

1 **MANAGEMENT OF A SHARED, AUTONOMOUS, ELECTRIC VEHICLE FLEET:**
2 **IMPLICATIONS OF PRICING SCHEMES**

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20 **ABSTRACT**

21 This paper models the market potential of a fleet of shared, autonomous, electric vehicles (SAEVs)
22 by employing a multinomial logit mode choice model in an agent-based framework and
23 different fare settings. The mode share of SAEVs in the simulated mid-sized city (modeled
24 roughly after Austin, Texas) is predicted to lie between 14 and 39%, when competing against
25 privately-owned, manually-driven vehicles and city bus service. This assumes SAEVs are priced
26 between \$0.75 and \$1.00 per mile, which delivers significant net revenues to the fleet
27 owner-operator, under all modeled scenarios, assuming 80-mile-range electric vehicles and
28 remote/cordless Level II charging infrastructure and up to \$25,000 of per-vehicle
29 automation costs. Various dynamic pricing schemes for SAEV fares show that specific fleet
30 metrics can be improved with targeted strategies. For example, pricing strategies that attempt
31 to balance available SAEV supply with anticipated trip demand can decrease average wait
32 times by 19 to 23%. However, tradeoffs also exist within this price-setting: fare structures that
33 favor higher revenue-to-cost ratios (by targeting high-value-of-travel-time [VOTT] travelers)
34 reduce SAEV mode shares, while those that favor larger mode shares (by appealing to a wider
35 VOTT range) produce lower payback.

36 **KEYWORDS**

37 Carsharing, autonomous vehicles, electric vehicles, mode choice, travel costs, taxis
38

39 **INTRODUCTION**

40 Technology is quickly changing the landscape of urban transportation. With mobile computing
41 enabling the fast rise of the shared-use economy, carsharing is emerging as an alternative mode
42 that is more flexible than transit but less expensive than traditional (private-vehicle) ownership.
43 Electric vehicle (EV) sales are on the rise with plug-in EVs' market share growing from 0.14%
44 in 2011 to 0.67% in 2014 (Plug in America 2015). Growing plug-in EV adoption should be
45 helpful to most regions in achieving air quality standards for ozone and particulate matter, and
ultimately greenhouse gases. Motivated by roadway safety and the growing burden of
congested urban driving, automated driving technologies are emerging and private
purchases of self-driving vehicles may be possible by 2020 (Bierstadt et al. 2014).

46 There are natural synergies between shared AV (SAV) fleets and EV technology. SAVs resolve
47 the practical limitations of today’s non-autonomous EVs, including traveler range anxiety, access
48 to charging infrastructure/special outlets, and charge-time management. A fleet of shared
49 autonomous electric vehicles (SAEVs) relieves such concerns, by managing range and charging
50 activities based on real-time trip demand and established charging-station locations, as
51 demonstrated in Chen et al. (2016). However, when SAEVs make their debut in cities, these
52 vehicles will not exist in a vacuum. SAEVs will be competing against existing modes (private
53 owned vehicles, transit, and non-motorized modes) for trip share. In this paper, a mode choice
54 model is added to Chen et al.’s (2016) agent-based framework in order to anticipate SAEV market
55 shares in direct competition with other modes. A fleet of 80-mile-range SAEVs is paired with
56 Level II charging infrastructure to deliver relatively fleet operations, and a variety of pricing
57 strategies are employed while examining the shifting mode shares.

58 **PRIOR RESEARCH**

59 Recent research has examined the operations of self-driving vehicles in a shared setting, primarily
60 focusing on metrics like empty-vehicle miles traveled (VMT), average wait times, and private
61 vehicle replacement rates (Kornhauser et al. [2013], Fagnant and Kockelman [2014], Spieser et al.
62 [2014], ITF [2015], Chen et al. [2016], etc.). Very few have yet simulated AV effects in
63 competition with other modes of travel.

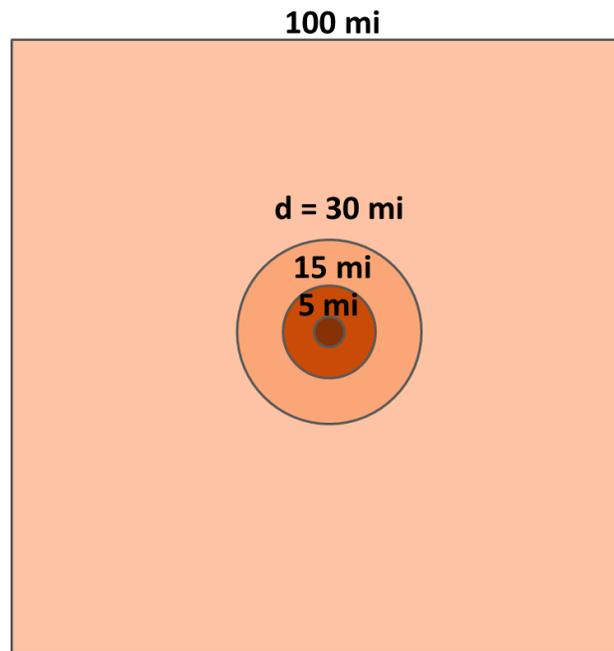
64 Levin and Boyles (2015) recently simulated mode choice of privately-owned AVs (versus transit,
65 private car travel, and walk/bike) with a fixed trip table for a small (downtown) section of Austin,
66 Texas. Their model allows such AVs to strategically re-position themselves to avoid high parking
67 fees (while incurring added fuel costs, but no traveler time costs), and uses dynamic traffic
68 assignment over a 2-hour peak (morning) period. Their special test cases showed transit demand
69 falling as more user classes (segmented by value of travel time [VOTT]) had access to AVs, with
70 61% of low-VOTT travelers decreasing their transit use. They allowed link capacities to rise as a
71 function of the proportion of AVs on each link, so congestion did not worsen as the number of
72 vehicle trips rose sharply (due to empty-vehicle parking repositioning). Childress et al. (2015) used
73 Seattle, Washington’s activity-based travel model (including short-term travel choices and long
74 term work-location and auto-ownership choices) to anticipate AV technology impacts (from higher
75 roadway capacities, lowered VOTTs, reduced parking costs, and increased car-sharing) on
76 regional travel patterns. Their model estimated that higher income households are more likely to
77 choose the AV mode, as expected (since the technology is costly and alternate use of in-vehicle
78 time VOTT reductions for higher-VOTT travelers are likely to be more significant). With SAVs
79 priced at \$1.65 per mile (reflecting costs of current ride-sharing taxi services, like Lyft and Uber),
80 drive-alone trips were predicted to fall by one-third and transit shares rose by 140%, as households
81 released traditional vehicles and acquired AVs or turned to SAVs along with other travel options,
82 since they were no longer “tied” to the fixed cost (and round-trip restrictions) of vehicle ownership
83 and storage.

84 The above two simulations are largely limited to private AV ownership (except for one scenario
85 [out of four] in Childress et al. [2015]). Furthermore, their mode choice simulations assumed fixed
86 prices/costs for AV (and SAV) use. Due to the variable nature of SAV availability and user wait
87 times, as well as different costs associated with empty VMT for refueling SAVs and passenger
88 pick-up, SAV pricing may best be “smart-priced” to improve fleet performance metrics. The agent-
89 based framework employed in this paper allows for mode choice in the context of each trip (based

90 on a trip's time-of-day [to allow for "surge pricing" during peak demand periods] and distance,
91 and its traveler's VOTT) and follows SAEV fleet utilization through a series of simulated travel
92 days to appreciate the effects of various dynamic pricing strategies on mode shares and SAV trip-
93 making behaviors.

94 **METHODOLOGY**

95 The model in this paper builds off of Chen et al.'s (2016) discrete-time agent-based model,
96 which examines the operations of SAEVs and conventionally-fueled SAVs serving roughly 10%
97 of all trips in a 100-mile by 100-mile region. The simulation is gridded to quarter-mile by
98 quarter-mile trip generation and service cells, as shown in Figure 1. Similar to Chen et al. (2016),
99 the trip generation process used here produces each trip based on an average daily rate for each
100 cell (which depends on the local population density, and thus the Euclidean distance to the
101 regional centerpoint in this idealized region), then assigns the destination cell based on trip
102 distance (drawn from the U.S. 2009 National Household Travel Survey's [NHTS's] distribution).
103 Average daily trip rates (as shown in Table 1) represent 100% of trips in the simulated region, with rates
104 roughly following the population densities and trip generation rates of Austin, Texas' travel demand
105 model. Here, a multinomial logit (MNL) mode choice model is added to the agent-based model to
106 allow all trips in the region to choose among private vehicle, transit, and SAEV modes. Trips less
107 than 1 mile in distance (under the NHTS 2009 distribution) are not studied here, since such
108 travelers may often prefer to walk. Since most walking trips in the U.S. are under 1 mile in
109 length, and bike trips are few in the U.S. (Santos et al. 2011), non-motorized modes are not
110 simulated here.



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Figure 1. Regional Zones System

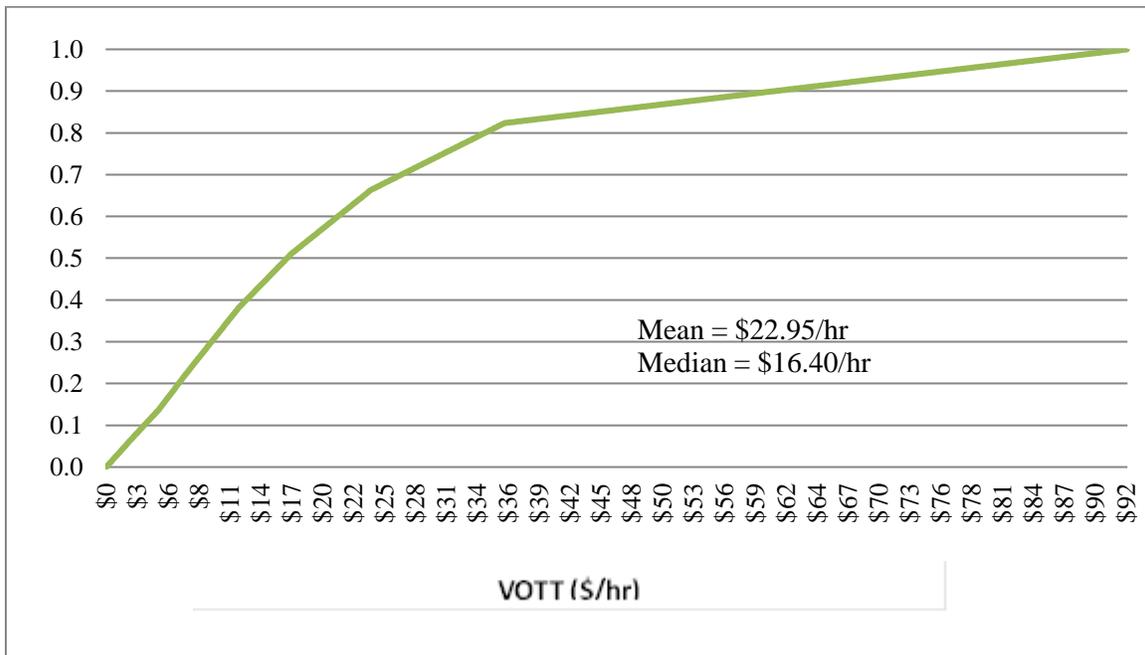
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Table 1. Total (Motorized) Trip Generation Rates and Travel Speeds by Zone

	Population Density (persons/mi ²)	Avg Trip Gen. Rate (trips/cell/day)	SAEV Travel Speed (mi/hr)	
			Peak	Off-Peak
Downtown	7500-50,000	1287	15	15
Urban	2000-7499	386	24	24
Suburban	500-1999	105	30	33
Exurban	<499	7	33	36

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The amount of money travelers are willing to pay to save travel time and distance varies with each traveler, trip type, day of week, and even driver’s state of mind. To relate each trip to an individual traveler and his/her mode choice in this model, a VOTT is generated for each trip, based on trip purposes and wage rates (per hour). According to the 2009 NHTS, 18.7% of person-trips per household are for work and work-related business trips (Santos et al. 2011). The other 81.3% of trips (for shopping, family/personal errands, school, worship, social, and recreational activities) are combined here, as non-work. After randomly assigning a trip purpose, an income is assigned for the individual traveler based on US Census (2009) data on personal income of individuals residing inside metropolitan areas. SAVs presumably operate more efficiently in densely developed locations than sparsely populated areas (Burns et al. 2013, Fagnant and Kockelman 2015), and individual incomes in metro areas tend to be higher than those in rural areas (with personal incomes averaging 33 percent higher, according to US Census [2009]). Hourly wages used in the model here are derived from 2009 Census data on personal income of this living inside metropolitan areas (an average of \$48,738 per person per year), and converted to an hourly wage assuming 2000 work hours per year.(US Census 2009).Using USDOT (2011) guidelines, VOTT is assumed to be 50% of hourly wage for personal trips and 100% of hourly wage for business/work trips, yielding Figure 2’s VOTT distributions.

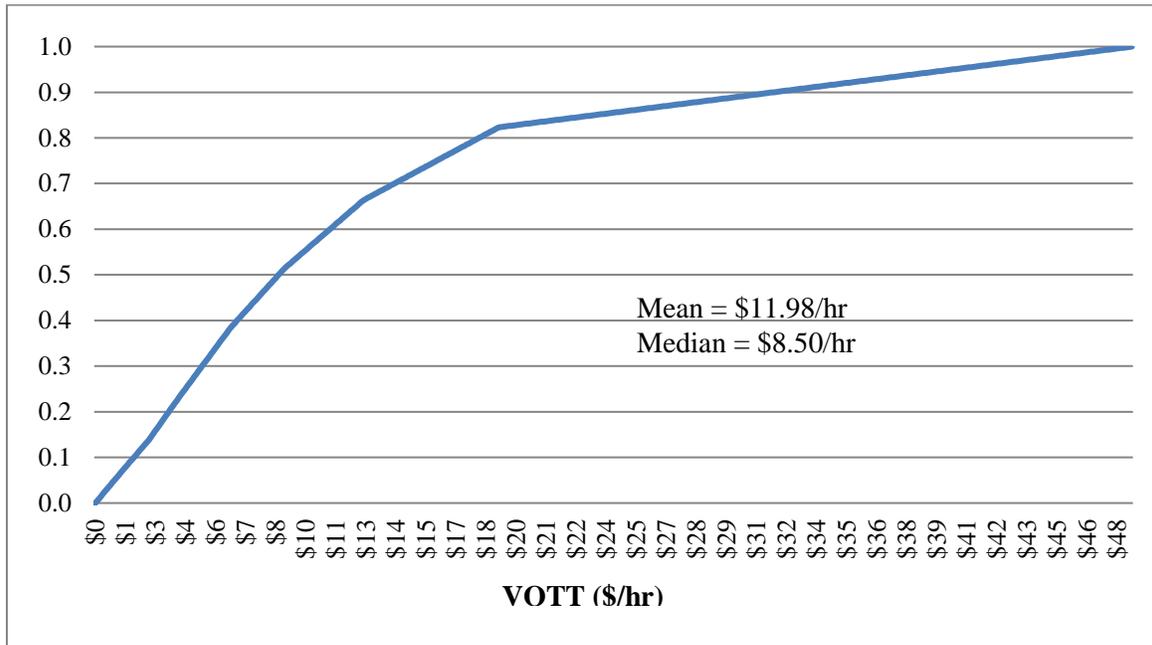


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Figure 2a. Work Trips

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Figure 2b. Non-Work Trips

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Figure 2. VOTT Distributions for Work (2a) and Non-Work (2b) Trips

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In an MNL model, the probability of an individual choosing an alternative is assumed to monotonically increase with that alternative's systematic utility (Koppelman and Bhat 2006), assuming all other modes' attributes remain constant, and can be expressed as the following:

142

$$\Pr(i) = \frac{\exp(V_i)}{\exp(V_{PV}) + \exp(V_{Transit}) + \exp(V_{SAEV})} \quad (1)$$

144

145

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where i denotes the alternative for which the probability is being computed; V_{PV} , $V_{Transit}$, and V_{SAEV} denote the systematic utilities of private vehicle, transit, and SAEV, respectively, for a specific origin-destination-traveler-time of day trip.

148

149 Private Vehicle

150

In this mode choice model, private vehicle utility is modeled as a function of VOTT, operating costs, and parking fees in the destination zone as seen in the equation below:

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$$V_{PV} = -VOTT \left(\frac{Distance_{trip}}{Speed_{PV}} \right) - \$0.152 (Distance_{trip}) - Parking_D \quad (2)$$

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153

where $VOTT$ is the individual monetary valuation of value of travel time drawn from distributions in Figure 2, $Distance_{trip}$ is the distance of the requested trip, $Speed$ is equivalent to SAEV average speeds shown in Table 1), \$0.152 is the equivalent vehicle operating cost per cell based

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158 on AAA’s (2014) estimate of \$0.608 per mile, and $Parking_D$ is the parking fee in the destination
 159 zone. In this model, parking cost is assumed to be \$0 for all business trips, since 95% of commuters
 160 who drive to work park for free at the workplace (Shoup and Breinholt 1997) and other business
 161 transportation are often priced in a distorted market with expense accounts. For personal trips,
 162 parking for private vehicles is assumed to be \$0 for trips that end in suburban or exurban cells, \$2
 163 for trips that end in urban cells, and \$4 for trips that end in downtown cells.

164
 165 **Transit**

166 For simplification, the transit mode modeled here emulates local city bus service, the most
 167 common form of transit in US cities. Similar to private vehicles, the utility of the transit mode also
 168 depends on transit travel speeds and individual traveler’s VOTT. In addition, access time and fare
 169 are considered in the transit utility equation below:

170
 171
$$V_{transit} = -(2) \left(\frac{VOTT}{60} \right) (AT_O + AT_D) - VOTT \left(\frac{Distance_{trip}}{Speed_{transit}} \right) - Fare_{transit} \quad (3)$$

172
 173 Where $Speed_{transit}$ is modeled at 25% slower than Table 1’s SAEV speeds during off-peak hours
 174 and 20% slower during peak hours due to stops (roughly based on Austin’s travel demand model’s
 175 travel time skims), \$2 is the assumed one way $Fare_{transit}$ based on the \$2.04 per unlinked trip
 176 fare average from the 2013 National Transit Database Urbanized Data (APTA 2013), and AT_O and
 177 AT_D are the access and wait times in minutes based on the trip’s origin and destination cell
 178 following Table 2.

179 **Table 2. Transit Access & Wait Time by Zone**

Zone	Transit Access & Wait Time (min.)
Downtown	3
Urban	9
Suburban	21
Exurban	60

180
 181 Transit access and wait time for exurban cells are penalized (valued at 60 minutes) in the utility
 182 function due to the fact that most transit trips to and from exurban areas require transfers (either
 183 from private car to transit, or one bus route to another bus route) in the majority of local bus service
 184 route designs. Furthermore, access time for transit is modeled at double the VOTT compared to
 185 in-vehicle travel time (IVTT). This penalty reflects the general discomfort of time spent walking,
 186 bicycling, and waiting outside of vehicles as compared to being inside a vehicle, as recommended
 187 in Wardman (2014). Though seated IVTT on transit modes is typically valued as less onerous
 188 than IVTT in a private car (presuming that the traveler can perform more productive or leisure
 189 activities while seated on a bus as compared to driving a car), standing IVTT on transit modes is
 190 considered more onerous than driving a private vehicle (Wardman 2014). Thus, in this model,
 191 transit IVTT is simplified to be valued the same as private vehicle IVTT.

192 **SAEV**

193 The structure of the SAEV utility valuation (Equation 4) is similar to that of transit, except where
 194 transit utility is modeled with a simplified flat price, the SAEV mode incorporates several pricing

195 schemes to examine the impact of pricing on SAEV mode share and fleet operations. The SAEV
196 utility is expressed as:

197
198
$$V_{SAEV} = -(2) \left(\frac{VOTT}{60} \right) (2.5 + 5n_{waitlist}) - (0.35)VOTT \left(\frac{Distance_{trip}}{Speed_{SAEV}} \right) - Fare_{SAEV} \quad (4)$$

199
200 Where $n_{waitlist}$ is the number of time steps a trip has been on the SAEV waitlist and $Fare$ is the
201 traveler out-of-pocket cost. The first term of this utility function models the onerousness of waiting
202 for an SAEV, valued at double the IVTT as is done in the transit utility equation. When a trip is
203 generated, the traveler assumes the wait time is 2.5 minutes (half of a time step). If the trip is
204 waitlisted, the traveler re-evaluates mode choice in each of the subsequent time steps the trip
205 remains on the waitlist, and adds 5 minutes to the wait time for each time step the traveler has been
206 on the waitlist. In other words, the longer a trip remains on the waitlist, the more the SAEV utility
207 decreases, and the less likely the traveler will choose SAEV mode.

208 The second term of this utility function models the cost of SAEV IVTT. Unlike transit, a traveler
209 will not have to stand in a SAEV. Thus, a traveler can use the IVTT in a SAEV to work, read,
210 listen to music, or pursue other productive or leisure activities. In the base case, this reduction in
211 travel time cost is modeled at 35% of the IVTT in a non-autonomous private vehicle (where the
212 traveler would be driving), equivalent to the valuation of seated riding time on transit (Concas and
213 Kolpakov 2009). This value is varied in the sensitivity analysis section to examine the impact of
214 IVTT valuation on SAEV mode share. SAEV speeds (shown in Table 1) are assumed to be the
215 same as private vehicle speeds.

216 The last term of the SAEV utility function is the fare. In this model, four pricing strategies are
217 explored: simple distance-based, origin-based, destination-based, and combination pricing. Each
218 pricing scheme is discussed in detail below.

219 *Distance-Based Pricing*

220 In simple distance-based pricing, the fare is determined proportional to the trip distance as seen in
221 Eq. 5. This pricing scheme is similar to the usage-based (by mileage or time) pricing schemes of
222 current non-autonomous carsharing services.

223
224
$$Fare_{SAEV} = \$0.2125 \times Distance_{trip} \quad (5)$$

225
226 Using overhead costs for similarly scaled transit services and assuming operating margins of 10%,
227 Chen et al. (2016) estimate a fleet of SAEVs can be offered at \$0.66 to \$0.83 per occupied mile of
228 travel, depending on type of fleet vehicles and charging infrastructure. To be conservative, \$0.85
229 per mile (\$0.2125 per cell) is used as the base fare for simple distance pricing. This per-mile fare
230 is also varied in the sensitivity analysis to examine the effects of higher and lower fares on SAEV
231 market share.

232 *Origin-Based Pricing*

233 Vehicle relocation is one of the biggest challenges facing operators of non-autonomous carsharing
234 services (see, e.g. Barth and Todd 1999, Correia and Antunes 2012). The origin-based pricing in
235 Equation 6 builds off of Correia and Antunes' (2012) suggestion that variable pricing policies
236 which encourage trips to balance the demand and availability of vehicles at carsharing stations
237 could contribute to more profitable operations. Here, origin-based pricing attempts to minimize

238 empty vehicles miles traveled for relocation by incentivizing trips originating in a cell that has a
 239 surplus of vehicles and penalizing trips originating in a cell that has a deficit of vehicles.

$$240 \quad 241 \quad \text{Fare}_{SAEV} = (\$0.2125 \times \text{Distance}_{trip}) \text{SDMultiplier} \quad (6)$$

$$242 \quad \text{where } \text{SDMultiplier} = 0.5, \text{ when } \left(\frac{\text{SAEVSupply}_{B,t}}{\text{SAEVSupply}_{b,t}} \right) \left(\frac{\text{TripDemand}_{b,t+1}}{\text{TripDemand}_{B,t+1}} \right) < 0.1$$

$$243 \quad \text{SDMultiplier} = 1, \text{ when } 10 > \left(\frac{\text{SAEVSupply}_{B,t}}{\text{SAEVSupply}_{b,t}} \right) \left(\frac{\text{TripDemand}_{b,t+1}}{\text{TripDemand}_{B,t+1}} \right) > 0.1$$

$$244 \quad \text{SDMultiplier} = 2, \text{ when } \left(\frac{\text{SAEVSupply}_{B,t}}{\text{SAEVSupply}_{b,t}} \right) \left(\frac{\text{TripDemand}_{b,t+1}}{\text{TripDemand}_{B,t+1}} \right) > 10$$

245
 246 In Eq. 6, $\text{SAEVSupply}_{B,t}$ is the total number of available SAEVs across all blocks B in the current
 247 time step, $\text{SAEVSupply}_{b,t}$ is the number of vehicles available in the 2-mile by 2-mile block b
 248 around the origin cell in the current time step, $\text{TripDemand}_{b,t+1}$ is the number of trips (based on
 249 average generation rates shown in Table 1) anticipated to originate from the 2-mile by 2-mile block
 250 b surrounding the origin cell in the subsequent time step, and $\text{TripDemand}_{B,t+1}$ is the total trip
 251 demand anticipated for the subsequent time step. Essentially, origin-based pricing compares the
 252 proportions of trip demand and available vehicle supply in a 2-mile by 2-mile block out of the
 253 entire region. Thus, trips that originate in a block with an excess of vehicles (defined by when the
 254 product of vehicle supply and trip demand ratios is less than 1) will be cheaper than trips that
 255 originate in a block with a deficit of vehicles (defined by when the product of vehicle supply and
 256 trip demand ratios is greater than 1). This ratio of ratios is then normalized by the SDMultiplier
 257 term, which halves the SAEV fare when supply is at least 10 times greater than demand and
 258 doubles the SAEV fare when demand is at least 10 times greater than supply. By incorporating the
 259 SDMultiplier term in place of using absolute ratios, extreme pricing scenarios are avoided. It is
 260 worth noting that this pricing strategy is rule-based and serves the purpose of illustrating the effect
 261 of demand-based pricing on SAEV mode share, but the pricing is not optimized for SAEV fleet
 262 performance or profit.

263 *Destination-Based Pricing*

264 As demonstrated in Chen et al. (2016), up to 5% of a SAEV fleet's VMT can be attributed to
 265 unoccupied miles traveled for charging purposes. The destination-based pricing scheme in
 266 Equation 7 attempts to minimize these empty vehicle miles by incentivizing trips that end in a cell
 267 close to a charging station site and penalize trips that end in a cell far away from a charging station
 268 site.

$$270 \quad \text{Fare}_{SAEV} = \$0.2125(\text{Distance}_{trip} + \text{Distance}_{charge}) \quad (7)$$

271
 272 In Equation 7, Distance_{charge} represents the distance from the destination cell to the closest
 273 charging station site. Thus, the destination-based fare prices both occupied miles traveled during
 274 the trip and the unoccupied miles traveled to a charging station after a trip is complete.

275 *Combination Pricing*

276 The last fare structure tested here (Equation 8) is simply a combination of origin- and destination-
 277 based pricing presented in Equations 6 and 7.

278

279
$$Fare_{SAEV} = \$0.2125(Distance_{trip} + Distance_{charge})SDMultiplier \quad (8)$$

280 **RESULTS**

281 In order to understand the impact of introducing a new SAEV mode on existing private vehicle
 282 and transit modes, it crucial to examine mode choice in the context of only having the latter two
 283 modes. In other words, before introducing SAEVs, what mode would the travelers have chosen
 284 for their trips? And what mode will they choose once SAEVs are available?

285 **Two-Mode Model**

286 Mode choice results from the two-mode model are shown in Table 3. Using the private vehicle
 287 and transit utility functions described previously, the model yielded 85.2% private vehicle trips
 288 and 14.8% transit trips. For comparison, according to the 2009 American Community Survey,
 289 76.4% of US workers who live and work inside the same metropolitan area commute by drive
 290 alone mode and 7.8% commute by public transit (McKenzie and Rapino 2011). While trips with
 291 low VOTT are served by both private vehicle and transit modes (both with minimum VOTTs of
 292 \$0), trips valued at over \$21.20 per hour are only served by private vehicles. The long right tail
 293 of the VOTT distribution for private vehicle trips (with maximum VOTT at \$90.80 per hour) is
 294 evident when looking at averages: mean VOTT for a private vehicle trip is 4.5 times the mean
 295 VOTT for a transit trip. In a similar manner, short trips are served by both private vehicles and
 296 transit, but transit is consistently the preferred mode for longer trips (over 119 miles).

297 In the simplified transit pricing modeled here, longer trips will incur higher operating costs for
 298 private vehicles while fare remains flat at \$2 for transit, hence the preference for transit mode as
 299 trip lengths grow longer. Model results also show that where there are significant parking costs,
 300 transit is preferred over private vehicle mode. Hypothetically, trips served by transit would have
 301 averaged \$1.15 in parking fees per trip had the trips been served by private vehicle. Trips that
 302 actually chose private vehicle mode averaged just \$0.32 in parking fees per trip. Likewise, when
 303 transit access times are significant, private vehicle mode is preferred. Trips that chose transit mode
 304 had an average total origin and destination access time of 44 minutes, while trips that chose private
 305 vehicle mode would have hypothetically averaged 74 minutes for origin and destination access
 306 had transit mode been chosen.

307 **Table 3. Attributes of Private-Vehicle and Transit Trips in Two-Mode Model**

		Private-Vehicle Trips	Transit Trips
Mode Share		85.19%	14.81%
VOTT (\$/hr)	Mean	\$16.16	\$3.56
	Median	\$11.40	\$2.75
	Std Dev	\$15.04	\$3.29
	Max	\$90.80	\$21.20
	Min	\$0.00	\$0.00
Trip Distance (mi)	Mean	8.83	17.21
	Median	5.00	10.13
	Std Dev	10.83	19.47

	Max	118.50	146.50
	Min	1.00	1.00
Avg Private Vehicle Parking Cost		\$0.32	\$1.15
Avg Transit Access & Wait Time (min.)		73.70	44.47

308 Note: Transit trips do not carry parking costs, and PV trips do not involve transit access and wait times. Table values
309 reflect the attributes of the competing (and the chosen) modes.

310 **Three-Mode Model**

311 *Simple Distance-Based Pricing*

312 Once SAEVs are introduced into the dynamic mode choice model, there is a significant shift away
313 from private vehicle use. In the results shown in Table 4, SAEVs fares are structured with simple
314 distance-based pricing at \$0.85 per trip mile. The model predicts this pricing scheme will attract
315 27.1% of all trips generated to the SAEV mode while reducing private vehicle and transit mode
316 shares to 60.8% and 12.1%, respectively. Comparing these mode shares to the two-mode results
317 in Table 3, it is clear that SAEVs are drawing the majority (89.9%) of its market share from trips
318 formerly made in private vehicles. The remaining 10.1% of SAEV trips come from former transit
319 trips.

320 Mean VOTT for SAEV trips are higher than that for the other two modes, averaging \$19.62 per
321 hour compared to \$17.97 for private vehicle trips and \$3.62 for transit trips. The average trip
322 distance of SAEV trips (10.7 miles) is in between that of private vehicle trips (7.8 miles) and transit
323 trips (19.4 miles). This model result suggests that SAEVs are attracting higher-income (as reflected
324 by higher VOTT) travelers who take advantage of the leisure or productive time during longer
325 trips in a SAEV that would have otherwise been spent driving a private vehicle, echoing results
326 from Childress et al. (2015). For shorter trips, this in-vehicle leisure time advantage is
327 overshadowed by the cost of the SAEV wait time. Note that due to the 80-mile range limitation of
328 SAEVs modeled here, the maximum distance of a SAEV trip is 77 miles, much shorter than the
329 maximum trip distances of private vehicle and transit modes.

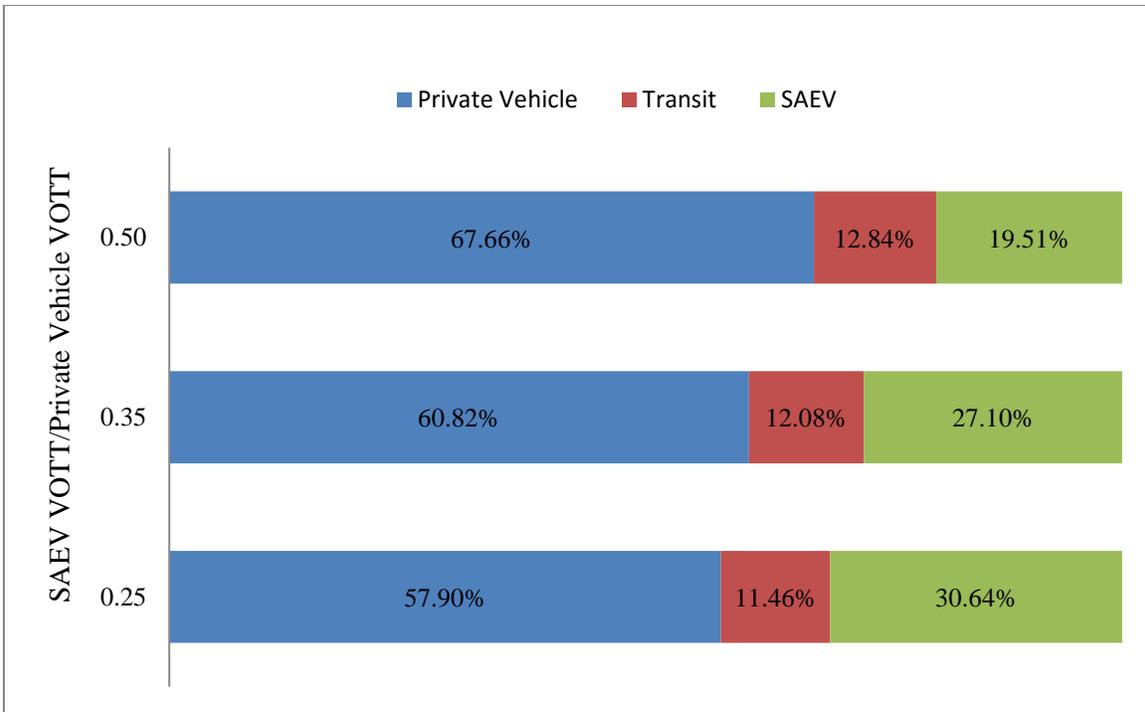
330 Model results also suggest that SAEVs are replacing some former short transit trips: the average
331 transit trip length increases from 17.2 miles (Table 3) to 19.4 miles (Table 4) once SAEVs are
332 introduced. This is likely due to the fact that for shorter trips traveling between zones served
333 sparingly by transit (such as suburban and exurban zones), the long transit access and wait times
334 inflict disproportionately high travel costs (as compared to the cost of IVTT and fare), thus
335 significantly reducing the utility of the mode. In such cases, a SAEV offers relatively short wait
336 times and, for trips less than 3 miles, a competitive fare to the \$2 flat transit price. A look at the
337 average transit wait times for each mode's trips confirms this explanation. SAEV trips would have
338 averaged 68 minutes of access and wait time per trip had they hypothetically selected transit,
339 whereas transit trips average 45 minutes of total access and wait times. Results also confirm that
340 trips which incur no or low parking fees prefer private vehicle mode while trips that incur higher
341 parking fees tend to select transit or SAEV mode, enforcing Catalano et al.'s (2008) finding that
342 carsharing activity can increase with a rise parking fees.

343 **Table 4. Attributes of Private-Vehicle, Transit, and SAEV Trips in Three-Mode Model**

		Private Vehicle Trips	Transit Trips	SAEV
Mode Share		60.82%	12.08%	27.10%
VOTT (\$/hr)	Average	\$17.97	\$3.62	\$19.62
	Median	\$12.50	\$2.80	\$13.30
	Std Dev	\$16.54	\$3.15	\$19.13
	Max	\$92.50	\$24.20	\$92.50
	Min	\$0.00	\$0.00	\$0.00
Trip Distance (mi)	Average	7.78	19.42	10.74
	Median	5.00	12.00	5.25
	Std Dev	8.05	21.37	12.51
	Max	100.00	150.25	77.00
	Min	1.00	1.00	1.00
Avg Private Vehicle Parking Cost		\$0.27	\$0.88	\$0.56
Avg Transit Access & Wait Time (min.)		65.82	45.17	68.04

344 Note: Transit trips do not carry parking costs, and PV trips do not involve transit access and wait times. Table values
345 reflect the attributes of the competing (and the chosen) models.

346 To test how model results vary with parameter changes to the SAEV utility function, sensitivity
347 testing was conducted by looking at higher and lower SAEV fares and valuation of SAEV IVTT
348 (using simple distance-based pricing). In the base three-mode model, SAEV IVTT was valued at
349 35% of the cost of private vehicle IVTT, based on evaluation of seated IVTT on transit modes.
350 However, travelers are likely to prefer the privacy and comfort of SAEVs over the often shared
351 and not-always guaranteed seated space on buses and trains. To reflect this preference, a lower
352 VOTT value (25% of private vehicle VOTT) was assigned in one sensitivity analysis scenario.
353 Alternatively, while being free of driving obligations is a distinct advantage for SAEVs, the type
354 of productive or leisure activity that can be pursued while traveling in a vehicle is still limited.
355 Cyganski et al. (2015) conducted a stated preference survey on AV use and found that only 13%
356 of respondents reported the ability to work as a primary advantage of AVs over manually-driven
357 vehicles. To ensure that the ability to pursue alternative activities while in a SAEV is not
358 overvalued, the sensitivity analysis here also includes a scenario where SAEV VOTT is valued at
359 50% of private vehicle VOTT. Mode choice model results (shown in Figure 3a) reveal that the
360 SAEV VOTT seems to have little impact on transit mode share. As the value of SAEV VOTT
361 approaches that of private vehicle VOTT, SAEV loses market share (almost directly) to private
362 vehicles, with relatively few SAEV trips switching to transit mode. These findings suggest that the
363 relative utility of SAEVs is highly dependent on the individual traveler's choice of in-vehicle
364 activity and valuation of that activity as compared to driving. Cyganski et al. (2015) found that
365 higher income travelers are more likely to work in AVs than lower income travelers, further
366 implicating SAEVs' attractiveness for high-VOTT travelers on longer, and thus more work-
367 productive, trips.
368

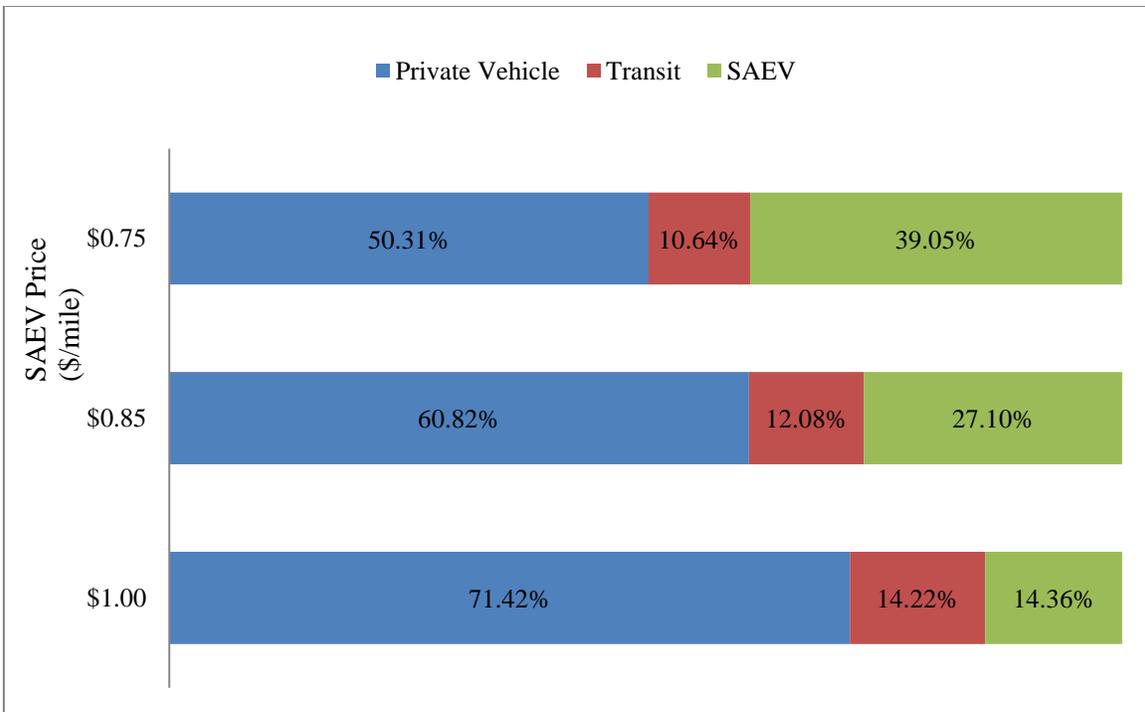


369

Figure 3a. Mode Share Sensitivity to SAEV VOTT Effects

370

371



372

Figure 3b. Mode Share Sensitivity to SAEV Fares

373

374 In the base three-mode model, SAEV fare is set at \$0.85 per mile. With varying operator missions
 375 (whether it be private operators wishing to maximize profit or public agencies focusing on
 376 reduction of congestion and mobile emissions), the price of SAEV service can differ drastically.
 377 This sensitivity analysis examines the impact of a higher SAEV fare (\$1.00 per mile) and a lower
 378 SAEV fare (\$0.75 per mile) on mode shares. Mode choice model results (shown in Figure 3b)
 379 show that a higher SAEV fare causes SAEV service to lose market share to mostly private vehicles
 380 (with some trips switching from SAEVs to transit), further confirming SAEV’s substitutability for
 381 private vehicles for high-income travelers. Elasticities show that private vehicle mode is slightly
 382 more sensitive to SAEV VOTT valuation than transit mode: For a 1% increase in SAEV VOTT,
 383 private vehicle mode share is predicted to increase 0.58% and transit mode share by 0.56%. On
 384 the other hand, variation in SAEV pricing demonstrates that transit mode share is more sensitive
 385 than private vehicle mode share to SAEV fare. For a 1% increase in SAEV fare, private vehicle
 386 mode share is expected to increase by 0.94% and transit mode share by 1.00%.

387 As SAEV VOTT and fare parameter changes increase and decrease projected SAEV mode share,
 388 the number (and concentration) of SAEV trips in the gridded region also changes. The agent-based
 389 model results (Table 5) show the effects of this change in SAEV trip demand on service metrics
 390 such as SAEV fleet size, average user wait times, and induced empty VMT (for relocation and
 391 charging). When SAEV mode share increases with Low SAEV VOTT and Low Price scenarios,
 392 the denser SAEV trip demand lead to decreased user wait times (by 4.8 and 12.2% compared to
 393 the base case) and increased vehicle utilization (as measured by the average daily miles per vehicle,
 394 which are 7.4 to 19.1% higher than the base case). Increase in SAEV trips also allows vehicles to
 395 travel fewer miles for traveler pickup, decreasing total induced empty VMT in the Low SAEV
 396 VOTT and Low Price scenarios by 16.1 and 26.5%, respectively, compared to the base case.
 397 Because trip characteristics (such as distance and traveler VOTT) are drawn from the same
 398 distributions for all region cells, there are only small decreases in empty VMT for relocation and
 399 charging purposes as a result of increased SAEV trip concentration. In other words, because there
 400 are no zonal variations in sociodemographic characteristics in this model, the geographic spread
 401 of SAEV trip demand is relatively consistent regardless of demand intensity.

402 **Table 5. SAEV Fleet Metrics across Sensitivity Analysis Scenarios**

	Base	Low SAEV VOTT	High SAEV VOTT	Low Price	High Price
SAEV VOTT (as % of Private Vehicle VOTT)	35%	25%	50%	35%	35%
Fare (\$/mile)	\$0.85	\$0.85	\$0.85	\$0.75	\$1.00
Fleet Size	84,945	106,686	54,787	137,323	45,496
Total Trips Served per Day	3.90M	4.03M	3.75M	4.26M	3.62M
Avg Daily Miles per Veh	142.7	153.3	125.0	169.9	105.0
Avg Daily Trips per Veh	45.9	37.7	68.4	31.0	79.6
Avg Trip Distance (mi)	10.6	11.4	8.50	11.9	8.54
Avg Wait Time Per Trip (min)	3.11	2.96	3.36	2.73	3.62
% Total “Empty Vehicle” Miles Traveled	7.70%	7.19%	9.06%	6.76%	9.43%
% of Empty VMT for Relocation	2.79%	2.76%	2.87%	2.69%	2.70%

% of Empty VMT for Charging	1.81%	1.83%	1.77%	1.79%	1.82%
% of Empty VMT for Traveler Pickup	3.10%	2.60%	4.43%	2.28%	4.90%
Max % of Concurrent In-Use Vehicles	38.6%	41.5%	34.7%	48.1%	29.1%
Max % of Concurrent Charging Vehicles	53.5%	54.1%	47.99%	58.0%	40.7%
Operational Cost per Equivalent Occupied Mile Traveled	\$0.389	\$0.383	\$0.400	\$0.378	\$0.409
Daily Revenue	\$9.41M	\$12.8M	\$5.24M	\$16.2M	\$4.29M
Revenue-to-Cost Ratio	2.00	2.04	1.92	1.85	2.19

403
404 Interestingly, the average trip distance of scenarios with high SAEV trip demand (Low SAEV
405 VOTT and Low Price) are longer than those of scenarios with low SAEV trip demand (High SAEV
406 VOTT and High Price). So while the vehicles in high-demand scenarios are utilized for more miles
407 each day, they actually serve fewer trips per day. However, the households who take these longer
408 trips as SAEV VOTT and fare decrease are different, as reflected by the revenue to cost ratios.
409 Both the Low SAEV VOTT and Low Price scenarios demand a bigger fleet (to serve increased
410 SAEV demand) compared to the base case, but the Low SAEV VOTT scenario registers a bigger
411 profit margin than the base case while the Low Price scenario does the opposite. As discussed
412 previously, travelers who can do productive work while traveling in a SAEV will view their time
413 in a SAEV as less costly, especially as trip distances increase. In the Low SAEV VOTT scenario,
414 more high income travelers' longer trips are captured by SAEV mode. On the other hand, the Low
415 Price scenario captures longer trips from lower income travelers, as the advantage of SAEVs'
416 shorter wait times outweigh the fare advantage of transit in trips that travel between suburban and
417 exurban zones.

418 Overall, the largest absolute daily revenue is generated by the Low Price scenario, simply due to
419 the significantly increased trip demand. However, when revenue is compared to costs, the High
420 Price scenario yields the most favorable ratio.

421 ***Origin, Destination, and Combination Pricing***

422 Sensitivity testing results revealed that different assumptions in SAEV VOTT and fare results in a
423 wide range (14-39%) of SAEV mode shares. These different trip demands require different
424 infrastructure investments and location placements to accommodate increasing and decreasing trip
425 densities. They also heavily impact revenue and profit margins, as shown in Table 5.

426 Next, this study analyzes how various pricing strategies can affect fleet operations (with the same
427 vehicle fleet size, charging infrastructure, and trip demand). Table 6's results employ the charging
428 strategies described in the Mode Choice Methodology section, all assuming SAEV VOTT to be
429 35% of private vehicle VOTT and a base distance pricing of \$0.85 per mile.

430

Pricing Scheme	Distance- Based	Origin- Based	Destination- Based	Combo
Private Vehicle Mode Share	60.8%	63.9%	67.2%	68.6%
Avg Private Vehicle VOTT (\$/hr)	\$17.97	\$17.57	\$17.01	\$17.57
Avg Private Vehicle Trip Distance (mi)	7.78	8.31	7.67	8.16
Transit Mode Share	12.1%	11.7%	12.0%	13.1%
Avg Transit VOTT (\$/hr)	\$3.62	\$3.58	\$3.31	\$3.57
Avg Transit Trip Distance (mi)	19.4	19.1	18.2	18.7

SAEV Mode Share	27.1%	24.4%	20.8%	18.3%
Avg SAEV VOTT (\$/hr)	\$19.62	\$18.78	\$21.92	\$23.17
Avg SAEV Trip Distance (mi)	10.6	10.1	12.6	12.2
Total Trips Served per Day	3.90M	3.85M	3.72M	3.68M
Avg Daily Miles per Veh	142.7	122.6	117.1	101.2
Avg Daily Trips per Veh	45.9	45.3	43.9	43.3
Avg Wait Time Per Trip (min)	3.11	2.51	3.03	2.40
% Total “Empty Vehicle” Miles Traveled	7.70%	8.11%	7.37%	7.83%
% of Empty VMT for Relocation	2.79%	3.72%	3.11%	4.24%
% of Empty VMT for Charging	1.81%	1.98%	1.80%	2.02%
% of Empty VMT for Traveler Pickup	3.10%	2.41%	2.46%	1.57%
Operational Cost per Equivalent Occupied Mile Traveled	\$0.389	\$0.398	\$0.395	\$0.405
Daily Revenue	\$9.41M	\$8.16M	\$8.35M	\$7.27M
Revenue to Cost Ratio	2.00	1.97	2.12	2.08

431

Table 6: SAEV Fleet Metrics across Distinctive Pricing Strategies

432 Compared to distance-based pricing, the origin-based pricing scheme seems effective in reaching
433 a more balanced vehicle supply and demand. This is reflected by the 22.3% reduction in
434 unoccupied VMT for traveler pickup (compared to distance-based pricing), which then
435 corresponds to a 19.3% reduction in average SAEV wait times. However, this efficiency
436 improvement comes with a 10% reduction in SAEV demand (mode share drops from 27.1% in
437 distance-based pricing to 24.4% in origin-based pricing) and 13.3% decrease in daily revenue. The
438 disproportionate revenue reduction is a result of discounted SAEV trips being more accessible to
439 lower-VOTT households, as witnessed in the 4.3% reduction in average SAEV VOTT between
440 distance- and origin-based pricing.

441 Destination-based pricing, compared to distance-based pricing, exhibits a negligible (less than 1%)
442 reduction in empty VMT for charging purposes. Due to the coverage-maximizing nature of the
443 charging station site generation methodology used here (discussed in detail in Chen et al. [2016]),
444 the distance between the destination cell and the nearest charging station varies little. However,
445 this pricing scheme did have the effect of discouraging shorter trips from choosing SAEV mode,
446 as the charging surcharge of the SAEV fare becomes a larger portion of the overall fare as trip
447 distances decrease. As discussed previously, high-VOTT travelers favor long SAEV trips. Thus,
448 the decrease in short SAEV trips is accompanied by an 11.7% increase in average SAEV VOTT.

449 The combination pricing scheme results shows some characteristics of both the origin- and
450 destination-based pricing schemes: Average SAEV wait times are reduced by 22.8% and average
451 SAEV VOTT increases 18.1%. The performance metrics of the combination pricing scheme seems
452 to have two aspects which appeal to time-sensitive/high-VOTT travelers: minimized wait times
453 and pricing which favors longer-distance trips. This pricing scheme also resulted in the highest
454 transit mode share and lowest SAEV mode share.

455 **SUMMARY AND CONCLUSIONS**

456 This study explores the impact of pricing strategies on SAEV market share in a discrete-timed
457 agent-based model of a simulated region with private vehicle, transit, and SAEVs serving as the

458 mode choice alternatives. The model specification delivers roughly an 85%/15% split between
459 private vehicles and transit trips before the introduction of SAEVs. When the SAEV mode is
460 offered at \$0.85 per mile (and users are assumed to value SAEV IVTT at 35% the cost of private
461 vehicle IVTT), the model estimates that 27% of all person-trips in the region (of at least 1 mile in
462 distance) will select SAEVs (with 90% of these trips previously choosing private vehicle travel,
463 before introduction of SAEVs).

464 Sensitivity analysis suggests that SAEV market share can range from 14% to 39% under plausible
465 variations in SAEV VOTT and fare assumptions. Under all scenarios, SAEVs prove to be
466 substitutable for private vehicle travel, assuming that single-occupant shared vehicle trips offer
467 equal utility as single-occupant private vehicle trips for all trip types. While private vehicle mode
468 share is most sensitive to persons' VOTT during SAEV travel, transit mode share is most sensitive
469 to SAEV fare assumptions. These results suggest that once EV and AV technologies gain market
470 maturity and become less costly, low-VOTT trip makers will start to choose SAEVs over transit,
471 particularly in areas with poor transit service (as reflected by longer transit-access and wait times),
472 echoing findings from Levin and Boyles' (2015) center-city, peak-period simulation. Model results
473 also suggest that SAEVs will attract longer trips away from private vehicles, particularly among
474 high-VOTT travelers who find SAEV travel much less burdensome than driving. Vehicle features
475 that encourage and enhance work productivity (such as reliable WiFi, ergonomic work surfaces
476 and seating, and reduced road noise) will likely attract longer trips from high-VOTT travelers
477 willing to pay higher fares (Mokhtarian et al. 2013). Like airlines, public SAEV operators may
478 find the best balance of profitability and service completeness by offering a refined, work-
479 enhancing vehicle environment at higher fares to serve high-VOTT travelers (similar to the first-
480 and business-class airplane cabins) and a discounted, sufficiently basic service to serve low-VOTT
481 travelers (similar to economy-class airplane cabins).

482 Model outputs from various SAEV pricing schemes show that specific fleet metrics can be
483 improved via targeted strategies. For example, fares that seek to balance available SAEV supply
484 with anticipated trip demand (over space and time) can decrease average wait times by 19 to 23%,
485 demonstrating the effectiveness of congestion pricing in a vehicle-balancing framework. However,
486 trade-offs are evident in these pricing schemes: fare structures that favor higher revenue-to-cost
487 ratios (by targeting higher-VOTT travelers) inevitably reduce SAEV mode shares, while those that
488 favor greater market share (by appealing to a wider range of travelers and VOTTs) inevitably
489 produce lower revenue-to-cost ratios. These pricing outputs emphasize the role of the SAEV
490 operators' goals when selecting a fare structure. For private SAEV operators, whose goal typically
491 is to maximize profits, a combination pricing scheme that minimizes user wait times while
492 discouraging shorter trips (which tend to incur a higher level of empty VMT-to-occupied VMT)
493 are most suitable. For a public SAEV operator, whose goal presumably is to maximize equitable
494 access to SAEVs while still reducing wait times, a supply-and-demand (origin-based) pricing
495 scheme may be most suitable.

496
497 The model outputs also reinforce the importance of efficient parking prices, since SAEVs will be
498 more competitive against private vehicles in areas which price parking marginally according to
499 usage rather than subsidies through development policies (e.g. requiring developers to provide
500 specific numbers of parking spaces per retail square footage) or employer-provided
501 benefits. Under-priced and inefficiently-priced parking spaces in most U.S. and non-U.S. cities
502 play a direct role in increasing traffic congestion, housing inaffordability, sprawl, and mobile-
503 source emissions (Litman 2011). Inefficient parking prices also cause undervaluation of one of

504 SAEVs' key benefits: reduced parking demand (and out-of-pocket parking costs), decreasing their
505 competitive advantage relative to private vehicles.

506 The pricing strategies and sensitivity analysis explored here offer insights on the many factors that
507 influence SAEV mode shares and fleet performance. However, this agent-base model and
508 application is limited in various ways. For example, more than three modes are possible, including
509 privately-held AVs, which may become very popular, so a vehicle-ownership model (upstream) is
510 needed, along with non-motorized modes and trip distances below 1 mile. Furthermore, a shared-
511 vehicle trip may not offer the same utility as a privately-owned-vehicle trip for all trip types. For
512 example, the transport of children and the elderly frequently require special equipment (carseats
513 and wheel-chair accessible features) that may not be available in fleet vehicles. Nevertheless, while
514 autonomous driving technology is in its infancy (and expensive), SAEVs offer users access to AV
515 technology without significant up-front investment. Additionally, as mentioned in the results
516 discussion, the lack of more individual trip-maker and trip-type attributes over space and time (by
517 time-of-day and day-of-year) oversimplifies the mode (and destination) choice process. In reality,
518 urban geography is highly heterogeneous in terms of trip generation and attraction rates, by time
519 of day and across demographic characteristics. Moreover, trips are segments of complex tours with
520 a variety of constraints on them. More clustered origins and destinations, and routing opportunities
521 may make the systems more efficient, but variations over the days of week and months of year
522 may make fixed fleets less able to serve all comers. Fortunately, pricing can be made flexible, and
523 vehicles can hold more than one traveler, so operators have a variety of price-setting strategies to
524 explore. The future is uncertain, but interesting and full of opportunity for those who make use of
525 these new technologies in socially meaningful ways.

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531

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