Analyzing the Shift in Travel Modes' Market Shares with the Deployment of Autonomous Vehicle Technology

Moein Khaloei
Department of Civil and Environmental Engineering, University of Washington
More Hall, Seattle, WA 98195
Email: moeinkh@uw.edu

Andisheh Ranjbari
Department of Civil and Environmental Engineering, University of Washington
More Hall, Seattle, WA 98195
Email: ranjbari@uw.edu

Don Mackenzie (Corresponding Author)
Department of Civil and Environmental Engineering, University of Washington
More Hall, Seattle, WA 98195
Tel: 206-685-7198; Fax: 206-685-7198
Email: dwhm@uw.edu

Word count = 5026 + 3 tables * 250 = 5776 words

Submitted August 1, 2019

ABSTRACT

It is generally accepted that automation as an emerging technology in transportation sector could have a potential huge effect on changing the way individuals travel. In this study, the impact of automation technology on the market share of current transportation modes has been examined. A stated preference (SP) survey was launched around the U.S. to ask 1500 commuters how they would choose their commute mode if they had the option to choose between their current mode and an autonomous mode. The survey included five transportation modes: car, transit, transit plus ride-sourcing for the first/last mile, solo ride-sourcing, and pooled ride-sourcing. Each of these modes could be presented as regular or autonomous in the choice scenarios. Then, a mixed logit model was developed using the collected data. Results from the analysis of the model showed that applying the automation in ride-sourcing services to decrease the fare, has the largest effect on the market share of transit ride-sourcing. Also, it was found that measures such as deploying more frequent services by ride-sourcing operators to minimize the waiting time of the services could lead to an increase in the market share of transit plus ride-sourcing but it might not improve the market share for solo and pooled ride-sourcing. Furthermore, it was concluded that if the ride-sourcing market share does not move toward the automation, the mode that will lose the market share is the transit plus ride-sourcing mode for which the market share will be decreased as a consequence of the high decrease in the cost of riding an autonomous private car.

Keywords: Autonomous vehicle, market share, mode choice, mixed logit model

INTRODUCTION

Innovations in business models and vehicle technologies are remaking what it means to travel by car. On-demand mobility services (e.g. Uber or Lyft) already provide a viable alternative to privately-owned cars and driving for many travelers. In addition, emerging technologies such as autonomous vehicles (AVs) are poised to accelerate the trend away from driving, whether in mobility services or in personally owned vehicles. One thing that mobility services and autonomous cars have in common is that they free the traveler from the effort of driving, which is expected to reduce the perceived cost of travel; another is that a decade ago, both concepts would have seemed as fanciful concepts. Looking to the future, there are still many questions about exactly how these transportation modes will function, but regardless of the details, we can expect them to have a profound effect on where people choose to live, work, and travel. So, it is important to know how people's travel behaviors will change when AVs enter the market, and how people will choose between AVs and other conventional modes.

Forecasting the impacts of AVs and other emerging transportation modes on mode choice behavior of individuals has received a lot of attention in recent years, and many studies have been devoted to exploring different aspects of AV use and adoption. Since AVs do not publicly exist at the present time, stated preference (SP) surveys have been used to collect data on hypothetical mode choice situations. SP surveys also enable the researchers to vary the attributes of different modes and to understand how the changes in attributes might affect the mode choice behavior of respondents.

Yap et al. (2016) investigated AVs as the egress mode for train trips in the transportation market and employed an SP survey to understand the sensitivity of travelers toward some of the AV attributes. Their estimated mode choice model showed that on average, first-class train travelers prefer AVs over bicycle or bus/tram/metro as the egress mode. In a research about the travel behavior impacts of shared autonomous vehicles , Krueger et al. (2016) used a mixed logit model fitted to SP data, and concluded that service attributes including travel cost, travel time and waiting time may be critical determinants of the use of shared autonomous vehicles and the acceptance of dynamic ride-sharing. Using SP data, Levin and Boyles (2015) developed a nested logit model for mode choice prediction among three modes of driving an AV and paying for parking at the destination, driving an AV and repositioning it back to the origin, and transit. They found that parking cost was the main incentive for transit and that the avoidance of parking costs through AV round-trips resulted in both an increase in AV round-trips relative to one-way and parking trips and a decrease in transit demand. Megens (2014) conducted an SP study in the Netherlands to determine the preferred levels and circumstances for automation and found that on average, vehicle users do not yet prefer full automation only assisted driving or partial automation is preferred. Howard and Dai (2014) developed a logit model to examine the effects of an individual's demographics and existing travel behavior on his opinion about autonomous cars. They concluded that males, high-income people, those with at least a college education, and those currently driving luxury cars are more likely to use this technology. They further concluded that individuals who place high importance on safety are more likely to use autonomous taxis. There are some contradictory views regarding age and the AV adoption in the literature: some researches claim that younger individuals have a higher interest in AVs (Megens, 2014; Missel, 2014; Yvkoff, 2012), while others show that older individuals are less willing to pay for AVs but more willing to accept it (Payre et al., 2014; Kyriakidis et al., 2015).

In another study, Kyriakidis et al. (2015) concluded that individuals who drive more would be willing to spend more for AVs.

Informed by the prior studies, the goal of current research is to develop a model for measuring how choices between new and conventional modes depend on the characteristics of available transportation options, and to develop initial estimates of the tradeoffs between different design parameters.

Data from the most recent National Household Travel Survey (NHTS) has shown that commuting to work constitutes approximately a large portion (16.6%) of all vehicle trips and all person miles of travel (15.8%) in the U.S., and plays an important role in determining peak travel demand across transportation systems (NHTS, 2017; Jabbari et al., 2018, 2019; Khaloei & Habibian, 2017). Therefore, in this study we have focused on commute trips to explore the factors that affect the utility of each transportation mode. Using SP data, this study has developed a model that explores how the adoption of a potential new mobility service depends on characteristics of various transportation modes.

Given the importance of knowing the factors that will change the mode choice behavior of people in the near future, this study aims to identify how the automation as an emerging technology in transportation area might affect the market share of existing modes.

This paper is organized as follows. In the next two sections, the survey method and data collection process are explained. Then, the model analysis results and elasticities are presented. The final section of the paper summarizes the findings and offer suggestions for future studies.

SURVEY DESIGN

To study the mode choice behavior of individuals, robust data is needed, which usually comes from two sources: revealed preference (RP) data, that refer to situations where the choice is made in the real choice situations; and stated preference (SP) data, that refer to situations where a choice is made in hypothetical situations (Hensher et al., 2015). It is difficult to capture the full trade-offs between various attributes in the RP data, since the levels of attributes are not widely varied in the real market (Swait et al. 1994) and are highly correlated. This multi-collinearity among attributes in the RP data may generate coefficients with wrong signs or unlikely values, which makes it difficult to separate the effects of attribute on the choices (Freeman, 1993; Greene, 1997; Louviere et al., 2000; Hensher et al., 2015). SP data, however, can be used to cover a wide variation of attribute levels, and it is especially useful when considering the choice among existing and new alternatives, whereas RP is not appropriate when it comes to exploring choice behavior of people in response to new transportation modes that are not yet present in the real market (such as autonomous vehicles).

In this study, an SP survey was used to develop a model specification (utility function) that appropriately explains the mode choice behavior of individuals. The survey consisted of three parts: socio-economic characteristics, information about their typical commute trip, and mode choice behavior in hypothetical scenarios featuring emerging transportation modes. The survey can be viewed at https://magiccarpetsurvey2018.com/.

In the first part, respondents were asked about their age, gender, driver's license holding, transit pass holding, education, disability, occupation, and parking status at work, as well as their household's income, size, number of full-time and part-time workers, number of members younger than 18, rental status and number of vehicles owned.

The second part asks respondents a number of questions about their commute trip on a typical workday, including the start time, number of intermediate stops and number of transfers along the trip, and their main mode of travel. Figure 1 shows the commute trip question as displayed to the respondents.

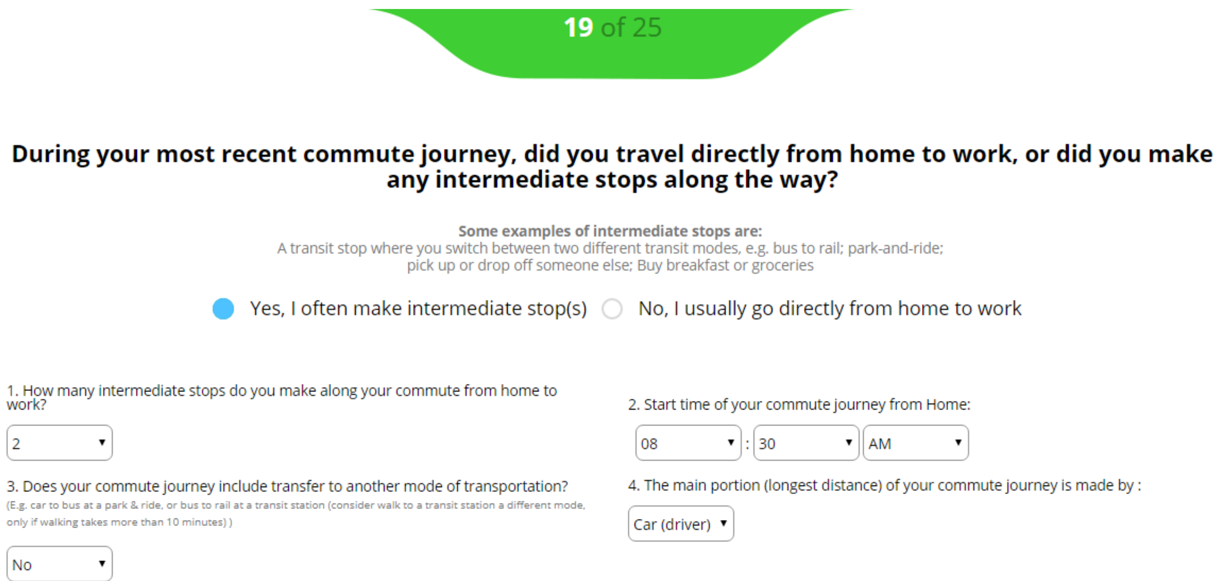


Figure 1. The survey question asking about commute trip on a typical workday

The third part is designed to collect the SP data. For this part, various choice scenarios are developed, and in each scenario the respondents are asked to choose between two modes. The survey included five transportation modes: car, transit, transit plus ride-sourcing for the first/last mile, solo ride-sourcing, and pooled ride-sourcing. Each of these modes could be presented as regular or autonomous in the choice scenarios.

Since respondents might have different perceptions about ride-sourcing modes, a brief explanation of ride-sourcing services was given to the respondents as follows, prior to starting the third part.

- **Ride-sourcing** services allow you to request a ride using a smartphone app, wait a few minutes for the vehicle to pick you up, and then be driven to work. When using ride-sourcing services, it is possible to make additional stops along the way, if needed. Uber and Lyft are examples of companies currently offering ride-sourcing services.
- In the **transit + ride-sourcing** service, a ride-sourcing service picks you up at home and transports you to a public transit hub, from which you can ride transit to your final destination. The public transit portion of the trip in this case can be completed without any additional transfers.
- In a **solo ride-sourcing** service you request a vehicle to be ridden just by you (similar to UberX or Lyft services).

- In a **pooled ride-sourcing** service you may be matched with other travelers who have a similar route to yours, and share the vehicle with these other passengers (similar to Uber Pool or Lyft Shared services).

To create SP choice scenarios, each mode was characterized by a number of attributes including travel time, waiting time, travel cost, and parking fee. Travel cost for car is the energy (gas or electricity) cost that is calculated based on the fuel economy of the car owned by the respondents (they report year, make and model of their car in the first part of the survey) and the trip distance as calculated between their home and workplace locations through the Google API. Travel times for the car and transit alternatives were also obtained from the Google API. To calculate the travel time of the transit plus ride-sourcing alternative, the estimated transit travel time is multiplied by a decreasing level (randomly selected from among 0.5, 0.7 and 0.9), as this alternative is expected to have a shorter travel time than the transit-only alternative. Waiting time, in-vehicle travel time, and travel cost for ride-sourcing services was obtained from the Uber API. Travel cost for the pooled ride-sourcing service is a product of the estimated travel cost for the solo ride-sourcing service and a decreasing level (randomly selected from among 0.5, 0.7 and 0.9) so that the scenarios sound reasonable to the respondents. Once these base values for attributes are calculated, they are multiplied by different levels before appearing in the choice scenario. The combination of various attribute levels in each choice situation is determined through an orthogonal experimental design. The attribute levels used in the experimental design of the survey are presented in Table 1.

TABLE 1 Attribute Levels Used to Characterize Alternatives in SP Scenarios

Attribute	Mode	Levels*
Travel time	All	0%, ±15%, ±30%
Waiting time	Transit Transit + ride-sourcing Solo ride-sourcing Pooled ride sourcing	3 min, 6 min, 9 min 3 min, 6 min, 9 min Uber API (Solo) * {0%, ±15%, ±30%} Uber API (Pooled) * {0%, ±15%, ±30%}
Travel cost	Car Transit Transit + ride-sourcing Solo ride-sourcing Pooled ride-sourcing	0%, ±15%, ±30% $1.50, $2.50, $3.50 $3, $6, $9 Uber API (Solo) * 0%, -25%, -50%, -75%, +25% Uber API (Solo) * 0%, -25%, -50%, -75%, +25% * {0.5, 0.7, 0.9}
Parking fee	Car	$0, $4, $8, $12

*The percentages represent the percent change relative to the base values.

DATA COLLECTION

Due to the large number of alternatives and their associated attributes, we conducted a random sampling approach to reduce the respondent burden. Requiring respondents to consider too many alternatives risks overwhelming them and pushing them to respond inattentively. The random sampling process does not violate the global utility maximization assumption under the strict condition of independent and identically distributed errors (IID), and while it needs a larger sample, it is recommended for the experiments with a large number of alternatives (Hensher et al., 2015).

To do this, each respondent was presented with two scenarios, wherein they had to choose between two modes. The First mode shown in the scenario for the respondents was their current commute mode (based on what reported in part 2 of the survey) and the second mode was randomly selected from the other four modes. One of these two modes was randomly displayed as autonomous (For the case of transit, its autonomous version would be transit plus autonomous ride-sourcing). The modes shown in the second scenario were exactly the same as those shown in the first scenario but with different attribute levels. If respondents' commute mode is transit and have a takes longer than 30 minutes or their daily commute includes a transfer, their current commute mode (first mode shown in choice scenarios) would be shown as transit plus ride-sourcing.

Figure 2 shows examples of two scenarios shown to two different respondents. For example, if a respondent reported "Solo ride-sourcing" as his/her current commute mode, in scenarios 1 and 2, he/she was asked to choose either between "Solo ride-sourcing" and autonomous version of a random mode, or between "Autonomous solo ride-sourcing" and the same random mode, where the random mode is randomly selected from the remaining modes including car, transit, transit plus ride-sourcing, and pooled ride-sourcing.

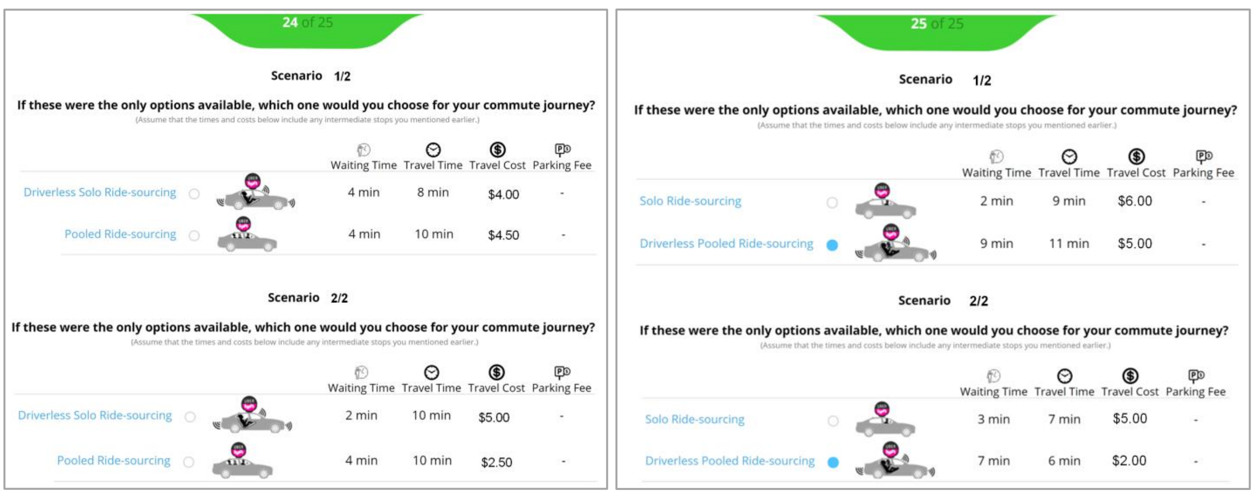
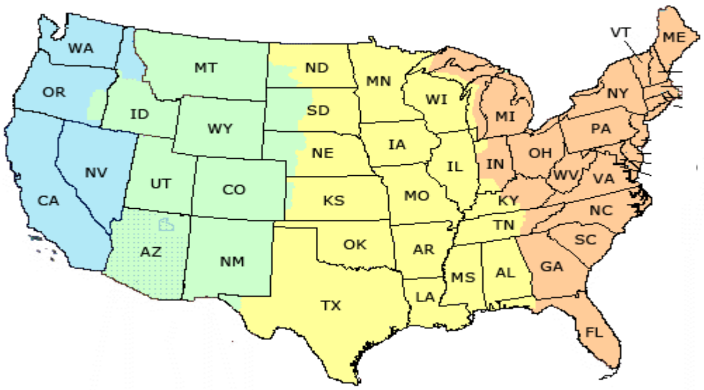


Figure 2. Examples of two sets of scenarios shown to two different respondents

The survey was implemented on the Amazon Web Services (AWS) and was administered on Amazon's Mechanical Turk (MTurk). MTurk is an online crowdsourcing marketplace that makes it easier for individuals and businesses to outsource their processes and jobs to a distributed workforce who can perform these tasks virtually. This could include anything from conducting simple data validation and research to more subjective tasks like survey participation, content moderation, and more. In order to have a high-quality data, only the respondents with approval rates of 95% or higher in previous surveys who have done at least 100 surveys were qualified to take this survey.

The survey was released on a nation-wide scale with a total sample size of 1500 respondents distributed proportionally to the population living in each of the four continental U.S. time zones. This generated a total of 3000 SP observations. The geographic distribution of the respondents participated in the survey is displayed in Figure 3, and Table 2 presents a summary of the sample's demographic statistics.



Time zone	Sample size
Pacific (plus Hawaiian and Alaskan)	256
Mountain	94
Central	435
Eastern	715
Total	**1500**

Figure 3. Geographic distribution of the respondents around the U.S.

TABLE 2 Summary of the Demographic Statistics of the Sample

Demographic Variable	**Category**	**Value**
Current commute travel mode	Car driver and Car passenger	85.5%
	Transit	9.0%
	Solo ride-sourcing	1.3%
	Pooled ride-sourcing	0.3%
	Bike	1.6%
	Walk	2.2%
Mean travel time	Car	20.6 min
	Transit	54.0 min
	Solo ride-sourcing	29.7 min
	Pooled ride-sourcing	12.9 min
	Bike	19.0 min
	Walk	22.1 min
Mean travel cost (gas/energy cost)	Car	$1.91
Gender	Female	45%
	Male	55%
Education	B.Sc. and higher	61%
	Graduate and higher	16%
Job	Full-time	86.4%
	Part-time	11.1%
	Student	2.5%
Median age		34
Median household annual income		$60,000-$79,000
Mean persons per household		2.75
Mean vehicles per household		2.57

RESULTS

Mode Choice Models

In this study, a multinomial logit (MNL) model and a mixed logit model (ML) were applied to model the mode choice behaviors. In the ML model, parameters can be defined to vary across respondents, and so not only the ML model is able to represent the heterogeneity of the respondents, but also it can account for the repeated choices made by each respondent (Hensher et al., 2015).

In order to find the possible factors affecting the mode choice behavior of individuals, the pairwise Spearman correlation test was conducted, and the variables with acceptable levels of significance (α=0.01, α=0.05, and α=0.10) were identified for the modeling process. Several models were developed with different attributes including socio-economic variables, population density of home and workplace location, and interactions of different income bins and travel cost.

The results of the final MNL and ML models built in NLOGIT 6.0 are presented in Table 3.

According to the results, the ML model shows a better fit. It is able to capture the heterogeneity of the respondents by employing random parameters in normal distributions (i.e. $\beta i = \beta + \sigma v_i$, $v_i \sim N[0,1]$) for travel time, waiting time and travel cost attributes. Therefore, here we discuss the results of the ML model.

Travel cost was implemented as a generic variable, and has the same coefficient in all the utility functions. The coefficients of automation and waiting time were also considered the same for all ride-sourcing services, solo and pooled ride-sourcing, as well as transit plus ride-sourcing. All other parameters were considered as alternative-specific variables and their coefficients varied across alternatives.

All travel time and travel cost parameters were found significant with negative signs for coefficients, which is consistent with institution. The coefficients for waiting also have negative signs, but waiting time is only significant for the transit plus ride-sourcing alternative. Automation was found to significantly affect the utility of car alternative in a negative way, while it showed a positive impact on ride-sourcing services.

The results also showed that the population density of the workplace location has a positive impact on choosing transit and transit plus ride-sourcing. This might be related to the higher level of transit accessibility in dense areas with a lot of parking and congestion issues which makes non-car modes more favorable.

TABLE 3 MNL and ML Choice Model Results for Commute Trips

Variables	**MNL**		**ML**	
	Coefficients	p-value	Coefficients	p-value
Car				
Car is autonomous: 1 ; Else: 0	-1.0925***	0.0001	-3.1707***	0.0047
Travel time (min)	-0.0333***	0.0000	-0.1160***	0.0000
Travel cost[1] ($) / Household income per year ($/1000)	-5.3385***	0.0000	-	-
Travel cost ($)	-	-	-0.6184***	0.0000
Transit				
Constant	-1.1976**	0.0424	-2.5685**	0.0159
Travel time (min)	-0.0149***	0.0011	-0.0950***	0.0005
Waiting time (min)	-0.0269	0.7239	-0.0985	0.4418
Travel cost[2] ($) / Household income per year ($/1000)	-5.3385***	0.0000	-	-
Travel cost ($)	-	-	-0.6184***	0.0000
Traveler has a transit pass: 1 ; Else: 0	0.3243**	0.0416	-	-
Population density at workplace zip code (# of people/mile^2)	1.813E-5**	0.0462	4.358E-05**	0.0477
Transit + Ride-sourcing				
Constant	-1.7395***	0.0000	-3.6474***	0.0021
Ride-sourcing car is autonomous: 1 ; Else: 0	0.3985	0.1161	1.4397*	0.1031
Travel time (min)	-0.0256***	0.0000	-0.1452***	0.0000
Waiting time (min)	-0.0306	0.1877	-0.1824*	0.0534
Travel cost[2] ($) / Household income per year ($/1000)	-5.3385***	0.0000	-	-
Travel cost ($)	-	-	-0.6184***	0.0000
Traveler has a transit pass: 1 ; Else: 0	0.3243**	0.0416	-	-
Population density at workplace zip code (# of people/mile^2)	1.328E-05*	0.0780	4.806D-05**	0.0490
Solo Ride-sourcing				
Constant	-0.9217***	0.0064	-3.0644**	0.0116
Ride-sourcing car is autonomous: 1 ; Else: 0	0.3985	0.1161	1.4397*	0.1031
Travel time (min)	-0.0390***	0.0000	-0.1153**	0.0197
Waiting time (min)	-0.0173	0.5222	-0.0044	0.9484
Travel cost[2] ($) / Household income per year ($/1000)	-5.3385***	0.0000	-	-
Travel cost ($)	-	-	-0.6184***	0.0000
Pooled Ride-sourcing				
Constant	-1.124***	0.0012	-3.5126***	0.0030
Ride-sourcing car is autonomous: 1 ; Else: 0	0.3985	0.1161	1.4397*	0.1031

Travel time (min)	-0.0403***	0.0064	-0.1552***	0.0013
Waiting time (min)	-0.0173	0.5222	-0.0044	0.9484
Travel cost^2 ($) / Household income per year ($/1000)	-5.3385***	0.0000	-	-
Travel cost ($)	-	-	-0.6184***	0.0000
Random effects				
Car				
Car is autonomous: 1 ; Else: 0			3.4835***	0.0000
Travel time (min)			0.0859***	0.0009
Travel cost ($)			0.4284***	0.0000
Transit + Ride-sourcing				
Travel time (min)			0.0742***	0.0000
Waiting time (min)			0.3927***	0.0013
Travel cost ($)			0.4284***	0.0000
Solo Ride-sourcing				
Travel time (min)			0.1619***	0.0033
Travel cost ($)			0.4284***	0.0000
Pooled Ride-sourcing				
Travel cost ($)			0.4284***	0.0000
N=	2,268		2,268	
LL=	-1131.863		-977.674	
ρ^2 =	0.280		0.378	

1: Gas/Electricity cost + Parking fee

2: Fare

*: 2-tail significance at α=0.10.

**: 2-tail significance at α=0.05.

***: 2-tail significance at α=0.01.

Sensitivity Analysis

After building the choice model, a sensitivity analysis is conducted to examine how the mode choice behaviors of commuters change with a change in different predictor variables.

"What-if" Scenarios

In this section, the effects of varying different attributes on the market share of each alternative are examined in several "what-if" scenarios. The baseline for these analyses is when none of the modes are autonomous, and they all keep their current attribute values.

- **Scenario 1**

A recent optimistic study by Rocky Mountain Institute (RMI) found that peak car ownership might arrive as early as 2020. Once the autonomous fleets enter the market, prices for Uber, Lyft, and other shared mobility services could drop by 60-70 percent. In this scenario, we assumed that the ride-sourcing services (i.e. solo, pooled, and first/last mile) are autonomous, and their travel cost (fare) is decreased. Figure 4(a) presents the change in the market shares of all modes for different percentages of decrease in the fare of autonomous ride-sourcing services.

As can be seen, decreasing the fare of autonomous ride-sourcing services would increase the market share of these modes, especially that of the transit plus autonomous ride-sourcing alternative, while it decreases the market share of transit and car, with car being the most affected.

- **Scenario 2**

In this scenario, it is assumed that the ride-sourcing services (i.e. solo, pooled, and first/last mile) are autonomous, and the waiting time of ride-sourcing services are decreased. Figure 4(b) presents the change in the market shares of all modes for different decrease percentages in the waiting time of autonomous ride-sourcing services.

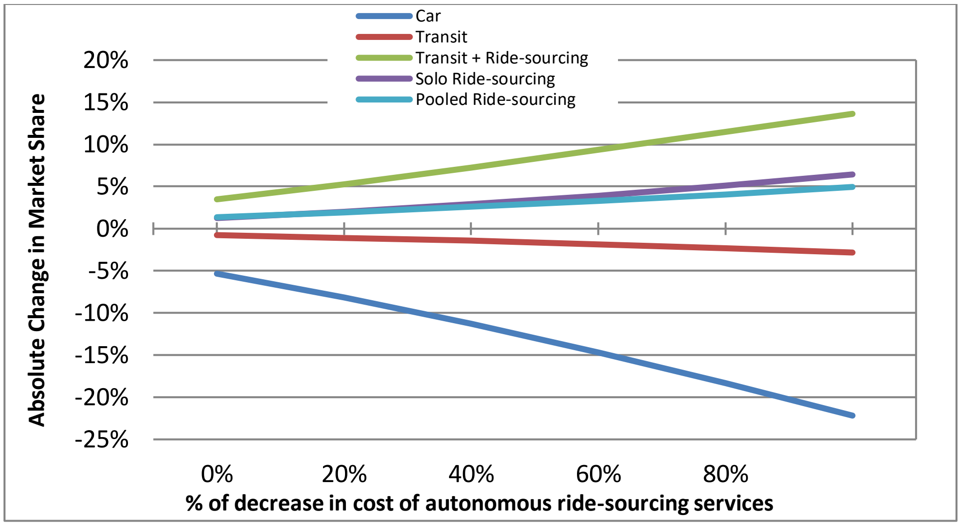
As can be seen, decreasing the waiting time for all autonomous ride-sourcing services would cause a slight increase in the market share of the transit plus autonomous ride-sourcing alternative, and about the same amount of decrease in the car market share. Decreasing ride-sourcing waiting times showed to be almost ineffective on market shares of transit, solo, and pooled ride-sourcing.

- **Scenario 3**

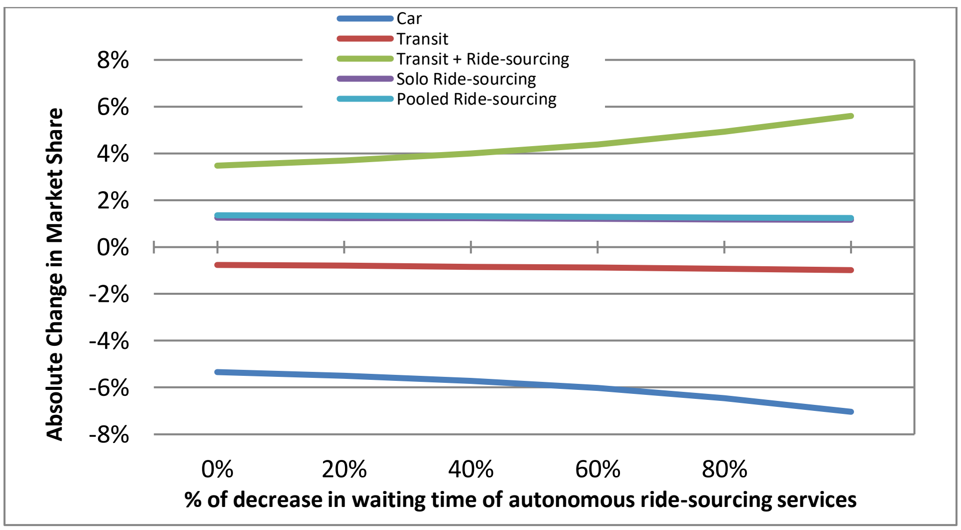
In scenario 3, we assumed that all cars are autonomous, while ride-sourcing services remain regular. Figure 4(c) shows the change in the market shares of all modes for different decrease percentages in the travel cost of autonomous cars.

The results show that automation had a negative effect on the car utility. According to Figure 4(c) this negative effect can be compensated by a bout 75% decrease in the travel cost of car (gas/electricity cost and parking fee). In other words, a decrease of 75% in travel cost of autonomous cars, could result in the same market share as when none of the modes were autonomous and attributes were kept at their current levels.

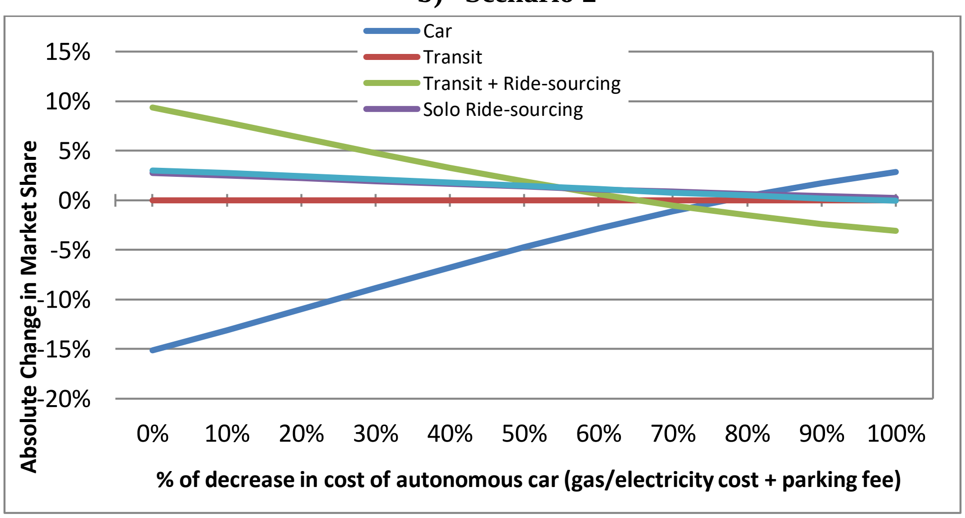
The results also show that decreasing the travel cost of autonomous cars significantly decrease the market share of transit plus ride-sourcing alternative, and encourages those who had already shifted to this alternative as a result of car automation to move back to cars. According to Figure 4(c), a 65% decrease in the travel cost of car can restore the market share of transit plus ride-sourcing alternative to the base market, when none of the modes were autonomous and attributes were the kept at their the current levels. Decreasing the car travel cost, however, does not show to affect the market share for solo and pooled ride-sourcing services much, and their market shares still remain higher than those in the baseline.



a) Scenario 1



b) Scenario 2



c) Scenario 3

Figure 4. Change in the market share as a result of assumptions in different scenarios

CONCLUSION

In this study, we explored how the automation of existing transportation modes might affect their market share.

Since we wanted to explore how the changes in the market share depend on the characteristics of transportation modes, a survey was designed and distributed nationally that consisted of three parts: socio-economic questions, actual mode choice questions (i.e. RP data), and hypothetical mode choice questions (i.e. SP data). In the third part, various choice scenarios were developed that included five transportation modes: car, transit, transit plus ride-sourcing for the first/last mile, solo ride-sourcing, and pooled ride-sourcing. In order to model the behavior of commuters a mixed logit (ML) model was employed, considering car as the reference mode.

The model results indicated that travel cost, waiting time, and travel time decrease utility, and higher population density at the work location increases the utility of transit and transit plus ride-sourcing modes. In addition, automation was found to have a negative effect on the utility of car whereas it has a positive effect on the usage of ride-sourcing services.

In addition to mere analysis of the choice model, we built and analyzed different scenarios, assuming different measures or set of measures for different modes.

It was also found that decreasing all autonomous ride-sourcing prices was the most effective measure to improve the market share for these modes, and transit plus ride-sourcing market share is increased the most by this measure. These results imply that measures such as using automation to reduce the price of ride-sourcing services might shift more commuters to use transit plus autonomous ride-sourcing for the first/last mile.

In addition, it can be inferred from the results that measures such as deploying more frequent services by ride-sourcing operators to minimize the waiting time of the services could lead to an increase in the market share of transit plus ride-sourcing but it might not improve the market share for solo and pooled ride-sourcing.

Furthermore, it was found that if the ride-sourcing market share does not move toward the automation, the mode that will lose the market share is the transit plus ride-sourcing mode for which the market share will be decreased as a consequence of high cost cuts offered by autonomous private cars.

For further studies, it is suggested to examine how the automation might affect other existing modes especially walk and bike.

ACKNOWLEDGMENTS

This study was sponsored by Toyota Motor North America, Inc.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: M. Khaloei, A. Ranjbari, D. MacKenzie; data collection: M. Khaloei; analysis and interpretation of results: M. Khaloei, A. Ranjbari, D. MacKenzie; draft manuscript preparation: M. Khaloei, A. Ranjbari. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

Freeman, A.M. (1993) The measurement of environmental and resource values. Baltimore, Resources for the Future Press.

Greene, W.G. (1997) The HEV model: A note. Department of Economics, Stern School of Business, New York University.

Hensher, D. A., Rose, J.M., Greene, W. H. (2015) Applied Choice Analysis: A Primer. New York: Cambridge University Press.

Howard, D., Dai, D. (2014) Public perceptions of self-driving cars: The case of Berkeley, California. Presented at the 94th Annual Meeting of the Transportation Research Board, Washington, D.C. January 2015.

Jabbari, P., Khaloei, M., MacKenzie, D. (2018) Locating Fast Charging Stations for Safe and Reliable Intercity Electric Vehicle Travel in Washington. Presented at the 97th Annual Meeting of the Transportation Research Board, Washington, D.C.

Jabbari, P., Khaloei, M., MacKenzie, D. (2019) Estimating potential demand for long-distance electric vehicle travel in Washington State. Presented at the 98th Annual Meeting of the Transportation Research Board, Washington, D.C.

Khaloei, M., Habibian, M. (2017) Tour Complexity and Transportation Demand Management: A Focus on CBD Work Tours. Presented at the Transportation Research Board 96th Annual Meeting Transportation Research Board.

Krueger, R., Rashidi, T. H., Rose, J. M. (2016) Preferences for shared autonomous vehicles. Transportation research part C, Vol. 69, pp. 343-355.

Kyriakidis, M., Happee, R., De Winter, J.C.F. (2015) Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transportation research part F: traffic psychology and behavior, 32, pp. 127-140.

Levin, M.W., Boyles, S.D. (2015) Effects of autonomous vehicle ownership on trip, mode and route choice. In: 94th Annual Meeting of the Transportation Research Board, Washington, D.C.

Louviere, J.J., Hensher, D.A., and Swait, J. (2000) Stated Choice Methods: Analysis and Applications in Marketing. Transportation and Environmental Valuation, Cambridge, Cambridge University Press.

Megens, I.C.H. (2014) Vehicle Users' Preferences Concerning Automated Driving: Implications for Transportation and Market Planning. Eindhoven University of Technology.

Missel, J. (2014) Ipsos Mori loyalty automotive survey. Retrieved July 12, 2015, from <https://www.ipsos-mori.com/researchpublications/researcharchive/3427/Only-18-per-cent-of-Britons-believe-driverless-cars-to-be-an-important-development-for-the-car-industry-to-focus-on.aspx>.

Payre, W., Cestac, J., Delhomme, P. (2014) Intention to use a fully automated car: attitudes and a priori acceptability. Transp. Res. Part F: Traffic Psychol. Behav., 27, pp. 252–263.

Swait, J., Louviere, J., Williams, M. (1994) A sequential approach to exploiting the combined strengths of SP and RP data: application to freight shipper choice. Transportation, 21, pp. 135-52.

US Department of Transportation. (2017) National Household Travel Survey (NHTS). http://nhts.ornl.gov/

Yap, Menno & Homem de Almeida Correia, Gonçalo & 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. 10.1016/j.tra.2016.09.003.

Yvkoff, L. (2012) Many car buyers show interest in autonomous car tech. Retrieved from <http://www.cnet.com/news/many-car-buyers-show-interest-inautonomous-car-tech/>.