Quantifying the Potential Employment Accessibility Benefits of Shared Automated Mobility Services: SCAG Region Case Study

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Key Findings

1. Young and low income workers may receive largest employment accessibility benefits from SAMS modes
2. Higher benefits of SAMS in suburban and rural areas than dense urban areas
3. Magnitude of benefits is heavily dependent on the service price of SAMS
4. Most of the benefits from the SAMS modes come from the SAMS only mode
   ◦ Rather than the SAMS plus Transit mode
Many commuters face challenges accessing employment opportunities that limit their economic potential and quality of life

- High parking cost and limited parking
- Long commute distance
- Poor transit service
Background

Shared AV mobility service or SAMS can help address these employment accessibility challenges as they:

- nearly eliminate the need to park in high parking cost areas and
- allow carless travelers or non drivers including persons with physical disabilities to enjoy the accessibility benefits of personal vehicle travel.
Study Objectives

• Provide a monetary measure of employment accessibility benefits from SAMS
• Capture the key employment accessibility benefits of SAMS modes
• Incorporate heterogeneity in the population of workers
Study Assumptions

- Two new modes: SAMS only and SAMS plus Transit
- Impact mode choice and subsequent destination choice
- No change in residential and workplace locations and road network travel times
- Lower cost than ridesourcing services and personal vehicle and no parking cost
- Travel time similar to personal vehicle but with minimal wait times
**Accessibility**

**Definition**
- Employment accessibility is the extent to which land-use and transport systems, particularly the available commute modes, enable individual workers to reach employment opportunities (motivated by Geurs and van Wee, 2004; Ben-Akiva and Lerman, 1979; Hansen, 1959)

**Measures**
- Distance (or travel time or travel cost) to the nearest destination of interest (e.g., bus stop, freeway interchange, school, hospital, retail job, office job, etc.)
- Cumulative activities/opportunities of a specific type within a specified distance or travel time or travel cost (known as the “isochrone” or “contour” measure)
- Gravity/entropy model denominators (known as Hansen’s measure (Hansen, 1959))
- Expected maximum random utility-based measure (e.g., logit model “logsums” (Ben-Akiva and Lerman, 1979))
Literature Review

- **Meyer et al. (2017)**
  - Focus on accessibility benefits arising from reductions in network travel times
  - Use the gravity model denominator

- **Milakis et al. (2018)**
  - Survey international experts on their opinions about AVs impacts on accessibility
  - Expectation is that AVs will have wide-ranging impacts on land-use, transportation, and temporal components of travel

- **Childress et al. (2015)**
  - Also use destination-mode choice model logsums
  - Also, find little difference in impact of AVs between low-income and high-income household
Conceptual Framework

Land-Use Transport System 1

Representative Worker

Work Destinations

Mode Options

Accessibility 1

Δ Accessibility

Land-Use Transport System 2
Study has two main hypotheses that involve interrelationship between
- Two new SAMS commute modes
- Spatial distribution of employment opportunities in specific sectors
- The characteristics of workers

Hypothesis 1: New commute modes with attributes similar to SAMS+Transit and SAMS-only will provide substantial improvements in employment accessibility for workers

Hypothesis 2: The benefits of the SAMS modes will vary across the working population
Methodological Overview

- **Marginal Distribution of Household Attributes**
  - ACS 2012
  - Household
  - Person
  - Vehicle

- **Hierarchical Logit Model**
  - (STATA)

- **Destination Choice Model**
  - Mode Choice Model
  - (Python Language)

- **Destination Choice Set Generation**
  - (Python Language)

- **Latent Class Analysis**
  - (R Language - poLCA)

- **Consumer Surplus/Accessibility Analysis**
  - (STATA)

- **Population Synthesis**
  - (TransCAD)

- **HH Size, Vehicles, Income Driving License, Gender, Age Work Flexibility Vehicle Body Type, Year, Cylinders**

  - Car Ownership Cost
  - Price
  - Body Type
  - Age
  - Cylinders
  - Fuel Type

- **OLS Model (STATA)**
  - Total Car Ownership Cost per Mile

- **LEHD 2012**
  - Number of Jobs
  - Four Classes of Workers
  - OD Job Flows

- **US EPA (2014)**
  - Employment Entropy
  - Population Density
  - Distribution of Wage

- **SCAG RTDM 2012**
  - Transit and Drive-Alone Skims
  - Drive-Alone Network Distance
  - Transit Fare
  - Parking Cost

- **Mitra & Saphores (2017)**
  - Land Use Entropy

- **CHTS 2012**
  - 30 Destinations for Each Worker
  - Four Classes of Workers
  - 30 Destination-Mode Coefficient Values

- **Methodological Overview**

- **acr 2012**
  - Marginal Distribution of Household Attributes
Study Area is Southern California Association of Government (SCAG) Region

Data

Socio-Economic Data
- 2012 California Household Travel Survey (CHTS)
- 2012 American Community Survey (ACS)

Mode Attribute
- SCAG Travel Demand Model Skim Matrices
- 2012 California Household Travel Survey (CHTS)
- Kelley Blue Book and Edmunds

Employment and Demographic Data
- 2012 Longitudinal Employer-Household Dynamics (LEHD)
- US EPA’s Smart Location Database
- Mitra and Saphores (2017)
Clustering Workers
Method

- Latent Class Analysis (LCA) is used to cluster workers based on their sociodemographic attributes.
- The posterior probability that individual $n$ belongs to a specific class $c$ can be calculated as

$$
\bar{P} (c_n|Y_n) = \frac{p_c f(Y_n; \pi_c)}{\sum_{c' \in C} p_{c'} f(Y_n; \pi_{c'})}
$$

Numerator = The probability an individual produces a specific set of outcomes on the manifest variables conditional on class membership

Denominator = The probability density function across all classes
Clustering Workers

Class Description

Class 1 – Graduate/Bachelors degree holders and Upper Middle/High income
Class 2 – Below High School education and Low/Lower Middle income group
Class 3 – Female and Middle income
Class 4 – Age 16 to 25 years and High School/Some College education

Class Share

Class 1 – 32%
Class 2 – 8%
Class 3 – 50%
Class 4 – 10%
Measuring Accessibility
Hierarchical Destination Mode Choice Model and Logsum Approach

Accessibility

\[ Accessibility_n = CS_n = \frac{1}{\alpha} \ln \sum_{j \in D_n} e^{\mu_j + \sum_{b \in A_d} \beta_b \cdot X_{bj}} + C \]

\[ \Delta Accessibility = \Delta CS = \frac{1}{\alpha} \left[ \ln \left( \sum_{j,m} e^{V^1_{jm}} \right) - \ln \left( \sum_{j,m} e^{V^0_{jm}} \right) \right] \]
# Mode Choice Model Results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Access and Egress Time (mins)</td>
<td>-0.021***</td>
</tr>
<tr>
<td>Total Wait Time (mins)</td>
<td>-0.017</td>
</tr>
<tr>
<td>Total Travel Time (mins)</td>
<td>-0.029***</td>
</tr>
<tr>
<td>Total Travel Cost ($)</td>
<td>-0.088***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mode (Base: Walk)</th>
<th>Drive Alone</th>
<th>Transit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.004**</td>
<td>-0.088</td>
</tr>
<tr>
<td>Gender: female</td>
<td>0.565***</td>
<td>0.581***</td>
</tr>
<tr>
<td>HH Size</td>
<td>0.109*</td>
<td>0.044</td>
</tr>
<tr>
<td>HH Vehicle per Driver: high (base: low)</td>
<td>1.201***</td>
<td>0.031</td>
</tr>
<tr>
<td>HH Income (base: low)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH Income: lower middle</td>
<td>-0.117</td>
<td>-0.334</td>
</tr>
<tr>
<td>HH Income: middle</td>
<td>0.282</td>
<td>-0.522*</td>
</tr>
<tr>
<td>HH Income: upper middle</td>
<td>0.244</td>
<td>-0.686**</td>
</tr>
<tr>
<td>HH Income: high</td>
<td>0.021</td>
<td>-1.488***</td>
</tr>
<tr>
<td>Work Flexibility (base: no)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work Flexibility: low</td>
<td>-0.587***</td>
<td>-0.455**</td>
</tr>
<tr>
<td>Work Flexibility: high</td>
<td>-0.378</td>
<td>-0.408</td>
</tr>
<tr>
<td>Land Use Entropy at Destination</td>
<td>1.582</td>
<td>0.961*</td>
</tr>
<tr>
<td>Population Density at Destination (persons/acre)</td>
<td>-0.013*</td>
<td>0.001</td>
</tr>
</tbody>
</table>
## Mode Choice Model Results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Class 1 (N=3,766)</th>
<th>Class 2 (N=849)</th>
<th>Class 3 (N=5,663)</th>
<th>Class 4 (N=1,078)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log of Distance</td>
<td>-0.733***</td>
<td>-0.668***</td>
<td>-0.718***</td>
<td>-0.917***</td>
</tr>
<tr>
<td>Retail Jobs</td>
<td>0.143***</td>
<td>0.112*</td>
<td>0.138***</td>
<td>0.356***</td>
</tr>
<tr>
<td>Office Jobs</td>
<td>0.029***</td>
<td>---</td>
<td>0.025***</td>
<td>---</td>
</tr>
<tr>
<td>Industrial Jobs</td>
<td>0.052***</td>
<td>0.082***</td>
<td>0.055***</td>
<td>0.049***</td>
</tr>
<tr>
<td>Service Jobs</td>
<td>0.024**</td>
<td>0.044**</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Entertainment Jobs</td>
<td>0.133***</td>
<td>0.118***</td>
<td>0.162***</td>
<td>0.159***</td>
</tr>
<tr>
<td>Education Jobs</td>
<td>0.091***</td>
<td>---</td>
<td>0.080***</td>
<td>0.106***</td>
</tr>
<tr>
<td>Health Jobs</td>
<td>0.133***</td>
<td>---</td>
<td>0.104***</td>
<td>0.095***</td>
</tr>
<tr>
<td>Public Administration Jobs</td>
<td>-0.022***</td>
<td>0.011*</td>
<td>-0.018***</td>
<td>---</td>
</tr>
<tr>
<td>Medium Wage Workers (%)</td>
<td>-0.013***</td>
<td>0.034***</td>
<td>0.011***</td>
<td>---</td>
</tr>
<tr>
<td>High Wage Workers (%)</td>
<td>0.026***</td>
<td>---</td>
<td>0.023***</td>
<td>---</td>
</tr>
<tr>
<td>Employment Entropy</td>
<td>0.276*</td>
<td>---</td>
<td>0.515***</td>
<td>---</td>
</tr>
<tr>
<td>Mode Choice Logsum</td>
<td>0.371***</td>
<td>0.554***</td>
<td>0.427***</td>
<td>0.618***</td>
</tr>
</tbody>
</table>
Employment Accessibility Improvements in SCAG
Benefits across Worker Classes

<table>
<thead>
<tr>
<th>Worker Class</th>
<th>Benefit per Capita ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>5</td>
</tr>
<tr>
<td>Maximum</td>
<td>35</td>
</tr>
<tr>
<td>25th Percentile</td>
<td>15</td>
</tr>
<tr>
<td>50th Percentile</td>
<td>20</td>
</tr>
<tr>
<td>75th Percentile</td>
<td>25</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Class</th>
<th>Total Benefit ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>504,056</td>
</tr>
<tr>
<td>Class 2</td>
<td>197,000</td>
</tr>
<tr>
<td>Class 3</td>
<td>842,098</td>
</tr>
<tr>
<td>Class 4</td>
<td>246,638</td>
</tr>
</tbody>
</table>
Employment Accessibility Improvements in SCAG

Benefits from each SAMS Mode

![Bar chart showing accessibility benefits from SAMS and SAMS+Transit for different classes.](chart.png)
Employment Accessibility Improvements
Spatial Distribution of Benefits in SCAG
Employment Accessibility Improvements in SCAG
Spatial Distribution of Benefits in Los Angeles County
Employment Accessibility Improvements in SCAG
Spatial Distribution of Benefits in Orange County
Employment Accessibility Improvements in SCAG
Density Dependent SAMS Wait Time

<table>
<thead>
<tr>
<th>Class</th>
<th>Total Benefit ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>$13,974</td>
</tr>
<tr>
<td>Class 2</td>
<td>$201,805</td>
</tr>
<tr>
<td>Class 3</td>
<td>$660,895</td>
</tr>
<tr>
<td>Class 4</td>
<td>$251,710</td>
</tr>
</tbody>
</table>

Legend:
- Landmark Location
- County Boundary
- Median Accessibility Benefit per Capita ($)
Employment Accessibility Improvements in SCAG
Accessibility Benefits with Changes in SAMS Costs
Conclusion

Limitations
◦ Aggregate nature of modal attributes
◦ Homogeneity of preferences for employment opportunities within each worker class
◦ Sequential estimation of hierarchical destination mode choice model

Future Research
◦ Capturing spatial competition for jobs
◦ Integrating hierarchical destination mode choice model with location choice
◦ Capturing how accessibility improvements from SAMS modes may induce persons to enter or return to workforce
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Thank You