

# ANTICIPATING LONG-DISTANCE TRAVEL SHIFTS DUE TO SELF-DRIVING VEHICLES

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## ABSTRACT

Increasing population and travel demand has prompted new efforts to model travel demand across the United States. One such model is rJourney that estimates travel demand among thousands of regions and models mode and destination choice. rJourney includes records representing 1.17 billion long-distance trips throughout the year 2010. Although inter-regional impacts caused by an increase of automated vehicles (AVs) has been investigated, there is little research on inter-regional travel and how longer distance destination and mode choices will change. Because of conveniences offered by AVs, the value of travel time of drivers is expected to fall, thus reducing the generalized cost of AV travel. To initially analyze the impacts of AVs in the United States, a new AV mode was added to a subset of the rJourney mode and destination choice models. With an initial scenario assuming an operating cost of AVs that is 118% of traditional cars, two outcomes are observed that are solely based on model results. First, the availability of AVs severely digs into the airline travel market, reducing airline revenues to 53%. Second, the introduction of AVs results in a shift of destination choice, increasing travel in further distances for personal vehicles by 9.6%, but favoring closer distances across all modes with a 6.7% overall trip-miles reduction. While this preliminary research has revealed an initial perspective on how an existing model can support AVs, the increasing availability of data as AVs emerge will refine nationwide long-distance modeling.

**Keywords:** autonomous vehicle; long distance; travel demand modeling; national scale

## INTRODUCTION

1 As the United States population grows, it is expected that the demand for inter-city travel will  
2 rise, running up against the limited capacity of existing infrastructure. The Federal government  
3 and states continuously seek to improve long-distance mobility; however, national-scale  
4 passenger travel demand modeling is still an emerging area of research. In efforts to enable  
5 proactive planning, the Federal Highway Administration (FHWA) commissioned several studies.  
6 One of the studies produced a passenger travel demand model called rJourney that models all  
7 long-distance travel in the entire United States for the duration of the year 2010 (Federal  
8 Highway Administration, 2015).

9 While the rJourney model surpasses the limitations of traditional travel demand forecasting  
10 methods by rigorously incorporating several forms of travel behavior, the prospect of applying  
11 the model to an increasingly automated future is challenged by the fact that automated vehicles  
12 (AVs) were not a mode of choice in 2010, and therefore are not represented in the model. While  
13 traveler behavior may gradually change as the future emerges and AVs continue to enter the  
14 marketplace, the most feasible and best-validated future-looking models at hand are inevitably  
15 based upon today's knowledge.

16 This preliminary research leverages the rJourney model to investigate how long-distance travel  
17 between pairs of regions across the continental United States may be affected by the option of  
18 having vehicles self-drive travelers to their destinations. Possible effects that arise include a  
19 general shift in destination choice that promotes a change in overall person-miles traveled  
20 (PMT), and a significant change in overall mode choice between personal vehicles and  
21 commercial air carriers.

## 22 **BACKGROUND**

### 23 *AVs and Long-Distance Travel*

24 While there have been several simulations of AVs' and shared AVs' effects on intra-regional  
25 travel (e.g., Fagnant and Kockelman (2014) and Childress et al. (2015)), there is little research on  
26 inter-regional travel and how longer-distance destination and mode choices will change.  
27 LaMondia et al. (2016) explored mode choices in Michigan for trips over 50 miles in length, and  
28 forecasted that over 25 percent of airline trips under 500 miles will shift to AVs. Such changes  
29 will have important impacts on airlines, infrastructure planning and future land use (especially  
30 around long-distance transportation facilities), highway congestion, and the travel industry more  
31 generally.

32 Long-distance travel is common in many countries and regions. Mercedes-Benz responded to the  
33 Google challenge in August 2013 with the S500 Intelligent Drive Autonomous Car long-distance  
34 test drive between Mannheim and Pforzheim without any driver input. Automated public  
35 vehicles may provide much of the long-distance travel between European countries (Heinrichs,  
36 2016). 19% of Americans with disabilities report leaving their homes relatively infrequently, and  
37 are less likely to take long-distance trips (BTS, 2003). However, Meyer and Deix (2014) noted  
38 that if AVs allow disabled individuals to make the same length and number of car trips, their  
39 vehicle-miles traveled (VMT) would probably increase by more than 50 percent.

40 AVs reduce the burden of travel for drivers and may improve the quality of travel for passengers,  
41 who can now focus on more meaningful interactions with those previously focused on driving.

1 The value of travel time (VOTT) of the driver (or his/her willingness to pay to save travel time)  
2 is expected to fall, by 20 to 50 percent or more, so the generalized cost of travel can fall by  
3 several dollars per hour to \$6 or more per hour, for many travelers. Auld et al. (2017) applied an  
4 integrated transportation system model to analyze the impact of hypothesized connected and  
5 autonomous vehicle (CAV) scenarios, varying the market penetration, capacity changes and  
6 travel time valuations, on performance of the transportation network and changes in mobility  
7 patterns for Chicago region. The results show that an increase in capacity of 80% can be  
8 achieved with only 4% induced additional VMT. Changes in travel time cost, or VOTT savings,  
9 have a significant impact, especially at very low levels of VOTT, increasing VMT by up to 59%.

#### 10 *Extensions of Prior Models*

11 With the impending introduction of AVs as a viable mode choice in the near future, it is  
12 necessary for today's future-looking travel demand forecasting models to incorporate them.  
13 Childress et al. (2015) used a Seattle, Washington activity-based travel model (including short-  
14 term travel choices and long term work-location and auto-ownership choices) to anticipate the  
15 impacts of AV technology introduction on regional travel (attributed to higher roadway  
16 capacities, lowered value of travel time (VOTT), reduced parking costs, and increased car-  
17 sharing). They estimated that higher income households are more likely to choose the AV mode,  
18 as costly technology and VOTT reductions for higher-VOTT travelers are likely to be more  
19 significant. When shared automated vehicles (SAVs) are modeled to cost \$1.65 per mile (similar  
20 to costs of current ride-sharing taxi services, like Lyft and Uber), drive-alone trips were  
21 estimated to be reduced by one-third and transit shares increased by 140%, as modeled  
22 households did away with traditional vehicles and bought AVs, or shifted to SAVs as well as  
23 other travel options.

24 Other existing projects introduced AVs as a new mode in mode choice or destination choice  
25 models. Gucwa (2014) used an activity-based model approach to simulate the travel decisions of  
26 individuals in the 9-county San Francisco Bay Area. The autonomous vehicle scenarios are  
27 modeled under different values of travel time and road capacity, using the Bay Area's Travel  
28 Model One. The mode choice confirms to a random utility model. The result showed that the  
29 automation can expect a short-run increase of 4-8% in daily VMT. Zhao and Kockelman (2017)  
30 extended the Austin, Texas 6-county region local municipal planning organization's  
31 conventional travel demand model with new CAV and SAV modes. The gravity model for trip  
32 distribution was replaced with a multinomial logit (MNL) model to allow destination choice to  
33 be influenced by the new modes. The mode choice model was also simplified and extended to  
34 support the new modes. Simulations varied the assumed operating and parking costs. Results  
35 suggested that by the year 2020, the introduction of these modes would add 20% demand to the  
36 region's current VMT. An added consequence is a reduction of transit system usage. Both of  
37 these were attributed to the relative value of time of CAV and SAV travelers as well as an  
38 anticipated competitive SAV pricing scheme. Results of this paper suggest that without full  
39 realization of other anticipated benefits of CAVs and SAVs (e.g. smaller headways, shared  
40 rides), overall congestion would worsen from that of today.

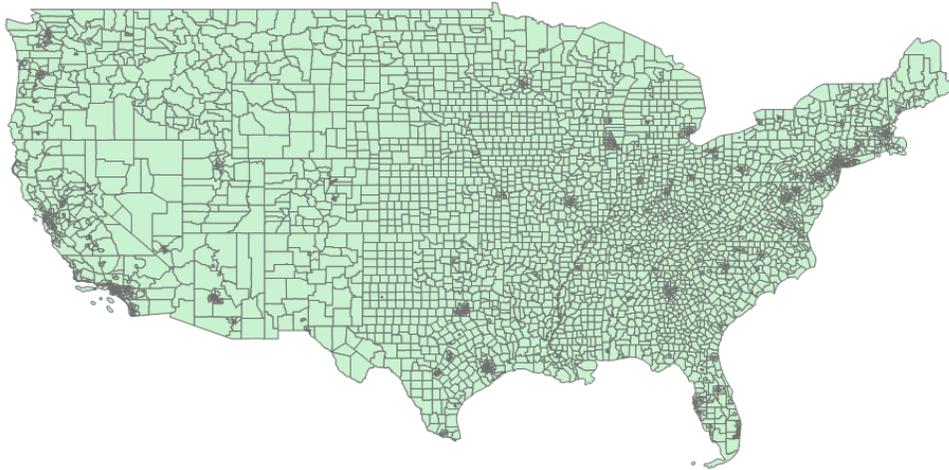
41 This research investigates a possible use of rJourney to forecast traditional personal car,  
42 commercial air carrier, and personal AV mode and destination choice offers insight on future  
43 United States inter-city travel. Since aircraft will still travel much faster than AVs between long-  
44 distance city pairs (e.g., New York City to Los Angeles), it is intuitive that those markets could

1 be largely immune to this new mode alternative. However, looking at what routes will be  
 2 significantly changed lacks research and is important for airline and infrastructure planning. If  
 3 for example the 240-mile (385 km) route between Houston and Dallas is largely dominated by  
 4 AVs, interstate planners should expect higher traffic on Interstate 45 and the airport managers  
 5 should expect less short distance travel between the two cities.

6 This remainder of this paper is organized as follows. First, the rJourney data set that is used in  
 7 this research is introduced, followed by the preliminary methodology. Then, results of the  
 8 research model are identified, as well as an exploration of how the model can be used to estimate  
 9 how the introduction of AVs may affect overall airline industry revenue. Finally, this paper  
 10 concludes and offers future research directions.

## 11 DATA SET

12 The rJourney data that is leveraged in this research is part of an extensive, nationwide tour-based  
 13 long-distance travel model created by RSG for the United States Department of Transportation  
 14 Federal Highway Administration. The motivation for the creation of rJourney is to study intercity  
 15 travel and to enhance interstate, long-distance modeling efforts. As noted earlier, long distance  
 16 travel is modeled among almost all pairwise combinations of 4,486 National Use Microdata Area  
 17 (NUMA) zones as shown in Figure 1. As part of the rJourney effort, NUMAs are derived from  
 18 both Census Bureau Public Use Microdata Areas (PUMAs) and county boundaries. The 1.17  
 19 billion rJourney tours are generated from a synthesized household population of 31.5 million,  
 20 representing all long-distance travel in the year 2010. Destination and mode choice are modeled  
 21 with cross-nested logit (CNL), supporting four modes: automobile, bus, rail and airlines. Trip  
 22 models are organized among five purposes: business travel, commuting, personal business for  
 23 shopping and relaxation, visiting friends and family, and leisure travel (Outwater et al. 2014).

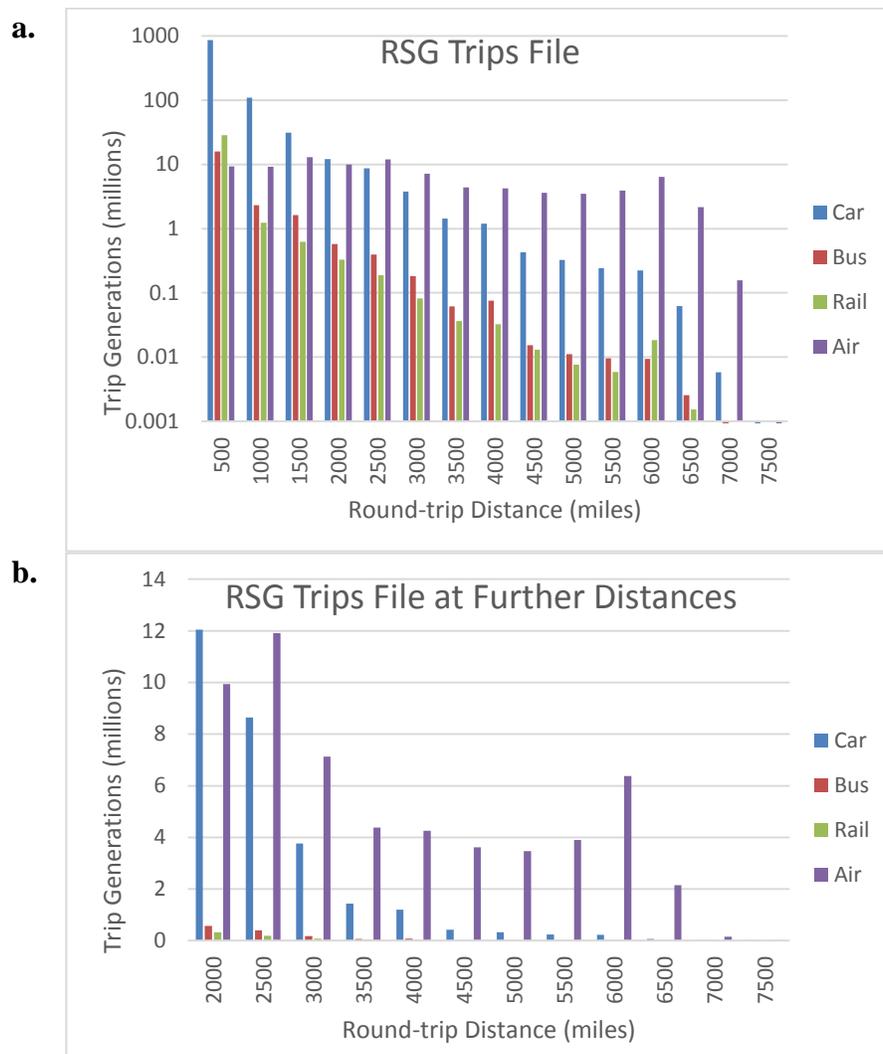


24  
 25

**Figure 1: NUMA boundaries within the continental United States**

26 The generated tours provided in the rJourney set across all trip types are distributed as shown in  
 27 Figure 2. Distances for all modes are measured as round-trip driving distance. All tours consist  
 28 of one outbound and one return trip over the same path. Important aspects to note about this  
 29 distribution are that no round-trips shorter than 100 miles (161 km) are expressed in the rJourney  
 30 tours data set since rJourney only looks at longer-distance trips that involve originating in one  
 31 NUMA and arriving at a distant NUMA. The longer-distance car trips amount to 1.2 trillion

1 VMT, which is 40% of the total 3.0 trillion highway VMT reported for 2010 (Bureau of  
 2 Transportation Statistics, 2011). As expected, car usage largely dominates shorter trips (less than  
 3 or equal to 500 miles, or 805 km), while air travel dominates for longer ranges. Bus and rail  
 4 consistently account for a small portion of all trips. The average party size in a tour is 2.15  
 5 people.



6 **Figure 2: Distribution of rJourney trips for all trip types for a. all distances (shown**  
 7 **logarithmically), and b. further distances**

8 The rJourney set also provides a skim file that includes mode statistics of traveling between most  
 9 possible pairs of NUMAs. These include estimated travel time by car or air, access and egress  
 10 times, traveling toll or cost, and other factors that would influence a traveler's choice of  
 11 transportation mode. Corresponding to these are mode choice and destination choice coefficients.  
 12 In these coefficients, value of travel time for car drivers is \$12/hour (in 2010 dollars). These  
 13 skims and data are used in this research for evaluating the effects of adding a new AV mode.

15

16 **METHODOLOGY**

1 This analysis leverages a subset of rJourney data and models, and uses pre-existing parameters as  
 2 a means to quickly characterize the trip distributions for each mode, while leaving the  
 3 opportunity to add a new mode such as AVs. The subset of data and coefficients were used to  
 4 closely reproduce the rJourney mode choice results, and then a new AV mode was added. For  
 5 this analysis, the model was set up as a nested logit model, where mode choice was a nest within  
 6 an overarching destination choice model.

7 For finding mode choice from each origin to each destination, parameters include direct costs  
 8 (value of time, tolls, and fares), NUMA household density, service frequency, transfer frequency,  
 9 and rail station/airport access and egress penalty. For simplicity, data that are not available to the  
 10 authors, and parameters not significantly influential in mode choice (e.g. with low T-stats) are  
 11 not represented in utility functions as they are in the rJourney model, including household size,  
 12 party size, and number of nights staying. Party size is currently assumed to be 1, and reporting  
 13 below focuses upon VMT and trip-miles, not person-miles traveled.

14 As a result, the model subset does not produce an exact replication of the rJourney tours data set.  
 15 Furthermore, the attempted addition of the AV mode inherently lacks supporting data, already  
 16 necessitating the use of a subset of existing parameters. Although model subset results show a  
 17 similar distribution to that of the rJourney tours data set, air travel in particular was  
 18 underrepresented, showing a correlation of 0.71 overall. To establish a closer representation, a  
 19 strategy for adjusting (or “pivoting”) the results off of the rJourney tours data set is described  
 20 further below in Equations 12 and 13.

22 While future work related to this research will continue to improve upon the rJourney model  
 23 usage, the preliminary exercise discussed in this paper illustrates the kinds of analyses that are  
 24 possible with such a model. These are the mode choice utilities, functions of NUMA  $i$ ,  
 25 destination NUMA  $j$ , and trip purpose  $p$ . Refer to (Federal Highway Administration, 2015) for  
 26 Table 40 that contains the coefficient values and T-stats for each of the trip purposes identified  
 27 by coefficient subscript number.

$$28 \quad V_{car,i,j,p} = (\beta_{11,p}X_{CT,i,j} + C_{OC}X_{D,i,j} + \beta_{10,p}X_{T,i,j})\beta_{1,p} + \gamma_{112,p}d_{500,i,j} + \gamma_{103,p} \cdot 1 \quad (1)$$

29 where

- 30  $X_{CT,i,j}$  = Car travel time from NUMA  $i$  to  $j$ ,  
 31  $X_{D,i,j}$  = Distance in miles from NUMA  $i$  to  $j$ ,  
 32  $X_{T,i,j}$  = Tolls incurred from NUMA  $i$  to  $j$ ,  
 33  $C_{OC}$  = Car operational cost in dollars per mile, \$0.17/mile in initial analysis,  
 34  $d_{500,i,j}$  = Indicator for one-way distance > 500 mi. (805 km) for NUMAs  $i$  and  $j$ , and  
 35  $\beta_{1,p}, \beta_{10,p}, \beta_{11,p}, \gamma_{103,p}, \gamma_{112,p}$  = Coefficients

36

$$V_{bus,i,j,p} = (\beta_{21,p}X_{BT,i,j} + \beta_{10,p}X_{BF,i,j})\beta_{1,p} + ASC_{200,p} + \beta_{209,p}Z_{LD,i} + \beta_{210,p}Z_{LD,i} + \gamma_{215,p}d_{150,i,j} + \gamma_{207,p} \cdot 1 \quad (2)$$

37 where variables remain as defined earlier, and

- 38  $X_{BT,i,j}$  = Bus travel time from NUMA  $i$  to  $j$ ,  
 39  $X_{BF,i,j}$  = Bus fare from NUMA  $i$  to  $j$ ,

- 1  $Z_{LD_i}$  = NUMA  $i$  log density (density is the sum of NUMA  $i$  total households and total  
2 employment divided by NUMA  $i$  square miles),  
3  $d_{150,i,j}$  = Indicator for one-way distance 50 mi. (81 km) to 150 mi. (242 km) from  
4 NUMA  $i$  to  $j$ , and  
5  $\beta_{21_p}, ASC_{200_p}, \gamma_{207_p}, \beta_{209_p}, \beta_{210_p}, \gamma_{215_p}$  = Coefficients.

6

$$V_{rail,i,j,p} = \left( \beta_{31_p} X_{RT,i,j} + \beta_{10_p} X_{RF,i,j,p} + \beta_{32_p} + X_{RX,i,j} + \beta_{33_p} X_{RQ,i,j} + \beta_{34_p} (X_{RA,i,j} + X_{RE,i,j}) + \beta_{35_p} \frac{X_{RA,i,j} + X_{RE,i,j}}{X_{D,i,j}} \right) \beta_{1_p} + ASC_{300_p} + \beta_{309_p} Z_{LD_i} + \beta_{310_p} Z_{LD_j} + \gamma_{315_p} d_{150,i,j} + \gamma_{307_p} \cdot 1 \quad (3)$$

7 where variables remain as defined earlier, and

- 8  $X_{RT,i,j}$  = Rail travel time from NUMA  $i$  to  $j$ ,  
9  $X_{RF,i,j,p}$  = Rail fare for NUMA  $i$  to  $j$ , business fare if “employer” purpose,  
10  $X_{RX,i,j}$  = Rail transfers incurred from NUMA  $i$  to  $j$ ,  
11  $X_{RQ,i,j}$  = Rail frequency for traveling from NUMA  $i$  to  $j$ ,  
12  $X_{RA,i,j}$  = Access time for getting to the rail station for NUMA  $i$  to  $j$ ,  
13  $X_{RE,i,j}$  = Egress time for departing from the rail station for NUMA  $i$  to  $j$ , and  
14  $\beta_{31_p}, \beta_{32_p}, \beta_{33_p}, \beta_{34_p}, \beta_{35_p}, ASC_{300_p}, \gamma_{307_p}, \beta_{309_p}, \beta_{310_p}, \gamma_{315_p}$  = Coefficients.

15

16

$$V_{air,i,j,p} = \left( \beta_{41_p} X_{AT,i,j} + \beta_{10_p} X_{AF,i,j,p} + \beta_{42_p} X_{AX,i,j} + \beta_{43_p} \sqrt{X_{AQ0,i,j} + \frac{X_{AQ1,i,j}}{2} + \frac{X_{AQ2,i,j}}{10}} + \beta_{46_p} X_{OT,i,j} + \beta_{44_p} (X_{AA,i,j} + X_{AE,i,j}) + \beta_{45_p} \frac{X_{AA,i,j} + X_{AE,i,j}}{X_{D,i,j}} \right) \beta_{1_p} + ASC_{400_p} + \beta_{409_p} Z_{LD_i} + \beta_{410_p} Z_{LD_j} + \gamma_{415_p} d_{150,i,j} + \gamma_{407_p} \cdot 1 \quad (4)$$

17 where variables remain as defined earlier, and

- 18  $X_{AT,i,j}$  = Air travel time from NUMA  $i$  to  $j$ ,  
19  $X_{AF,i,j,p}$  = Airfare for NUMA  $i$  to  $j$ , business fare if “employer” purpose  
20  $X_{AX,i,j}$  = Air transfers incurred from NUMA  $i$  to  $j$ ,  
21  $X_{AQ0,i,j}, X_{AQ1,i,j}, X_{AQ2,i,j}$  = Air service frequency for direct flights from NUMA  $i$  to  $j$  for  
22 direct flights, flights with one transfer, and flights with two transfers  
23  $X_{OT,i,j}$  = Air on-time rate for flights from NUMA  $i$  to  $j$ ,  
24  $X_{AA,i,j}$  = Access time for getting to the airport for NUMA  $i$  to  $j$ ,  
25  $X_{AE,i,j}$  = Egress time for departing from the airport for NUMA  $i$  to  $j$ , and  
26  $\beta_{41_p}, \beta_{42_p}, \beta_{43_p}, \beta_{46_p}, \beta_{44_p}, ASC_{400_p}, \gamma_{407_p}, \beta_{409_p}, \beta_{410_p}, \gamma_{415_p}$  = Coefficients.

27

1 Coefficients are drawn from the rJourney model. In this analysis, the data series pertaining to  
 2 cost of traditional vehicle operation was drawn using the estimated value of \$0.17/mile. Because  
 3 this model focuses on mode choice at the time of travel, the ownership cost is not incorporated as  
 4 in (AAA, 2015). While this serves as a rough estimate, it would be possible with further research  
 5 to better quantify operation costs as a function of each trip-maker's annual driving distance. The  
 6 results of the initial analysis shall inform how this function can be evaluated in the future.

7 The rJourney data includes 285,579 NUMA pairs that lack car mode statistics. These NUMA  
 8 pairs and corresponding trips are omitted from this analysis because of lack of car-distance data,  
 9 which is needed in estimating the distance of all modes of travel.

10 The introduction of AVs into the model presents challenges in implementation, mainly in that the  
 11 rJourney models and results obviously do not consider the presence of AVs, and little data  
 12 currently exist to specifically justify model parameters. For AVs to be considered as a new  
 13 modal alternative, existing data and coefficients are leveraged to arrive at a "best-guess"  
 14 parameter set. In initially designing how the new modal alternative is integrated, the following  
 15 assumptions are made: a) a future time is modeled where AVs cost on average \$0.20 per mile to  
 16 operate; b) the \$6.00 value of time to the occupant is half of that of traditional car; and c) all  
 17 other parameters are that of traditional cars. The utility function for the AV mode choice is then:

$$18 \quad V_{AV_{i,j,p}} = \left( \frac{\beta_{11,p}}{2} X_{CT_{i,j}} + C_{AC} X_{D_{i,j}} + \beta_{10,p} X_{T_{i,j}} \right) \beta_{1,p} + \gamma_{112,p} d_{500_{i,j}} + \gamma_{103,p} \cdot 1 \quad (5)$$

19 where variables remain as defined earlier, and

20  $C_{AC}$  = AV operational cost in dollars per mile (\$0.20 per mile for the initial analysis).  
 21

22 Probability splits for mode choice given each origin, destination, and purpose are then found:

$$23 \quad P_{m|i,j,p} = \frac{e^{V_{m,i,j,p}}}{\sum_{m \in M} e^{V_{m,i,j,p}}} \quad (6)$$

24 where

25  $V_{m,i,j,p}$  = Utility function for mode  $m$ , from NUMA  $i$  to  $j$  for purpose  $p$ ,

26  $M$  = Set of all modes being analyzed.  
 27

28 The destination choice portion of the model incorporates the logsum of the mode choice utility  
 29 functions along with indicators pertaining to distance ranges, as well as household and  
 30 employment counts that come from the NUMA zone data set. Again, for simplicity as well as  
 31 lack of access to data, parameters that are not strongly influential in mode choice and destination  
 32 choice were omitted. However, as noted later, preliminary results are helpful in identifying  
 33 investigations of the model in future work. As an observation, the rJourney model does not  
 34 include gross domestic product per NUMA zone, which could possibly be helpful for future  
 35 efforts in better representing destination attractiveness.

36 The following represents the destination choice model, using coefficients drawn from (Federal  
 37 Highway Administration, 2015) Table 39. Future research efforts will evaluate how more of the  
 38 rJourney destination-choice model can be leveraged for arriving at an improved representation of  
 39 attractiveness.

$$1 \quad LOGSUM_{i,j,p} = \log \sum_{m \in M} e^{V_{m,i,j,p}} \quad (7)$$

$$2 \quad D_{i,j,p} = \alpha_{1,p} LOGSUM_{i,j,p} + \alpha_{2,p} \log(X_{D,i,j}) + (\alpha_{3,p} + \alpha_{6,p}) \left( \frac{X_{D,i,j}}{100} \right)^2 + \alpha_{8,p} d_{100,i,j} +$$

$$3 \quad \alpha_{9,p} d_{150,i,j} + \alpha_{10,p} d_{250,i,j} + \alpha_{11,p} d_{500,i,j} + \alpha_{12,p} d_{1000,i,j} + \alpha_{13,p} d_{1500,i,j} +$$

$$4 \quad \alpha_{14,p} d_{2000,i,j} + \alpha_{15,p} d_{DU,j} + \alpha_{16,p} d_{DR,j} + \alpha_{17,p} d_{ODU,i,j} + \alpha_{18,p} d_{ODR,i,j} \quad (8)$$

$$5 \quad P_{j|i,p} = \frac{e^{D_{i,j,p} + \theta_{19,p} \log S_{j,p}}}{\sum_k^N e^{D_{i,k,p} + \theta_{19,p} \log S_{k,p}}} \quad (9)$$

6 where variables remain as defined earlier, and

7  $S_{j,p}$  = Size for NUMA  $j$ , purpose  $p$ . This leverages employment, land use, and education  
 8 data as identified here, selected by purpose, multiplied with given log-coefficients  
 9 and summed together:

Coeff.	1-Personal	2-Visit	3-Leisure	4-Commute	5-Employer
1	Medical	Accommodation	Accommodation	Other service	Accommodation
$\log \alpha_{20,p}$	Entertainment	Entertainment	Entertainment	Entertainment	Entertainment
$\log \alpha_{21,p}$	Other service	Medical	Other service	Retail + wholesale	Retail + wholesale
$\log \alpha_{22,p}$	All other empl	All other empl	All other empl	All other empl	All other empl
$\log \alpha_{23,p}$	University enrollment	Households	Park area (sqm)	University enrollment	University enrollment

10

11  $d_{100,i,j}, d_{150,i,j}, d_{250,i,j}, d_{500,i,j}, d_{1000,i,j}, d_{1500,i,j}, d_{2000,i,j}$  = Indicators for respective  
 12 distance ranges from NUMA  $i$  to NUMA  $j$ ,  
 13

14  $d_{DU,i}, d_{DR,j}$  = Indicators for destination NUMA  $j$  urban and rural indications,  
 15 respectively. Urban is defined to have a density of  $\geq 1000$ , and rural is defined to  
 16 have a density of  $\leq 25$ ,

17  $d_{ODU,i,j}, d_{ODR,i,j}$  = Indicators for both origin and destination NUMAs  $i$  and  $j$  having both  
 18 urban or rural indications, respectively,

19  $\theta_{19,p}$  = Size multiplier for purpose  $p$ ,

20  $N$  = Number of NUMAs being analyzed, and

21  $\alpha_{1,p}, \alpha_{2,p}, \alpha_{3,p}, \alpha_{6,p}, \alpha_{8,p}, \alpha_{9,p}, \alpha_{10,p}, \alpha_{11,p}, \alpha_{12,p}, \alpha_{13,p}, \alpha_{14,p}, \alpha_{15,p}, \alpha_{16,p},$   
 22  $\alpha_{17,p}, \alpha_{18,p}$  = Coefficients.

23

24 From this, joint mode/destination choice probabilities are found by combining the mode choice  
 25 and destination choice conditional probabilities for each origin/destination pair:

$$26 \quad P_{m,j|i,p} = P_{j|i,p} P_{m|i,j,p} \quad (10)$$

27 The last step is to use the joint probabilities to distribute trips that are generated from each origin  
 28 across all modes and destinations. For this analysis, the number of generated trips are obtained  
 29 from the rJourney tours data that was simulated from generated households across the United  
 30 States. Because the idea is to study how mode choice and destination choice changes with the  
 31 introduction of AVs, the mode choices represented in the rJourney tours dataset are ignored to  
 32 allow the same number of generated tours to be redistributed according to the post-AV  
 33 introduction model. The modeled tours are defined as:

$$34 \quad T_{i,j,m,p} = P_{m,j|i,p} \sum_k^N R_{i,k,p} \quad (11)$$

1 where variables remain as defined earlier, and

2  $R_{i,k,p}$  = Number of trips in the rJourney trips dataset from origin NUMA  $i$  to destination  $k$   
 3 for purpose  $p$ .

4  
 5 As mentioned earlier, the model subset does not produce an exact replication of the rJourney  
 6 tours data set. The authors therefore “pivoted” modeled tours  $T_{i,j,m}$  with the rJourney tours data  
 7 set  $R_{i,j,m}$  to arrive at  $T^*_{i,j,m}$  as follows:

$$8 \quad T^*_{i,j,m \neq AV} = \frac{T_{i,j,m}^{w/AV}}{T_{i,j,m}^{w/o AV}} \times R_{i,j,m}^{w/o AV}, \quad m \in \{\text{car, bus, rail, air}\} \quad (12)$$

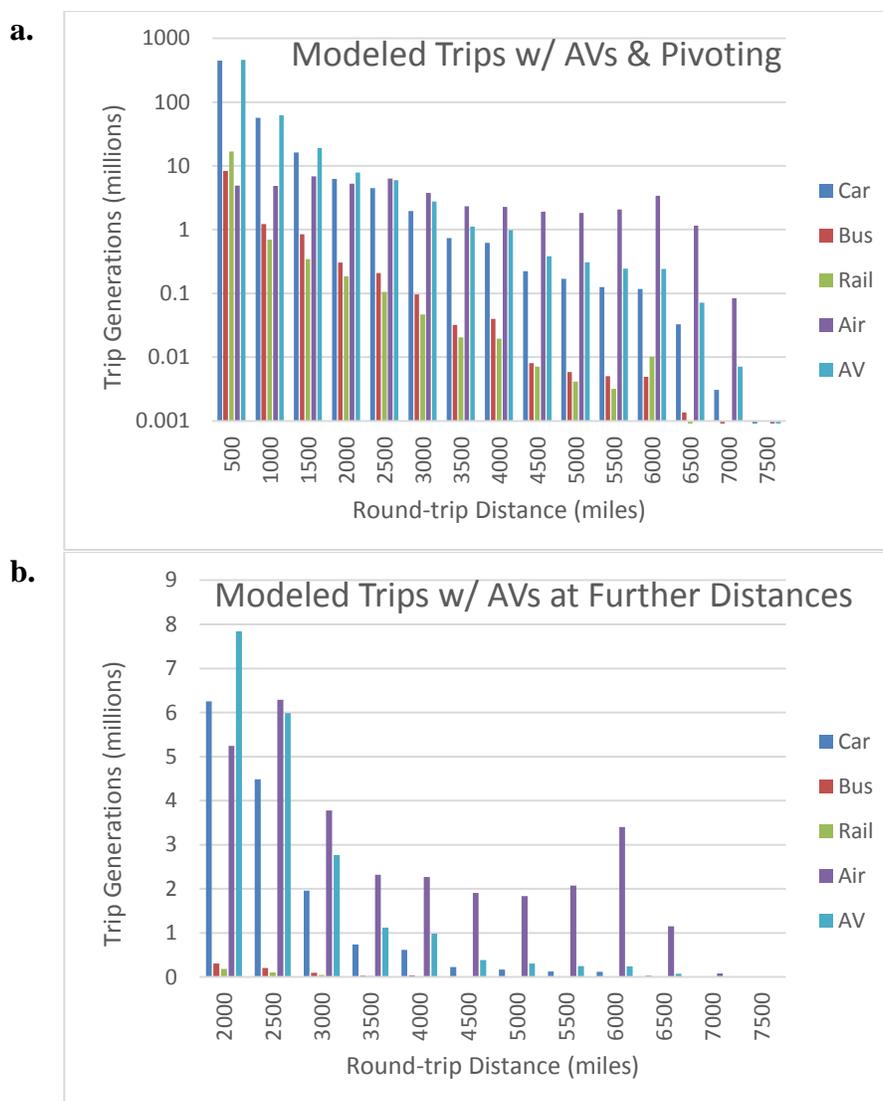
$$9 \quad T^*_{i,j,m=AV} = \frac{T_{i,j,m=AV}^{w/AV}}{T_{i,j,m=car}^{w/o AV}} \times R_{i,j,m=car}^{w/o AV} \quad (13)$$

10 Computation of this model can be classified as a big data problem. In representing the expanded  
 11 1.17 billion trips, 38 million rJourney trip records over 2 million NUMA pairs constitute 4 GB of  
 12 data, and files representing the intermediate and final computational results for all trip purposes  
 13 amount to gigabytes of additional storage requirements. The Python Pandas library is used to  
 14 perform the computations along with HDF5 file format support. With a number of considerations  
 15 made for vectorized matrix operations, the entire set takes on the order of 30 minutes to run on a  
 16 modern, high-end computer. Operations that read and write files from flash storage account for  
 17 over half of the run time.

## 18 RESULTS

19 Figure 3 shows the resulting number of trips after the AV mode is added to the initial model as  
 20 described in the methodology. This can be compared with the tours data set distribution in Figure  
 21 2. A notable observation is that the distribution of AV trips tracks the distribution of traditional  
 22 vehicles with an increase in mode share at further distances. This can be attributed to high  
 23 correlation of several parameters that are represented in the traditional vehicles. The key  
 24 differences with AVs are the increase in operating cost, and reduced value of time driving. With  
 25 similarity in parameters, this mode split is influenced by the independence from irrelevant  
 26 alternatives (IIA) property (or, noted many times in the literature as the “red bus/blue bus  
 27 paradox”) inherent in multinomial logit models. This property causes highly correlated inputs to  
 28 be treated as independent, which creates an artificial demand that may not necessarily happen in  
 29 reality. The high degree of correlation and presence of IIA can best be addressed by creating a  
 30 nest (e.g. “personal vehicles”) that contains both of the AV and car results, an area for future  
 31 work.

32



1 **Figure 3: Number of trips from the mode choice/destination choice analysis, all purposes,**  
 2 **at a. all distances (shown logarithmically), and b. further distances**

3 There are two notable outcomes that offer insight on the possible effects of AV introduction to  
 4 the market, as well as a shift in destination choice. First, results show that the introduction of  
 5 AVs deeply cuts into the number of trips that had formerly been air trips. See the first two sets in  
 6 Table 1 for results in terms of shorter and longer trips (e.g. < 500 miles (805 km) versus  $\geq$  500  
 7 miles). As largely influenced by the  $\gamma_{112,p}$  coefficient as well as travel time, trips over 500 miles  
 8 in length are penalized because of the negative “captivity factor” of remaining in a car for a long  
 9 period of time possibly over several days. It is assumed in this model that this disutility would be  
 10 similar for AVs as it would be for traditional cars. Note that in Table 1, “Car+AV” is shown as a  
 11 means to represent respective totals of personally owned vehicles.

12 Second, among traditional cars and new AVs, more destinations are chosen after introduction of  
 13 AVs that are further in distance from origins. When looking at the long-distance personal vehicle  
 14 travel represented in the model, the 3.0 trillion highway VMT reported for 2010 (Bureau of  
 15 Transportation Statistics, 2011) increases to 3.1 trillion. However, if all modes are considered,

1 the trend is reversed, possibly because of the severe reduction of air trips that dominate the  
 2 longer-distance trips. The third set in Table 1 shows a change in distribution across overall trip  
 3 distances. For both pre- and post-AV introduction the model uses the same number of trip  
 4 generations per NUMA per trip purpose. The significant decrease of air travel may be a  
 5 consequence of the aforementioned IIA property. In addition to treating cars and AVs as a single  
 6 nest, further work on characterizing VOTT and operating cost, as well as specifying additional  
 7 factors in the destination-choice portion of the model may have the outcome of evolving how trip  
 8 distances are biased among closer and further long-distance trips.

9 **Table 1: Trip mode choice impact of AV introduction for all trip purposes**

TOURS BY MODE	AV Market Penetration	Car+AV < 500 mi. round trip	Car+AV ≥ 500 mi. round trip	Air < 500 mi. round trip	Air ≥ 500 mi. round trip
Before AV	0%	860.5 M	168.8 M	9.3 M	79.5 M
After AV	51%	906.9 M	189.0 M	4.9 M	42.0 M
% change	-	105.4%	112.0%	52.9%	52.8%

10

VEHICLE- MILES	Car+AV < 500 mi. round trip	Car+AV ≥ 500 mi. round trip	Car+AV Total	Air < 500 mi. round trip	Air ≥ 500 mi. round trip	Air Total
Before AV	400.8 B	821.0 B	1,221 B	6.4 B	437.9 B	444.3 B
After AV	425.2 B	913.7 B	1,339 B	3.4 B	232.3 B	235.7 B
% change	106.1%	111.3%	109.6%	52.9%	53.0%	53.0%

11

TOURS FOR ALL MODES	Tours < 500 mi. one way	VMT for tours < 500 mi.	Tours ≥ 500 mi. one way	VMT for tours ≥ 500 mi.
Before AV	914.1 M	422.4 B	256.1 M	1,294 B
After AV	937.0 M	437.1 B	235.2 M	1,165 B
% change	102.5%	103.5%	91.8%	90.0%

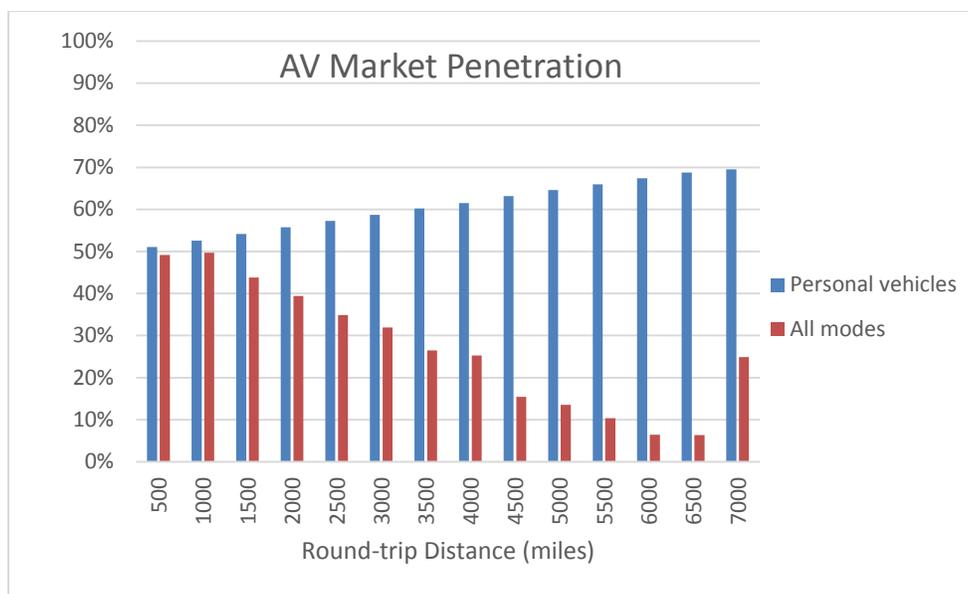
12

AIRLINE REVENUE	Tours < 500 mi. round trip	Tours ≥ 500 mi. round trip	Total revenue
Before AV	\$16.0 B	\$159.1 B	\$175.1 B
After AV	\$8.4 B	\$83.9 B	\$92.3 B
% change	52.7%	52.7%	52.7%

13

#### 14 *Market Penetration*

15 The degree that AVs penetrate the market varies according to trip distance. Figure 4 shows  
 16 market penetration both for AVs among the personal vehicle modes (e.g. car and AV), and also  
 17 AVs among all mode choices. With respect to personal vehicles, the market penetration increases  
 18 as distance increases because of the significance of lower VOTT. However, air travel continues  
 19 to be preferred for longer distances and results in the AV mode share diminishing at further  
 20 distances. The deviation in penetration for the 7000-mile bin is likely a result of fewer trip  
 21 samples for that furthest distance.



1  
2 **Figure 4: Penetration of AVs among personal vehicles (car+AV) and all modes**

3 *Passenger Airline Sales*

4 Given that large-scale introduction of AVs has not yet happened and that no data can be  
5 collected directly from AV usage today, a model such as this rJourney subset with AVs added as  
6 a new mode can be helpful in roughly estimating market effects that could result from the  
7 widespread introduction of AVs. One question that can be addressed with this model is how  
8 much revenue the airline industry can possibly lose due to more travelers choosing AVs over air  
9 travel. The rJourney data set gives airfare estimates in USD for all NUMA pairs that have  
10 suitable access to airports served by commercial passenger carriers. The fourth set in Table 1  
11 shows estimated airline sales before and after the addition of AVs for all modeled trips. Note that  
12 because these are based upon cost to the traveler, these sales figures include airport taxes.

13 In this result, the percent changes between sales between shorter and longer long-distance trips  
14 are similar. This is counterintuitive because of the idea that AVs should have a more significant  
15 attractiveness for shorter trips and thus cut more into the shorter distance market. It may be here  
16 that the model is dominated by the IIA property in adding AVs as a separate mode rather than as  
17 a car+AV “personal vehicle” nest. Additionally, with refinements in the mode choice and  
18 destination choice models the split may improve in accuracy.

19 *AV Parameter Sensitivity*

20 As mentioned earlier, the parameters and assumptions given to AVs are largely unknown and  
21 must be estimated. Two notable parameters include cost of operating the vehicle, as well as  
22 personal VOTT. (Another parameter that is relevant but not yet analyzed includes a more  
23 pronounced representation of the 500-mile captivity factor, which may be different for car  
24 drivers than it is for AV passengers.) A thorough analysis should offer a set of scenarios that  
25 span a range of expected operational costs and personal VOTT, given the targeted years,  
26 expected AV market penetration, and socioeconomic classes of trip-makers that are being  
27 analyzed.

1 To further understand the sensitivity of these variables on the resulting mode split and  
2 destination choice, six new scenarios are created for the “leisure” trip purpose. Scenarios are:

Scenario	Oper. Cost (\$/mile)	VOTT (\$/hr)	Notes
A	\$0.20	\$6.00	Base case
B	\$0.10	\$6.00	Operating cost is cheaper
C	\$0.50	\$6.00	Operating cost is more expensive
D	\$0.20	\$3.00	VOTT is decreased
E	\$0.20	\$9.00	VOTT is increased
F	\$1.65	\$6.00	AVs are modeled as shared vehicles

3 Recall that dollar amounts are expressed in year 2010 dollars. The scenario of AVs having the  
4 same operating cost and VOTT of cars has been omitted because there would be no distinction  
5 between the car and AV modes. Scenario F in particular has been included as a hypothetical  
6 scenario to roughly model all AVs on the roadways as shared autonomous vehicles (SAVs).  
7 With SAVs, passengers do not own their vehicles, but rather pay per mile for travel in a  
8 borrowed vehicle that others can use for other trips, in this case \$1.65 per mile. As more data  
9 emerges, an improved model would likely offer SAVs as a mode choice that is separate from  
10 personally-owned AVs. Table 2 shows the results of each of these scenarios.

11 **Table 2: Trip generations with varied AV parameters, for “leisure” trip purpose**

Mode	Dist.	Scenario	A	B	C	D	E	F
Car+AV	Trips < 500 mi.	Before AV	253.5 M					
		After AV	271.5 M	267.2 M	279.4 M	268.1 M	274.3 M	280.3 M
		% change	107.1%	105.4%	110.2%	105.7%	108.2%	110.6%
	Trips ≥ 500 mi.	Before AV	55.7 M					
		After AV	63.4 M	65.7 M	57.8 M	65.3 M	61.7 M	46.7 M
		% change	113.8%	118.0%	103.7%	117.2%	110.7%	83.9%
Air	Trips < 500 mi.	Before AV	2.30 M					
		After AV	1.23 M	1.20 M	1.28 M	1.21 M	1.24 M	1.40 M
		% change	53.2%	52.1%	55.7%	52.3%	54.0%	60.9%
	Trips ≥ 500 mi.	Before AV	18.11 M					
		After AV	9.65 M	9.43 M	10.16 M	9.47 M	9.81 M	11.17 M
		% change	53.3%	52.1%	56.1%	52.3%	54.2%	61.7%

12

13 In observing Scenarios B, A, and C in order of increasing operation cost, it can be seen that  
14 closer trip generations increase and longer trips decrease because of the significance of operating  
15 cost on longer trips. Meanwhile, the cut into the air market decreases as the operation cost  
16 increases. In the rough SAV Scenario F, the results coincide with a similar trend, where longer  
17 distance trips are more significantly curtailed. For Scenarios D, A, and E in order of increasing  
18 VOTT, a similar phenomenon occurs. The reduction of air trips decreases as VOTT increases.

19 In all cases, the variations that are evaluated do not show an extreme difference in outcomes. In  
20 considering travelers’ expenses and VOTT, it is possible to reason that the results should be  
21 more distinct. Two factors may be dominating the models as these inputs are varied. First, the  
22 addition of the AV mode as an independent choice may be an inaccurate model structure that is  
23 highly correlated and represented too significantly in the results. As mentioned earlier, it may be

1 more appropriate to treat cars and AVs as a “personal vehicle” nest and estimate the correlation  
2 that is to be expected among the mode choices of hypothetical travelers. Second, the  
3 representation of AVs in the model is somewhat indistinct from cars, as few parameters exist to  
4 offer better differentiation. The addition of new parameters to the car and AV modes can help  
5 with this and reduce the correlation between the two modes.

## 6 **CONCLUSIONS**

7 This preliminary research has leveraged the nationwide, inter-regional rJourney travel demand  
8 model for estimating impacts of future introduction of AVs. While models such as rJourney had  
9 been created in efforts to better understand intercity travel and offer enhanced capabilities for  
10 planning, little research today addresses the introduction of AVs in such models. This effort  
11 therefore is intended as an early investigation in allowing AVs to be treated as a viable mode  
12 within the same class of modeling framework.

13 A subset of the rJourney model was implemented to predict mode and destination choice of long-  
14 distance travelers with AVs fully considered as a viable mode alternative. The integration of  
15 AVs into the model includes some of the preexisting car-specific parameters while employing  
16 higher cost of vehicle operation and reduced VOTT that are expected of AVs within the  
17 oncoming years.

18 These preliminary results are solely based upon the rJourney results after adding AVs as a  
19 distinct mode. First, in the initial scenario where the cost of ownership and operation for an AV  
20 is assumed to be \$0.20 per mile and VOTT is half of that of car travel, air travel trip generation  
21 for shorter and further long-distance trips is cut to 53% of the original value, largely replaced  
22 with an increased demand for AVs. It follows that commercial passenger air carriers may benefit  
23 from understanding the implications of AV introduction, perform research on the problem, and  
24 target their services and marketing accordingly. Second, with the introduction of AVs, trips  
25 among cars and AVs favor further distances for trips; but trips appear to favor closer distances  
26 when considering all modes. Here, the total number of car and AV trips increases by 5% for  
27 shorter-distance trips and 12% for longer-distance trips; however, among all modes there is a  
28 6.7% reduction in trip-miles. It can be surmised that federal and state DOTs should further  
29 investigate possible needs for upgrading interregional infrastructure in preparation for specific  
30 levels of AV market penetration.

31 For further future research, it will be prudent to find and analyze data that is collected in the field  
32 as AVs emerge, including willingness to pay, technology cost, travel time savings, and  
33 socioeconomic aspects of AV usage. Along the way, it would be helpful to have data on public  
34 resistance and acceptance to aid in estimating future AV market penetration. The model would  
35 also possibly benefit from nesting together the car and AV modes to account for correlation  
36 among the two modes. These are all factors that can help to establish a more accurate,  
37 nationwide AV mode and destination-choice model that reflects current and future trends.

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