUE OF TRAVEL TIME?*

2.1. Introduction

The advent of autonomous vehicles (AVs) has given rise to high expectations regarding how transportation systems and cities may look like in the near future (Hancock et al., 2019; Kent et al., 2017). The feature that no driver is needed and the possibility of customized vehicle space may bring substantial improvements in the comfort and productivity of commuting time. As a consequence, such improvements may affect people's perception of travel time cost, especially commuters who devote a substantial amount of their time to traveling on a regular basis, potentially resulting in broader impacts on cities and society.

A widespread expectation is that a reduction in the value of travel time (VOT) by AV technologies will make travel time less onerous or more productive (e.g., Fagnant & Kockelman, 2015). This, in turn, may exacerbate car dependency and urban sprawl. Another possible change attributed to the deployment of AVs is the improved efficiency of the transportation system in cities, partially because of the reduced travel time cost and connected vehicle technology, making urban living more attractive (W. D. Larson & Zhao, 2017; Zakharenko, 2016; W. Zhang & Guhathakurta, 2018). Nonetheless, those expectations indicate the fundamental role of the value of travel time that not only affect

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travel behavior in the short term but also alter the urban spatial structure in the long term—by influencing location choices of households and firms.

Transportation planners and city managers are eager to understand what role AV may play in influencing urban development. However, current regional land use-transportation plans have difficulty envisioning the future with AVs and incorporating long-range decisions due to considerable uncertainty associated with the scale, impacts, and timing of introduction of AVs (Guerra, 2015; Yigitcanlar et al., 2019). Furthermore, shaping the development of AVs is particularly challenging in small and medium-sized metropolitan areas (SMMAs). These communities account for the majority of population growth in the US (Frey, 2017), but their political power, technical knowledge, and planning capacity are generally less than what is available in larger urban areas. However, the smaller cities are largely "off the map" in urban studies and planning practices (Bell & Jayne, 2009); and autonomous vehicle studies are no exception.

This chapter fills this gap by developing a stated choice experiment that focuses on commuters in SMMAs. In addition to capturing the unique commuting experience in SMMAs, this chapter also considers the spatial contexts that produce different commuting experiences for commuters but also are inhabited by different groups of people. Using a stated choice experiment, I collected responses regarding preferences and valuation of travel time associated with AVs from 2111 auto commuters who live in SMMAs in the US. I then analyze the impact of AVs on the value of travel time using mixed logit models that take into account the effects of individual characteristics and spatial contexts. The study's results contribute the recent debate on the impact of automated driving on the VOT by revealing that such a VOT reduction effect is spatially differentiated. Moreover, by taking into account respondents being a driver or passenger in their commuting trips, the results reveal that even though passenger respondents appear to prefer riding in AVs and SAVs compared to RVs, but automated driving have little impact on their VOT.

Next, I review studies regarding the value of travel time and spatial contexts in Section 2, introduce the experimental design in Section 3, describe econometric strategies in Section 4, discuss models and results in Section 5, and conclude with research limitations and future research directions in Section 6.

2.2. Related Literature

Autonomous vehicles (AVs) are expected to decrease how onerous it is to drive and thus decrease a driver's willingness to pay to reduce their travel time, or their value of time (VOT). The subjective value of travel time is how much the individual is willing to pay to reduce their travel time. Many theories of value of time have elaborated on the time allocation framework of Becker (1965), but the basic idea has remained consistent that an individual's labor supply constrained by the total time available, which is divided among work, leisure, and travel (Small, 2012). The hidden components behind the value of travel time measurement are the values of productive activities, leisure activities, and activities in general (Jara-Díaz, 2000). Moreover, many factors can influence the value of travel time. In general, the factors can be summarized as 1) level of service (e.g., travel time and travel costs), 2) socioeconomic characteristics of the traveler, 2) trip characteristics (e.g., trip purposes, distances, and schedule), and 3) social and spatial contexts (De Borger & Fosgerau, 2008; Devarasetty et al., 2012; Small, 2012).

Indeed, travel behavior is situated in the context of people's surrounding technical, social, and spatial landscapes (Geels, 2012) and becomes a way of life (Sheller & Urry, 2006). Earlier literature on the value of travel time mostly focused on the level of service and individuals' socioeconomic characteristics. Later, researchers in geography and planning have demonstrated how travel experiences are influenced by different contexts across neighborhoods and cities (Calastri et al., 2017; Cervero, 2002; Ewing & Cervero, 2010; Schwanen et al., 2004; M. Zhang & Zhang, 2018). By analyzing Twitter data, Horner and Richard (2016) found that public opinions and sentiments about AVs have a significant level of spatial variability. However, few studies examined the influence of spatial contexts on the value of travel time in AVs for commuting, which is important to the understanding of the impacts of AVs on future urban footprints.

Spatial contexts within a metropolitan area, to a large extent, are related to other dimensions of contexts: social norm, class, lifestyle, and the built environment, given the high degree of spatial segregations in income, race and ethnicity, and housing types in the US (Crowell & Fossett, 2018; Owens, 2019; S. F. Reardon & Bischoff, 2011). Such spatial variations, de facto social/racial variations, not only capture in commuting trips (Preston & McLafferty, 2016; Zax, 1990) but also produce differentiated commuting (Bissell, 2018). For example, commuting experiences in urban areas are characterized by heavy traffic and complex driving circumstances, while commuting in rural areas faces higher risks of fatal crashes, particularly for older adults (Payyanadan et al., 2018; Zwerling et al., 2005). Further, people's lifestyles and patterns of activities often coincide with different geographic areas, which are built differently. These lifestyles and built environments also contribute to how commuting time is valued (Paleti et al., 2015;

Schwanen et al., 2002). Therefore, it is reasonable to expect AVs to affect how people value commuting time differently across different geographic areas.

Commuting experiences are, of course, different by metropolitan area. Often, the size and structure of a metropolitan area are interrelated, and the two together influence the mode, time, volume, safety of the travel (Ewing & Dumbaugh, 2009; Ewing et al., 2003; Ewing et al., 2018). Although I measure commuting experiences in economic terms, they are also personal and emotional, resulting from the social environment of the city. For example, Diana (2012) found that people have the highest levels of satisfaction with transit services in smaller towns and the lowest ones in large cities. Also, larger cities have witnessed substantial job growth in the tech and service sectors, which result in nontraditional work schedules and thus, different rush hours for commuting. For instance, the New York Metropolitan Transportation Authority had to reoptimize its system for its high ridership at all hours of the day (New York Metropolitan Transportation Authority, 2013). However, the experience of particular metropolitan areas, often the larger ones, can be overrepresented and become stylized facts (Kanai et al., 2018). Smaller cities in the US with distinctive social and physical environments might face unique challenges in the broader revolution of automated and networked vehicles.

To date, there is only a small number of studies that examine the effects of AVs on the value of travel time (i.e., de Almeida Correia et al., 2019; Kolarova et al., 2019; Krueger et al., 2016; Steck et al., 2018; Yap et al., 2016). On the other hand, studies questioned the effect of AVs on VOT may be not as significant as researchers expect due to various reasons (Singleton, 2018), such as limited productivity impacts (Cyganski et al., 2015; Milakis et al., 2017; Schoettle & Sivak, 2014), motion sickness in the vehicle (Diels &

Bos, 2016), more discomfort for car passengers at lower acceleration levels compared to car drivers (Le Vine et al., 2015), limited multi-taskability due to vehicle interior design (Sivak & Schoettle, 2016), and the pleasure of driving (Anable & Gatersleben, 2005; Mokhtarian et al., 2015; Steg, 2005).

The review of the literature serves to illustrate that the potential effects of AV technologies on the value of travel time may be spatially differentiated across different locations within and between metropolitan areas. This study focuses on personal vehicle commuters in SMMAs in the US with a focus on their spatial contexts across urban, suburban and rural areas. It examines how these commuters might value their in-vehicle time differently while in autonomous vehicles. More specifically, this study contributes to the literature by addressing the following two questions.

1. How much would AVs change the value of in-vehicle time compared to taking regular vehicles (RVs)?
2. How would the change to the value of in-vehicle time vary by the spatial contexts of the commuter?

2.3. Development of the Discrete Choice Experiment

2.3.1. Overview of the Experiment

Stated preference data from a discrete choice experiment (DCE) are used to evaluate commuters' valuation of commuting time in RVs, AVs, and SAVs. DCEs are a stated preference approach of producing behavioral data and widely used in program evaluation and new product forecasting (Hensher, 1994; McFadden & Train, 2017). The current nonexistence of AVs poses a challenge for participants to envision what it would be like to ride AVs/SAVs for commuting. Variation in their envisioning might influence their answers and thus outcomes in VOT. To tackle this challenge, I design the DCE based on respondents' commuting trips and include instructions and questions that help them envision the use of AVs. The following sections describe the development of attributes and levels, construction of experimental choice designs, design of reference-dependent choice tasks, and recruitment.

The stated choice experiment was completed on-line using the LimeSurvey platform (LimeSurvey, 2018). LimeSurvey is an open-source survey platform that allows the design of algorithms to assign choice sets based on respondents' reference trip information. The survey had five groups of questions. Group 1 collected information on a reference trip made by respondents. Respondents were asked to provide the travel monetary cost and time cost of their most recent trip to work or school made by personal vehicles. Group 2 evaluated respondents' awareness of and attitudes towards transportation technologies (e.g., ridesharing, connected vehicle, AV, and how much do they enjoy driving). Group 3 introduced AV and SAV technologies and asked how likely they would engage in various activities when riding an AV or an SAV. Group 4 presented four choice tasks with travel cost and travel time based on the reference trip provided in Group 1. The respondents were asked to select their preferred choice. Finally, Group 5 collected respondents' socioeconomic characteristics.

2.3.2. Development of Attributes and Levels

The study includes two attributes, travel cost and travel time since I focus on the valuation of in-vehicle time. The attribute levels are calculated based on the respondent-provided reference trip and various public data. I categorize the reported reference trips into five segments based on (Polzin & Pisarski, 2013): short trip (travel time < 20 min), lower medium trip (20 min < travel time < 40 min), higher medium trip (40 min < travel time < 60 min), long trip (60 min < travel time < 90 min), and extremely long trip (travel time > 90 min). I gather cost per mile and average commuting speed information from the Bureau of Transportation Statistics publications and National Household Travel Survey publications.

We set cost per mile \$0.2 and average speed 30 miles/h for short trips, 40 miles/h for medium trips, and 50 miles/h for long and extremely long trips. The cost per mile includes fuel cost and other unobserved costs perceived by respondents without including vehicle depreciation, as suggested by Hang et al. (2016). The time and cost attributes of AV and SAV are pivoted around the travel time and cost of the calculated reference trip in each trip segment.

Table 2.1 summarizes all the attributes and their levels. A few rules are followed when pivoting around the reference trip attributes. SAV has a higher time and lower cost than AV and RV. AV has a higher cost but can have lower, same, and higher time compared to RV. AV is more expensive and faster than SAV.

2.3.3. Experimental Design

Ngene software (ChoiceMetrics) was used to generate a pivot design optimized for the panel mixed logit model. The pivot design process can generate a design with a reference alternative based on the proportions of various segments. As illustrated in Table 1, I designed different pivoting levels and assigned different weights to the 5 segments. The weight is the average trip length share in SMMAs. I firstly optimize the design for a multinomial logistic model using Bayesian priors and then evaluate the design for a panel mixed logit model, as recommended by Bliemer and Rose (2011). The Bayesian priors for travel time and travel cost are based on recent studies using a similar experimental design (Bliemer & Rose, 2013; Devarasetty et al., 2012). The resulting design has a D-error of 0.1303, indicating good overall efficiency and statistical power of the design. More importantly, I have intensively tested the choice sets with general individuals with no relevant education background to ensure they are realistic, familiar, and not too complex.

Table 2.1 Overview of Attributes, Levels, and Assignment Rules

Segment	Travel Time		Travel Cost		Assignment Rule
	Ref. Level	*Pivot Level*	*Ref. Level*	*Pivot level*	
Short<20	15 min	(3, 5, 7)	\$2	(1.5, 1, 0.5)	Assign, if travel time <20
20<Medium 1<40	30 min	(8, 12, 16)	\$4	(5, 3, 2)	Assign, if 20≤travel time <40
40<Medium 2<60	50 min	(8, 12, 16)	\$7	(5, 3, 2)	Assign, if 40≤ travel time <60
60<Long<90	70 min	(15, 20, 25)	\$12	(3, 5, 7)	Assign, if 60≤travel time <90
Extreme>90	100 min	(15, 25, 35)	\$17	(5, 7, 10)	Assign, if travel time ≥90
Short<20	15 min	(-5, 0, 5)	\$2	(5, 3, 2)	Assign, if travel time <20
20<Medium 1<40	30 min	(-5, 0, 5)	\$4	(11, 8, 6)	Assign, if 20≤ travel time <40
40<Medium 2<60	50 min	(-7, 0, 7)	\$7	(11, 8, 6)	Assign, if 40≤ travel time <60
60<Long<90	70 min	(-10, 0, 10)	\$12	(14, 12, 9)	Assign, if 60≤travel time <90
Extreme>90	100 min	(-10, 0, 10)	\$17	(18, 15, 12)	Assign, if travel time ≥90

Note: Attribute levels of SAVs and AVs are calculated by the reference level plus pivot level
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Part D. Introduction of Driverless Vehicle

In a **Driverless Vehicle**, all driving tasks are completely autonomous and you only need to tell the vehicle where to go. Theoretically, driverless vehicles do not crash. You can do things like work, sleep, read, watch TV, maybe even exercise while the vehicle takes you to your destination. You might either ride a **Driverless Vehicle** alone or hire a **Shared Driverless Vehicle** for carpooling (like Uber) that may pick up other passengers during the trip.

*

Suppose you are traveling in a driverless vehicle you own, how likely are you to do following activities?

	Highly Unlikely	Unlikely	Neutral	Likely	Highly Likely
Communicating: by phone, email, etc.	○	○	○	○	○
Entertainment/recreation: resting, reading, hobbies, TV, exercise, etc.	○	○	○	○	○
Formal: paid work, education, religious activity, etc.	○	○	○	○	○
Household/personal: eating/drinking, prepare meal, personal care, etc.	○	○	○	○	○
Information search: online shopping, journey information, employment information, etc.	○	○	○	○	○
Other	○	○	○	○	○

Figure 2.1 Introduction of autonomous vehicles and the possible range of in-vehicle activities

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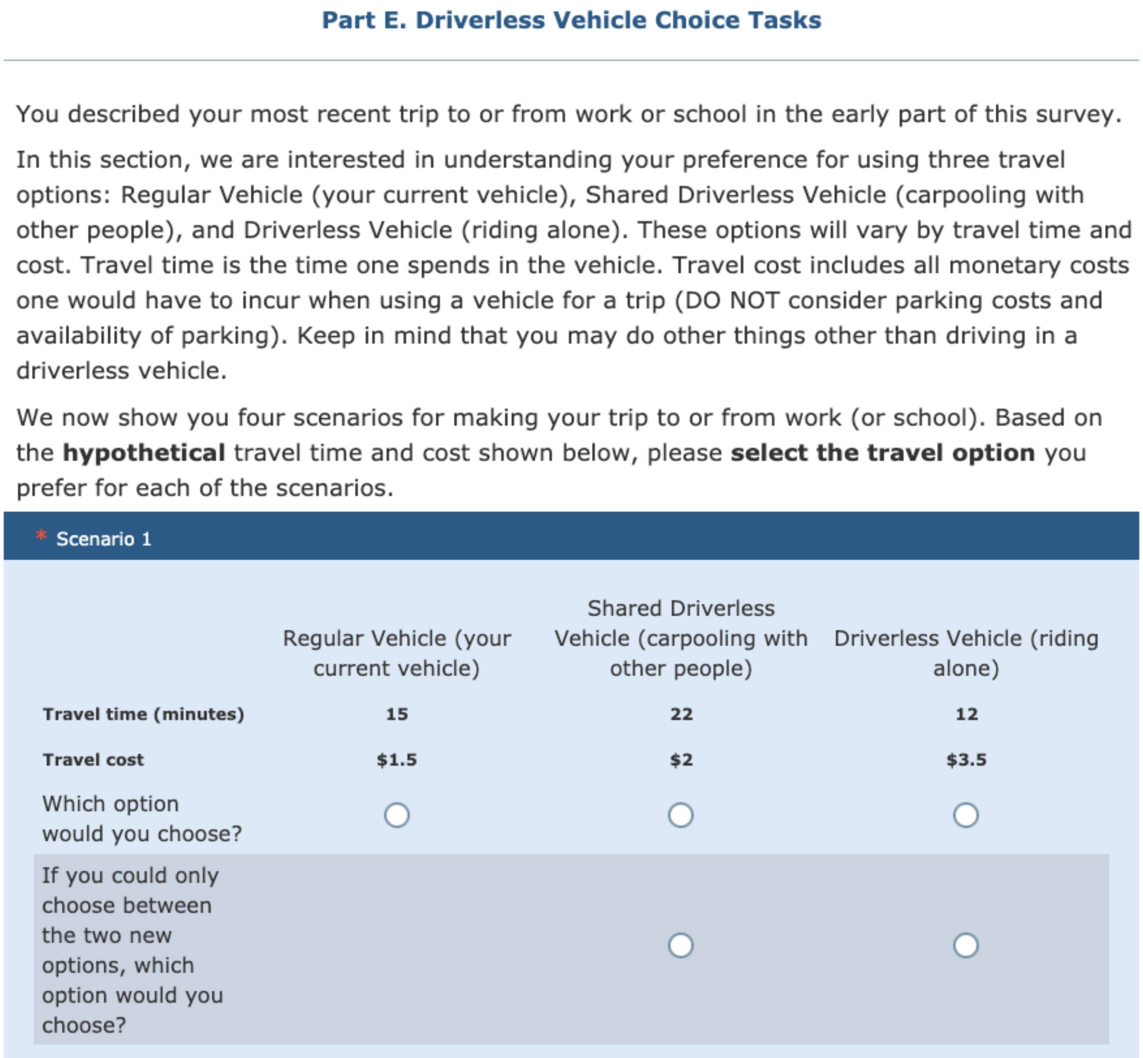

Part E. Driverless Vehicle Choice Tasks

You described your most recent trip to or from work or school in the early part of this survey.

In this section, we are interested in understanding your preference for using three travel options: Regular Vehicle (your current vehicle), Shared Driverless Vehicle (carpooling with other people), and Driverless Vehicle (riding alone). These options will vary by travel time and cost. Travel time is the time one spends in the vehicle. Travel cost includes all monetary costs one would have to incur when using a vehicle for a trip (DO NOT consider parking costs and availability of parking). Keep in mind that you may do other things other than driving in a driverless vehicle.

We now show you four scenarios for making your trip to or from work (or school). Based on the **hypothetical** travel time and cost shown below, please **select the travel option** you prefer for each of the scenarios.

* Scenario 1

	Regular Vehicle (your current vehicle)	Shared Driverless Vehicle (carpooling with other people)	Driverless Vehicle (riding alone)
Travel time (minutes)	**15**	**22**	**12**
Travel cost	**$1.5**	**$2**	**$3.5**
Which option would you choose?	○	○	○
If you could only choose between the two new options, which option would you choose?		○	○

Figure 2.2 An example of a choice set

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2.3.4. Choice Task

Each choice set presents three alternatives: a regular vehicle, a shared driverless vehicle, and a driverless vehicle (i.e., RVs, SAVs, and AVs). All alternatives are described in terms of travel time and travel costs. The regular vehicle (or your current vehicle) alternative is important because it increases the realism of the survey and serves the purpose to compare RVs with AVs. The respondents are asked to choose the most preferred option from the three alternatives, and between carpooling and riding alone in a driverless vehicle. As noted above, 12 choice sets are generated for each trip segment. Each respondent is randomly assigned with four choice sets from the 12 choice sets in each trip segment. The respondent is asked to choose the most preferred option from the three alternatives, and between sharing and riding alone in a driverless vehicle. **Figure 2.1** illustrates how I introduce AV technologies, including automated driving, safety benefits, and a wide range of in-vehicle activities. **Figure 2.2** illustrates a choice set example faced by the respondents.

2.3.5. Recruitment and Data Collection

The target population of the stated choice experiment is auto commuters living in SMMAs (see **Figure 2.3**). The SMMAs in this study are those with a population between 200,000 and 450,000, whose populations are growing and mostly dependent on automobiles for mobility (Frey, 2017). For example, Boulder (CO), Memphis (MI), and Charlotte (VA) are included in the sampling framework.

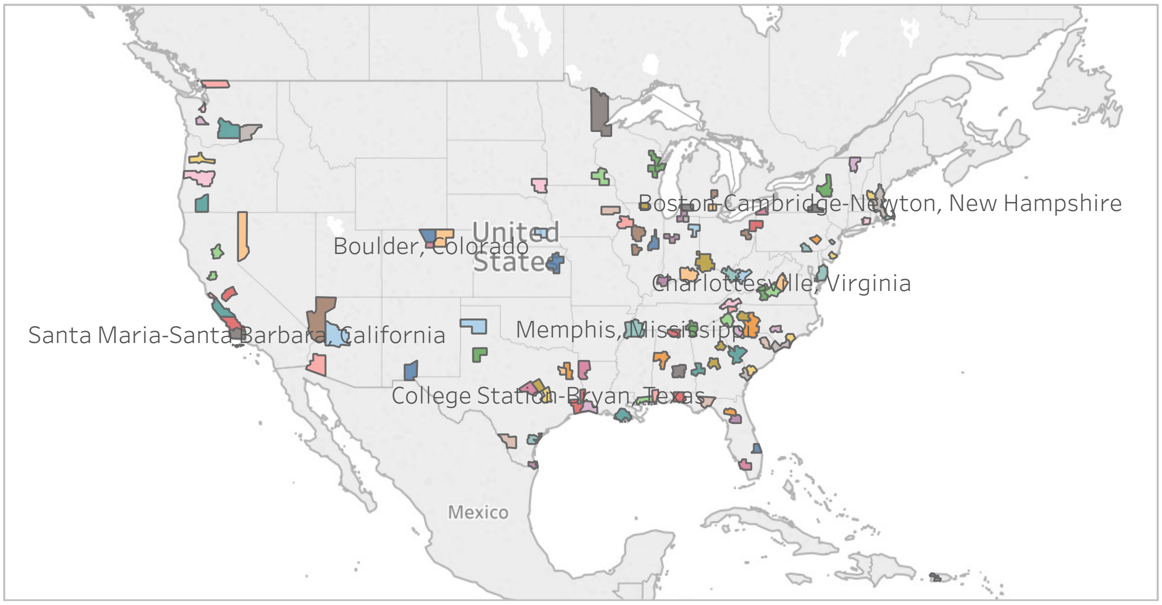

Figure 2.3 Metropolitan areas in the sampling framework
Note: Reprinted from Zhong, H., Li, W., Burris, M. W., Talebpour, A., & Sinha, K. C. (2020). Will autonomous vehicles change auto commuters' value of travel time? Transportation Research Part D: Transport and Environment, 83, 102303.

A market research company—LightSpeed Research LLC, implemented the survey. LightSpeed Research has over 5.5 million people in 40 plus countries that have opted to be on their panel of potential survey participants. A subset of these people was alerted to the survey and allowed to participate in the survey. Specifically, individuals aged 18 or above, currently commuting to work or school by private passenger vehicles and living in SMMAs in the US, were eligible to participate. The potential survey participants will receive basic information about the survey, and then they can choose to participate or not. I distributed the online survey from November 3 to 8, 2017.

In total, 4,625 participants responded to the survey. 2,111 of them were eligible and completed the survey. Of those who completed responses, 230 participants were excluded because of their extremely short answering time (< 3 minutes), leaving 1,881 valid responses as the final sample. The survey takes at least 5 minutes for researchers in this study. I decide to use 3 minutes as the threshold in case of any fast readers. **Table 2.2** compares the demographics of the sample with those of SMMAs in the US using the 2017 National Household Travel Survey (NHTS). The sample appears to slightly under-represent individuals that are younger (age 18 to 54), male, and wealthy (household income $200,000 and more), but over-represent individuals that are older (age 55 and more), and have a Bachelor's degree and above. The difference between the sample and the 2017 NHTS data may lead to smaller estimates of the VOTs than the true value, because VOT is positively associated with income and negatively associated with disposable time based on previous literature (Small, 2012).

Table 2.2 Summary Statistics about Survey Respondents

	Sample		**2017 NHTS (Auto Commuters)**	
Variable	Mean	S.D.	Mean	S.D.
Average Household Size	2.383	1.24	3.060	0.25
	Percentage		Percentage	
Male	41.9%		52.3%	
With a Bachelor's Degree and Above	47.0%		39.0%	
Age 18-24	6.5%		13.4%	
Age 25-34	11.0%		22.7%	
Age 35-44	14.9%		20.3%	
Age 45-54	18.4%		20.0%	
Age 55-64	27.5%		18.1%	
Age 65 and more	21.7%		5.4%	
Household Income Less than $24,999	12.7%		0.9%	
Household Income Between $25,000 and $49,999	26.1%		13.2%	
Household Income Between $50,000 and $74,999	23.0%		23.9%	
Household Income Between $75,000 and $99,999	17.1%		20.7%	
Household Income Between $100,000 and $199,999	17.7%		14.2%	
Household Income $200,000 or more	3.4%		23.2%	

Table 2.2 Continued

Variable	Sample Mean	Sample S.D.	2017 NHTS (Auto Commuters) Mean	2017 NHTS (Auto Commuters) S.D.
Household Income No Answer	4.6%		3.9%	
Short Trip < 20 min	44.8%		48.0%	
20=<Medium Trip < 40 min	35.5%		38.9%	
40=<Medium Trip < 60 min	9.3%		8.6%	
60=<Long Trip < 90 min	5.7%		2.7%	
Extreme Long Trip >= 90 min	4.7%		1.8%	

Note: Population descriptive statistics are based on weighted sample characteristics of auto commuters in Metropolitan Statistical Areas with populations greater than 25,000 and less than 499,999 in the 2017 National Household Travel Survey (NHTS). Reprinted from Zhong, H., Li, W., Burris, M. W., Talebpour, A., & Sinha, K. C. (2020). Will autonomous vehicles change auto commuters' value of travel time? Transportation Research Part D: Transport and Environment, 83, 102303.

2.4. Econometric Analysis

2.4.1. Modeling Framework

In most transportation models, the underlying assumption is that people trade off money and time, and are willing to pay monetarily to reduce their travel time. My analysis of the choice data relies on the random utility model framework (McFadden, 1973). The model based on the assumption that a rational individual selects the alternative that maximizes the derived utility. The utilities "U" are assumed to be a function of observed variables relating to decision-maker, n, and alternative, j. Thus, in a choice experiment, the utility respondent *n* derives from choosing alternative *j* in choice scenario *s* is given by

$$U_{nsj} = \beta X_{nsj} + \varepsilon_{nsj}, \qquad n = 1, \dots, N, j = 1, \dots, J, s = 1, \dots, S \tag{1}$$

where the X_{nsj} is a $K \times 1$ vector of observed variables relating to alternative *j* and the respondent; β is a vector of coefficients that are fixed over respondents and alternatives. The standard multinomial logit model assumes the idiosyncratic error term ε_{nsj} is independent of irrelevant alternatives (IIA) and is identically distributed as a Gumbel distribution. That is to say, for a given set of choices, the IIA assumption could be violated due to omitted variables from the model that are correlated with the choices. The simplistic and restrictive assumptions are not realistic in the study context since one might expect the SAVs to draw disproportionately more from people who carpool. This issue is analogous to the statistical independence of the errors in the linear regression model, as described by McFadden et al. (1977). See Cheng and Long (2007) for a Monte Carlo simulation testing for IIA property. In light of this concern, I use one widely used extension of the standard multinomial logit model, a mixed logit model, in order to account for the dependence between alternatives.

2.4.2. The Mixed Logit Model

The mixed logit model extends the standard multinomial logit model by allowing flexible substitution patterns and, thus, relaxes the restrictive IIA assumption (McFadden & Train, 2000). The resulting choice probability that respondent *n* choose alternative *j* in choice scenario *s* can be written as:

$$P_{nsj} = \frac{exp\left(\beta X_{nsj} + [\mu Z_{nsj} + \ \varepsilon_{nsj}]\right)}{\sum_{j=1}^{J} exp\left(\beta X_{nsj} + [\mu Z_{nsj} + \ \varepsilon_{nsj}]\right)}, n = 1, \ldots, N, j = 1, \ldots, J, s = 1, \ldots, S \qquad (4)$$

Where the μ is a random vector with zero mean; the Z_j is a vector of observed variables relating to alternative *j*; and the ε_j is independent and identically distributed (Brownstone & Train, 1998). The parameters are continuously distributed across respondents, which would allow us to derive willingness to pay distributions.

The utility function associated with each alternative as chosen by respondent n in situations *s* is given by:

$$U_{SAVns} = \beta_n TT_{SAVns} + \theta TC_{SAVns} + \varepsilon_{SAVns} \tag{5}$$

$$U_{AVns} = ASC_{AV} + (\beta_n + \beta_{ASC} ASC_{AV}) TT_{AVns} + \theta TC_{AVns} + \varepsilon_{AVns} \tag{6}$$

$$U_{RVns} = ASC_{RV} + (\beta_n + \beta_{ASC} ASC_{RV}) TT_{RVns} + \theta TC_{RVns} + \varepsilon_{RVns} \tag{7}$$

where ASC_j is the alternative specific constant for alternative mode j; TT and TC are the travel time and travel cost of each alternative; θ is the fixed coefficient vector of travel cost for each alternative; ε_{jns} is not observed by the analyst and are considered as stochastic factors; β_n is the random coefficient vector of travel time; β_{ASC} is an alternative-specific coefficient of travel time. The subjective value of travel time is not only determined by individual characteristics (e.g., income) but also affected by the spatial contexts where trips are realized. Therefore, β_n may vary across population segments (X_n) and spatial contexts (U_n). β_n in choice situation s for alternative j can be defined as:

$$\beta_{jns} TT_{jns} = (\beta'_{jns} + \delta_{jns} X_{jns} + \lambda_{jks}) TT_{jns} \tag{8}$$

where δ_{jns} denotes the heterogeneity of preferences for the travel time across socio-economic levels or travel time ranges; λ_{jks} modifies the mean of the distribution of the travel time parameter, which varies across the place of living (i.e., urban, suburban, and rural area). λ_{jks} (neighborhood level) is a function of associated contextual characteristics and can be written as:

$$\lambda_{jks} = \gamma_{k0} + \gamma_{kp} u_{kp} + v_{kn} \tag{9}$$

where γ_{kp} is the p_{th} category of residence location (0 is the intercept); u_{kp} is the associated contextual variables in p_{th} place; v_{kn} is a random term associated with β_{jns}.

When no contextual variables are collected, Equation (8) collapses to $\lambda_{jks} = \gamma_{kp} + v_{kn}$. Combine (7) and (8), Equation (3) can be rewritten as:

$$P_{nsj} = \frac{exp\left(ASC_j + (\beta_{ASC}ASC_j + \beta_{jns}^{'} + \delta_{jns}X_{jns})TT_{jns} + (\gamma_{kp} + v_{kn})TT_{jns} + +\theta TC_{jns} + \varepsilon_{jns}\right)}{\sum_{j=1}^{J} exp\left(ASC_j + (\beta_{ASC}ASC_j + \beta_{jns}^{'} + \delta_{jns}X_{jns})TT_{jns} + (\gamma_{kp} + v_{kn})TT_{jns} + +\theta TC_{jns} + \varepsilon_{jns}\right)},$$

$$n = 1, \dots, N, j = 1, \dots, J, s = 1, \dots, S, k = 1, \dots, K \qquad (10)$$

The utility equations account for both observed and unobserved heterogeneity by scaling the random parameter time by individual-specific ($\delta_{jns}X_{jns}$), alternative-specific ($\beta_{ASC}ASC_j$), and contextual characteristics ($\gamma_{kp} + v_{kn}$).

2.5. Results

2.5.1. Model Results

In the estimated models, I set the travel time and alternative-specific constants as random parameters and travel cost as a fixed variable scaled by travel time when computing willingness to pay, as Hensher and Button (2007) recommended. The random parameter travel time draws from triangular distribution, which has relatively better model performance by comparing the Akaike information criterion (AIC) and Bayesian information criterion (BIC), in the final models. I also test different functional forms of the random parameters, including normal distribution, lognormal distribution, and triangular distribution. Most of the distributions produce consistent estimates. The alternative-specific constants draw from a normal distribution. I also estimated separate models for different subgroups, which are defined by driver/passenger and place of living. To account for the observed heterogeneity in preferences, I also specified travel time to have alternative-specific, individual-specific, and context-specific parameter estimates in the two extended models for both drivers and passengers. All models are estimated using the “gmnl” package in R Statistical Software (Sarrias & Daziano, 2017).

Table 2.3 Model Specifications and Performance of Estimated Models

	Model 1	Model 2	Model 3	Model 4	Model 5
Travel cost as a fixed variable	Yes	Yes	Yes	Yes	Yes
Travel time as a random variable	Yes	Yes	Yes	Yes	Yes
Alternative-specific travel time	Yes	Yes	Yes	Yes	Yes
Random ACSs	Yes	Yes	Yes	Yes	Yes
Include socioeconomic variables	No	No	No	Yes	No
Include trip characteristics	No	No	No	Yes	No
Include place of living	No	No	No	Yes	No
Distribution of travel time	Triangular	Triangular	Triangular	Triangular	Triangular
Distribution of ACSs	Normal	Normal	Normal	Normal	Normal
Sample	Urban drivers	Suburban drivers	Rural drivers	All drivers	All passengers
Draws	1000	1000	1000	1000	1000
Log-likelihood	-1053	-1491.8	-435.53	-2896.6	-360.62
BIC	2174.195	3057.671	935.370	6093.53	779.555
AIC	2123.932	3001.668	889.063	5861.133	739.234

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Table 2.3 reports the specifications and model fits of the presented models. Models 1-3 only include alternative-specific information and random effects for estimation and estimate respondents who drive in the reference trips and live in urban areas, suburbs, and rural areas, respectively. Model 4 pools drivers together and adds further information about their socioeconomic characteristics, trip conditions, and place of living. Model 5 estimates the preferences of respondents who are passengers in the reference trips. Although the fully-specified model does not increase the model fit, it provides insights into the heterogeneity in preferences. Therefore, I discuss estimated coefficients across all models and rely on Models 1 – 3 to derive the values of commuting time (VOT) for RVs, SAVs, and AVs.

Table 2.4 reports the estimated results of the mixed logit models. It should be noted that all the results are based on stated preferences as no trips were made. Across models, alternative attribute coefficients are statistically significantly different from zero with expected signs, indicating preferences over different travel modes exist. The large and positive coefficient of ASC RV indicates that the majority of respondents prefer their current RVs over SAVs and AVs. On average, respondents prefer RVs over SAVs and prefer SAVs over AVs. Such preferences also present significant heterogeneity over the sample, as the random effect components enter significantly and are large relative to the means.

Further, it is not surprising that the estimates are different between respondents who drive (hereafter termed drivers) and those who are passengers (hereafter termed passengers) in the reference trips. For those drivers, the attribute coefficients have the expected sign: on average, drivers prefer shorter travel time and lower travel costs. Based on Model 1 – 4, a few noteworthy effects on drivers are behaviorally meaningful. First, compared to taking SAVs, drivers prefer their time in AVs but not in RVs, as indicated by the signs of the coefficients.

Second, interacting with travel time, having children at home have a negative coefficient, as expected. This is consistent with the time allocation theory that those respondents have to spend more time on family-related activities other than commute would more value commuting time savings, given the total time constraint.

Third, short trips have a positive coefficient; it is slightly larger than that of AVs (AV x Time). The positive utility on the travel time of short trip may be as explained by Redmond and Mokhtarian (2001) that people value the transition time between work and home if the travel time is within an acceptable range. Also, on a short trip (less than 20 minutes), it is unlikely to save a significant amount of time that can put into other uses that can substantially reduce the disutility of travel. This has an implication for planning for accessibility.

Finally, drivers living in urban areas place higher utility value on travel time than those living in suburban areas, possibly due to the driving in urban areas that are onerous with the traffic conditions and conflicts in high-density areas.

Based on Model 5, passengers seem to be less sensitive to travel time and costs but still have a negative coefficient on riding in RVs, compared to riding in SAVs. It is unexpected, as being a passenger in different vehicles is expected to matter little in the changes in the valuation of travel time. This is possibly due to hailing SAVs and AVs presents a sense of control than being driven by someone else, which has positive effects on commuting stress. Another explanation could be that passengers may prefer being driven by robotics over strangers if their current commutes are not driven by people they know. Although the coefficient of the interaction with AV is not significant, it has a positive sign, weakly indicating a preference of not sharing the ride.

Table 2.4 Estimated Mixed Logit Models

	Model 1: Urban Drivers			Model 2: Suburban Drivers			Model 3: Rural Drivers			Model 4: All Drivers			Model 5: All passengers		
	Est.	SE		Est.	SE		Est.	SE		Est.	SE		Est.	SE	
Alternative-specific constants															
Reference Level: ASC SAV															
ASC AV	-3.596	0.769	***	-4.245	0.755	***	-2.523	1.222	*	-4.743	0.605	***	-3.208	1.148	**
ASC RV	3.740	0.441	***	5.755	0.519	***	5.646	0.873	***	4.565	0.373	***	3.838	0.762	***
Alternative-specific attribute															
Cost	-0.091	0.052	.	-0.302	0.052	***	-0.792	0.184	***	-0.467	0.050	***	-0.012	0.037	
Time	-0.139	0.043	**	-0.195	0.040	***	-0.203	0.073	**	-0.149	0.078	.	-0.055	0.042	
Time x AV	0.026	0.014	.	0.055	0.013	***	0.037	0.020	.	0.062	0.010	***	0.008	0.016	
Time x RV	-0.033	0.011	**	-0.044	0.012	***	-0.028	0.017		-0.027	0.008	**	-0.035	0.015	*
Random Effect															
Time	0.137	0.054	*	0.212	0.052	***	0.178	0.091	*	0.194	0.038	***	0.109	0.103	
ASC AV	4.057	0.540	***	3.935	0.507	***	3.437	0.856	***	4.441	0.389	***	3.400	0.778	***
ASC RV	3.558	0.334	***	4.272	0.338	***	4.047	0.612	***	3.992	0.230	***	3.470	0.539	***
Individual-specific effect															
Reference Level: Age (45- 54)															
Time x Age (18-24)										0.014	0.054				
Time x Age (25-34)										0.019	0.052				
Time x Age (35-44)										-0.048	0.050				
Time x Age (55-64)										0.010	0.047				
Time x Age (65 and more)								`		0.035	0.054				
Reference Level: (Less than $24999)															
Time x Household Income ($25,000 to 49,999)										0.017	0.045				
Time x Household Income ($50,000 to 74,999)										-0.020	0.049				
Time x Household Income ($75,000 to 99,999)										-0.003	0.050				
Time x Household Income ($100,000 to 199,999)										0.005	0.055				
Time x Household Income (More than $200,000)										-0.024	0.093				
Reference Level: Part-time worker															
Time x Fulltime Worker										0.031	0.051				
Time x Retired										0.115	0.055	*			

Table 2.4 Continued

	Model 1: Urban Drivers Est.	SE	Model 2: Suburban Drivers Est.	SE	Model 3: Rural Drivers Est.	SE	Model 4: All Drivers Est.	SE		Model 5: All passengers Est.	SE
Time x Student							0.102	0.055			
Time x Male							-0.030	0.055			
Time x Have a Bachelor's Degree							-0.056	0.052			
Time x Household Size							-0.055	0.039			
Time x Have Children							-0.100	0.049	*		
Trip context effect											
Time x Peak Hour							-0.018	0.030			
Reference Level: 40 min < Trip < 60 min											
Time x Trip < 20 min							0.077	0.030	**		
Time x 20 min ≤ Trip < 40 min							-0.012	0.036			
Time x 60 min ≤ Trip < 90 min							-0.052	0.052			
Time x Trip ≥ 90 min							-0.134	0.086			
Spatial context effect											
Reference Level: Urban Area											
Time x Living in City Center							-0.048	0.015	**		
Time x Living in Suburb							0.158	0.041	***		
Time x Living in Rural Area							0.004	0.029			
N (# of choice scenarios)	1968		3742		1268		6872			652	

Note: 1. Statistically Significant level codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1. 2. Cost is in US dollar; Time is in minutes. 2. ASC denotes alternative specific constant.
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2.5.2. Value of Travel Time

To offer more behavioral insights, I make use of the model estimates to derive the value of travel time (i.e., the willingness to pay for travel time savings) for drivers by location. The model for passengers is not used due to its insignificance in travel time and cost not being significant in the model. Although the insignificance does not mean there are no preferences, it just does not allow us to know the accuracy of the values since the confidence interval would be large for passengers' derived value of travel time. The value of travel time (VOT) is calculated as unconditional willingness to pay by:

$$VOT = 60\,mins \times \left(\beta_{Time} + \frac{\sum_N \beta_{ASC-Time} ASC}{N} + |v|T\right)/\beta_{Cost} \tag{11}$$

where n indicates each individual; N is the sample size; v is the random effect of travel time follows triangular distribution T. In light of the nature of random parameter, I generate a distribution of individual VOT by drawing randomly from the triangular distribution with the mean β_n and the standard deviation v. I report the mean, first quantile, and third quantile of the distribution of individual VOT.

Table 2.5 reports the VOT directly addresses the two key research questions raised in the Literature Review section.

1. How much would AVs change the value of in-vehicle time compared to taking regular vehicles (RVs)?

Riding AVs reduces the value of in-vehicle time ranging from 8% to 32% compared to driving RVs, depending on vehicle types and place of living. AVs present larger reductions in VOT (18% - 32%) than those presented by SAVs (8% - 14%). Passengers appear to have reductions in VOT when taking AVs and SAVs, but an accurate VOT cannot be derived.

2. How would the change to the value of in-vehicle time vary by the spatial contexts of the commuter?”

With respect to spatial contexts, drivers who live in suburbs have the most substantial reduction in VOT by AV technologies (AVs: 32% and SAVs: 14%), followed by their urban counterparts (AVs: 24% and SAVs: 13%) and then the rural counterparts (AVs: 18% and SAVs: 8%). I use Kolmogorov-Smirnov test to determine whether the distributions of VOTs differ significantly between different places of living. Kolmogorov-Smirnov test is a nonparametric method that is more reliable when the samples are not normally distributions (Massey Jr, 1951). The results of the test all suggest to reject the null hypothesis that the two distributions are the same, as I present in the lower part of Table 5. Moreover, there are no containment or inclusion relationships between the VOTs of each place of living as revealed by the values at 1st quantile and 3rd quantile, which indicates the existence of spatial differences in VOT. My estimates are in agreement with the findings from Steck et al. (2018) and de Almeida Correia et al. (2019), where reduction rates are 31% to 41% for AVs and around 10% for SAVs. Except that, I demonstrate that the spatial variations of the changes in in-vehicle VOT are nonnegligible.

Table 2.5 Values of travel time by vehicle types and place of living

		Regular Vehicle	Autonomous Vehicle		Shared Autonomous Vehicle	
		VOT	VOT	VOT Reduction Rate	VOT	VOT Reduction Rate
Urban/City Center	1st quantile	$40.61	$27.69		$33.30	
	Mean	$53.71	$40.89	23.88%	$46.53	13.38%
	3rd quantile	$66.90	$53.82		$59.74	
Suburban	1st quantile	$14.36	$7.83		$11.39	
	Mean	$20.54	$13.98	31.95%	$17.58	14.43%
	3rd quantile	$26.67	$20.18		$23.69	
Rural	1st quantile	$7.38	$5.73		$6.66	
	Mean	$9.36	$7.71	17.59%	$8.64	7.69%
	3rd quantile	$11.33	$9.68		$10.62	
Kolmogorov-Smirnov test on the differences between the VOTs						
AV	D statistics					
Urban vs. Suburban	0.69	***				
Urban vs. Rural	0.92	***				
Suburban vs. Rural	0.53	***				
SAV						
Urban vs. Suburban	0.72	***				
Urban vs. Rural	0.95	***				
Suburban vs. Rural	0.64	***				

Note: *** denotes statistical significance of 0.01.
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2.5.3. Predicted Mode Choices

I predict the mode shares of AVs by different places of living, assuming that travel monetary costs by AV and SAV are reduced by 87.5%. The parameter of 87.5% is based on the cost structure analysis of autonomous mobility service by Bösch et al. (2017). The predicted results by place of living demonstrate a potential landscape of future AV market segments and travel demand changes. **Figure 2.4** presents the predicted commuting mode choices of AV, SAV, and RV of the study sample. The baseline mode share is the current probability under the cost and time scenarios in my stated choice experiment. The predicted results demonstrate that regular vehicles will still dominate the market, even with such a dramatic cost reduction in S/AV technology. Urban areas have the highest share of AV and SAV that could account for almost 40 percent of the market, followed by urban centers. The most substantial increase of AV and SAV shares are found in rural areas, while AV share increases almost half in suburban areas.

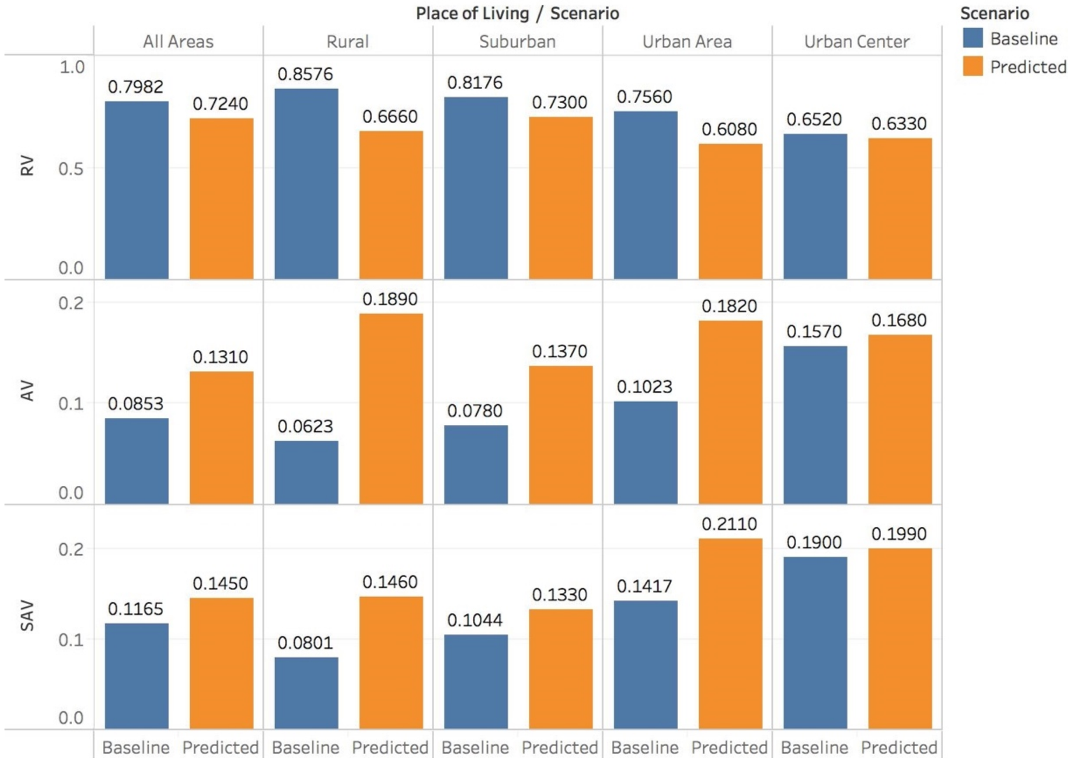


Figure 2.4 Predicted mode choices in the study sample

Notes: 1. These are the probabilities that each vehicle type is chosen. 2. Baseline scenario refers to the case when all of the attributes for each type of vehicle remain the same as the original data. 3. Predicted scenario refers to the case when the travel cost reduced by 7/8. 4. The numerical labels of each bar indicate the market share.

2.6. Discussion and Conclusion

In this study, I investigated how current auto commuters, if taking AVs and SAVs, might value their travel time differently, by conducting discrete choice experiments for commuters in SMMAs and applying mixed logit models. I have several conclusions from this study. First, my results support the assumption that AVs and SAVs can potentially reduce the VOT for commuting trips compared to RVs. Yet the results also highlight that the impact on passengers is less significant than driver; this might be due to the fact that passengers are already able to access some of the in-vehicle opportunities I presented in the study. In-vehicle activity opportunities are valued by commuters and may be translated into utility in monetary values.

Second, this study also finds that even though AVs reduce drivers' valuation of travel time, its impact on the VOT appears to be spatially differentiated across urban, suburban and rural areas. On one hand, reduction in VOT for urban drivers would make traffic congestion more tolerable and thus urban living might become more attractive. On the other hand, suburban drivers enjoy a larger reduction in VOT than their urban counterparts. When their overall transportation cost is reduced, living in suburban areas also becomes more attractive. These two competing forces (urban densification vs sprawl) may be settled differently in different regions. However, in SMMAs, urban amenities are scarce and congestion cost is perceived to be much less than large metropolitan areas. These might create a condition that nurtures sprawl more than urban densification.

However, changes in urban spatial structure are also influenced by other complex factors besides transportation cost. One of them might be the self-selection effect, as populations living in urban, suburban, and rural areas might have different preferences and socio-demographic characters. Unfortunately, I am unable to control for this effect due to the cross-sectional design of this study.

This study is subject to three limitations that necessitate future research. First, I only focus on the in-vehicle time of commuting trips. Commuting trips are central in determining urban form changes, but account for a small portion of total trips. It is crucial to understand how AVs could affect other types of trips, such as grocery shopping, healthcare, and recreational trips. Moreover, out-of-vehicle time is not considered in the choice experiment, as I focus on the changes in the value of in-vehicle time. For mode choice decisions, particularly non-commuting trips, out-of-vehicle time can play a role in travelers' decision making. Second, the results and implications above are for the short term as the values and norms can change when AVs are adopted widely in the future. Also, even though urban, suburban and rural areas are examined in my models, it is important to note that each of the spatial categories is diverse by itself in terms of social and physical structures. Future research should conduct more detailed analysis on how AVs may affect individuals across different socio-demographic spectrums. Third, I presented a hypothetical setting of commuting in AVs/SAVs, the specific vehicle designs might influence commuting experience.

3. WHO BENEFITS FROM IN-VEHICLE ACTIVITIES IN AUTONOMOUS VEHICLES?

3.1. Introduction

The potential opportunity of in-vehicle activities in autonomous vehicles might further expand what has come to be known as "travel-based multitasking" (Kenyon & Lyons, 2007). It suggests a gap between the assumptions about wasted travel time and people undertaking meaningful activities while on the move (see e.g., Laurier, 2004; Lyons & Urry, 2005). A central implication of travel-based multitasking is that transportation modes become a moving space for various activities, which produce travel time (Bissell, 2018; Sheller & Urry, 2006). These activities can include work, leisure, or doing nothing, which can, in turn, affect people's travel experience (Ettema & Verschuren, 2007; Singleton, 2018). Particularly significant is that autonomous vehicles could be customized with a much wider range of amenities than other transportation options such as trains and airplanes.

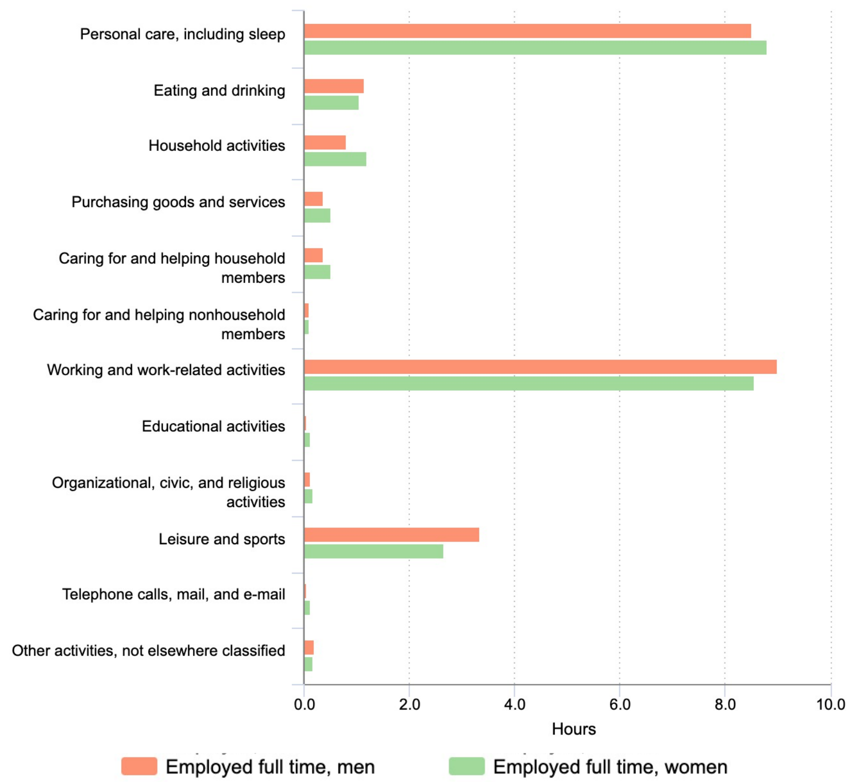
However, the development of autonomous vehicles also faces concerns over the distribution of benefits across social groups. Historically, inequalities driven by transportation improvements attribute to two factors: 1) unequal access to and 2) differentiated use of the technologies (Chesley, 2005; DiMaggio et al., 2004; Neutens et al., 2011; Schwanen & Kwan, 2008; Warschauer, 2004). Of particular interest to us, engagement in in-vehicle activities in autonomous vehicles could change the capacities for working, relaxing, and saving time for other activities beyond in-vehicle, but it may vary depending on the individual. Such differentiated engagement in in-vehicle activities is likely not only a matter of personal preference but also of personal constraints (Van Wee & Geurs, 2011). By implication, I argue that a thorough understanding of the social effects of autonomous vehicles requires examining how people would use this technology.

In this study, I investigate how might the development of autonomous vehicles reflect the desired activity participation of specific groups of people in their everyday life? I focus on commuters who spend a substantial amount of time on travel on a daily basis. Specifically, I aim to answer the following questions:

First, what would commuters do while riding in autonomous vehicles with various factors affecting activity participation?

Second, to what extent does the engagement in in-vehicle activities vary for different groups of commuters, particularly women?

Throughout the chapter, I analyze the data with a focus on women, who bear a disproportionate burden of household responsibility and face more time-related constraints in daily activity participation. On average, women who are employed full time spend 30 minutes more than their men counterparts on household activities every day (see **Figure 3.1**). Such a gap prevents women from participating in activities that can improve personal well-being (e.g., leisure and sports) and promote productivity (e.g., work), which has been a widely documented inequality between men and women in activity participation (Beebeejaun, 2017; Scheiner & Holz-Rau, 2017; Srinivasan & Bhat, 2005). For example, an employed mother with children tends to be excluded from opportunities due to time constraints and juggling demands between work, childcare, and household responsibilities. In contrast, income-related or transportation-related constraints are not the main barriers (Kwan, 1999a, 1999b).



Source: 2019 American Time Use Survey, U.S. Bureau of Labor Statistics

Figure 3.1 Average hours per day spent on selected activities on weekdays: full-time employed men vs. full-time employed women

In the ongoing development of autonomous vehicle systems, it is more likely that women may continue to be marginalized in the process, as the relevant fields, such as vehicle technologies, transportation planning, and automation engineering, are male-dominated (Bissell et al., 2018). By comparing how men and women would potentially engage in in-vehicle activities in autonomous vehicles, this study can provide insights on whether and to what extent the development of autonomous vehicles reflects women's preferences and needs, given the temporal dimension of inequalities.

This chapter proceeds as follows. Next, I explain the conceptual frameworks used to assess the equity implications of in-vehicle activities in autonomous vehicles in Section 2; describe data collection, measurement, and analytic approach in Section 3; present results in Section 4; discuss equity implications in Section 5; and conclude with study limitations and future research directions in Section 6.

3.2. Conceptual Frameworks

I draw on space-time perspective and midfare perspective that are not only two sides of the coin but also intertwined in understanding the distributional effects of autonomous vehicles on everyday activity participation.

3.2.1. Conceptual Frameworks: Space-Time Perspective

The first conceptual framework that I draw on is the time-space conceptualization of activity participation (Hägerstrand, 1970), which captures a person's activity participation in space and time within a given set of constraints (e.g., individual, land use and transportation-related constraints). Over the last three decades, travel-based multitasking has been increasingly enabled by the Internet and communications technologies (ICT) that are lighter, faster, more portable, and more connected. One important strand of time geography literature related to this study focuses on the implications of ICTs on space-time autonomy. This line of research has explored how ICTs relaxed the space-time constraints and expanded the conceptualization of accessibility to encompass both the physical and the digital worlds. For example, online shopping makes tradable goods and services accessible to national, even global customers (Glaeser & Kohlhase, 2004). Furthermore, ICTs enable people to multitask during travel time, such as calling or searching for information while traveling, making the travel time not so wasteful (Jain & Lyons, 2008).

Likewise, autonomous vehicles might boost the possibility of participating in activities in the constrained space and time by not only using ICTs while on the move (e.g., Kenyon & Lyons, 2007; Lyons & Urry, 2005) but also offering a customized space for various activities beyond the digital space. Such disruptive changes require a reconceptualization of activity participation in a hybrid (digital/physical/temporal) space, contrasting the conventional practices that assume a strict separation between travel trips and activity participation at a location. Indeed, such improvements in transportation technologies appear to represent a variety of Marx's phrase "the annihilation of space by time" that annihilate time through in-vehicle space, as noted by Smith (2010, p. 281, note 46). But as much as autonomous vehicles annihilate time (i.e., time costs), so too do they produce time (i.e., disposable time), transforming otherwise wasted travel time to time that can be used for work and leisure activities. Thus, autonomous vehicles become a moving space more than a means to overcome the friction of distance.

The production of in-vehicle space and time represents a social practice of travel, as the different possibilities for in-vehicle activities are situated in the context of people's personal, social, and economic circumstances. If space and time are social phenomenon, then they are perceived and experienced differently by different social groups (Lefebvre, 1991). For example, the time produced by in-vehicle space may not be able to lift the time constraint of the employed mother discussed in the previous section if the inequality of household responsibilities between wives and husbands persists. Instead, autonomous vehicles might help inequality in time use extends its grip on everyday life. Empirical evidence on the effects of ICTs suggests that the existing gender inequality associated with household responsibilities may be reinforced by the use and adoption of ICTs (Chesley, 2005; Schwanen & Kwan, 2008). Moreover, the complex circumstances of people create different needs and desires, which further complicate the potential benefits wrought by autonomous vehicles. For autonomous vehicles to enhance activity participation, they must provide desired activities or fill the gap of people's daily needs due to spatial-temporal constraints. If people were not interested in in-vehicle activities, then the feature of in-vehicle activities might not be able to enhance activity participation.

To conclude, space-time perspective points to the role of in-vehicle activities that might increase the possibility of multitasking and thus relax individuals' space-time constraints. In light of the potential differentiated in-vehicle activity participation, I introduce the framework I rely on for equity evaluations.

3.2.2. Conceptual Frameworks: Midfare Perspective

To evaluate the distributional effect of in-vehicle activity benefits, I rely on a midfare perspective, which represents the opportunity for improved welfare or increases in utility. According to G. A. Cohen (1990, p. 368):

> "Midfare is constituted of states of the person produced by goods, states in virtue of which utility levels take the values they do. It is 'posterior' to 'having goods' and 'prior' to 'having utility.'"

The midfare, therefore, focuses on what goods do to (or for) people rather than on the amount of goods that people possess, as Resourcists do, or, as Welfarists do, on the amount of utility that people derive from the goods. Using an example of a person's well-being, Cohen emphasized the distinct dimensions of midfare from that of welfare and goods. He clarified that, for example, we should examine the person's nutrition level, not just the person's food supply (Resourcists' view) or the derived utility from eating food (Welfarists' view). There are two motivations for developing the midfare perspective: (1) it is necessary to attend to the states that a person can attain, in addition to the actual state; and (2) it is necessary not to reduce the evaluation of the actual state either to a resource-oriented examination or to a utility-focused assessment.

The question "equality of what" is seriously disputed in political philosophy and has recently been considered in transportation research(Hananel & Berechman, 2016; Martens & Golub, 2012). That is, what is the appropriate entity to be equalized? Justice considerations in transportation decision-making was once dominated by maximizing welfare/utility (e.g., the value of travel time and travel satisfaction) and increasing access to infrastructure and destinations (e.g., cumulative accessibility). Although none of the perspectives have been perfectly justified as superior to the others, Martens and Golub (2012) argued that the midfare perspective is the most suitable one for transportation equity analysis. They define midfare in transportation as the extent to which a person is able to translate transportation resources into the possibility of participating in activities.

Table 3.1 Focus of Different Egalitarian or Equity Approaches and Application to Transportation

Author	The Entity to Be Equalized	Application	Limitations
Rawls	Goods	Number of destinations within a given distance	Does not fully capture the inequality due to being unlucky (Sen, 1980).
Dworkin	Resources	Number of destinations within a given distance, corrected for mobility (physical disability or access to mobility options)	Does not capture what a person can do with those resources (Sen, 1980).
Cohen	Midfare	Number of destinations within a given distance corresponds to the needs of person	Often not practical to know individuals' needs and wants
Sen	Capability	Activity participation	Narrower than midfare. Some goods can provide welfare without any exercise of capability (G. A. Cohen, 1990).
Bentham/Mill	Welfare/Utility	Satisfaction derived from driving a luxury car	Welfare can be derived from making somebody else's trip less appealing (offensive taste), and highest disutility needs the best services (expensive taste)(G. A. Cohen, 1989). Welfare can be influenced by expectation (Sen, 1980).

Note: This table extends Table 11.1 in Martens and Golub (2012) by adding limitations and applying to transportation.

Table 3.1 illustrates focuses of different perspectives and their limitations. Applied to travel-based multitasking evaluation, midfare can be defined as the extent to which a person is able to translate the available in-vehicle activities into welfare or utility, given personal characteristics and circumstance characteristics.[2] In this study, I choose midfare to evaluate the equity issues in in-vehicle activities for the following reasons. First, midfare measures the potential opportunities and activities, as travel behaviors rather than the actual travel behaviors are what matters in comparing individuals. Moreover, such potential travel behaviors are due to not only the available destinations via their transportation resources but also those destinations that match the person's needs and desires. Relatedly, the midfare perspective focuses on not only the actual state but also what one can potentially achieve. Empirically, individuals may or may not engage in in-vehicle activities during a single trip, which leads to what researchers call "unobservable" information (Angrist & Pischke, 2008). In this case, a stated preference approach may be more aligned with the midfare perspective than a revealed preference approach for capturing the extent to which people can translate in-vehicle activities into utility and welfare. In contrast, people's stated choices, in general, can reveal how well the in-vehicle activities match their needs and their willingness to engage in those activities while on the move, not limited to a few observed or reported trips.

Second, midfare recognizes that utilitarian methods may, to a no small extent, capture the differences between socio-spatial groups rather than the impact of transportation improvements (similar to the endogeneity issue in the econometric literature). On the other hand, utility or subjective well-being derived from travel can be very different even

[2] Practically, it is not feasible to comprehensively know personal tastes, desires, and needs in most cases. Therefore, we acknowledge that existing approaches may be more useful to evaluating equity in transportation and land-use research (e.g., tools examined in Levine et al. (2017) and Merlin et al. (2018) for project evaluations).

between people within the same population group, depending on the scales and reference points in their mind, as noted by Graham (2012).

Third, midfare makes room for how individual preferences play a role in equity analysis. Being better off in activity participation is not only a question of access to transportation infrastructure and destinations but also a matter of the fit between the resources and the needs and desires of individuals (Neutens et al., 2011). For example, the number of available meat markets at a given distance threshold provides meaningless information about accessibility of shopping for vegetarians. The fit issue, in turn, highlights the importance of examining the inequalities associated with the potential differentiated engagement of in-vehicle activities in autonomous vehicles, a gap I address in this study.

To summarize, the midfare perspective leads us to focus on the extent to which different groups or individuals can translate in-vehicle activities into welfare or utility, which could indicate those engaged activities either fit their personal preferences or complement their daily needs. Given that both time geography theory and midfare perspective emphasize the possibilities to enact certain activities and personal circumstances, the case of engagement of in-vehicle activities in autonomous vehicles is ideal for an equity analysis that can address both frameworks.

3.3. Data, Measures, and Methods

3.3.1. Data

The stated choices data about in-vehicle activities were collected in an online survey conducted in 2017. The target population of the survey is auto commuters living in small and medium-sized metropolitan areas (SMMAs) whose populations are between 200,000 and 450,000 (see **Figure 3.2**). I focus on SMMAs because the majority of the US populations live in these areas and cars are their primary travel modes. A market research company—LightSpeed Research LLC—implemented the survey via their panel of potential survey participants. Individuals aged 18 or above, currently commuting to work or school by private passenger vehicles, and living in SMMAs in the United States, were eligible to participate in the study.

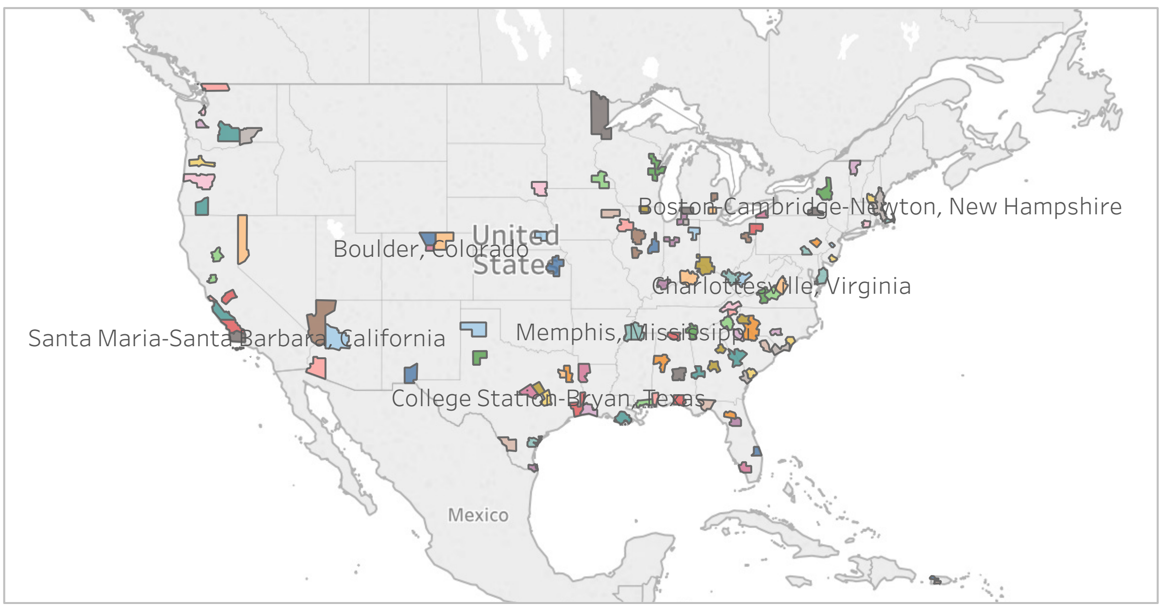


Figure 3.2 Metropolitan areas in the sampling framework

A total of 2,111 eligible participants completed the survey. After excluding 230 respondents whose answering time was too short (< 3 minutes), I had 1,881 valid responses as the final sample. I dropped respondents who identified themselves as other than male and female (0.25%) in the modeling procedures due to the small number of observations. Still, I did check their in-vehicle activity choices, which do not deviate from the rest of the sample. **Table 2** compares the sample demographics with those of small and medium metropolitan areas in the United States using the 2017 National Household Travel Survey data. The sample is generally representative of the population in small- and medium-sized metropolitan areas but appears to slightly under-represent young individuals (ages 18 to 24) and poor individuals (household income less than $24,999).

The key outcome variables were generated from the following questions (see **Figure 3.3**). The choice questions include a variety of in-vehicle activities that have been empirically examined while people use other travel modes (Berliner et al., 2015; Ettema & Verschuren, 2007; Singleton, 2018) or are expected activities by transportation experts and the public (Bansal et al., 2016; Fagnant & Kockelman, 2015; Schoettle & Sivak, 2014). I define two types of travel modes: 1) riding privately owned autonomous vehicles alone (AVs) and 2) hiring shared autonomous vehicles (SAVs). Since SAVs can be operated in various ways, I broadly define the term by emphasizing the nature of sharing with others and may or may not pick up passengers during the trip. The difference between the two types of vehicles is that people can do household or personal activities in privately owned AVs but not in SAVs.

Table 3.2 Summary Statistics about Survey Respondents

Variable	Sample Mean	Sample S.D.	2017 NHTS (Auto Commuters) Mean	2017 NHTS (Auto Commuters) S.D.
Average Household Size	2.383	1.24	3.060	0.25
	Percentage		Percentage	
Male	41.9%		52.3%	
With a Bachelor's Degree and Above	47.0%		39.0%	
Age 18-24	6.5%		13.4%	
Age 25-34	11.0%		22.7%	
Age 35-44	14.9%		20.3%	
Age 45-54	18.4%		20.0%	
Age 55-64	27.5%		18.1%	
Age 65 and more	21.7%		5.4%	
Household Income Less than $24,999	12.7%		0.9%	
Household Income Between $25,000 and $49,999	26.1%		13.2%	
Household Income Between $50,000 and $74,999	23.0%		23.9%	
Household Income Between $75,000 and $99,999	17.1%		20.7%	
Household Income Between $100,000 and $199,999	17.7%		14.2%	
Household Income $200,000 or more	3.4%		23.2%	
Household Income No Answer	4.6%		3.9%	
Short Trip < 20 min	44.8%		48.0%	
20=<Medium Trip < 40 min	35.5%		38.9%	
40=<Medium Trip < 60 min	9.3%		8.6%	
60=<Long Trip < 90 min	5.7%		2.7%	
Extreme Long Trip >= 90 min	4.7%		1.8%	

Note: Population descriptive statistics are based on weighted sample characteristics of auto commuters in Metropolitan Statistical Areas with populations greater than 25,000 and less than 499,999 in the 2017 National Household Travel Survey (NHTS).

In a **Driverless Vehicle**, all driving tasks are completely autonomous and you only need to tell the vehicle where to go. Theoretically, driverless vehicles do not crash. You can do things like work, sleep, read, watch TV, maybe even exercise while the vehicle takes you to your destination. You might either ride a **Driverless Vehicle** alone or hire a **Shared Driverless Vehicle** for carpooling (like Uber) that may pick up other passengers during the trip.

*

Suppose you are traveling in a driverless vehicle you own, how likely are you to do following activities?

	Highly Unlikely	Unlikely	Neutral	Likely	Highly Likely
Communicating: by phone, email, etc.	○	○	○	○	○
Entertainment/recreation: resting, reading, hobbies, TV, exercise, etc.	○	○	○	○	○
Formal: paid work, education, religious activity, etc.	○	○	○	○	○
Household/personal: eating/drinking, prepare meal, personal care, etc.	○	○	○	○	○
Information search: online shopping, journey information, employment information, etc.	○	○	○	○	○
Other	○	○	○	○	○

*

Suppose you are traveling in a shared driverless vehicle (carpooling), how likely are you to do following activities?

	Highly Unlikely	Unlikely	Neutral	Likely	Highly Likely
Communicating: by phone, email, etc.	○	○	○	○	○
Entertainment/recreation: resting, reading, etc.	○	○	○	○	○
Formal: paid work, education, religious activity, etc.	○	○	○	○	○
Information search: online shopping, journey information, employment information, etc.	○	○	○	○	○
Other	○	○	○	○	○

Figure 3.3 In-vehicle activity choice questions

3.3.2. Measuring Midfare

The midfare perspective provides the basis for developing the measurement of midfare gains resulting from the potential engagement of in-vehicle activities in autonomous vehicles. I transform each individual's likelihood level of each activity category into numbers, and the resulting numbers are added up to obtain the total score, which is:

$$S_i = \sum_1^j P_{ij} \tag{1}$$

where S_i is the midfare score that measures the potential engagement in in-vehicle activities of individual i, and P_{ij} is the score of potential engagement of individual i in activity j. Based on the stated likelihood of in-vehicle activity engagement, P is assigned with a value of one if the choice of likelihood is "Likely," and a value of two if it's "Highly Likely." The other choices are assigned a value of zero; they are considered as not contributing to the improvement of activity participation.

Conceptually, S_i captures the benefits of a person riding in an autonomous vehicle on two dimensions: (1) it measures the extent of multitasking afforded by the vehicle that relaxes the separation between the trip and activity site (analog to utility levels or subjective wellbeing levels); and (2) it measures the desired activities and needs of a person during travel that often vary by individuals and between socio-demographic groups. Although the numbering scale is the same for all individuals, such a midfare score allows us to compare the differences among individuals and groups in a continuous spectrum. This leads to the practical advantage of this score that I can measure the overall benefit of in-vehicle activities rather than summing up probabilities predicted by a set of models. Furthermore, S_i is more consistent with the concept of midfare that focuses on the extent to which a person translates in-vehicle activities into welfare (e.g., recreational activities that improve subjective well-being) or utility (e.g., productive activities), compared to the number of available in-vehicle activities and the increased welfare/utility due to activity participation. Despite the theoretical advantage of the midfare perspective, midfare gains of different activities may not be perfectly additive as in Equation (1), a limitation I should address in the future.

3.3.3. Analytic Approach

My analytical work includes three steps. First, I summarize discrete responses of in-vehicle activity engagement—namely, "Highly Unlikely," "Unlikely," "Neutral," "Likely," and "Highly Likely," — by their frequencies and counts. Second, I estimate in-vehicle activity choice models to understand how people's socioeconomic characteristics, attitudes toward driving and transportation technologies, place of residence, and travel contexts affect their potential in-vehicle activities. Since the outcome variable is categorical and has a meaningful sequential order indicating the likelihood of activity participation, I follow previous studies (Long et al., 2006) and estimate the activity choice models through the ordered logit regressions. Third, I calculate midfare gains based on the measurement developed in Section 3.2. and run linear regressions on the midfare score S_i against the personal, social, and spatial characteristics of commuters. I use the results from the models to assess the disparities of potential engagement in in-vehicle activities between groups. The above analyses were conducted using the statistical software package Stata version 14 (Stata, 2015).

3.4. Results

I present the estimated results in three parts. First, I describe a general overview concerning the type and potential engagement level of in-vehicle activities. Next, I present the estimated results from ordered logit regressions exploring the influencing factors of engaging in in-vehicle activities. Finally, I calculate midfare gains and compare the disparities across different groups.

In **Table 3.3**, I present the descriptive analysis of engagement in in-vehicle activities for commuters in AVs and SAVs. The results highlight that activity participation patterns are similar between AVs and SAVs. Overall, I find in-vehicle activity engagement is not as high as we would expect; around 40% to 50% of people expressed they were likely or highly likely to engage in activities, except for work. People are least likely to engage in working activities (approximately 25%), including productive work, formal activities, and study. The most preferred activity is communication, including phone, email, and etc.

I then checked whether people who are likely to engage in in-vehicle activities are systematically different from those who are not using an imbalance check measure (L_1) developed by Iacus et al. (2012). This measure summarizes the difference between the multivariate empirical distributions of the covariates for people who engage in in-vehicle activities and people who do not. This measure provides information on how much the two distributions of the two groups overlap, not just, as most other measures do, simply compare differences in means. Using this method, I find a telling pattern, which is that between people who are likely to engage in at least one in-vehicle activity and those who do not, they are systematically different, as the multivariate imbalance measure shows more than 99% of the distributions are not overlapped between the two groups of people. This means that concerning the observables of the two groups, they are from two different populations in terms of socioeconomic characteristics, attitudes, residential contexts, and commuting patterns. Specifically, people who will not engage in any in-vehicle activity fall into one or more following categories such as more than 55 years old, have less than $49,999 household income, do not enjoy driving at all, commute less than 20 minutes, and live in city centers or rural areas. These results indicate that people may engage in in-vehicle activities differently depending on their characteristics and circumstances. I then turn to examine how those factors influence people's potential engagement of in-vehicle activities using ordered logit regressions.

Table 3.3 Percentages of Commuters Engaging in Each In-Vehicle Activity

	Communication	**Entertainment**	**Work**	**Household**	**Info Search**	**Others**
Likelihood	Percentage	Percentage	Percentage	Percentage	Percentage	Percentage
AV :						
Highly Unlikely	13.4%	20.6%	26.0%	20.3%	18.9%	22.3%
Unlikely	11.6%	18.7%	24.3%	20.0%	17.7%	11.5%
Neutral	17.9%	18.4%	23.8%	20.2%	20.0%	45.7%
Likely	37.2%	29.3%	18.9%	30.5%	31.1%	13.9%
Highly Likely	19.9%	13.1%	7.0%	9.1%	12.3%	6.6%
SAV :						
Highly Unlikely	13.1%	15.8%	25.7%	NA	17.9%	21.4%
Unlikely	12.8%	14.9%	24.2%	NA	17.8%	11.6%
Neutral	19.6%	18.3%	24.5%	NA	21.7%	45.6%
Likely	36.0%	36.7%	18.5%	NA	31.4%	14.4%
Highly Likely	18.6%	14.5%	7.0%	NA	11.2%	7.1%
Observations	1791	1791	1791	1791	1791	1791

Figures 3.4 and **3.5** present the results of the ordered logit regressions explaining the determinants of in-vehicle activity participation in AVs and SAVs. The plots are generated using the Stata package "coefplot" written by Jann (2014). In the two figures, blue dots represent the estimated coefficients, and blue lines across the dots represent the 95% confidence intervals; the x-axis includes the corresponding values and signs for the coefficients and confidence intervals. There are 11 regressions in total. These regressions' R-square values are around 0.4.

I found that generally, in both AVs and SAVs, people are more likely to engage in in-vehicle activities if they are younger, more affluent, well educated, have children in their household, and have longer commutes. I found that the sole factor of being male does not increase the likelihood of engaging in-vehicle activities. To illustrate the potential engagement of in-vehicle activities for different individuals, I consider a few examples.

1. A person with a Bachelor's degree is more likely to engage in communication activities in the AV than in the SAV.

2. A person who lives in the suburb and commutes more than 60 minutes to work is more likely to engage in work, information search, and other activities, while a similar person will be likely to only engage in household activities if the commuting time is between 20 to 40 minutes.

Paradoxically, people who more enjoy driving also are more likely to want to conduct in-vehicle activities and vice versa. This may be because the increasing features of automobile technology are powerful means of keeping people attached to their cars (Bijsterveld, 2010; Wells & Xenias, 2015). Therefore, it is reasonable to expect people who enjoy driving will also enjoy improved in-vehicle space. With respect to differences between AV and SAV, AVs are more likely to meet the entertainment demands of men and provide opportunities for household activities during peak hours than SAVs, *ceteris paribus*.

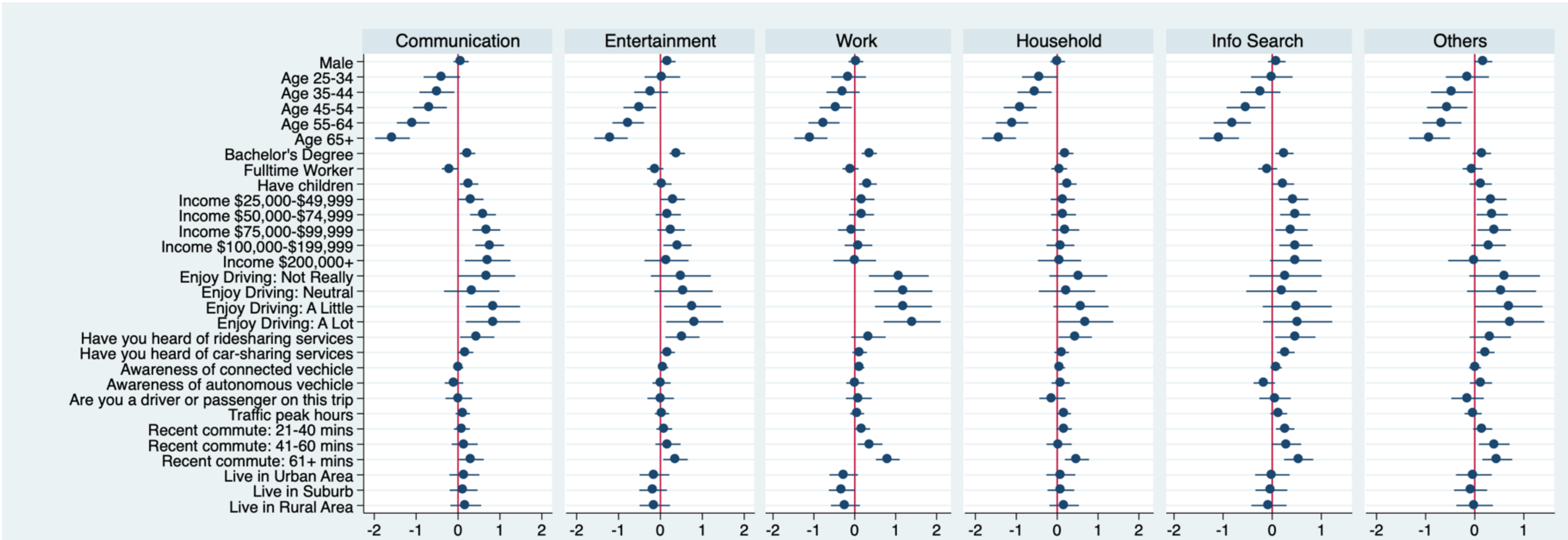


Figure 3.4 Coefficients plot for estimated ordered logit regressions of in-vehicle activities: privately owned autonomous vehicles.

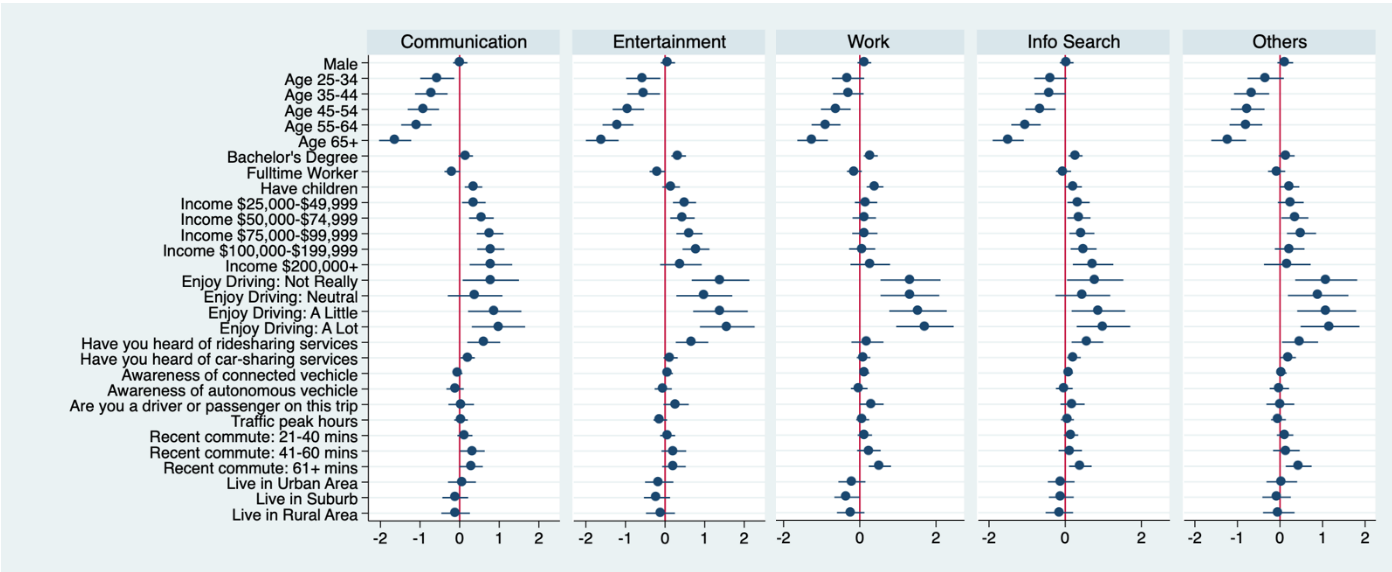
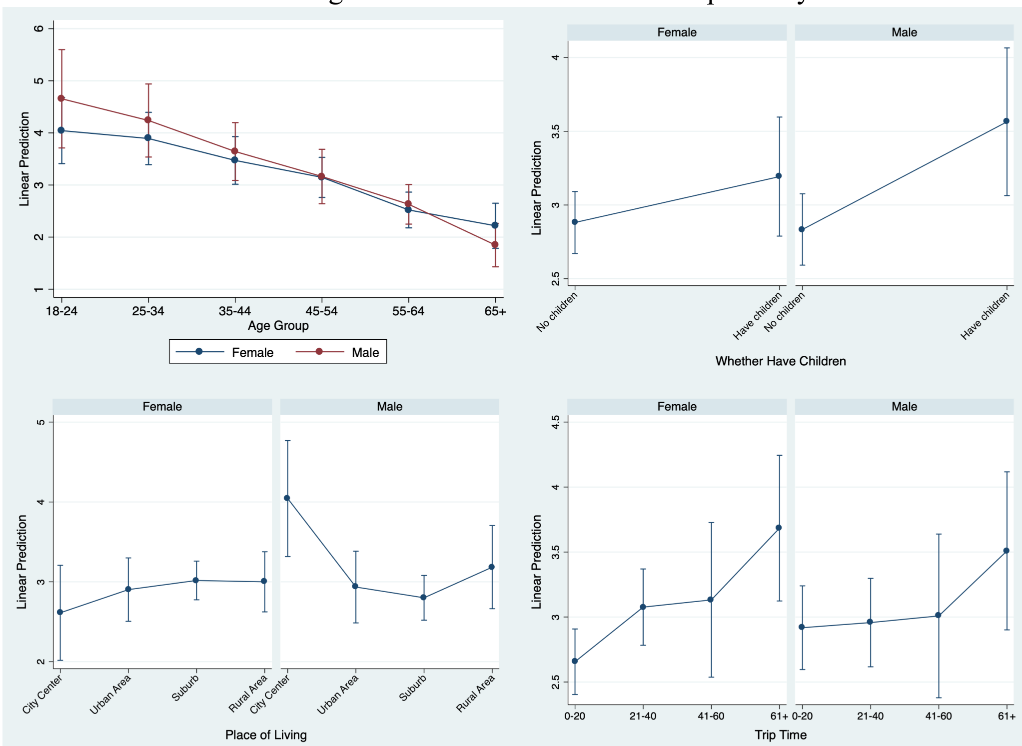


Figure 3.5 Coefficients plot for estimated ordered logit regressions of in-vehicle activities: shared autonomous vehicle

To uncover possible complex patterns underlying the regression coefficients, I predicted midfare gains (S_i) using a series of linear regressions for more granular population groups. Midfare gains were calculated based on equation (1). **Figure 3.6** illustrates the midfare gains (S_i) by participants of various groups with a focus on gender because the U.S. Bureau of Labor Statistics (2019) reveals that women face more time constraints in their daily lives. One unit increase in the predicted midfare gains indicates that people have a considerable increase in their likelihood (e.g., highly unlikely/unlikely /neutral to likely, or likely to highly likely) to engage in in-vehicle activities that can result in utility or welfare gains.

Panel A: Predicted midfare gains for in-vehicle activities in privately owned autonomous vehicles



Panel B: Predicted midfare gains for in-vehicle activities in shared autonomous vehicles

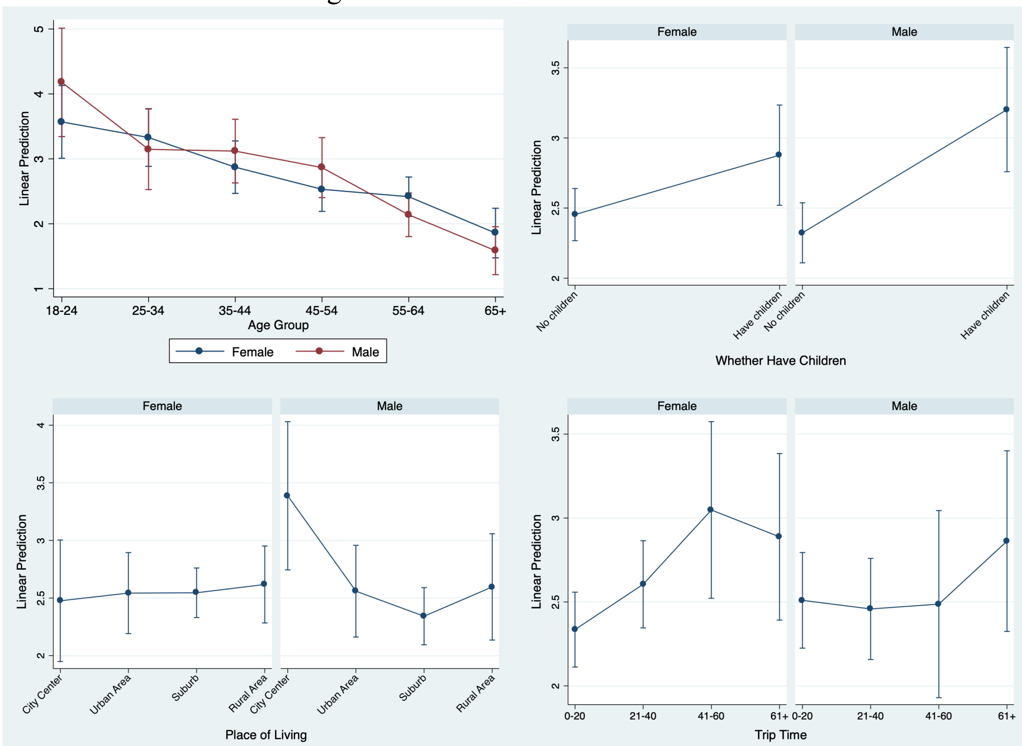


Figure 3.6 Predicted midfare gains in AVs (Panel A) and SAVs (Panel B)

The midfare gains in AVs by engaging in in-vehicle activities decline as age increases, and the trend does not differ by gender, which is consistent with what I found from the ordered logit regressions. In those households with children, male commuters appear to have higher midfare gains, but the difference is not statistically significant. Both male and female commuters have larger midfare gains when they have longer commuting trips. In terms of spatial patterns, midfare gains tend to increase as residential locations move from urban areas to suburban areas and to rural areas, but only commuters in suburban areas present more statistically significant gains. The midfare gains in SAVs have similar trends with in AVs, but the maximum value is smaller partly because household activities were not included as an option in the choice question for SAV. One difference is that female commuters have the largest midfare gains in SAVs if their trips are between 41 to 60 minutes, in contrast to AVs trips lasting more than 60 minutes.

Overall, I do not find substantial disparities in midfare gains between male and female, as I observed from the ordered logit regressions, but the marginal predictions reveal a noteworthy pattern that the midfare gains are not equally distributed within each gender group, depending on income levels, commuting times, and residential locations.

3.5. Discussion and Conclusion

In this study, I investigated how autonomous vehicles might transform what people do while on the move and how the changes might reflect the preferences and needs of specific groups of people. I have several conclusions from this study. First, I find that younger, more educated, and more affluent commuters are more likely to use and benefit from the in-vehicle activities. This finding supports the possibility that autonomous vehicles could improve people's activity participation by providing in-vehicle activity opportunities. Among those people who engage in in-vehicle activities, most of them do not conduct productive activities that can generate monetary value, implying the changes in willingness to pay for travel time savings in autonomous vehicles may not be the more productive use of travel time.

My second conclusion is that although autonomous vehicles can improve activity participation that was previously constrained by space and time, the effects vary between and within-population segments such as gender, age, education level, income level, commuting trip, and residential location. This finding supports the previous argument that not only unequal access to new technologies but also the differentiated use of these technologies are linked to social inequality (DiMaggio et al., 2004). One noteworthy pattern that requires some discussion is that older respondents show less interest in engaging in in-vehicle activities. There might be two explanations. One is that older adults are more interested in independent mobility provided by autonomous vehicles rather than the capability of in-vehicle activities.[3] The other explanation is that the elderly might find it difficult to envision participating in in-vehicle activity if they feel the development of autonomous vehicles is out of their control. I believe this explanation has important implications. In many cases, older adults may be the first adopters to new technologies (Peine et al., 2017); involving older populations in the development of autonomous vehicles could facilitate the coevolution of diffusion and innovation. Under the midfare perspective and space-time framework, I also argue that the differentiated use of in-vehicle activities can be personal preferences as well as socially produced constraints, which may be the reason why the disparities exist both between and within population groups.

I conducted the analysis with the awareness that women generally face more time constraints than men, mostly attributing to committing more time to household responsibilities even if they are full-time workers (U.S. Bureau of Labor Statistics, 2019). Overall, there is no substantial difference in the midfare gains between men and women, but variations exist within gender groups. According to the Difference Principle (Rawls,

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[3] This explanation is based on conversations with older adults during a few conference presentations. The authors did not find any evidence from the literature.

1971), such equal gains fail to address the inequity in activity participation between men and women, as the group that needs the most (i.e., women) fails to receive the most of the gains and thus the existing gap remains. The more challenging question is, then, whether engaging in in-vehicle activities would reinforce or exaggerate the current existing inequality in household responsibility, both of which have been observed in the effects of digital development on inequality (Wajcman, 2007). It is more likely that the existing gap will be reconfigured than alleviated if the development and design of the vehicles remain gender-neutral.

This study makes two methodological contributions. I showcase the usefulness of combining the midfare perspective and space-time framework to measure the social effects of new transportation technologies. This unified framework allows us to capture dimensions of activity participation beyond accessibility to destinations, namely the fit of activities and capacity/willingness to take advantage of the transportation improvements. In addition, I demonstrate how the complexity of who benefits can be further explored using marginal predictions by different combinations of factors. These predictions allow us to examine the intertwined impacts of different socioeconomic factors that may be masked by overall effects (i.e., the Simpson's paradox in statistical terms and the intersectionality in sociological terms). I recommend both of these methods as ways to acquire a more thorough understanding of transportation inequality underlying the development of new mobility options.

Taken together, my findings demonstrate that autonomous vehicles have the potential to improve activity participation for the population as a whole, but such benefits are neither equally distributed nor help to reduce the existing inequality with respect to activity participation and social inclusion. I suggest that policymakers explore the possibility of involving disadvantaged populations in terms of income level, age, and health status, and develop understandings of the quantity and quality of activity participation for those groups. This would not only inform the development of the future driverless system, but it could also help disadvantaged groups gain the technical knowledge necessary to access and use the new mobility technologies.

3.6. Limitations and Future Research

This study has limitations that should be considered when interpreting my findings for future research. First, I assume ubiquitous access to autonomous vehicles in a variety of ways, such as leasing, owning, and hiring. That is, the potential unequal access to autonomous vehicles is not considered in this study. Second, race and ethnicity are likely to play a role in the access and the use of new technology; the data do not account for this. Also, my analysis is based on a heteronormative understanding of households. It is not clear how autonomous vehicles might affect the power relationships in households with two male partners and two female partners. Future research should examine how the access and use of autonomous vehicles may vary in a more disperse context of social, racial, and economic groups. Third, my sample consists only of travelers in small and medium-sized metropolitan areas who go to work or school, and the activities take place during the commute. The analysis does show direct evidence on how autonomous vehicles affect overall activity participation. Future research should link the overall activities participation with the potential engagement in in-vehicle activities.

My efforts in developing the midfare measure were an initial attempt to define and operationalize an equity measure of transportation improvements. At this point, I acknowledge two limitations of this formula. First, I assume that the intervals between "Highly Likely," "Likely," and the other choices are equal, which may deflate or inflate the actual magnitudes of disparities but will not change the trend of the distributions across groups. There is virtually no theoretical or empirical guidance on how to measure midfare (Martens & Golub, 2012). I am not attempting to suggest that the measure used in this study can be applied to other studies. Second, although stated preference approaches may better assess people's needs and desires, people are guessing what they can do in the autonomous vehicles in this study due to no real experience in the vehicle. Future studies might build upon what I have discussed on the convergence of the midfare perspective and space-time framework to develop further measures that reflect the meaning of accessibility to opportunities and activities as midfare.

4. HOW WOULD THE SPATIAL STRUCTURE OF CITIES CHANGE IF AUTONOMOUS VEHICLES WERE IN TOWN?

4.1. Introduction

The emergence of "the Age of Artificial Intelligence" is accompanied by expectations that automated/connected transportation technologies will once again alter urban space, where people ride hands-free along interconnected roadways into futuristic cities. Fully automated vehicles (AVs) may be years, if not decades, away, but they are among the most visible examples of the transition toward smart and connected urban systems. But the development of AVs led to hype, then skepticism, which spread across transportation researchers and urban planners.

There is substantial evidence that transportation and communication technologies change the spatial structure of cities by reducing the costs of the movement of goods, people, and information (Baum-Snow, 2007; Baum-Snow et al., 2017; Ferrell, 2005; Ioannides et al., 2008; Mokhtarian et al., 2004). The disruption of autonomous vehicles has significant implications since many cities around the world have declining public transportation systems, follow a car-oriented development pattern, and suffer from traffic congestion. A distinctive theme is that —aside from reducing travel costs that induce suburbanization—AVs may also reduce congestion costs that attract people moving into cities. These two opposite effects on the spatial development of cities make the effects of AVs on cities ambiguous.

What are the implications of AVs for the urban spatial structure? What factors affected the spatial expansions in U.S. cities? And how, and what, policies may effectively ensure more sustainable urban development in an era of rapidly advancing transportation technologies? Recent work on autonomous vehicles and urban spatial structure illustrates the uncertainty of potential futures. For instance, Zakharenko (2016) developed a model with endogenous locations of residence and work and found that increased AV availability increases worker welfare, commuting distance, and the size of cities. The effect of AVs on cities with mass transit will depend on how AVs compete with or complement mass transit. W. Larson and Zhao (2019) also predicted that the introduction of AVs coupled with ridesharing services increases welfare but may either lead to sprawl or increase density in different model settings. By considering cities across the United States, Rappaport (2016) predicted that autonomous vehicles may put upward pressure on the large cities and downward pressure on the small cities, as they increase the responsiveness of population to total factor productivity (TFP) through reducing driving burden and improving commuting efficiency. Rappaport concluded that traffic congestion proves to be the most critical force reducing the responsiveness of population to TFP. While their findings indicate autonomous vehicles will change the structure of cities, the changes vary by different sizes of cities and different parts in a city, largely depending on how the technology will be implemented.

There are uncertainties indeed, and it also reminds us that the development of AVs is not yet settled (Stilgoe, 2018). As spatial economics theories predict, the spatial structure of the economy is determined by the balance between the advantage of population and economic activity density (agglomeration force) and the congestion or competition for resources (dispersion force) (Barkley et al., 1996; Henderson, 1974; Redding & Rossi-

Hansberg, 2017). Such tension between the two forces depends on a range of factors, including production methods, institutional contexts, urban amenities, and transportation costs. Autonomous vehicles are likely to alter the parameters of these factors in multiple ways. Autonomous vehicles can make congestion more tolerable in central areas (Steck et al., 2018), reduce the level of congestion (van den Berg & Verhoef, 2016), and enable allocating more urban space for uses other than roads and parking (W. Zhang et al., 2015), thus increasing the agglomeration. On the other hand, autonomous vehicles can increase vehicle miles traveled (VMT) (W. Zhang et al., 2018), exaggerate congestion (van den Berg & Verhoef, 2016), and compete with public transportation systems (Krueger et al., 2016), thus increasing the dispersion force.

To move the debate forward, this study anticipates the future by looking back to the past. I estimate the effect of reductions in congestion costs and distance costs. My results suggest that autonomous vehicles may have induced greater urban expansion if they had been introduced to cities.

I begin with a theoretical argument of how AVs will affect the balance between agglomeration and dispersion forces, with an emphasis on demystifying the effect of congestion on cities. Section 3 presents empirical strategies informed by the theories. Section 4 presents descriptive facts. Section 5 examines the spatial dynamics of metropolitan areas in the United States over the past decades by estimating the effects of shocks in the agglomeration and dispersion forces. As the future is full of uncertainty, Section 5 extends the analysis to examine the potential effect of autonomous vehicles if they had been previously introduced to cities. Section 6 concludes and highlights a number of policy implications.

4.2. Theoretical Development

This section lays the groundwork for the empirical analysis and policy simulations and shows the theories and evidence of which changes in urban spatial structure should be modeled in a dynamic and interdependent setting. The theoretical framework, whose structure is presented in **Figure 1**, is related to a large body of theoretical literature on urban economics that stresses the tradeoffs between transportation costs and land rents, and to a broader literature on economic geography that explains that mechanisms for agglomerations. The synthesis of the mechanisms provides a fundamental theoretical explanation of the dynamic spatial structures of cities and highlights the interdependent relationship between transportation costs, public policies, agglomeration, and urban spatial structure.

4.2.1. Agglomeration and Dispersion Forces

In the process of urbanization, human settlement has been highly unevenly distributed over space in the form of cities and urban centers within cities. The spatial structure of city and cities themselves are determined by the relative strengths of the agglomeration forces (i.e., production and residential externalities) and dispersion forces (i.e., an inelastic supply of land and commuting costs) that underlie the uneven distribution of economic activities (Fujita & Ogawa, 1982; Lucas & Rossi–Hansberg, 2002). The two sets of forces are both with externalities—improved productivity due to spillover in production and better urban amenities for households producing the agglomerative tendencies, and congestion or nuisance externalities due to higher density, in turn, limiting the size and density of the agglomerations. Since the land supply is inelastic, excessive congestion costs within the existing urban development may cause decentralization of firms and households to the urban periphery to pursue reductions in congestion and land costs, while facing lower productivity and fewer urban amenities (see Figure 4). An example of this is the two processes of population movements: the urbanization between 1870 and 1920 in the United States—that is, a striking increase of urban population lured by improved productivity in cities—and the ongoing decentralization since the 1950s—that is, people moving out from central districts to outlying areas to escape problems resulting from overcrowding.

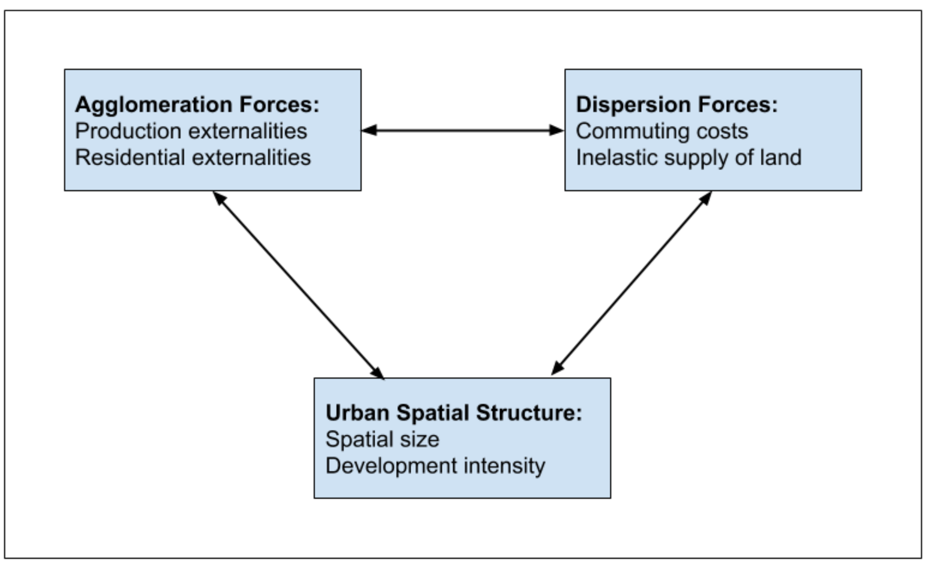

Figure 4.1 The theoretical model of the interdependent relationship between agglomeration forces, dispersion forces, and internal structure of the city

Agglomeration and dispersion forces are both related to the surrounding density of workers and residents. Agglomeration forces take the form of production spillover and amenities, in addition to other fundamentals such as access to natural features. For example, empirical evidence by Schiff (2014) found that population size and population density have a substantial effect on consumption amenities, which is the amount of restaurant and cuisine variety in this case, in a city.[4] In turn, driving by the agglomeration forces, the city's population will grow until eventually exhausting scale economies from the concentrated population and employment.[5] At the same time, dispersion forces (e.g., congestion costs) are also a function of surrounding density, technology level, and policy. The two forces and the interplay between them illustrate the basic insight that the urban spatial structure is determined by a trade-off between agglomeration effects and congestion costs.

Several well-known debates on ideal urban form perfectly illustrate that excessive density can result in undesirable outcomes, depending on technology level and policy effectiveness.[6] While the benefits of density are well documented Ewing (1997) and Ewing and Cervero (2017), a recent study compiles evidence on the costs of density related to congestion, health, and well-being and points out the importance of

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4 This research is related to theoretical work by Brueckner et al. (1999), Glaeser et al. (2001), and Ng (2008). The related empirical research has examined the demand for consumption amenity (Couture, 2013; Rappaport, 2008), historical amenity(Koster et al., 2014), natural amenity(Lee & Lin, 2017), and mobility(Couture et al., 2018), and its impact on urban spatial structure.
5 See Anas (1988) and Anas (1992) for the explanation of the distribution of activity evolves over time.
6 See the debates between Gordon and Richardson (1997) and Ewing (1997), and between Ewing and Cervero (2017) and Stevens (2017). Recently, Ewing et al. (2018)found empirical evidence that neighther support the idea of sprawl nor compact development as the pancena to traffic congestion. Also, Hall (1997) and Anas et al. (1998) provided a good review of related theories, empirical evidence, and discussions.

accompanying policy and technology intervention to minimize the costs associated with higher density (G. Ahlfeldt et al., 2018). As Hall (1997) suggested, the idea of compactness has “a small element of truth and a much larger element of myth,” therefore, understanding the relative strength of the agglomeration and dispersion forces underlying these debates is central to a range of planning questions. (Kasraian et al., 2016)

Recent developments in quantitative spatial economics by Redding and Rossi-Hansberg (2017) perhaps mark a huge leap in analyzing the two forces and undertaking counterfactual exercises. Along with this line of research, G. M. Ahlfeldt et al. (2015) explicitly estimated the agglomeration and dispersion forces and their effects on city structure changes by taking advantage of the division and reunification of Berlin as a natural experiment. Later, Brinkman (2016) developed a similar model but added congestion as a separate component to the transportation cost. The comparative statics from Brinkman’s study found that the positive effect on congestion costs of congestion pricing is offset by the loss of productivity due to the dispersion of employment. Before that, only a few studies concerned the simultaneity of the two forces. Among them, Anas and Kim (1996) first developed an equilibrium model with tradeoffs between agglomeration and accessibility. Combining discrete choice models and agent-based simulations, Waddell (2006) built the bidirectional influence of individual choices and neighborhood dynamics into the modeling process.

4.2.2. Congestion and Urban Spatial Structure

Transportation cost is a key delivery mechanism of infrastructure and mobility technology will affect the structure of cities. It consists of two components: a distance cost and a congestion cost, taking the form of both money and time. Holding the spatial distribution of employment fixed, a reduction in distance cost reduces the relative value of living closer to the employment concentrations (i.e., induce decentralization), while a reduction in congestion costs increases the relative value of locating nearer the employment centers (i.e., induce densification).

The literature on the effect of congestion presents mixed findings (e.g., Boarnet, 1997; Marshall & Dumbaugh, 2018; Sweet, 2011). For instance, Jin and Rafferty (2017) found that congestion is negatively associated with income growth and economic growth, but Sweet (2014) suggested that job growth is expected to be negatively affected only if at very high levels of congestion. This is not a surprise. Instead, the mixed findings demonstrate the nature of the congestion. It results from economic growth and inefficient infrastructure, and it tends to maintain equilibrium (Duranton & Turner, 2011).

The process of reaching the equilibrium shapes the structure of cities (Barkley et al., 1996; Proost & Thisse, 2019; Redding & Rossi-Hansberg, 2017). For example, Baum-Snow et al. (2017) and Baum-Snow (2007) found that transportation infrastructure causes decreases in the central city population and employment in both the United States and China, while Duranton and Turner (2012) found a 10% increase in interstate highways causes about a 1.5% increase in employment in U.S. metropolitan areas between 1984 and 2004. The combined findings from the two sets of studies illustrate the agglomeration dynamics are linked together to give rise to decentralization and growth at different spatial levels, which may, in turn, induce secondary agglomerations (Garcia-López et al., 2017; Helsley & Sullivan, 1991). Therefore, instead of focusing on one side of the transportation and urban structure feedback cycle, researchers pointed out the need for bidirectional studies (Kasraian et al., 2016).

While the spatial dynamics are well-informed by the theories, there remain some disconnections with the empirical studies. One factor contributing to the disconnections is that there are no good measures for the decomposed transportation costs: distance costs and congestion costs. In a study on urban expansion, Paulsen (2012) pointed out that congestion data provided by Texas A&M Transportation Institute (TTI) are admittedly poor proxies for distance costs, and per-mile distance costs should not differ across metropolitan areas, except for differences in gasoline prices. Using the congestion data from TTI, Spivey (2008) found a negative relationship between congestion and urban spatial sizes in a cross-sectional setting. However, in a longitudinal setting, congestion is expected to increase the urban spatial sizes, if transportation costs can be properly decomposed.

To summarize, theories and empirical evidence discussed in the preceding paragraphs have the following implications. First, urban spatial expansion is the cause and consequence of the interactions between agglomeration and dispersion forces. Second, empirically, population and employment density can represent agglomeration forces; and dispersion forces can be represented by congestion costs and an inelastic supply of land. Third, autonomous vehicles can affect the balance between these agglomeration and dispersion forces through its effects on distance costs and congestion costs.

4.3. Empirical Strategies

This section introduces my empirical strategies based on the theoretical framework. I begin with a spatial dynamic analysis examining the interdependent mechanisms between agglomeration forces, congestion, and urban land area underlying the urban spatial expansion process. Then, I decompose the contribution of each factor to spatial changes over time. Finally, I perform a counterfactual analysis to assess the effects of autonomous vehicles on urban expansion, answering the question of what would have happened if autonomous vehicles had previously been introduced to cities.

4.3.1. Panel Vector Autoregressive Model

The theoretical framework highlights the bidirectional dynamic nature of the distribution of economic activities. In particular, the reviewed theories and evidence imply that autonomous vehicles can affect agglomeration and dispersion forces by reducing distance cost and congestion cost and therefore influence urban spatial expansion. My approach to deal with the simultaneity of centripetal and centrifugal effects is borrowed from macro-econometric literature that faces similar econometric problems. In this literature, the panel version of vector autoregressive (PVAR) models has been widely used in monetary policy and investment behavior (Assenmacher & Gerlach, 2008), supply of development aid (Gravier-Rymaszewska, 2012), and security economics (Drakos & Konstantinou, 2014). Not until recently, the VAR models have been introduced to transportation analyses, especially with respect to transportation investment and economic and behavioral outcomes (G. M. Ahlfeldt et al., 2014; Melo et al., 2012; Pereira & Andraz, 2012). A PVAR model consists of a system of equations that are estimated simultaneously. Each variable in this system is explained by its own lags and lagged values of the other variables. The general form is given by:

$$Y_{it} = A_0 a_{i,t} + A_1 Y_{i,t-1} + \cdots + A_p Y_{i,t-p} + BX_{i,t} + u_{i,t} + e_{i,t} \tag{1}$$

where Y_{it} is a (1×k) vector of urban spatial extent for city i in year t; $X_{i,t}$ is a (1×l) vector of exogenous covariates; $u_{i,t}$ and $e_{i,t}$ are (l×k) vectors of dependent variable-specific fixed-effects and idiosyncratic errors, respectively. The (k×k) matrices, $A_1 \ \ldots A_p$, and the (l×k) matrix B are parameters to be estimated, p denotes the number of lags and $a_{i,t}$ is a vector of deterministic terms (linear trend, dummy or a constant) with the associated parameter matrix A_0.

Specifically, I estimated a system of equations to empirically approximate the multi-lateral relationship between congestion(C), population (P), employment (E), and urban land supply (U). All variables are log transformed and identified over time using constant geographies (2010 MSA boundaries). As the geographical boundaries are constant, population and employment changes essentially capture their changes in density.

$$C_{i,t} = \theta_1 + a_{11}C_{i,t-1} + a_{12}P_{i,t-1} + a_{13}E_{i,t-1} + a_{14}U_{i,t-1} + u_{1i,t} + e_{1i,t} \tag{2}$$

$$P_{i,t} = \theta_2 + a_{21}C_{i,t-1} + a_{22}P_{i,t-1} + a_{23}E_{i,t-1} + a_{24}U_{i,t-1} + u_{2i,t} + e_{2i,t} \tag{3}$$

$$E_{i,t} = \theta_3 + a_{31}C_{i,t-1} + a_{32}P_{i,t-1} + a_{33}E_{i,t-1} + a_{34}U_{i,t-1} + u_{3i,t} + e_{3i,t} \tag{4}$$

$$U_{i,t} = \theta_4 + a_{41}C_{i,t-1} + a_{42}P_{i,t-1} + a_{43}E_{i,t-1} + a_{44}U_{i,t-1} + u_{4i,t} + e_{4i,t} \tag{5}$$

The lagged values of agglomeration and dispersion forces (i.e., employment density, population density, and congestion) are included to capture the direct impact of their changes on urban extent, and the lagged values of urban extent are included to control the normal dynamics of urban growth. In theory, the three fundamental factors, employment density, population density, and congestion, can capture a significant degree of the socioeconomic variations (G. M. Ahlfeldt et al., 2015; Redding & Rossi-Hansberg, 2017).

The implementation of the PVAR follows Love and Zicchino (2006). PVAR estimation requires stationary variables. I used first difference for controlling the time-invariant factors at the MSA level. The panel unit root tests developed by Im et al. (2003) were used to test the null hypothesis of all variables having a unit root. I suppose that the spatial changes, relocation of population and employment, and congestion do not respond to any contemporaneous shocks, only to lagged variables. This is because population migration and real estate markets take time to absorb and adjust to shocks (G. M. Ahlfeldt et al., 2014; Love & Zicchino, 2006). To account for the time-to-build effects, I used the first to fifth lags of all variables as instruments, as the housing market takes around five years to adjust to regional shocks (Jean & Katz, 1992). Equations 2 to 5 were then estimated using a generalized method of moments (GMM) framework (Arellano & Bover, 1995).

Next, I computed the impulse response functions to evaluate the reaction of one variable to the changes in another variable in the system, keeping all other variables constant. For the identifying restriction, I adopted the following recursive ordering of causality: congestion (C), population (P), employment (E), and urban expansion (U). The identifying assumption is that the earlier the variables appear in the system, the more exogenous they are. This is the usual convention to isolate shocks in the system, known as Choleski decomposition (see Hamilton, 1994, for details on impulse response functions). Also, I estimated forecast-error variance decompositions to evaluate how much the variation in one variable is explained by the shock to another variable, accumulated over time.

A potential shortcoming of the PVAR analysis is that it assumes time-invariant causal mechanisms throughout the estimation period (Lucas, 1976). We would argue that the estimated causal structure is theoretically informed and the resulting findings should be interpreted under the theoretical framework. Also, my data only date back to the 1990s; since then, U.S. cities have continued auto-oriented development, implying that there have been no substantial changes in the urban growth mechanisms.

4.3.2. Counterfactual Analysis

With the understanding of the underlying mechanisms of the spatial dynamics, I seek to infer the counterfactual distribution of urban expansion that would prevail if autonomous vehicles had been introduced. I use a counterfactual distributions approach developed by Chernozhukov et al. (2013) to answer this question. This approach generates counterfactual covariates by transforming observed covariates. It then integrates the conditional distributions estimated from the observed covariates over the counterfactual covariates to get the effect of a change in agglomeration and dispersion forces on the marginal distribution of urban expansion. With this it can predict counterfactual marginal distributions such as the distribution of urban expansion in the past decade, given that congestion costs have had been reduced by the introduction of autonomous vehicles. The urban expansion can be described by the following function:

$$F_{Y_m|X_m}(y|x) \tag{6}$$

where y is urban expansion conditional on dispersion and agglomeration forces x. The notation m denotes that outcomes and covariates are observed. Then counterfactual distribution can be obtained by changing the observed covariate distribution x_m:

$$X_k = g_k(X_m), \quad where \quad g_k: x_m \rightarrow x_k \tag{7}$$

The counterfactual effect (CE) of changing the observed covariate distribution is then calculated as $F_{Y_m|X_m}(y|x) - F_{Y_k|X_k}(y|x)$. Informed by the PVAR results, urban expansion (U) is estimated as a function of the past congestion (C), VMT (V), employment (E), and population (P). The state gas price (G) is also included to control cross-sectional variations, as the data in this exercise is not a panel structure. The function can be written as:

$$U_m = \beta_p P_{m,t-1} + \beta_e E_{m,t-1} + \beta_c C_{m,t-1} + \beta_v V_{m,t-1} + \beta_g G_{m,t-1} \tag{8}$$

The main counterfactual of interest is the distribution if congestion costs were affected by the introduction of autonomous vehicles. The CE can have a causal interpretation as the changes in the covariate distribution is exogenous due to technological innovation (i.e., autonomous vehicles), under the assumption that autonomous vehicles do not affect the underlying mechanisms of urban expansion. The CE can be computed at each quantile τ as

$$\Delta(\tau) = U_m(\tau) - U_k(\tau) \tag{9}$$

where the counterfactual population is obtained by sampling the observed population and setting the observed congestion levels to the value that it would take under different scenarios of autonomous vehicle deployment.

4.4. Data and Summary Statistics

4.4.1. Measuring Urban Spatial Changes

Nighttime lights data and NLCD data are used to derive urban spatial structure using Google Earth Engine. As people light the places where they live and work, a growing number of economists have used the data to measure urban growth and decentralization (Baum-Snow et al., 2017; Gonzalez-Navarro & Turner, 2018; Henderson et al., 2012; Storeygard, 2016). Since the data were collected by different satellites over the years, I used an inter-calibrated version of the data by Q. Zhang et al. (2016) that allow longitudinal comparison. Each of these nighttime lights images is a composite of 30 arc cells and the value for each cell measures average light intensity ranging from 0-62 with 63 used as a top-code. I measured urbanized area (light intensity > 31) within 2010 each MSA boundary from 1992 to 2012.[7] The calculations were performed on Google Earth Engine.

[7] Dingel et al. (2019) measure urbanized area using a light intensity value of 30 and find that nighttime light areas are 80% consistent with MSAs in terms of land area. This is expected, as there are undeveloped land parcels within MSAs, and confirms that my selection of light intensity is robust to capture urban expansion within MSAs.

Using NLCD data to measure urban spatial chances is more straightforward. The data are classified into difference classes and include four levels of developed land: open space, low intensity, medium intensity, and high intensity. I calculate the total developed land by adding up the four levels of development within each MSA boundary for 2001, 2006, 2011, and 2016. The calculations were performed on Google Earth Engine.

4.4.2. Data

My primary data are computed from two products of satellite imagery using Google Earth Engine, a cloud-based computing platform for geospatial analysis. The first product of satellite imagery is DMSP-OLS Nighttime Lights Time Series, which captures light intensities at night time on Earth and spans 1992 to 2013. The nighttime light data are 30 arc second grids, which may not allow researchers to conduct research at a neighborhood level but only above city level. To exploit the decades-long nighttime light data, I use it to conduct urban spatial dynamic analysis from 1992 to 2013. The second product of satellite imagery National Land Cover Database (NLCD), which is based on Landsat satellite imagery and provides comparable data for 2001, 2004, 2006, 2008, 2011, 2013, and 2016. The resolution of the NLCD data is at 30-meter, which is a more accurate measure for urban expansion than nighttime lights. With the range and accuracy of the NLCD data, I use it to perform decomposition analyses of urban spatial changes from 2001 to 2016 and construct counterfactuals of whether autonomous vehicles had been introduced at the beginning of 2000s.

I also use the 2019 Mobility Scorecard Report produced by Texas A&M Transportation Institute (Schrank et al., 2019), to obtain congestion costs and populations in each urban area from 1990 to 2016. The report contains a number of frequently cited indexes of traffic congestions for urbanized areas in the United States, which are widely used by researchers for transportation and urban studies (e.g., Sarzynski et al., 2006; Spivey, 2008). The data are available for 100 selected urbanized areas from 1982 to 2017 and for all urban areas from 2014 to 2017. I also used other data describe natural amenities and socioeconomic characteristics of each MSA, which are obtained from Bureau of Labor Statistics, National Historical Geographic Information System, and Lee and Lin (2017), to test the robustness of the model.

The units of analysis in this study are metropolitan statistical areas (MSAs) in the United States. The US Census Bureau defines an MSA as consisting of one or more urban centers with a high degree of social economic integration with adjacent communities (US Census Bureau, 2013). The MSA is the statistical analog to the theoretical model of urban expansion. The urban expansion, resulted from the interaction between agglomeration and dispersion forces in core urban areas, mainly occurs in the hinterland. The hinterland is the remaining parts of the MSA that are not in the core urban area.[8] By linking urbanized areas (UAs) with metropolitan statistical areas (MSAs), I construct urban core (where agglomeration and dispersion forces interact) information in the MSAs (i.e., include both core area and hinterland). The 2010 MSA boundaries are used to in my data curation.

[8] This conceptual category for my model building follows the definitions used for analyzing intra-urban changes by Fenton (2013).

I select delayed hour per capita as the measurement for congestion costs and population density as the measurement for agglomeration forces. Since I keep the spatial boundaries consistent over the years, population size changes, in fact, measure the population density changes.

4.5. Results

4.5.1. Spatial Dynamics

Table 4.1 presents the reduced form results of the PVAR model, including area lit, congestion, employment, and population. Overall, the results are in line with the interdependent relationship between agglomeration forces (population and employment) and dispersion force (land supply and congestion) as expected theoretically. Higher employment predicts smaller lit areas, while congestion, resulting from the tension between employment/population and land supply, predicts urban expansion. The negative coefficient of L.Area Lit indicates that metropolitan areas with larger areas lit tend to have smaller marginal growth. Also, employment and population were found to be co-developing, mutually attracting each other.

Table 4.1 Estimated PVAR model for urban extent, congestion, population and employment

VARIABLES	(1) Area Lit (log)	(2) Congestion (log)	(3) Population (log)	(4) Employment (log)
L. Area Lit (log)	-0.147***	-0.0166*	-0.00409	-0.0991***
	(0.0402)	(0.00862)	(0.00291)	(0.0149)
L. Congestion (log)	0.530***	0.624***	0.0526***	0.206***
	(0.0742)	(0.0335)	(0.00850)	(0.0386)
L. Population (log)	0.118	0.325***	0.856***	0.707***
	(0.147)	(0.0477)	(0.0229)	(0.0897)
L. Employment (log)	-0.138**	0.0404***	0.00698*	0.272***
	(0.0686)	(0.0131)	(0.00405)	(0.0460)
Observations	1,900	1,900	1,900	1,900

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

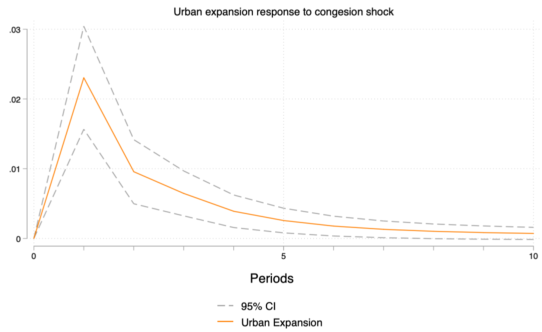
The IRF displayed in **Figure 4.2** allow a structural interpretation of the reduced form results of the PVAR model, as I note in the methodology section. Compared with the PVAR estimates above, the IRF allow for additional insights into the dynamic effects for shocks (one standard deviation increase) in a certain variable on the other variable. Translated into the research question, this becomes: What is the effect on the urban expansion of a surprise increase in the congestion, population, and employment for central areas of cities?

The urban expansion response to congestion shocks (Panel A (1)) is significantly positive in the first few periods but eventually fade to almost no effect after the fifth period. As the urban area expands (Panel B (1)), congestion decreases in the first five periods but returns to nearly no effect after the fifth period. It is expected that expanded infrastructure and land supply will induce congestion and return to equilibrium (Duranton & Turner, 2011). At the same time, the population responds negatively to congestion shock (Panel D (1)) in the first a few periods but eventually fade to almost no effect after the fifth period, while employment has a positive spike as a response to congestion shock (Panel C(1)) and remains positive with a small magnitude after the initial spike. The results agree with Osman et al. (2019) that congestion is a sign of economic vibrancy and increases the competition for commercial land use, thus displacing population to periphery locations.

The urban expansion response to population shocks (Panel A (2)) is positive but not significant as the confidence intervals include zero. It turns significantly in the third period, indicating regional population growth along with the population growth in urban cores. On the contrary, the urban expansion response to employment shocks (Panel A (3)) is negative and moderately significant. Echoing the observations in Panel A, urban expansion shocks (Panel D (3)) have decreasingly positive effects on population in urban core areas and eventually turns to no effect. On the other hand, urban expansion shocks (Panel C (3)) have a strong negative effect on employment in central areas in the first period and the impact remains small and negative after the third period. Taken together, I conclude that employment plays a stronger role than population in influencing the spatial structures of cities over the study period.[9]

[9] Population can be more influencing in a different time period. For example, urban expansion started with the suburbanization of population. In this study, economic factors are considered at a macro dimension. However, in the early time, social factors such as racial discrimination and exclusionary financing and housing policies played an important role in suburbanization in the mid 1900s.

Panel A



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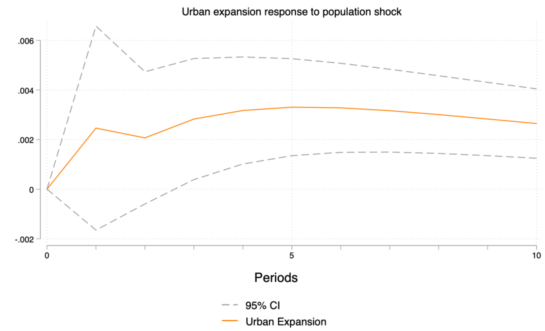
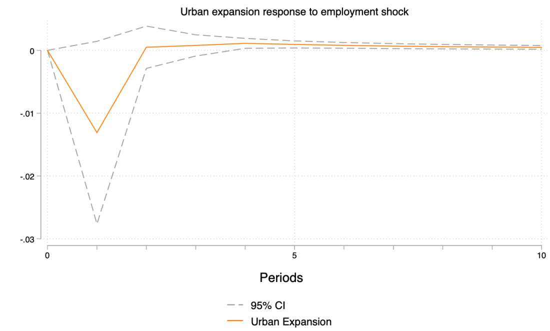
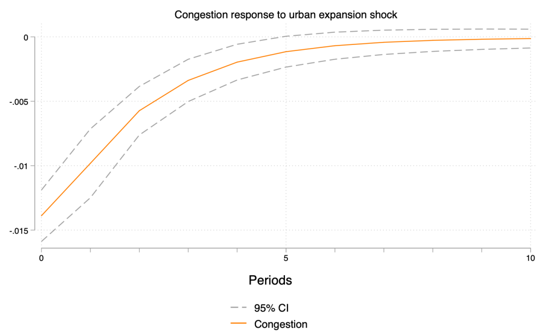


(2)



(3)

Panel B



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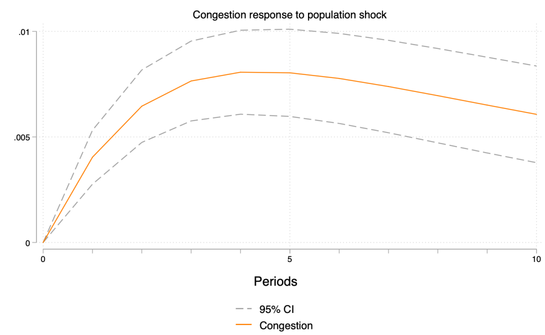

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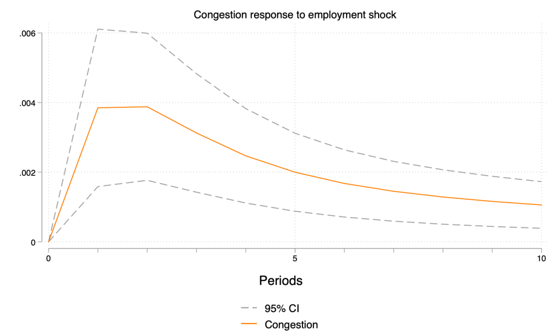

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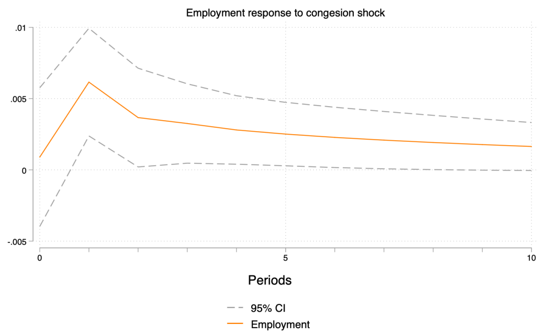
Panel C



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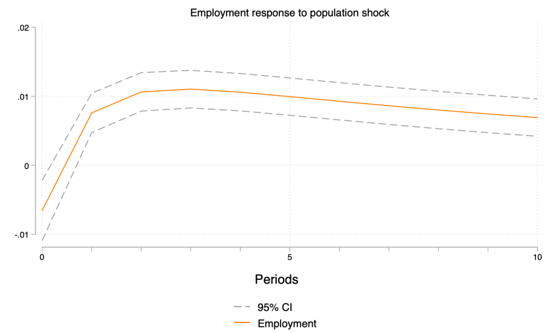

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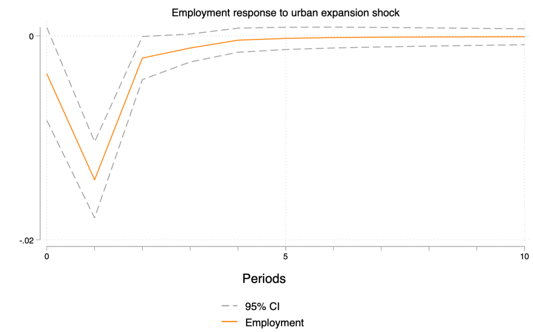

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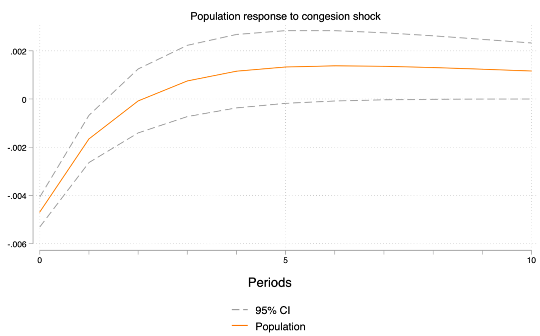
Panel D



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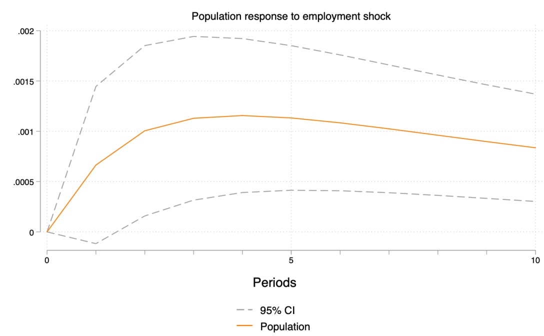

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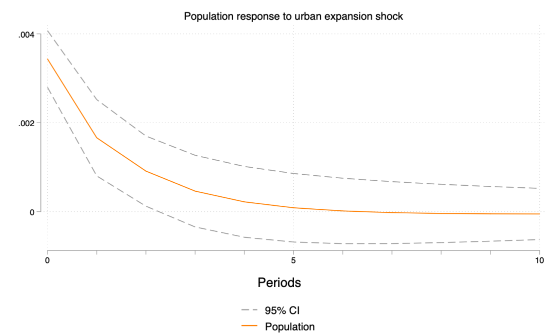


(3)

Figure 4.2 Impulse responses. IRF illustrate the effect of one standard deviation shock in log on the response variable in log

4.5.2. Counterfactual Analysis

In this section, I examine how autonomous vehicles might influence the spatial changes of cities if they had been introduced in the 2000s. Recall that transportation technologies and infrastructures affect the cost of commuting over an uncongested distance (i.e., distance costs) and also affect the cost due to the level of congestion.

In an abstract way, changes in congestion costs and distance costs can represent the introduction of autonomous vehicles, analogous to the role of transportation parameters in Brinkman (2016). Without a doubt, autonomous vehicles can affect urban structure differently because of differences in mode choice, adoption rate, vehicle miles traveled, parking space, market share, and ownership (Faisal et al., 2019; Hawkins & Nurul Habib, 2019; Soteropoulos et al., 2019). However, from the perspective of spatial economics, those factors ultimately modify the parameters of the efficiency of the transportation system, namely, the congestion cost and the distance cost. As noted in Section 4.2, these two types of transportation costs have opposite effects on urban spatial structure (as shown in **Figure 4.3**). Based on Chapter 2 and Chapter 3 of this dissertation, we could expect that autonomous vehicles can reduce travel costs by providing in-vehicle activities and reducing driving demand. In Scenario 1, such reductions in travel costs naturally allow longer travel and thereby potentially encourage urban expansion. On the other hand, in Scenario 2, congestion, one key feature of urban living, might become less onerous due to the usage of autonomous vehicles. Thus, central areas of cities may expect a higher density. In reality, these two chained changes coincide. Whether the net effect on people is to move farther away or choose to live in denser areas largely depends on individual preferences and the surrounded socio-technical system. This ambiguity makes it difficult to predict the effect of autonomous vehicles on the urban structure under various autonomous vehicle deployment scenarios. Moreover, the future is not static. The existing simulation studies on the impact of autonomous vehicles on land use are likely to subject to the Lucas Critique that it is naïve to predict future changes based on estimated parameters from the past. Therefore, this counterfactual analysis has the advantage of just focusing on examining which of the two opposite effects could have dominated, given the historical context.

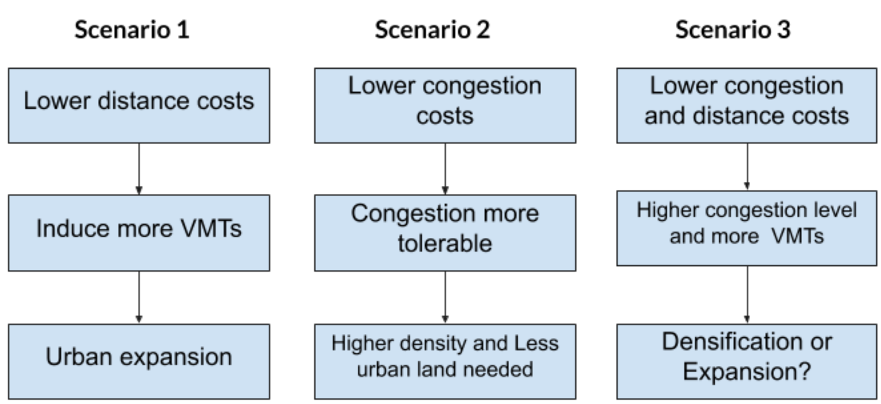


Figure 4.3 Three hypothetical all-AV scenarios

In this study, transportation parameters are assumed to not be affected by autonomous vehicles. That is, autonomous vehicles do not change how individuals and economies respond to transportation costs, but they can change the level of costs. I examine the influence of autonomous vehicles on the spatial structure of cities in different scenarios by adjusting the congestion costs and distance costs, holding other variables constant. Three scenarios examined are described as follows:

> ***Scenario 1*****:** Autonomous vehicles make per-mile distance cost less costly, thus induce more VMT, which is set to be 50% more VMT than the observed value. Employment, population, and congestion remain the same.
>
> ***Scenario 2*****:** Autonomous vehicles make congestion more tolerable in central areas, thus higher congestion level at equilibrium. Employment, population, and VMT remain the same. The counterfactual congestion level is set to be 50% more than the observed value.
>
> ***Scenario 3*****:** Autonomous vehicles make congestion more tolerable and induce more VMT. Employment and population remain the same. The VMT and congestion level increase (i.e., reductions in per-mile/hour costs) at the same rate from 10% to 100%.

In the three scenarios, employment and population are always kept constant. Therefore, the tradeoff between agglomeration and dispersion forces are manifested through the interaction of congestion costs (delayed hours), distance costs (VMT), and developed urban areas (built up land).

Figure 4.4 presents the distribution of counterfactual changes of each scenario. The x-axis denotes the distribution of spatial size of metropolitan areas; the y-axis denotes the counterfactual changes (the difference between counterfactual urban expansion and observed urban expansion). The results are fairly intuitive and theoretically expected in Scenario 1 and Scenario 2. The effects also appear to be monotonic with respect to the different sizes of cities. In Scenario 1, reduced per-mile distance costs lead to increased VMT. This represents the scenario in which agglomeration and productivity remain the same and competitive in the central areas. In this case, people are still willing to travel to central areas for higher productivity but also are able to live farther away for larger lower land prices, leading to urban expansion. This follows the fact that declining transportation costs have led to population suburbanization and employment decentralization in the last two centuries. On the other hand, in Scenario 2, reduced per-hour congestion costs allow a higher level of congestion without a loss in productivity for the economy. Therefore, each unit of employment or population demands fewer land resources, reducing developed land areas for the city. That is, each unit of transportation infrastructures in the city can support higher density.

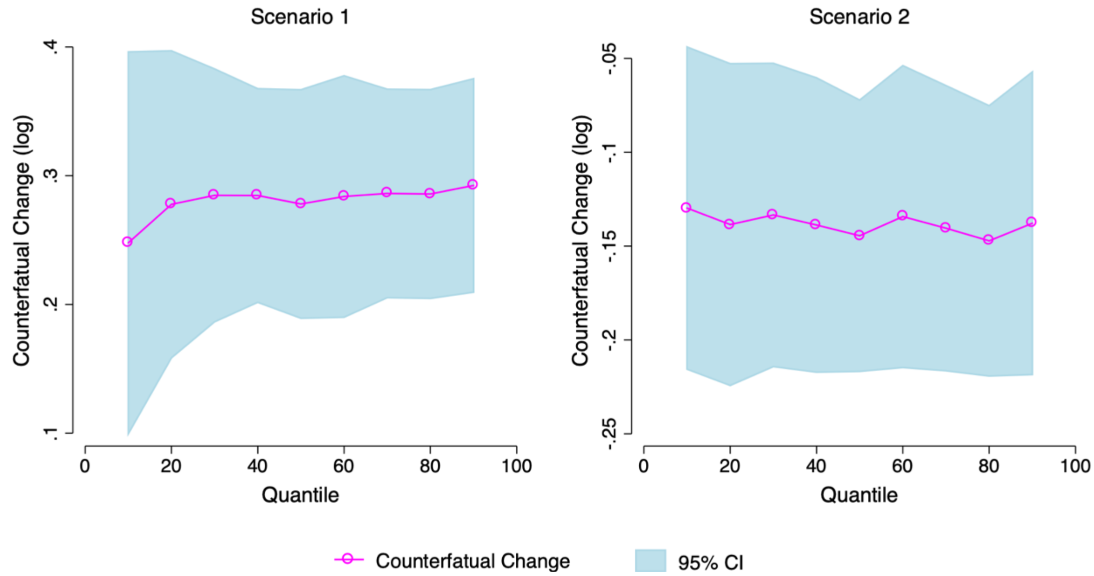


Figure 4.4 Spatial effects of reductions in transportation costs. Scenario 1: reduction in distance costs. Scenario 2: reduction in congestion costs.

In the real world, the centrifugal effect in Scenario 1 and the centripetal effect in Scenario 2 most likely will occur at the same time. The relative extent of the two scenarios will determine the net effect of autonomous vehicles on spatial structure. To understand how the two effects might change the structure of the city, Scenario 3 tests the effect of reducing both distance and congestion costs. The results in **Figure 4.5** shows that the net effects are positive and around 0.15%. The positive net effects suggest that induced urban expansion would be the dominant effect if autonomous vehicles were introduced to the cities in the last two decades.

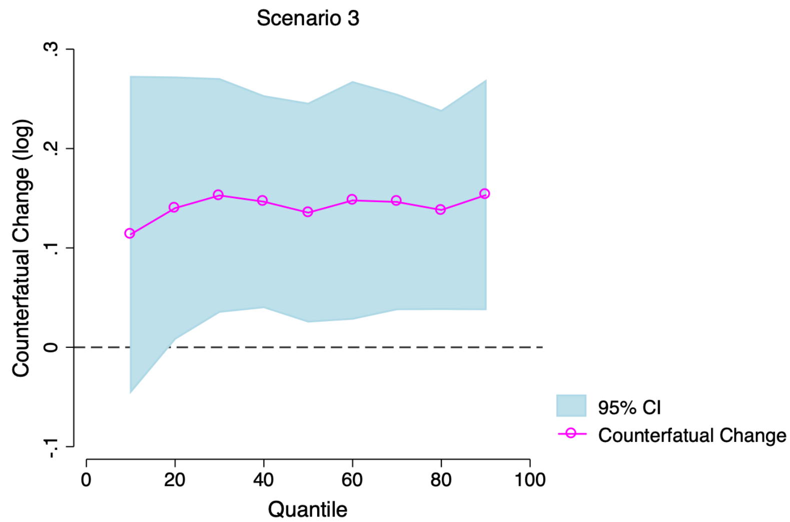
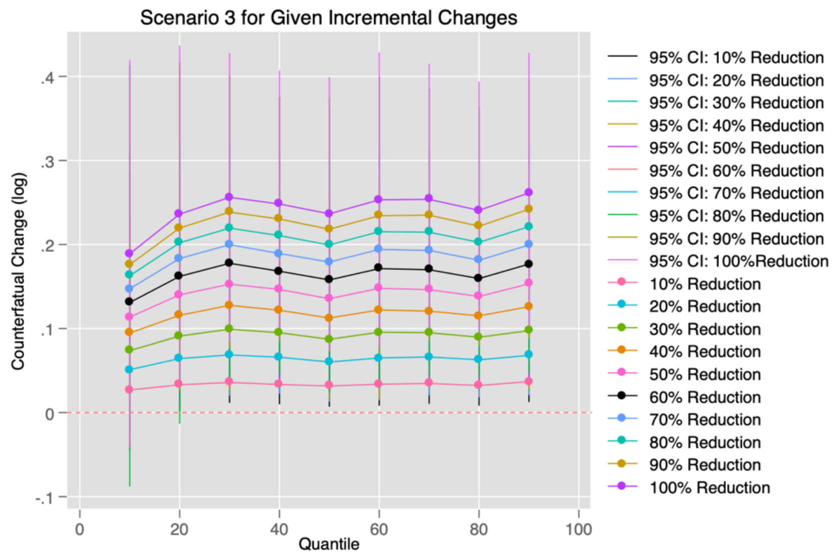


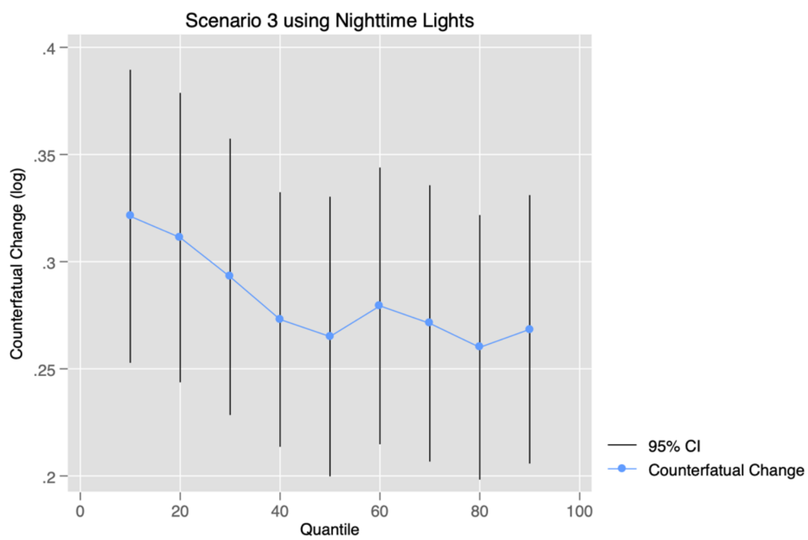
Figure 4.5 Spatial effects of simultaneous reductions in distance costs and congestion costs

In Panel A of **Figure 4.6**, I show the net effect in Scenario 3 for given incremental changes in distance costs and congestion costs. At each level of reductions in the types of transportation costs, the net effect of the two forces is positive and significant, except that cities at the 10^{th} and 20^{th} quantiles are not significant. Smaller cities are expected to be less responsive to changes in transportation costs, as congestion is less prevalent in those areas. Such a net effect also increases as the reduction becomes larger. Overall, these results suggest that urban expansion would be the dominant effect if autonomous vehicles were introduced to the cities in the last two decades.

In Panel B of **Figure 4.6**, the positive net effect is confirmed by using nighttime lights data, although with a larger magnitude. I do not expect the net effect to be very similar between using nighttime lights data and land cover data, as one measures the spatial distribution of economic activities and the other measures physical structures of cities. Nighttime lights data are of interest as a check on the results from land cover data. The counterfactual effects using nighttime lights data confirm the positive effect of autonomous vehicles on urban expansion. The inconsistency between using nighttime lights data and land cover data lies in the lower quantiles. Nighttime lights are more responsive in smaller cities than land cover changes, which might because smaller cities have less capital to build new development or simply the less accuracy of nighttime lights data. I focus on results using land cover data which are the most reliable satellite data product.



(A)



(B)

Figure 4.6 Sensitivity tests for Scenario 3

Note: (A) Counterfactual Effects of reductions in distance costs and congestion costs for given incremental changes; (B) Counterfactual analysis in Scenario 3 using nighttime lights data

4.6. Conclusion

Autonomous vehicles have emerged as one of the most anticipated technological developments over the last decade, which could reshape the structure of cities. In this chapter, I present the dynamics of urban spatial structure over the last three decades, resulting from the tension between agglomeration and dispersion forces. I also show that autonomous vehicles most likely would have induced more urban expansion (around 0.15%) if they had been introduced to cities.

What is the implication of a net effect of 0.15% on urban expansion? Urban expansion rate in the US is about 0.33% since 1973 (Melillo et al., 2014). The cumulative impact of this expansion rate is significant and the resulted urban expansion is roughly equivalent to total land area of California and Oregon (Loveland et al., 2012). And the net effect of 0.15% indicate that the introduction of autonomous vehicles could accelerate the expansion rate by 50%. Thus, the net effect of 0.15% is environmentally significant, as urban areas only occupy 5% of the land but generate 80% of human-caused greenhouse gas emissions (Reidmiller et al., 2017).

It is important to note that this study only considers the changes in transportation technologies. No structural changes in policies, economy, and social norms are taken into consideration, but these factors may substantially affect the prediction of the net effects of autonomous vehicles in the future. For example, younger generations may be more adaptable to urban living, sharing vehicles and rides, and taking public transportation in the future, which will amplify the centrifugal effect of reduced congestion costs. In addition, changes in transportation costs may have a different magnitude of effect on VMT than congestion, which is not differentiated here. Most likely, people will be more responsive to changes in congestion costs than distance costs. Because congestion costs are associated with many perceived conditions, such as sense of control (Schaeffer et al., 1988) and predictability of the trip (Kluger, 1998), which would largely determine people's commuting behavior and residential location choices.

By constructing the counterfactual scenarios of the past, I am able to characterize the effects of the changes in transportation technologies, as the broader context of social, economic, and political structures has settled. My data (2001–2016) reflect a period of a growing trend toward moving back to central cities for the first time since the 1950s (Couture & Handbury, 2015). Most alarming, perhaps, is that significant urban expansions are found in almost all levels of changes in transportation costs in Scenario 3 during this time period. This finding should warn us that autonomous vehicles will most likely lead to greater urban expansion if we taking a laissez-faire approach toward this new technology. On this front, we may find it difficult to know how to act in a situation of great and many uncertainties (T. Cohen & Cavoli, 2019), as we do not know how individual preferences and values, regulations, and economies will shift. But the advantage of looking back to the historical trend is that we do know urban development still favored automobility and suburbanization, resulting from individual preferences as well as the broader socioeconomic context.

The development of transportation technologies has played an important role in the spatial development of cities over the past two centuries. It reshapes, and is shaped by, the locational choices and movement of people, economic activities, and information. This chapter contributes to the debate whether autonomous vehicles will lead to urban sprawl or increase the capacity of cities for compact development by examining the spatial dynamics and counterfactual scenarios of the past urban development. Future scenarios studies can build upon this study and examine the potential consequences of structural changes to provide policy tools to guide the development of autonomous vehicles.

5. CONCLUSIONS

5.1. Recap

Recall the questions motivating this research, will autonomous vehicles change commuters' value of travel time? Can autonomous vehicles fulfill the purpose of reducing the gap in activity participation between men and women? Will autonomous vehicles induce more urban expansion?

I started my inquiry into these questions with a stated choice experiment, eliciting how commuters will trade off time and money differently with the availability of autonomous vehicles. In a choice experiment, the time and monetary costs are included as attributes in the experimental design. Choice tasks are also defined by whether respondents need to share the ride and whether they can engage in in-vehicle activities. In ***Chapter 2***, the results of the choice experiment suggest that autonomous vehicles reduce the perceived travel time costs to no small extent (around 20%). But who benefits more? The reductions also exhibit spatial heterogeneity, where suburban commuters appear to have the greatest benefits of reduced travel time costs, followed by their urban and suburban counterparts. However, only a small portion of the commuters prefer autonomous vehicles for their trips, which could temper the broader effects of autonomous vehicles on transportation systems.

Despite the significance of understanding the spatial heterogeneity in behavioral effects, it is not surprising that AVs can reduce the perceived travel time costs. The more salient question regarding this technology is whether it helps to fulfill our visions of what cities should be. Therefore, in ***Chapter 3***, drawing on distributive justice theories, I explored the equity implications of AVs for time use and activity participation. Specifically, I examined whether in-vehicle activities in autonomous vehicles reduce the daily activity participation gap between men and women ─ a distributional injustice. By enabling more possibilities of in-vehicle activities than what people can do in existing transportation options, autonomous vehicles become a space for daily activities on the move, thus producing disposable time beyond the trip. Yet, the production of disposable time could be experienced differently, as daily needs vary across different groups of people. Using a concept of "midfare," which captures the extent to which people can translate opportunities (i.e., in-vehicle activities) into welfare, I estimated a choice model examining the likelihood of potential engagement of in-vehicle activities, conditioning on individuals' characteristics and contexts associated with their trips and residential locations. I found that people are generally willing to conduct in-vehicle activities when riding in autonomous vehicles, especially commuters who live in suburban areas and have longer trips. Unfortunately, male and female commuters do not differ in the potential engagement of in-vehicle activities; thus, the gap of daily activity participation persists, given that female workers face disproportionally more time poverty in society (Beebeejaun, 2017).

As planners and researchers debate and investigate the effect on urban structures in the future, many uncertainties associated with the predictions simply cannot be addressed by better data and more advanced methods. Instead, in ***Chapter 4***, I looked back into the spatial changes over the last three decades in the United States. Then, I constructed counterfactual scenarios in which autonomous vehicles had been introduced into our cities. By doing so, structural changes (the Lucas Critique) are less of a threat for the analysis, as the broad social, economic, and political contexts in the past are known to researchers. The results of the study empirically demonstrate how urban expansion has resulted from the tension between agglomeration and congestion. More importantly, the counterfactual analysis suggests that autonomous vehicles would have induced more urban expansion in all scenarios, in which re-urbanization in central cities was a prevalent trend. Yet, one caveat is that: the impact on urban structures might not be substantial if the future market share of autonomous vehicles is small.

5.2. Technology, Planning, and Future Research

Technological advances and planning are both ongoing attempts to bring the world to the way one wishes it to be. Indeed, over the last two centuries, when humans started to urbanize themselves after the Industrial Revolution, technologies have been successful at raising the standard of urban living and improving individuals' prosperity. In most developed countries, people now can live longer, move faster, access better food, and achieve more goals. To be sure, there are millions of people still struggle along on the verge of famine, epidemics, and other lagged conditions, partially as a result of uneven access to technologies.

On the other hand, people could be living in a better world. A wave of obesity and chronic diseases, traffic congestion and crashes, and extreme events caused by climate change is sweeping across cities globally. These issues are new and did not emerge or explode in prevalence until the 1800s when technologies became the primary mode of production.

Planning has then emerged as a response to the externalities of technological advances and urbanization. At this time, AVs could clearly lead to various effects on people and cities, but not all effects are positive. From the urban planning perspective, I discuss implications of this research for the full introduction of AVs to the market and consider how policy and technological changes can improve the quality of urban living and ensure a transition toward equitable, sustainable, and healthy mobility systems and cities in the future.

Improving Rural Mobility

One of the promising benefits of AVs is to serve rural communities. As discussed in ***Chapter 2***, rural commuters show the highest interest in adopting AVs. Different from large urban areas that proved to be better served by public transportation systems, rural areas, due to their small population and slim capital, are struggling to provide public transportation services to their residents. Moreover, rural areas lack sidewalks and have longer trip distances to destinations, making it challenging to choose walking and biking as travel options (Glasgow & Blakely, 2000). Thus, access to cars is essential for mobility in rural areas. AVs have the potential to provide the same level of service as private cars in rural areas and be more environmentally friendly if being operated as shared autonomous buses. There are several benefits to this type of AV service. First, it can fulfill a large portion of unmet travel needs, especially for older people and children who cannot drive (Luiu et al., 2017). Second, it can provide a space for social interaction and combat isolation, particularly in a rural context where people tend to know each other (Glasgow & Blakely, 2000; Shergold et al., 2012). Third, it is cheaper for local governments to provide such services, as the labor costs are eliminated. The discourse revolved around AVs has been largely focusing on metropolitan areas (Freemark et al., 2019; Guerra, 2015). I argue that scholars and planners need to pay more attention to what unmet travel needs AVs can fulfill in rural areas and how to deliver the services.

Just Transitioning

Changes driven by technological advances produce inequalities or exaggerate existing ones. As I discussed the distributional effect of in-vehicle activities in ***Chapter 3***, AVs fail to level the playing ground for women, who suffer more time constraints than men. On the contrary, commuting time in AVs might extend women's unpaid household labor if the structural gender inequality persists.

The distributive injustice of in-vehicle activity benefits is also closely related to both recognitional and procedural injustice. Technological development is a collective process of humans, but not everyone is equally involved in the process. For example, as the technology industries are male-dominated (Bærenholdt, 2013; Misa, 2010; Wajcman, 2002), women have been long marginalized in the process of technological development, resulting in their values and preferences not being recognized, and vice versa. As such, the ongoing development of autonomous vehicles might continue to marginalize not only women but also other disadvantaged groups such as older adults, disabled people, and children.

Planners do not have a loud voice in designing and developing technologies, compared to global technology and car companies with significantly more financial and intellectual resources. However, planners are in a unique position of power, with citizen engagement approaches, planning regulations, and pricing schemes in their toolbox. Planners need to *enable* AVs to serve the public interest and *ensure* the benefits of AVs to be equitably distributed. In light of the wicked problem nature of AV development, engaging diverse groups of the population is critical to identify what would be the public interest and the distribution of effects at each stage of AV development (Hopkins & Schwanen, 2018; L. Reardon, 2018). The within-group difference of women in ***Chapter 3*** also highlights the importance of recognizing the intersections of various characteristics of people when engaging people of diverse backgrounds. The intersections pose seemingly infeasible actions but, in turn, necessitate citizen engagement in technological development.

Apart from the marginalized groups in technological development, I also contend that the capitalist system might be the root cause of inequalities. The capitalist system constructs and translates individuals' wants, needs, and desires into consumer demands (choices) that realize the profit-making process (Harvey, 2017). The resulting social and spatial inequalities have been well documented, for example, in digital development (Parayil, 2005; Pfohl, 2005), car development (Lutz, 2014), and suburban living (Wei, 2015). I see the development of AVs as a means for capitalists to once again construct individual desires for capital accumulation, continuing and perhaps even amplifying the trend of an auto-dominated culture that is high in carbon and high in cost. The future world will require more cars. However, more people are being excluded from the transportation system, as the system becomes more mobile (Kenyon, 2003). Without radical transformations of the capitalist system, there will be only remedial measures.

Responding to Climate Change

Urban expansion is inevitable. It affects climate processes at all geographical levels and influence cities' vulnerability to the effects of climate change. There is a pressing need to ensure urban areas to expand sustainably, as the world becomes increasingly warmer and urban. In ***Chapter 4***, the counterfactual analysis shows that AVs would induce more urban expansion under most of the scenarios if they had been introduced to our cities. Although AVs may increase the efficiency of the economy, such as supporting a higher level of agglomeration, the benefits are most likely at the cost of environmental losses if cities continue expanding at the historical rate. For example, urban expansion has been the primary reason for the loss of forests in the Northeast and Southwest over the past few decades within the United States (Melillo et al., 2014).

Do we have to choose between economic growth and natural preservation during the ongoing technological development? If yes, I would argue that we should preserve nature for generations. However, it is not necessarily a binary choice. First of all, climate change and economic growth are interconnected. Climate-related extreme events disrupt the economy, damage infrastructure, and reduce labor productivity. Without mitigation and adaption efforts, the climate-related economic losses are expected to be more than the current gross domestic product of many US states (Reidmiller et al., 2017). Second, AVs can be used to curb urban expansion by reducing congestion and charging VMTs. I show that the reason why AVs induce more urban expansion is because of the dominant effect of reduction in distance costs. As such, AVs can have the flexibility of pricing vehicle usage by distance, which is one of the features of mobility as a service. With the increased distance costs and reduced congestion costs in cities, we can expect a smaller scale of urban expansion, and the amount of expansion can support more population than without intervention efforts. Also, the development of AVs may promote the adoption of cleaner energy, as they are expected to be fully electric. Taken together, AVs offer an opportunity to transform our cities to be more efficient and sustainable, if coupled with a package of interventions on congestion, private car ownership, and VMTs.

However, we must not treat technological changes as a silver bullet for addressing climate change. Equally important is that it requires a critical mass for AV technologies to have an impact. In ***Chapter 2***, I show that a fairly small percentage of people would choose AVs for commuting. If such a low adoption rate remains for a long time, the effects of AVs will be subtle, and investments in technological development and infrastructure for AVs are not cost-effective. As we have witnessed, many of the expected effects of information and communication technology do not come true, because they made simplistic assumptions about the technology and ignored the social effects, such as cultural changes, alternative technological futures, co-evolution of technology and society, social needs, and technical barriers (Geels & Smit, 2000). These neglected aspects can all apply to the imaginations of autonomous futures, which may never come true. Nonetheless, telecommunications still substitute and complement physical travels to a large extent, augmenting the communicating capacity of our society. There is no doubt that AVs can play a role in future cities the way telecommunications do today.

Apart from providing technological solutions, AVs also inspire us to rethink our transportation systems and cities. Many of the anticipated transformations in the transportation system, such as sharing cars/rides and moving to denser areas, are not necessarily technology-focused. Instead, the transformations are changes in our mentalities and lifestyles rather than in technologies. Recently, Creutzig et al. (2016) highlighted this type of change as demand-side solutions, which include behavioral (norms and habits) and infrastructural changes (the built environment). The demand-side solutions challenge us to ask: What communities do we value and plan for? Planners do not plan for AVs nor prepare for AVs. We must define and shape the development of AVs to meet our planning goals. Planners can determine whether and how AVs can play a role in the transformations. For them to be effective, these transformations may manifest across social, environmental, mental, and technological ecologies (Bissell, 2018; Guattari, 2015). Thus, a transdisciplinary approach and citizen engagement are critical to identifying the role of AVs for them to be optimally used, as planners cannot create communities alone.

Future Research

Overall, the analyses presented in this dissertation inform us that the effect of autonomous vehicles on travel choices is modest, socially differentiated, and location-specific. Even so, my counterfactual analysis demonstrates that AVs can aggravate urban expansion if there are no proactive policies in place. There are a few directions that future research can take to engage the future and to proactively design policies.

Future research should build an interdisciplinary framework to tackle analytical and methodological problems pertaining to emerging technologies and cities. It links the planning research to other relevant realms of inquiry, such as political economy. In doing so, it builds data collection and data analysis that can capture the multilevel and cross-classified nature of the impact presented by new technologies. For example, in ***Chapter 2***, the analysis is a neoclassical study that builds on the assumption of utility maximization in microeconomics. In addition to theories that challenge the assumption of utility maximization, travel choices are natural but naturalized by the capitalist system (Obeng-Odoom, 2016). Consequently, a utility-based analysis of travel choices ignores the broader structures beyond the local built, social, and political environment where individuals reside. Ignoring that auto-dependent behavior and development are naturalized by the broader structures and not natural, we might neglect the possibilities of structural changes. This is by no means to diminish the value of microeconomic analysis, but future research should incorporate the political economy of travel behaviors into their inquiry when it is feasible or necessary.

In this research, I minimize the so-called '*Lucas critique*' of economic analysis in ***Chapter 4*** by examining counterfactual scenarios of the past. Lucas's point is that empirical relationships can change and thus make predicting models useless. By looking back into history, my simulated introduction of AVs will not alter the underlying structure of data that my model was based on, so the counterfactual results are relatively robust. However, when predicting the future, the anticipation of AVs is very likely to alter the underlying mechanisms of travel behaviors and urban development. Specific examples of the alteration can be changes in collective habits and different urban policies. As the empirical equations change, static models based on empirical data significantly lose their predicting power. In this case, the increasing emphasis on big data and machine learning techniques simply do improve our capability of managing future uncertainties. On the contrary, the explosion of data and technologies may make the models and theories derived from the past even less relevant to present and future—***a wicked problem***.

Future research should endeavor to develop planning frameworks that can effectively engage the future. First, these frameworks should accommodate two types of uncertainties: *epistemological* uncertainty and *ontological* uncertainty (Derbyshire, 2019). Epistemological uncertainty describes unknown and bounded knowledge, reality, and future possibilities; it can be addressed through better data and modeling techniques. In contrast, ontological uncertainty focuses on unknown unknowns, which make data and methods less useful in policymaking. Derbyshire (2019) pointed out that the ontological uncertainties may be a source of social transformation, rather than just analysis barriers. This argument echoes Bissell (2018) that we should not ignore the creativity of humans and the potential new forms of everyday life, where transformational changes could take place. Derbyshire recommends an approach that can link computational methods to scenario planning to assist in framing the future by presenting a manageable range of potential futures after a process of variation and elimination. Such an approach helps in governing the disruption of emerging technologies through scenario building and demonstrates how the so-called wicked problem can, to some extent, be addressed in planning.

6. REFERENCES

Ahlfeldt, G., Pietrostefani, E., Schumann, A., & Matsumoto, T. (2018). Demystifying compact urban growth.

Ahlfeldt, G. M., Moeller, K., & Wendland, N. (2014). Chicken or egg? The PVAR econometrics of transportation. *Journal of economic geography, 15*(6), 1169-1193.

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica, 83*(6), 2127-2189.

Anable, J., & Gatersleben, B. (2005). All work and no play? The role of instrumental and affective factors in work and leisure journeys by different travel modes. *Transportation Research Part A: Policy and Practice, 39*(2-3), 163-181.

Anas, A. (1988). Agglomeration and taste heterogeneity: Equilibria, stability, welfare and dynamics. *Regional Science and Urban Economics, 18*(1), 7-35.

Anas, A. (1992). On the birth and growth of cities:: Laissez-faire and planning compared. *Regional Science and Urban Economics, 22*(2), 243-258.

Anas, A., Arnott, R., & Small, K. A. (1998). Urban spatial structure. *Journal of economic literature, 36*(3), 1426-1464.

Anas, A., & Kim, I. (1996). General equilibrium models of polycentric urban land use with endogenous congestion and job agglomeration. *Journal of Urban Economics, 40*(2), 232-256.

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*: Princeton university press.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics, 68*(1), 29-51.

Assenmacher, K., & Gerlach, S. (2008). Monetary policy, asset prices and macroeconomic conditions: a panel-VAR study.

Bærenholdt, J. O. (2013). Governmobility: The powers of mobility. *Mobilities, 8*(1), 20-34.

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies, 67*, 1-14.

Barkley, D. L., Henry, M. S., & Bao, S. (1996). Identifying" spread" versus" backwash" effects in regional economic areas: A density functions approach. *Land Economics*, 336-357.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*, 775-805.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., & Zhang, Q. (2017). Roads, railroads, and decentralization of Chinese cities. *Review of Economics and Statistics, 99*(3), 435-448.

Becker, G. S. (1965). A Theory of the Allocation of Time. *Economic Journal*, 493-517.

Beebeejaun, Y. (2017). Gender, urban space, and the right to everyday life. *Journal of urban affairs, 39*(3), 323-334.

Bell, D., & Jayne, M. (2009). Small cities? Towards a research agenda. *International Journal of Urban and Regional Research, 33*(3), 683-699.
Berliner, R. M., Malokin, A., Circella, G., & Mokhtarian, P. L. (2015). *Travel-based multitasking: modeling the propensity to conduct activities while commuting.* Paper presented at the Transportation Research Board 94th Annual Meeting.
Bijsterveld, K. (2010). Acoustic cocooning: How the car became a place to unwind. *The Senses and Society, 5*(2), 189-211.
Bissell, D. (2018). *Transit life: How commuting is transforming our cities*: MIT Press.
Bissell, D., Birtchnell, T., Elliott, A., & Hsu, E. L. (2018). Autonomous automobilities: The social impacts of driverless vehicles. *Current Sociology*, 0011392118816743.
Bland, J. M., & Altman, D. G. (1997). Statistics notes: Cronbach's alpha. *Bmj, 314*(7080), 572.
Bliemer, M. C., & Rose, J. M. (2011). Experimental design influences on stated choice outputs: an empirical study in air travel choice. *Transportation Research Part A: Policy and Practice, 45*(1), 63-79.
Bliemer, M. C., & Rose, J. M. (2013). Confidence intervals of willingness-to-pay for random coefficient logit models. *Transportation Research Part B: Methodological, 58*, 199-214.
Boarnet, M. G. (1997). Infrastructure services and the productivity of public capital: the case of streets and highways. *National tax journal*, 39-57.
Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2017). Cost-based analysis of autonomous mobility services. *Transport Policy*.
Brinkman, J. C. (2016). Congestion, agglomeration, and the structure of cities. *Journal of Urban Economics, 94*, 13-31.
Brownstone, D., & Train, K. (1998). Forecasting new product penetration with flexible substitution patterns. *Journal of econometrics, 89*(1-2), 109-129.
Brueckner, J. K., Thisse, J.-F., & Zenou, Y. (1999). Why is central Paris rich and downtown Detroit poor?: An amenity-based theory. *European Economic Review, 43*(1), 91-107.
Calastri, C., Hess, S., Daly, A., & Carrasco, J. A. (2017). Does the social context help with understanding and predicting the choice of activity type and duration? An application of the Multiple Discrete-Continuous Nested Extreme Value model to activity diary data. *Transportation Research Part A: Policy and Practice, 104*, 1-20.
Cervero, R. (2002). Built environments and mode choice: toward a normative framework. *Transportation Research Part D: Transport and Environment, 7*(4), 265-284.
Chernozhukov, V., Fernández-Val, I., & Melly, B. (2013). Inference on counterfactual distributions. *Econometrica, 81*(6), 2205-2268.
Chesley, N. (2005). Blurring boundaries? Linking technology use, spillover, individual distress, and family satisfaction. *Journal of Marriage and Family, 67*(5), 1237-1248.
Cohen, G. A. (1989). On the currency of egalitarian justice. *Ethics, 99*(4), 906-944.

Cohen, G. A. (1990). Equality of what? On welfare, goods and capabilities. *Recherches Économiques de Louvain/Louvain Economic Review, 56*(3-4), 357-382.
Cohen, T., & Cavoli, C. (2019). Automated vehicles: exploring possible consequences of government (non) intervention for congestion and accessibility. *Transport Reviews, 39*(1), 129-151.
Couture, V. (2013). Valuing the consumption benefits of urban density. *University of California, Berkeley. Processed*.
Couture, V., Duranton, G., & Turner, M. A. (2018). Speed. *Review of Economics and Statistics, 100*(4), 725-739.
Couture, V., & Handbury, J. (2015). *Urban revival in America, 2000 to 2010.* Paper presented at the American Economic Association annual meeting. https://www. dropbox. com/s/hlmnbjsx32eaafb/UrbanizationPatterns_vCurrentPublic. pdf.
Creutzig, F., Fernandez, B., Haberl, H., Khosla, R., Mulugetta, Y., & Seto, K. C. (2016). Beyond technology: demand-side solutions for climate change mitigation. *Annual Review of Environment and Resources, 41*, 173-198.
Crowell, A. R., & Fossett, M. (2018). White and latino locational attainments: Assessing the role of race and resources in US metropolitan residential segregation. *Sociology of Race and Ethnicity, 4*(4), 491-507.
Cyganski, R., Fraedrich, E., & Lenz, B. (2015). *Travel-time valuation for automated driving: A use-case-driven study.* Paper presented at the Proceedings of the 94th Annual Meeting of the TRB.
de Almeida Correia, G. H., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. *Transportation Research Part A: Policy and Practice, 119*, 359-382.
De Borger, B., & Fosgerau, M. (2008). The trade-off between money and travel time: A test of the theory of reference-dependent preferences. *Journal of Urban Economics, 64*(1), 101-115.
Derbyshire, J. (2019). Answers to questions on uncertainty in geography: Old lessons and new scenario tools. *Environment and Planning A: Economy and Space*, 0308518X19877885.
Devarasetty, P. C., Burris, M., & Shaw, W. D. (2012). The value of travel time and reliability-evidence from a stated preference survey and actual usage. *Transportation Research Part A: Policy and Practice, 46*(8), 1227-1240.
DeVellis, R. F. (2016). *Scale development: Theory and applications* (Vol. 26): Sage publications.
Diana, M. (2012). Measuring the satisfaction of multimodal travelers for local transit services in different urban contexts. *Transportation Research Part A: Policy and Practice, 46*(1), 1-11.
Diels, C., & Bos, J. E. (2016). Self-driving carsickness. *Applied ergonomics, 53*, 374-382.

DiMaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). Digital inequality: From unequal access to differentiated use *Social inequality* (pp. 355-400): Russell Sage Foundation.
Dingel, J. I., Miscio, A., & Davis, D. R. (2019). Cities, lights, and skills in developing economies. *Journal of Urban Economics*, 103174.
Drakos, K., & Konstantinou, P. T. (2014). Terrorism, crime and public spending: Panel VAR evidence from europe. *Defence and peace economics, 25*(4), 349-361.
Duranton, G., & Turner, M. A. (2011). The fundamental law of road congestion: Evidence from US cities. *American Economic Review, 101*(6), 2616-2652.
Duranton, G., & Turner, M. A. (2012). Urban growth and transportation. *The Review of Economic Studies, 79*(4), 1407-1440.
Ettema, D., & Verschuren, L. (2007). Multitasking and value of travel time savings. *Transportation Research Record, 2010*(1), 19-25.
Ewing, R. (1997). Is Los Angeles-style sprawl desirable? *Journal of the American Planning Association, 63*(1), 107-126.
Ewing, R., & Cervero, R. (2010). Travel and the built environment: a meta-analysis. *Journal of the American Planning Association, 76*(3), 265-294.
Ewing, R., & Cervero, R. (2017). "Does compact development make people drive less?" The answer is yes. *Journal of the American Planning Association, 83*(1), 19-25.
Ewing, R., & Dumbaugh, E. (2009). The built environment and traffic safety: a review of empirical evidence. *Journal of Planning Literature, 23*(4), 347-367.
Ewing, R., Pendall, R., & Chen, D. (2003). Measuring sprawl and its transportation impacts. *Transportation Research Record: Journal of the Transportation Research Board*(1831), 175-183.
Ewing, R., Tian, G., & Lyons, T. (2018). Does compact development increase or reduce traffic congestion? *Cities, 72*, 94-101.
Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice, 77*, 167-181.
Faisal, A., Kamruzzaman, M., Yigitcanlar, T., & Currie, G. (2019). Understanding autonomous vehicles. *Journal of Transport and Land Use, 12*(1), 45-72.
Fenton, A. (2013). Urban Area and Hinterland: Defining Large Cities in England, Scotland and Wales in terms of their constituent neighbourhoods. *The Centre for Analysis of Social Exclusion (Case)*(SPCCRN004), 1-9.
Ferrell, C. E. (2005). *The Effects of Teleshopping on Travel Behavior and Urban Form.* (Dissertation).
Freemark, Y., Hudson, A., & Zhao, J. (2019). Are cities prepared for autonomous vehicles? Planning for technological change by US local governments. *Journal of the American Planning Association, 85*(2), 133-151.
Frey, W. H. (2017). Census shows a revival of pre-recession migration flows. *The Avenue*. Retrieved from https://www.brookings.edu/blog/the-avenue/2017/03/30/census-shows-a-revival-of-pre-recession-migration-flows/

Fujita, M., & Ogawa, H. (1982). Multiple equilibria and structural transition of non-monocentric urban configurations. *Regional Science and Urban Economics, 12*(2), 161-196.
Garcia-López, M.-À., Hémet, C., & Viladecans-Marsal, E. (2017). Next train to the polycentric city: The effect of railroads on subcenter formation. *Regional Science and Urban Economics, 67*, 50-63.
Geels, F. W. (2012). A socio-technical analysis of low-carbon transitions: introducing the multi-level perspective into transport studies. *Journal of Transport Geography, 24*, 471-482.
Geels, F. W., & Smit, W. A. (2000). Failed technology futures: pitfalls and lessons from a historical survey. *Futures, 32*(9-10), 867-885.
Glaeser, E. L., & Kohlhase, J. E. (2004). Cities, regions and the decline of transport costs. *Papers in Regional Science, 83*(1), 197-228.
Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of economic geography, 1*(1), 27-50.
Glasgow, N., & Blakely, R. M. (2000). Older nonmetropolitan residents' evaluations of their transportation arrangements. *Journal of Applied Gerontology, 19*(1), 95-116.
Gonzalez-Navarro, M., & Turner, M. A. (2018). Subways and urban growth: Evidence from earth. *Journal of Urban Economics, 108*, 85-106.
Gordon, P., & Richardson, H. W. (1997). Are compact cities a desirable planning goal? *Journal of the American Planning Association, 63*(1), 95-106.
Graham, C. (2012). *Happiness around the world: The paradox of happy peasants and miserable millionaires*: Oxford University Press.
Gravier-Rymaszewska, J. (2012). *How aid supply responds to economic crises: A panel VAR approach*: WIDER Working Paper.
Guattari, F. (2015). Ecosophical Practices and the Restoration of the “Subjective City.”. *Machinic Eros: Writings on Japan. Minneapolis, MN: Univocal*, 97-115.
Guerra, E. (2015). Planning for Cars That Drive Themselves Metropolitan Planning Organizations, Regional Transportation Plans, and Autonomous Vehicles. *Journal of Planning Education and Research*, 0739456X15613591.
Hägerstrand, T. (1970). What about people in spatial science? *Papers of the Regional Science Association, 24*, 7-21.
Hall, P. (1997). The future of the metropolis and its form. *Regional studies, 31*(3), 211-220.
Hamilton, J. D. (1994). *Time series analysis* (Vol. 2): Princeton New Jersey.
Hananel, R., & Berechman, J. (2016). Justice and transportation decision-making: The capabilities approach. *Transport Policy, 49*, 78-85.
Hancock, P., Nourbakhsh, I., & Stewart, J. (2019). On the future of transportation in an era of automated and autonomous vehicles. *Proceedings of the national academy of sciences*, 201805770.
Hang, D., McFadden, D., Train, K., & Wise, K. (2016). Is vehicle depreciation a component of marginal travel cost?: A literature review and empirical analysis. *Journal of Transport Economics and Policy (JTEP), 50*(2), 132-150.

Harvey, D. (2017). *Marx, Capital, and the Madness of Economic Reason*: Oxford University Press.

Hawkins, J., & Nurul Habib, K. (2019). Integrated models of land use and transportation for the autonomous vehicle revolution. *Transport Reviews, 39*(1), 66-83.

Helsley, R. W., & Sullivan, A. M. (1991). Urban subcenter formation. *Regional Science and Urban Economics, 21*(2), 255-275. doi: http://dx.doi.org/10.1016/0166-0462(91)90036-M

Henderson, J. V. (1974). The sizes and types of cities. *The American Economic Review*, 640-656.

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review, 102*(2), 994-1028.

Hensher, D. A. (1994). Stated preference analysis of travel choices: the state of practice. *Transportation, 21*(2), 107-133.

Hensher, D. A., & Button, K. J. (2007). *Handbook of transport modelling*: Emerald Group Publishing Limited.

Hopkins, D., & Schwanen, T. (2018). Automated mobility transitions: governing processes in the UK. *Sustainability, 10*(4), 956.

Horner, M. W., & Richard, A. (2016). Social data mining for understanding public perceptions of autonomous vehicles: National trends and the case of florida.

Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political analysis, 20*(1), 1-24.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of econometrics, 115*(1), 53-74.

Ioannides, Y. M., Overman, H. G., Rossi-Hansberg, E., & Schmidheiny, K. (2008). The effect of information and communication technologies on urban structure. *Economic Policy, 23*(54), 202-242.

Jain, J., & Lyons, G. (2008). The gift of travel time. *Journal of Transport Geography, 16*(2), 81-89.

Jann, B. (2014). Plotting regression coefficients and other estimates. *The Stata Journal, 14*(4), 708-737.

Jara-Díaz, S. R. (2000). Allocation and valuation of travel time savings. *Handbooks in Transport, 1*, 303-319.

Jean, B. O., & Katz, L. F. (1992). Regional Evolutions. *Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, 23*(1).

Jin, J., & Rafferty, P. (2017). Does congestion negatively affect income growth and employment growth? Empirical evidence from US metropolitan regions. *Transport Policy, 55*, 1-8.

Kanai, J. M., Grant, R., & Jianu, R. (2018). Cities on and off the map: A bibliometric assessment of urban globalisation research. *Urban Studies, 55*(12), 2569-2585.

Kasraian, D., Maat, K., Stead, D., & van Wee, B. (2016). Long-term impacts of transport infrastructure networks on land-use change: an international review of empirical studies. *Transport Reviews, 36*(6), 772-792.

Kent, J., Dowling, R., & Maalsen, S. (2017). Catalysts for transport transitions: Bridging the gap between disruptions and change. *Journal of Transport Geography, 60*, 200-207.
Kenyon, S. (2003). *Understanding social exclusion and social inclusion.* Paper presented at the Proceedings of the Institution of Civil Engineers-Municipal Engineer.
Kenyon, S., & Lyons, G. (2007). Introducing multitasking to the study of travel and ICT: Examining its extent and assessing its potential importance. *Transportation Research Part A: Policy and Practice, 41*(2), 161-175.
Kluger, A. N. (1998). Commute variability and strain. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 19*(2), 147-165.
Kolarova, V., Steck, F., & Bahamonde-Birke, F. J. (2019). Assessing the effect of autonomous driving on value of travel time savings: A comparison between current and future preferences. *Transportation Research Part A: Policy and Practice, 129*, 155-169.
Koster, H. R., van Ommeren, J. N., & Rietveld, P. (2014). Historic amenities, income and sorting of households. *Journal of economic geography, 16*(1), 203-236.
Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies, 69*, 343-355.
Kwan, M. P. (1999a). Gender and individual access to urban opportunities: a study using space–time measures. *The professional geographer, 51*(2), 210-227.
Kwan, M. P. (1999b). Gender, the home-work link, and space-time patterns of nonemployment activities. *Economic Geography, 75*(4), 370-394.
Larson, W., & Zhao, W. (2019). Self-driving cars and the city: Effects on sprawl, energy consumption, and housing affordability. *Regional Science and Urban Economics*, 103484.
Larson, W. D., & Zhao, W. (2017). Self-Driving Cars and the City: Long-Run Effects On Land Use, Welfare, and the Environment.
Laurier, E. (2004). Doing office work on the motorway. *Theory, culture & society, 21*(4-5), 261-277.
Le Vine, S., Zolfaghari, A., & Polak, J. (2015). Autonomous cars: The tension between occupant experience and intersection capacity. *Transportation Research Part C: Emerging Technologies, 52*, 1-14.
Lee, S., & Lin, J. (2017). Natural amenities, neighbourhood dynamics, and persistence in the spatial distribution of income. *The Review of Economic Studies, 85*(1), 663-694.
Lefebvre, H. (1991). *The production of space* (Vol. 142): Oxford Blackwell.
Levine, J., Merlin, L., & Grengs, J. (2017). Project-level accessibility analysis for land-use planning. *Transport Policy, 53*, 107-119.
LimeSurvey. (2018). LimeSurvey: An open source survey tool: LimeSurvey Project GmbH, Hamburg, Germany. URL http://www.limesurvey.org.
Long, S. J., Long, J. S., & Freese, J. (2006). *Regression models for categorical dependent variables using Stata*: Stata press.

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. *The Quarterly Review of Economics and Finance, 46*(2), 190-210.

Loveland, T., Mahmood, R., Patel-Weynand, T., Karstensen, K., Beckendorf, K., Bliss, N., & Carleton, A. (2012). National climate assessment technical report on the impacts of climate and land use and land cover change. *US Geological Survey Open-File Report 2012–1155, 2012*, 1-87.

Lucas, R. E. (1976). *Econometric policy evaluation: A critique.* Paper presented at the Carnegie-Rochester conference series on public policy.

Lucas, R. E., & Rossi–Hansberg, E. (2002). On the internal structure of cities. *Econometrica, 70*(4), 1445-1476.

Luiu, C., Tight, M., & Burrow, M. (2017). The unmet travel needs of the older population: a review of the literature. *Transport Reviews, 37*(4), 488-506.

Lutz, C. (2014). The US car colossus and the production of inequality. *American Ethnologist, 41*(2), 232-245.

Lyons, G., & Urry, J. (2005). Travel time use in the information age. *Transportation Research Part A: Policy and Practice, 39*(2-3), 257-276.

Marshall, W. E., & Dumbaugh, E. (2018). Revisiting the relationship between traffic congestion and the economy: a longitudinal examination of US metropolitan areas. *Transportation*, 1-40.

Martens, K., & Golub, A. (2012). A justice-theoretic exploration of accessibility measures *Accessibility analysis and transport planning: challenges for Europe and North America* (Vol. 195).

Massey Jr, F. J. (1951). The Kolmogorov-Smirnov test for goodness of fit. *Journal of the American statistical Association, 46*(253), 68-78.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 447-470.

McFadden, D., & Train, K. (2017). *Contingent Valuation of Environmental Goods: A Comprehensive Critique*: Edward Elgar Publishing.

McFadden, D., Tye, W. B., & Train, K. (1977). *An application of diagnostic tests for the independence from irrelevant alternatives property of the multinomial logit model*: Institute of Transportation Studies, University of California.

Melillo, J. M., Richmond, T., & Yohe, G. (2014). Climate change impacts in the United States. *Third national climate assessment, 52*.

Melo, P., Graham, D., & Canavan, S. (2012). Effects of road investments on economic output and induced travel demand: evidence for urbanized areas in the United States. *Transportation Research Record: Journal of the Transportation Research Board*(2297), 163-171.

Merlin, L. A., Levine, J., & Grengs, J. (2018). Accessibility analysis for transportation projects and plans. *Transport Policy, 69*(C), 35-48.

Milakis, D., Van Arem, B., & Van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems*, 1-25.

Misa, T. J. (2010). Gender Codes. *Why Women are Leaving Computing*.
Mokhtarian, P. L., Collantes, G. O., & Gertz, C. (2004). Telecommuting, residential location, and commute-distance traveled: evidence from State of California employees. *Environment and planning A, 36*(10), 1877-1897.
Mokhtarian, P. L., Salomon, I., & Singer, M. E. (2015). What moves us? An interdisciplinary exploration of reasons for traveling. *Transport Reviews, 35*(3), 250-274.
Neutens, T., Schwanen, T., & Witlox, F. (2011). The prism of everyday life: Towards a new research agenda for time geography. *Transport Reviews, 31*(1), 25-47.
New York Metropolitan Transportation Authority. (2013). *Looking Ahead: A Context for the Next Twenty Year Needs Assessment*. Retrieved from http://web.mta.info/mta/news/books/docs/TYN_Vision_7-22-13.pdf.
Ng, C. F. (2008). Commuting distances in a household location choice model with amenities. *Journal of Urban Economics, 63*(1), 116-129.
Nunnally, J. C., & Bernstein, I. (1994). Psychometric Theory (McGraw-Hill Series in Psychology): McGraw-Hill New York.
Obeng-Odoom, F. (2016). *Reconstructing urban economics: Towards a political economy of the built environment*: Zed Books Ltd.
Osman, T., Thomas, T., Mondschein, A., & Taylor, B. D. (2019). Does traffic congestion influence the location of new business establishments? An analysis of the San Francisco Bay Area. *Urban Studies, 56*(5), 1026-1041.
Owens, A. (2019). Building Inequality: Housing Segregation and Income Segregation. *Sociological Science, 6*, 497.
Paleti, R., Vovsha, P., Givon, D., & Birotker, Y. (2015). Impact of individual daily travel pattern on value of time. *Transportation, 42*(6), 1003-1017.
Parayil, G. (2005). The digital divide and increasing returns: Contradictions of informational capitalism. *The information society, 21*(1), 41-51.
Paulsen, K. (2012). Yet even more evidence on the spatial size of cities: Urban spatial expansion in the US, 1980–2000. *Regional Science and Urban Economics, 42*(4), 561-568.
Payyanadan, R. P., Lee, J. D., & Grepo, L. C. (2018). Challenges for older drivers in urban, suburban, and rural settings. *Geriatrics, 3*(2), 14.
Peine, A., van Cooten, V., & Neven, L. (2017). Rejuvenating design: Bikes, batteries, and older adopters in the diffusion of e-bikes. *Science, Technology, & Human Values, 42*(3), 429-459.
Pereira, A. M., & Andraz, J. M. (2012). On the regional incidence of highway investments in the USA. *The Annals of Regional Science, 48*(3), 819-838.
Pfohl, S. (2005). New global technologies of power: Cybernetic capitalism and social inequality. *The Blackwell companion for social inequalities*, 546-592.
Polzin, S., & Pisarski, A. (2013). Commuting in america 2013: Technical report, American Association of State Highway and Transportation Officials.
Preston, V., & McLafferty, S. (2016). Revisiting gender, race, and commuting in New York. *Annals of the American Association of Geographers, 106*(2), 300-310.

Proost, S., & Thisse, J.-F. (2019). What can be learned from spatial economics? *Journal of economic literature, 57*(3), 575-643.
Rappaport, J. (2008). Consumption amenities and city population density. *Regional Science and Urban Economics, 38*(6), 533-552.
Rappaport, J. (2016). Productivity, congested commuting, and metro size.
Rawls, J. (1971). *A theory of justice*: Harvard university press.
Reardon, L. (2018). Ensuring Good Governance: The Role of Planners in the Development of Autonomous Vehicles. *Planning Theory & Practice, 19*(5), 773-776.
Reardon, S. F., & Bischoff, K. (2011). Income inequality and income segregation. *American journal of sociology, 116*(4), 1092-1153.
Redding, S. J., & Rossi-Hansberg, E. (2017). Quantitative spatial economics. *Annual Review of Economics, 9*, 21-58.
Redmond, L. S., & Mokhtarian, P. L. (2001). The positive utility of the commute: modeling ideal commute time and relative desired commute amount. *Transportation, 28*(2), 179-205.
Reidmiller, D. R., Avery, C. W., Easterling, D. R., Kunkel, K. E., Lewis, K. L., Maycock, T., & Stewart, B. C. (2017). Impacts, risks, and adaptation in the United States: Fourth National Climate Assessment, Volume II.
Sarrias, M., & Daziano, R. (2017). Multinomial logit models with continuous and discrete individual heterogeneity in R: the gmnl package. *Journal of Statistical Software, 79*(2), 1-46.
Sarzynski, A., Wolman, H. L., Galster, G., & Hanson, R. (2006). Testing the conventional wisdom about land use and traffic congestion: The more we sprawl, the less we move? *Urban Studies, 43*(3), 601-626.
Schaeffer, M. H., Street, S. W., Singer, J. E., & Baum, A. (1988). Effects of control on the stress reactions of commuters 1. *Journal of Applied Social Psychology, 18*(11), 944-957.
Scheiner, J., & Holz-Rau, C. (2017). Women's complex daily lives: a gendered look at trip chaining and activity pattern entropy in Germany. *Transportation, 44*(1), 117-138.
Schiff, N. (2014). Cities and product variety: evidence from restaurants. *Journal of economic geography, 15*(6), 1085-1123.
Schoettle, B., & Sivak, M. (2014). A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia.
Schrank, D., Eisele, B., & Lomax, T. (2019). *2019 urban mobility report*.
Schwanen, T., Dieleman, F. M., & Dijst, M. (2004). The impact of metropolitan structure on commute behavior in the Netherlands: a multilevel approach. *Growth and change, 35*(3), 304-333.
Schwanen, T., Dijst, M., & Dieleman, F. M. (2002). A microlevel analysis of residential context and travel time. *Environment and planning A, 34*(8), 1487-1507.
Schwanen, T., & Kwan, M.-P. (2008). The Internet, mobile phone and space-time constraints. *Geoforum, 39*(3), 1362-1377.

Sen, A. K. (1980). Equality of What? In S. McMurrin (ed.) Tanner Lectures on Human Values, Cambridge: Cambridge University Press.
Sheller, M., & Urry, J. (2006). The new mobilities paradigm. *Environment and planning A, 38*(2), 207-226.
Shergold, I., Parkhurst, G., & Musselwhite, C. (2012). Rural car dependence: an emerging barrier to community activity for older people. *Transportation Planning and Technology, 35*(1), 69-85.
Singleton, P. A. (2018). How useful is travel-based multitasking? Evidence from commuters in Portland, Oregon. *Transportation Research Record, 2672*(50), 11-22.
Sivak, M., & Schoettle, B. (2016). Would Self-Driving Vehicles Increase Occupant Productivity?
Small, K. A. (2012). Valuation of travel time. *Economics of Transportation, 1*(1–2), 2-14. doi: http://dx.doi.org/10.1016/j.ecotra.2012.09.002
Smith, N. (2010). *Uneven development: Nature, capital, and the production of space* (Third ed.): University of Georgia Press.
Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. *Transport Reviews, 39*(1), 29-49.
Spivey, C. (2008). The Mills—Muth Model of Urban Spatial Structure: Surviving the Test of Time? *Urban Studies, 45*(2), 295-312.
Srinivasan, S., & Bhat, C. R. (2005). Modeling household interactions in daily in-home and out-of-home maintenance activity participation. *Transportation, 32*(5), 523-544.
Stata, A. (2015). Stata base reference manual release 14.
Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S., & Lenz, B. (2018). How autonomous driving may affect the value of travel time savings for commuting. *Transportation Research Record*, 0361198118757980.
Steg, L. (2005). Car use: lust and must. Instrumental, symbolic and affective motives for car use. *Transportation Research Part A: Policy and Practice, 39*(2-3), 147-162.
Stevens, M. R. (2017). Does compact development make people drive less? *Journal of the American Planning Association, 83*(1), 7-18.
Stilgoe, J. (2018). Putting Technology in its Place: ROUTLEDGE JOURNALS, TAYLOR & FRANCIS LTD 2-4 PARK SQUARE, MILTON PARK ….
Storeygard, A. (2016). Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa. *The Review of Economic Studies, 83*(3), 1263-1295.
Streiner, D. L. (2003). Starting at the beginning: an introduction to coefficient alpha and internal consistency. *Journal of personality assessment, 80*(1), 99-103.
Sweet, M. (2011). Does traffic congestion slow the economy? *Journal of Planning Literature, 26*(4), 391-404.
Sweet, M. (2014). Traffic congestion's economic impacts: Evidence from US metropolitan regions. *Urban Studies, 51*(10), 2088-2110.
U.S. Bureau of Labor Statistics. (2019). *American time use survey summary*
. (USDL-19-1003). Retrieved from https://www.bls.gov/news.release/atus.nr0.htm.

US Census Bureau. (2013). Geographic areas reference manual: US Department of Commerce, Economic, and Statistics Administration ….
van den Berg, V. A., & Verhoef, E. T. (2016). Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. *Transportation Research Part B: Methodological, 94*, 43-60.
Van Wee, B., & Geurs, K. (2011). Discussing equity and social exclusion in accessibility evaluations. *European journal of transport and infrastructure research, 11*(4).
Waddell, P. (2006). Reconciling household residential location choices and neighborhood dynamics. *Under revision, Sociological Methods and Research*.
Wajcman, J. (2002). Addressing technological change: The challenge to social theory. *Current Sociology, 50*(3), 347-363.
Wajcman, J. (2007). ICTs and inequality: Net gains for women? *The Oxford Handbook of Information and Communication Technologies*.
Warschauer, M. (2004). *Technology and social inclusion: Rethinking the digital divide*: MIT press.
Wei, Y. D. (2015). Spatiality of regional inequality. *Applied Geography, 61*, 1-10.
Wells, P., & Xenias, D. (2015). From 'freedom of the open road'to 'cocooning': Understanding resistance to change in personal private automobility. *Environmental Innovation and Societal Transitions, 16*, 106-119.
Yap, M. D., Correia, G., & Van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice, 94*, 1-16.
Yigitcanlar, T., Wilson, M., & Kamruzzaman, M. (2019). Disruptive impacts of automated driving systems on the built environment and land use: An urban planner's perspective. *Journal of Open Innovation: Technology, Market, and Complexity, 5*(2), 24.
Zakharenko, R. (2016). Self-driving cars will change cities. *Regional Science and Urban Economics, 61*, 26-37.
Zax, J. S. (1990). Race and commutes. *Journal of Urban Economics, 28*(3), 336-348.
Zhang, M., & Zhang, W. (2018). When Context Meets Self-Selection: The Built Environment–Travel Connection Revisited. *Journal of Planning Education and Research*, 0739456X18755495.
Zhang, Q., Pandey, B., & Seto, K. C. (2016). A robust method to generate a consistent time series from DMSP/OLS nighttime light data. *IEEE Transactions on Geoscience and Remote Sensing, 54*(10), 5821-5831.
Zhang, W., & Guhathakurta, S. (2018). Residential location choice in the era of shared autonomous vehicles. *Journal of Planning Education and Research*, 0739456X18776062.
Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society, 19*, 34-45.
Zhang, W., Guhathakurta, S., & Khalil, E. B. (2018). The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation. *Transportation Research Part C: Emerging Technologies, 90*, 156-165.

Zwerling, C., Peek-Asa, C., Whitten, P. S., Choi, S.-W., Sprince, N. L., & Jones, M. P. (2005). Fatal motor vehicle crashes in rural and urban areas: decomposing rates into contributing factors. *Injury prevention, 11*(1), 24-28.

APPENDIX A

SURVEY QUESTIONNAIRE

A. Recent Trip Information

Please tell us about your most recent one-way Commuting (to or from work or school) trip by personal vehicles (car/ SUV/ pick-up truck/ motorcycle).

1. What time of day was this trip __________?

2. Were you the driver or a passenger on this trip?

☐ Driver
☐ Passenger

3. How long was the trip (in miles)?

__________________ miles

4. How long was the trip (time spent in the vehicle including the stops – in minutes)?

__________________ minutes

B. Awareness

5. Are you familiar with ride-sharing services, such as Uber, Lyft?

☐ No

☐ Yes

6. Are you familiar with car-renting services, such as ZipCar, Car2Go?

☐ No

☐ Yes

7. Do you use a smartphone?

☐ No

☐ Yes

8. Do you enjoy driving?

☐ Yes, a lot ☐ Yes, a little ☐ Neutral ☐ No, not really ☐ No, I really dislike driving

9. Have you heard of the following?

Type of vehicles	**YES**	**NO**
Connected vehicles	☐	☐
Driverless / Autonomous / Self-driving vehicles	☐	☐

C. Choice Tasks

For this section, we will ask you to choose between different travel options. Travel options will vary by travel time, cost, and mode. Travel time is the time one spends in the vehicle. Cost includes gasoline cost, parking fees, tolls, and bus or taxi fares (if any).

C.1 Travel by Connected Vehicle: A connected vehicle is a car that can communicate with other connected vehicles. It can provide the driver instant information about traffic conditions and possible road blockages.

10. For the recent trip you made (described in the early part of survey), imagine you are driving a vehicle that is receiving traffic information from other vehicles on the road. What would you do if:

A) You see **no** congestion on the road but your vehicle warns that there is congestion ahead in 2 miles. It estimates a XX minute trip if you stay on your current road, or a XX minute trip on a different road.

How likely would you be to switch to the new road?

☐ I would take the new road

☐ I would likely take the new road

☐ I am unsure

☐ I would probably not take the new road

☐ I would definitely not take the new road

B) You see **some** congestion on the road ahead and your vehicle warns that there is congestion ahead. It estimates a XX minute trip if you stay on your current road, or a XX minute trip on a different road.

Now that you can see some congestion, how likely would you be to switch to the new road?

- ☐ I would take the new road
- ☐ I would likely take the new road
- ☐ I am unsure
- ☐ I would probably not take the new road
- ☐ I would definitely not take the new road

C.2 Travel by Driverless Vehicles You will now be asked about traveling in a driverless (or automated) vehicle. In a driverless vehicle, all driving tasks are completely automated and you only need to tell the vehicle where to go. Theoretically, driverless vehicles do not crash. You can do things like sleep, read, watch TV, maybe even exercise while the vehicle takes you to your destination. You can either own a driverless vehicle or request a shared driverless vehicle (like Uber) that may pick up other passengers during the trip (waiting time for a shared driverless vehicle is not counted here).

11. Suppose you are traveling in a driverless vehicle, would you do following activities?

	Not Likely	Less Likely	Neutral	Moderate likely	Very likely
Communicating: with others in vehicle, by phone, email, etc.	1	2	3	4	5
Entertainment/recreation: resting, reading, hobbies, TV, exercise, etc.	1	2	3	4	5
Formal: paid work, education, religious activity, etc.	1	2	3	4	5
Household/personal: eating/drinking, prepare meal, personal care, etc.	1	2	3	4	5
Information search: online shopping, Journey information, employment information, etc.	1	2	3	4	5
Other/personal	1	2	3	4	5

12. **You described your most recent trip to or from work or school in the early part of this survey. Imagine you are conducting a similar trip with your most recent trip to or from work or school. Please compare the following three travel options, and then make your choices.**

Game One	Regular Vehicle (your current vehicle)	Driverless Vehicle You Own	Shared Driverless Vehicle You Request (like Uber)
Travel time (minutes)	X	X	X
Travel cost	$X	$X	$X
Which option would you choose?	☐	☐	☐
If you could only choose between the two new options, which option would you choose?		☐	☐

Game Two	Regular Vehicle (your current vehicle)	Driverless Vehicle You Own	Shared Driverless Vehicle You Request (like Uber)
Travel time (minutes)	X	X	X
Travel cost	$X	$X	$X
Which option would you choose?	☐	☐	☐
If you could only choose between the two new options, which option would you choose?		☐	☐

Game Three	Regular Vehicle (your current vehicle)	Driverless Vehicle You Own	Shared Driverless Vehicle You Request (like Uber)
Travel time (minutes)	X	X	X
Travel cost	$X	$X	$X
Which option would you choose?	☐	☐	☐
If you could only choose between the two new options, which option would you choose?		☐	☐

Game Four	Regular Vehicle (your current vehicle)	Driverless Vehicle You Own	Shared Driverless Vehicle You Request (like Uber)
Travel time (minutes)	X	X	X
Travel cost	$X	$X	$X
Which option would you choose?	☐	☐	☐
If you could only choose between the two new options, which option would you choose?		☐	☐

13. **If there are driverless vehicles in the traffic, how comfortable would you feel about driving your own regular car?**

- ☐ Very comfortable
- ☐ Moderately comfortable
- ☐ Neutral
- ☐ A little uncomfortable
- ☐ Not comfortable at all

14. If the annual cost of ownership and use of a driverless vehicle is same as that of a regular car, would you be willing to buy a driverless car?

- ☐ Yes
- ☐ No

15. If you need a vehicle for making daily trips and the cost of a driverless vehicle is the same as the cost of a regular vehicle, which would you prefer?

- ☐ Owning a regular vehicle
- ☐ Owning a driverless vehicle
- ☐ Renting a driverless vehicle (for as little as 1 trip, or for weeks)
- ☐ Using a SHARED driverless vehicle service with other passengers (like Uber or Lyft)

D. Socioeconomic Characteristics

16. What is your gender?

- ☐ Male
- ☐ Female
- ☐ Prefer not to answer

17. What is your current level of employment? Please select choices that best describe you.

- ☐ Employed full-time
- ☐ Employed part-time
- ☐ Not currently employed
- ☐ Retired
- ☐ Student

18. If you are employed, where is your primary work location?

- ☐ At home
- ☐ NOT at home
- ☐ N/A (e.g. retired; not currently employed; student)

19. What is your age?

- ☐ Between 18 and 24 years old
- ☐ Between 25 and 34 years old
- ☐ Between 35 and 44 years old

- ☐ Between 45 and 54 years old
- ☐ Between 55 and 64 years old
- ☐ More than 65 years old

20. Including yourself, how many people live in your household?

- ☐ 1 person
- ☐ 2 persons
- ☐ 3 persons
- ☐ 4 persons
- ☐ More than 4 persons (please specify the number)____________________

21. How many household members are less than 16 years old?

- ☐ 0 people
- ☐ 1 person
- ☐ 2 people
- ☐ 3 people
- ☐ More than 3 people (please specify the number)____________________

22. What is the highest level of education that you have completed?

- ☐ Less than high school
- ☐ High School Graduate (includes equivalency)
- ☐ Some college
- ☐ Bachelor's degree
- ☐ Master's degree
- ☐ Professional school degree
- ☐ Doctorate degree

23. Which of the following ranges define the total annual income of your household in 2016?

- ☐ Less than $24,999
- ☐ Between $25,000 and $49,999
- ☐ Between $50,000 and $74,999
- ☐ Between $75,000 and $99,999
- ☐ Between $100,000 and $199,999
- ☐ $200,000 or more

24. How do you describe your place of living?

- ☐ Central city

☐ Urban area outside the central city

☐ Suburb

☐ Rural

APPENDIX B

GENERATING EFFICIENT EXPERIMENTAL DESIGN IN NGENE

```
Design
;alts(small)= nv,sav,av
;alts(medium) = nv, sav, av
;alts(large) = nv, sav, av
;alts(xlarge) = nv, sav, av

;rows = 12
;eff = fish(mnl,d)
;rdraws=gauss(3)
;bdraws=gauss(3)
;rep = 1000

;fisher(fish) = design1(small[0.60], medium[0.35], large[0.03], xlarge[0.02])

;model(small):
U(nv) = c0[-1.5] +b1[n, (n, -0.2,0.1),(u,0.1,0.3)] * A.ref[1.5] + b2[n,(n,-
0.045,0.3),(u,0.1,0.3)]  * B.ref[16]         /
U(sav) = c1[-0.76] +b1 * A.piv[1.5,1,0.5]  + b2 * B.piv[3,5,7] /
U(av) =          b1 * A.piv[5,3,2]+ b2* B.piv[-2,0,2]



;model(medium):
U(nv) = c 0[-1.5] +b1[n, (n, -0.2,0.1), (u,0.1,0.3)] * A.ref[5]  + b2[n,(n,-
0.04,0.3),(u,0.1,0.3)] * B.ref[30]        /
U(sav) = c1[-0.76] +b1 * A.piv[5,3,2] + b2 * B.piv[8,12,16] /
U(av) =          b1 * A.piv[11,8,6]+ b2 * B.piv[-5,0,5]



;model(large):
U(nv) = c0[-1.5] + b1[n, (n,-0.2,0.1),(u,0.1,0.3)] * A.ref[12]  + b2[n,(n,-
0.035,0.3),(u,0.1,0.3)]  * B.ref[70]        /
U(sav) = c1[-0.76] + b1 * A.piv [7,5,3]   + b2 * B.piv[15,20,25] /
U(av) =          b1 * A.piv[14,12,9]   + b2 * B.piv[-10,0,10]



;model(xlarge):
```

```
U(nv) = c0[-1.5] + b1[n, (n, -0.2,0.1), (u,0.1,0.3)] * A.ref[17]   + b2[n,(n,-
0.02,0.3),(u,0.1,0.3)]   * B.ref[100]         /
U(sav) = c1[-0.76] + b1 * A.piv [10,7,5]   + b2 * B.piv[15,25,35] /
U(av) =           b1 * A.piv[18,15,12]  + b2 * B.piv[-10,0,10]  $
```

APPENDIX C

RELIABILITY TEST OF SURVEY QUESTIONS

I computed Cronbach's alpha to evaluate the reliability of the questions asking respondents' likelihood to conduct various in-vehicle activities in AV and SAV. The in-vehicle activities serve two purposes, inform respondent the possibility of multi-tasking and understand the impact of in-vehicle activities on mode choices in latter modeling process. Table C1 presents the reliability test. The acceptable values of alpha range from 0.70 to 0.95(Bland & Altman, 1997; DeVellis, 2016; Nunnally & Bernstein, 1994). Streiner (2003) recommended that 0.90 as a maximum alpha value. The overall alpha values for in-vehicle activities in AV and SAV are 0.892 and 0.891 respectively. It leads to a smaller value when we delete any of the items, indicating the item is not redundant. The data appear have high internal consistency.

Table C1. Reliability test of in-vehicle activities questions

Item	Obs	Mean	S.D.	Alpha, if item deleted
Question: Suppose you are traveling in a driverless vehicle you own, how likely are you to do following activities?				
Likert scale: Highly Unlikely (1) to Highly Likely (5)				
Communicating: by phone, email, etc.	1881	3.36	1.30	0.872
Entertainment/recreation: resting, reading, hobbies, TV, exercise, etc.	1881	2.94	1.36	0.868
Formal: paid work, education, religious activity, etc.	1881	2.55	1.25	0.878
Household/personal: eating/drinking, prepare meal, personal care, etc.	1881	2.86	1.29	0.882
Information search: online shopping, journey information, employment information, etc.	1881	2.97	1.32	0.859
Other Activities	1881	2.69	1.15	0.877
Test scale				0.892
Question: Suppose you are traveling in a shared driverless vehicle (carpooling), how likely are you to do following activities?				
Likert scale: Highly Unlikely (1) to Highly Likely (5)				
Communicating: by phone, email, etc.	1881	3.32	1.29	0.871
Entertainment/recreation: resting, reading, hobbies, TV, exercise, etc.	1881	3.17	1.30	0.861
Formal: paid work, education, religious activity, etc.	1881	2.56	1.24	0.881
Information search: online shopping, journey information, employment information, etc.	1881	2.98	1.29	0.849
Other Activities	1881	2.73	1.15	0.875
Test scale				0.891

APPENDIX D

HUMAN SUBJECTS RESEARCH STATEMENT

The HRPP determined on 08/09/2017 that this research meets the criteria for Exemption in accordance with 45 CFR 46.101(b) under Category 2.

IRB ID: IRB2017-0482M