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Authors

Hyland, Michael, PhD
Ahmed, Tanjeeb
Sarma J S, Navjyoth
et al.

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Assessment of the Employment Accessibility Benefits of Shared Autonomous Mobility Services

Michael Hyland, Assistant Professor, Institute of Transportation Studies and Department of Civil and Environmental Engineering, University of California, Irvine

Tanjeeb Ahmed, Ph.D. Student, Institute of Transportation Studies, University of California, Irvine

Navjyoth Sarma J S, Ph.D. Student, Institute of Transportation Studies and Department of Civil and Environmental Engineering, University of California, Irvine

Suman Mitra, Assistant Professor, Department of Civil Engineering, University of Arkansas

Arash Ghaffar, Ph.D. Student, Institute of Transportation Studies and Department of Civil and Environmental Engineering, University of California, Irvine

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16. Abstract
The goal of this study is to assess and quantify the potential employment accessibility benefits of Shared Autonomous Mobility Service (SAMS) commute modes across a large diverse metropolitan region considering heterogeneity in the working population. To meet this goal, this study employs a welfare-based (i.e. logsum-based) measure of accessibility, obtained via estimating a hierarchical work destination-commute mode choice model. The employment accessibility logsum measure incorporates the spatial distribution of worker residences and employment opportunities, the attributes of the available commute modes, and the characteristics of individual workers. This research further captures heterogeneity of workers using latent class analysis (LCA). The LCA model inputs include the socio-demographic characteristics of workers to subsequently account for different worker clusters valuing different types of employment opportunities differently. The accessibility analysis results indicate: (i) the accessibility benefit differences across latent classes are modest but young workers and low-income workers do see higher benefits than high- and middle-income workers; (ii) there are substantial spatial differences in accessibility benefits with workers living in lower density areas benefiting more than workers living in high-density areas; (iii) nearly all the accessibility benefits come from the SAMS-only mode as opposed to the SAMS+Transit mode; and (iv) the SAMS cost per mile assumption significantly impacts the magnitude of the overall employment accessibility benefits.

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February 2020

Michael Hyland, Assistant Professor, Institute of Transportation Studies and Department of Civil and Environmental Engineering, University of California, Irvine

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Suman Mitra, Assistant Professor, Department of Civil Engineering, University of Arkansas

Arash Ghaffar, Ph.D. Student, Institute of Transportation Studies and Department of Civil and Environmental Engineering, University of California, Irvine

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Executive Summary

This study quantifies the potential impact of Shared Autonomous Mobility Service (SAMS) modes on access to employment opportunities in the Southern California region. These future mobility services can be compared to Didi, Uber and Lyft, except the vehicles will be driverless and completely controlled by the mobility service provider, rather than individual drivers.

With the current transportation system, many commuters face challenges accessing employment opportunities that ultimately limit their economic potential and quality of life, particularly low-income households that do not own personal vehicles and live in job-poor neighborhoods. Specifically, workers in Southern California face challenges, including: (i) high parking costs and/or limited parking availability in dense employment and residential areas; (ii) long commute distances between residential areas and employment opportunities; and (iii) poor transit service quality in many areas. The combination of long commute distances and poor transit service quality are particularly burdensome for individuals who cannot physically operate a vehicle or cannot afford to purchase, insure, maintain, fuel, and park a personal vehicle.

SAMS modes can help address these employment accessibility challenges as they (i) nearly eliminate the need to park in high parking cost areas and (ii) allow travelers to enjoy the accessibility benefits of personal vehicle travel without the high cost of purchase, operation, maintenance and insurance (which are expected to be spread across multiple passengers). This study is the first comprehensive attempt to evaluate the benefits of SAMS for commuters using a data-intensive welfare-based (logsum) approach. Key objectives of this study include:

- Provide a monetary measure of employment accessibility benefits for economic (e.g. cost-benefit) analyses,
- Capture key employment accessibility benefits of SAMS modes, and
- Incorporate heterogeneity in the population of workers with respect to the types of employment opportunities that are valuable to different worker segments.

To fulfil these objectives, a hierarchical destination-mode choice model was developed which includes two SAMS modes (SAMS-only and SAMS+Transit) in the future in addition to the existing drive-alone, transit, and walk modes. In addition, the latent class analysis (LCA) method was used to distinguish the workers based on four socio-economic characteristics – gender, age, income and education. The proposed methodology required data from several sources including 2012 California Household Travel Survey (CHTS), the Southern California Association of Governments (SCAG) metropolitan planning organization (MPO), 2012 Longitudinal Employer-Household Dynamics (LEHD), 2012 American Community Survey (ACS) and the US Environmental Protection Agency's Smart Location Database. For drive-alone mode, the cost per mile was estimated using an OLS model considering price, vehicle body type, cylinder, and age of vehicle.

While developing this methodology, the scope of this study was set to model the impact of SAMS on mode choice and destination choice of workers. This study assumed no major changes in the residential locations of workers, workplace locations of employers, and road network travel times. With the help of the travel cost coefficient, the increase in accessibility to work locations were converted to dollar units for a 5% representative population generated for each census tract of the SCAG region.

The results can be summarized as follows:

- Young workers and workers from low-income households may receive larger employment accessibility benefits from SAMS modes than workers from high- and middle-income households.
- Benefits of SAMS in suburban and rural areas would be significantly higher than dense urban areas when considering both same and variable service quality (service quality is lower in less dense areas and vice versa). Although the distributions of benefits are similar there is a slight (2%) increase in accessibility benefits across all classes under the assumption of variable service quality.
- Magnitude of employment accessibility benefits is heavily dependent on the service price of SAMS in the future – employment accessibility benefits decrease by 26% for workers in Class 1 (the high-income, high-education attainment class) as the SAMS service price increases from $0.10/mile to $0.50/mile.
- Most of the accessibility advantages from the SAMS modes come from the SAMS-only mode rather than the SAMS+Transit mode. Therefore, it is more likely that first-mile SAMS modes will provide very little value to commuters and will not significantly increase commute-based transit ridership.

The results in this report provide valuable insights into the potential impacts of SAMS on different clusters of the working population and different regions of Southern California. Transport planners and policy makers can use the findings to inform the design and deployment of SAMS. The use of a disaggregate agent-based modeling framework allows this research methodology to have significant potential to provide further insights into the impacts of SAMS modes on employment accessibility.

Introduction

Motivation

Car manufacturers, technology companies, and ridesourcing companies are currently trying to develop fully automated or driverless vehicles (AVs) (Muoio, 2016) with initial plans to deploy these vehicles as a mobility service rather than sell AVs to individual consumers (Waymo, 2017; Wingfield, 2017). Some companies envision a Shared Autonomous Mobility Service (SAMS); an approach similar to existing vehicle-based shared mobility services—like those provided by Didi, Uber and Lyft—except SAMS vehicles will be driverless and completely controlled by the mobility service provider, rather than individual drivers (Fagnant and Kockelman, 2014; Spieser et al., 2014).

The recent academic (Fagnant and Kockelman, 2015; Mahmassani, 2016) and non-academic (Hars, 2010; Thompson, 2016) literature identifies potential economic and environmental benefits of AVs and SAMS modes. These potential benefits have motivated significant research in recent years related to understanding the impacts of AVs and SAMS modes on trip generation (Truong et al., 2017); land-use, energy, and emissions (Wadud et al., 2016); residential location choice (Zhang and Guhathakurta, 2018); and vehicle miles traveled and associated emissions (Fagnant and Kockelman, 2014). The present study aims to understand and quantify another potential impact of SAMS modes, namely, access to employment opportunities.

One of the main design objectives of transportation systems is to connect people to their jobs and other employment opportunities. However, many commuters face challenges accessing employment opportunities that ultimately limit their economic potential and quality of life, particularly low-income households that do not own personal vehicles and live in job-poor neighborhoods (Blumenberg and Ong, 2001). Employment accessibility challenges vary from country-to-country, state-to-state, city-to-city, and neighborhood-to-neighborhood; nevertheless, there are a few common challenges across most large non-Northeast Corridor metropolitan areas in the United States that are particularly burdensome for workers in Southern California, including: (i) high parking costs and/or limited parking availability in dense employment and residential areas; (ii) long commute distances between residential areas and employment opportunities; and (iii) poor transit service quality in many areas. The combination of long commute distances and poor transit service quality are particularly burdensome for individuals who cannot physically operate a vehicle or cannot afford to purchase, insure, maintain, fuel, and park a personal vehicle. Moreover, the challenges have increased in recent decades as employment opportunities have moved away from central business districts and into the suburbs, which makes planning and operating efficient transit routes challenging in many cases and unviable in others (Hu, 2015).

Fortunately, SAMS modes can help address these employment accessibility challenges as they (i) nearly eliminate the need to park in areas with high parking costs (Zhang et al., 2015) and (ii) allow travelers to enjoy the accessibility benefits of personal vehicle travel, which Kawabata

and Shen (2006) show are significant compared to transit in most areas (especially Southern California), without having access to a personal vehicle. While commuters will still need to pay for SAMS modes for commute trips, the purchasing, maintenance, and insurance costs associated with vehicle ownership can be spread across several SAMS users. Even operating (i.e. fuel) costs can be spread across multiple passengers if workers are willing to share rides with other travelers during the commute trip. SAMS modes also have the potential to improve employment accessibility for people who are unable to operate a personal vehicle due to age or disability.

Research Objectives

The goal of this study is to quantify the employment accessibility benefits of SAMS modes, using a systematic and theoretically valid methodology to:

1. Provide a monetary measure of employment accessibility benefits for economic (e.g. cost-benefit) analyses,
2. Capture key employment accessibility benefits of SAMS modes, and
3. Incorporate heterogeneity in the population of workers with respect to the types of employment opportunities that are valuable to different worker segments.

To meet this overarching goal and satisfy the methodological constraints, this study employs the logsum measure of accessibility, which is a welfare-based accessibility measure that can be converted to monetary terms for economic analyses. To capture the key employment accessibility benefits of SAMSs, this study adds two commute modes – SAMS-only and SAMS+Transit – to the mode choice set of workers and captures the beneficial attributes of the two SAMS modes (i.e. no parking costs and travel times that are consistent with driving a personal vehicle). Lastly, to capture heterogeneity among workers, this study clusters workers based on their socio-demographic attributes using latent class analysis (LCA) methods.

This appears to be the first study to quantify the employment accessibility benefits of SAMS modes for an entire metropolitan region using a logsum- or welfare-based approach. While Childress et al. (2015) present logsum-based accessibility measures associated with the impact of AVs on accessibility, their study provides few methodological details and only one set of computational results. The current study presents a detailed methodology that additionally involves clustering workers into classes based on their socio-demographics. In addition to improving destination choice model parameter estimates, this clustering is especially valuable for evaluation purposes as analysts, planners, and policymakers can easily see the impact(s) of SAMS modes on different worker clusters. To illustrate the usefulness of the proposed methodology, this study generates a synthetic population of workers in the six-county SCAG region, then applies the LCA, mode choice, and destination choice model parameters, which were estimated on a sample of workers from the SCAG region, to quantify the employment accessibility benefits of SAMS modes for every member of the synthetic working population.

SAMS Commute Modes

This study analyzes the employment accessibility benefits of adding two SAMS modes to the choice set of commuters, namely, the SAMS-only and SAMS+Transit commute modes. This subsection describes these two modes and their potential commuting benefits relative to existing travel modes.

In this study, the SAMS-only commute mode is effectively a ride-hailing/ridesourcing service with driverless vehicles. From a user-perspective the main difference between SAMS and current ride-hailing services is the travel cost/price (and the fact that the vehicle does not have a driver). The study assumes, as a result of the elimination of labor/driver costs and improved operational efficiency due to central control of the AV fleet, the SAMS-only mode is considerably cheaper than current ridesourcing services and even cheaper than the average cost per mile of personal vehicle travel. From a commute mode attributes perspective, the SAMS-only mode in this study is quite similar to a personal vehicle (e.g., the same in-vehicle travel times and zero walk distances) with three notable exceptions. First, the SAMS commute mode does not include any parking costs. Second, the cost per mile of SAMS is slightly lower than the personal vehicle cost per mile. Third, on the negative side, commuters need to wait a few minutes at their residence for the SAMS vehicle to pick them up for work.

In this study, the SAMS+Transit commute mode involves an inter-modal commute trip wherein the commuter takes a SAMS ride from home to a convenient transit station/stop before using the transit network to travel from this transit stop/station to her workplace. The SAMS+Transit mode does not require the commuter to pay for parking at the transit station. Additionally, the travel times for the SAMS portion of the trip are commensurate with personal vehicle travel. However, the SAMS portion of the trip does include a short wait time. Ideally, the SAMS+Transit mode would provide a cost-effective alternative to SAMS-only and personal vehicle travel while allowing commuters to utilize the transit network for longer distance commutes, overcoming the transit first-mile problem. In addition to connecting commuters to previously inaccessible (via walking) transit stations, the SAMS+Transit mode should also reduce the total travel time and number of transfers compared to a transit-only trip. This would be particularly beneficial in low-density areas where transit stations are not accessible by walking and also in cases where commuting with transit requires a significant number of inefficient transfers between bus and/or rail lines.

In summary, in this study the SAMS-only mode is commensurate with the personal vehicle mode except it eliminates parking costs, has lower per mile costs, and involves a pickup wait time. The SAMS portion of the SAMS+Transit commute option has the same characteristics. The study assumes AV/SAMS travel times remain the same as current personal vehicle travel. The study also assumes the disutility of in-vehicle travel time is the same in AVs/SAMS as current personal vehicle travel. Hence, the employment accessibility benefit results in this study are likely conservative compared to other studies that assume reduced travel times (Meyer et al., 2017) and in-vehicle travel time disutility (Vyas et al., 2019) with SAMS modes. Finally, the

study assumes that the SAMS modes impact commute mode choice and work destination locations; however, it assumes worker residences and employment locations remain fixed.

Report Outline

The remainder of the report is structured as follows. The next section provides relevant theoretical, methodological, and conceptual background information. Section 3 presents the data sources and research methodology to quantify the employment accessibility benefits of SAMS modes. Section 4 presents and discusses a variety of computational results. The final section concludes the report with a summary of the study and a discussion of limitations and future research.

Background

The current study builds upon and applies the methods and ideas from several existing areas of research, including: (employment) accessibility measures and analysis; logsums as a measure of consumer surplus and accessibility; modeling the transportation system impacts of AVs and SAMS modes; and accessibility analysis of AVs and SAMS modes. This section aims to provide relevant conceptual, theoretical, and methodological background information on these topics, in order to provide context. A review of all the relevant literature in each of these areas is beyond the scope of this report; therefore, where possible, recent review articles are provided for the reader's reference.

Accessibility Measures

Adapting the definition in Geurs and van Wee (2004) and to a lesser extent several other definitions (Ben-Akiva and Lerman, 1979; Hansen, 1959), this study defines employment accessibility as the extent to which land-use and transport systems enable workers to reach employment opportunities by means of the available transport modes.

Geurs and van Wee (2004) suggest four theoretically important components of accessibility, namely, land-use components, transportation components, temporal components, and individual components. As this study considers employment accessibility, the land-use component consists of the spatial distribution, type, and number of employment opportunities (by type) throughout the analysis area. The transportation components in the current study include the modal attributes of driving alone, taking transit, or walking to work as well as using the SAMS-only or SAMS+Transit modes to commute in the future. Modal attributes include travel costs, travel times, and other service quality attributes. These modal attributes are heavily dependent on the underlying transportation infrastructure in the analysis area. The current study assumes workers commute during the morning peak period; hence, the modeling framework does not include temporal differences in employment accessibility. Finally, by using the logsum measure of accessibility and clustering users based on socio-demographic characteristics, the current study models the individual component of accessibility in significant detail.

Four of the most common accessibility measures in the academic literature and used in practice are (Handy and Niemeier, 1997; Miller, 2018):

- 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)); and
- Expected maximum random utility-based measure (e.g. logit model "logsums"; (Ben-Akiva and Lerman, 1979)).

The distance/time/cost to the nearest destination measure is the most straightforward accessibility measure and the easiest to calculate. Handy and Niemeier (1997) employ this measure to analyze accessibility to supermarkets and convenience stores for communities in the San Francisco Bay Area. For grocery shopping, this simple accessibility measure can be useful. However, for other activity/opportunity types, such as employment opportunities, the nearest destination of interest measure provides limited information for planning and policy analysis.

The isochrone/contour measure is the most common accessibility measure in practice and has been widely applied to cities across the country (Owen and Murphy, 2018). The measure provides the number of opportunities that can be reached from an origin of interest within a specified threshold of travel time, distance, and/or cost by various modes. This accessibility measure has been used to: calculate the number of jobs reachable by socially disadvantaged residents in Montreal, Canada, based on travel time and travel cost thresholds (El-Geneidy et al., 2016); assess the gains in job accessibility for people belonging to different wage groups with the opening of a new light-rail line in the Twin Cities, Minnesota, region (Fan et al., 2012); and, create a space- and time-sensitive accessibility measure for subregions within the SCAG region (Chen et al., 2011). The two main shortcomings of this method are (i) the results are highly dependent on the isochrone travel time or distance cut-off value and (ii) the relative value of an opportunity within the isochrone is independent of the travel time/distance from the origin of interest to the opportunity. For example, if the isochrone threshold is 45 minutes, an additional grocery store 1 minute away is given the same weight as an additional grocery store 44 minutes away but the grocery store 46 minutes away is given zero weight. Xi et al. (2018) explore the best cut-off time to determine accessibility using the isochrone measure.

The gravity model denominator, or Hansen's measure, considers the number of opportunities available at destinations surrounding an origin of interest, wherein the measure weights the opportunities as a function of the impedance between the origin of interest and each opportunity's location. The impedance function typically captures travel time and/or generalized cost. Hence, this measure overcomes the shortcomings of the isochrone measure described in the previous paragraph. Grengs (2010) uses the gravity model denominator to

measure accessibility to jobs for people living in different places and using different travel modes in the city of Detroit. Liu et al. (2004) present a geographical information systems (GIS) tool that combines both the gravity model-based approach and the cumulative opportunities within a certain impedance level method to measure accessibility. The main shortcoming of the gravity model denominator is its inability to easily differentiate between individuals in terms of the value of opportunities. That is, without explicit segmentation, the value of an additional employment opportunity in the education sector 5 miles away from the origin of interest is the same for everyone who resides in the origin, including people with and without any college or high school education. Even with explicit segmentation, there is no 'built-in' mechanism to quantify the value of each type of (employment) opportunity. Ben-Akiva and Lerman (1979) address these shortcomings via linking accessibility to consumer surplus and illustrating that the logsum value obtained from work destination-commute mode choice models is an accessibility measure consistent with random utility theory under the typical MNL assumptions. The next subsection details the logsum measure, including its theoretical underpinning as a measure of consumer surplus and accessibility.

Logsums, Consumer Surplus, and Accessibility

This section parallels the overviews presented in several studies (de Jong et al., 2007; Geurs et al., 2010; Kohli and Daly, 2016) and one textbook (Train, 2009).

To model discrete choices, a typical assumption is that the utility the decision maker n obtains from a choice alternative j can be decomposed into an observed component (V_{nj}) and an unobserved, random component (ε_{nj}), as shown in Eqn. 1:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

where U_{nj} represents the utility that decision maker n obtains from alternative j; V_{nj} is known as the 'representative utility' and includes factors the analyst can measure; and ε_{nj} includes all the factors that affect U_{nj} that the analyst cannot capture. In this study, let N denote the set of all decision makers (i.e. workers) and J the set of all discrete choice alternatives (i.e. destinations, modes, or destination-mode pairs). Assuming the ε_{nj} values are independent and identically distributed (iid) across alternatives $j \in J$ and decision-makers $n \in N$, and the distribution is Gumbel with standard variance ($\pi^2/6$), then the choice probabilities are given by the standard multinomial logit (MNL) model, as shown in Eqn. 2:

$$P_{nj} = \frac{e^{V_{nj}}}{\sum_{j' \in J} e^{V_{nj'}}} \tag{2}$$

By definition, a person's consumer surplus is the utility, in monetary terms, this person receives in a choice situation. Moreover, consistent with the utility-maximizing framework from which the MNL model can be derived, the decision maker, n, chooses the alternative, j, that maximizers her utility. Hence, consumer surplus can be defined as shown in Eqn. 3:

$$CS_n = \frac{1}{\alpha_n}\left(\max_j U_{nj} \; \forall j\right) \tag{3}$$

where α_n is the marginal utility of income ($\alpha_n = dU_{nj}/dY_{nj}$ and Y_n is the income of decision-maker n). Division by α_n in Eqn. 3 converts utility units into monetary units.

Since the analyst does not and cannot observe U_{nj} and therefore cannot directly calculate the decision maker's consumer surplus, the analyst can only use the observable component of the utility, V_{nj}, and the distribution of the unobserved portion of utility, ε_{nj}, to determine the decision maker's expected consumer surplus:

$$E[CS_n] = \frac{1}{\alpha_n} E\left[\max_j (V_{nj} + \varepsilon_{nj})\right] \tag{4}$$

where the expectation in Eqn. 4 is over ε_{nj}. Given the iid Gumbel distribution assumptions on ε_{nj} mentioned previously, and an assumption that utility is linear in income (i.e. α_n is constant with respect to income), then the expectation in Eqn. 4 transforms into Eqn. 5, as shown in Small and Rosen (1981):

$$E[CS_n] = \frac{1}{\alpha_n} \ln\left(\sum_{j \in J} e^{V_{nj}}\right) + C \tag{5}$$

where *C* is an unknown constant capturing the fact that analyst cannot measure absolute levels of utility. (Notice that the summation term ($\sum_{j \in J} e^{V_{nj}}$) is in the denominator of the MNL model in Eqn. 2. The natural log of this summation term is known as the "logsum." The summation term that appears in both Eqn. 5 and the denominator in Eqn. 2 has no economic meaning, it is simply a property of the MNL model assumptions (Train, 2009). Nevertheless, the closed-form expression for consumer surplus, which is simply the natural log of the denominator of the MNL model, is convenient for analysis purposes.

Although Eqn. 5 shows that an analyst cannot obtain an absolute level of expected consumer surplus for a decision-maker because of the constant *C*; fortunately, the analyst can obtain the difference in expected consumer surplus that arises from an investment or policy or technology that impacts the observable component of utility, V_{nj}. Equation 6 shows the result of comparing the expected consumer surplus of decision-maker n before (subscript 0) and after (subscript 1) the implementation of a policy/investment/technology, where the constant *C* in Eqn. 5 drops out when calculating the difference in expected consumer surplus before and after the policy/investment/technology. The current study extends and utilizes the formulation in Eqn. 6 extensively to analyze the increase in consumer surplus associated with the inclusion of two SAMS modes in the mode choice sets of commuters.

$$\Delta E[CS_n] = \frac{1}{\alpha_n} \left[\ln\left(\sum_{j \in J^1} e^{V_{nj}^1} \right) - \ln\left(\sum_{j \in J^0} e^{V_{nj}^0} \right) \right] \tag{6}$$

Ben-Akiva and Lerman (1979) argue that the most appropriate accessibility measure is the maximum utility obtainable from a travel choice for a given traveler. Similar to the arguments in Eqn. 3 and Eqn. 4, Ben-Akiva and Lerman (1979) also suggest that in a model of random utility, where the utility of each travel alternative is not known exactly, the expected maximum utility is an appropriate measure of accessibility. The paper goes on to show that accessibility and consumer surplus are equivalent under the MNL model assumptions and the logsum is a measure of accessibility.

Ben-Akiva and Lerman (1979) describe important properties of the MNL model assumptions. One notable property is monotonicity in accessibility with respect to the choice-set size, meaning including additional choice alternatives (e.g. SAMS modes) in the choice set must increase consumer surplus/accessibility.

Niemeier (1997), in one of the first studies to employ the logsum accessibility measure, analyzes employment accessibility by estimating a joint work destination-commute mode choice model. Zondag et al. (2015) use logsums to measure accessibility and analyze the interactions between land-use and transportation in Netherlands. Standen et al. (2019) use the logsum to measure accessibility and subsequently appraise non-motorized modes such as walking and biking.

In limited applications, the logsum has provided significant value in transportation and land-use policy analysis and investment decisions (de Jong et al., 2007; Kohli and Daly, 2016; Villanueva et al., 2018; Zondag et al., 2015). However, the logsum measure still suffers from several negative attributes that have limited its use in practice, namely: (i) it is difficult to communicate the economic measure and the quantitative results to non-technical decision-makers; and, (ii) calculating and validating logsum measures is difficult for modelers who use highly detailed, data-intensive activity-based travel demand modeling software and dynamic network modeling software (Villanueva et al., 2018).

Modeling the Impacts of SAMS Modes

The potential societal benefits and pitfalls of AVs and SAMS modes have motivated significant research in recent years. Fagnant and Kockelman (2015) present a macro-analysis of the potential benefits and negative impacts of AVs on existing transportation systems and society in general, including, decreases in crashes and fatalities, parking cost savings, and congestion reductions. Early SAMS research focused on understanding the road network congestion and vehicle emissions impacts of SAMS modes while simultaneously trying to estimate SAMS fleet sizes (Burns et al., 2013; Fagnant and Kockelman, 2014; Zachariah et al., 2014). Later work has focused on improving models and algorithms for the operation of SAMS fleets (Dandl et al., 2019; Hörl et al., 2019; Hyland and Mahmassani, 2018; Iglesias et al., 2017; Tsao et al., 2018).

Additionally, researchers are conceptualizing and modeling the potential impacts of SAMS modes on trip generation (Truong et al., 2017); land-use, energy, and emissions (Wadud et al., 2016); and residential location choice (Zhang and Guhathakurta, 2018). Vyas et al. (2019) incorporate AVs within an existing activity-based travel demand model (ABM) by including new ABM sub-models and making changes to parameters in existing ABM sub-models. A recent review article details the modeling advances related to AVs and SAMS modes in the academic literature (Soteropoulos et al., 2019). Several studies also present stated preference (SP) survey results regarding the willingness of travelers to use and pay for AV and SAMS modes. Becker and Axhausen (2017) and Gkartzonikas and Gkritza (2019) present recent reviews of these SP survey studies.

Accessibility Analysis of AVs and SAMS Modes

There are a few studies in the existing literature that examine the potential accessibility benefits of AVs and SAMS modes. Meyer et al. (2017) examine the accessibility improvements of AVs under three different conditions: (i) AVs can only operate on highways; (ii) AVs can operate anywhere but SAMS modes do not exist (only personally owned AVs do); and (iii) AVs can operate anywhere and SAMS modes exist. Unlike the current study, Meyer et al. (2017) focus on the accessibility benefits associated with the improved travel times (assuming AVs significantly increase roadway capacities) and the study also explicitly captures induced demand. However, Meyer et al. (2017) use the gravity model denominator measure of accessibility rather than the logsum-based measure and their analysis does not capture variations in accessibility as a function of the attributes of individual travelers, nor does it capture the relative worth of opportunities across segments of the population, whereas, the current study does capture these effects.

Milakis et al. (2018), using the four components of accessibility identified by Geurs and van Wee (2004), survey seventeen international experts to examine how experts expect AVs to impact accessibility. According to this qualitative study, the experts expect AVs to have wide-ranging impacts on land-use, transportation, temporal, and individual components of accessibility. However, the experts disagree in terms of how AVs will impact accessibility.

Similar to the current study, Childress et al. (2015) also use destination-mode choice model logsums to evaluate the impacts of AVs. However, the accessibility analysis section of their study includes limited methodological details and only one set of results. The current study provides a much more in-depth description of the employment accessibility analysis methodology as well as a wide range of results relating to the employment accessibility impacts of SAMS modes using destination-mode choice logsum measures. Moreover, the current study also clusters workers based on their socio-demographic characteristics to improve the ability of the model to capture accessibility differences across the working population. Interestingly though, similar to the current study, Childress et al. (2015) also find little difference in the impact of AVs on accessibility across households with high and low incomes.

Data and Methodology

Overview

Figure 1 displays the methodological framework for this study. The data sources and relevant variables are shown in blue text boxes; the models, software, and calculations are shown in orange text boxes; and the dashed white boxes show the model/calculation outputs. The research methodology clearly involves a variety of different data sources, models, and calculations to quantify the employment accessibility benefits (i.e. consumer surplus) associated with the inclusion of two SAMS modes in the mode choice sets of workers.

The remainder of this section describes the data sources and variables; provides the scope of the modeling framework and key modeling assumptions; presents the LCA clustering approach; details the hierarchical destination-mode choice modeling procedure; and shows how this study employs the logsum measure of accessibility presented in Section 2. The population synthesis procedure, destination choice set generation procedure, and the OLS car cost per mile model are relatively straightforward; thus, they are only described briefly in the subsections below.
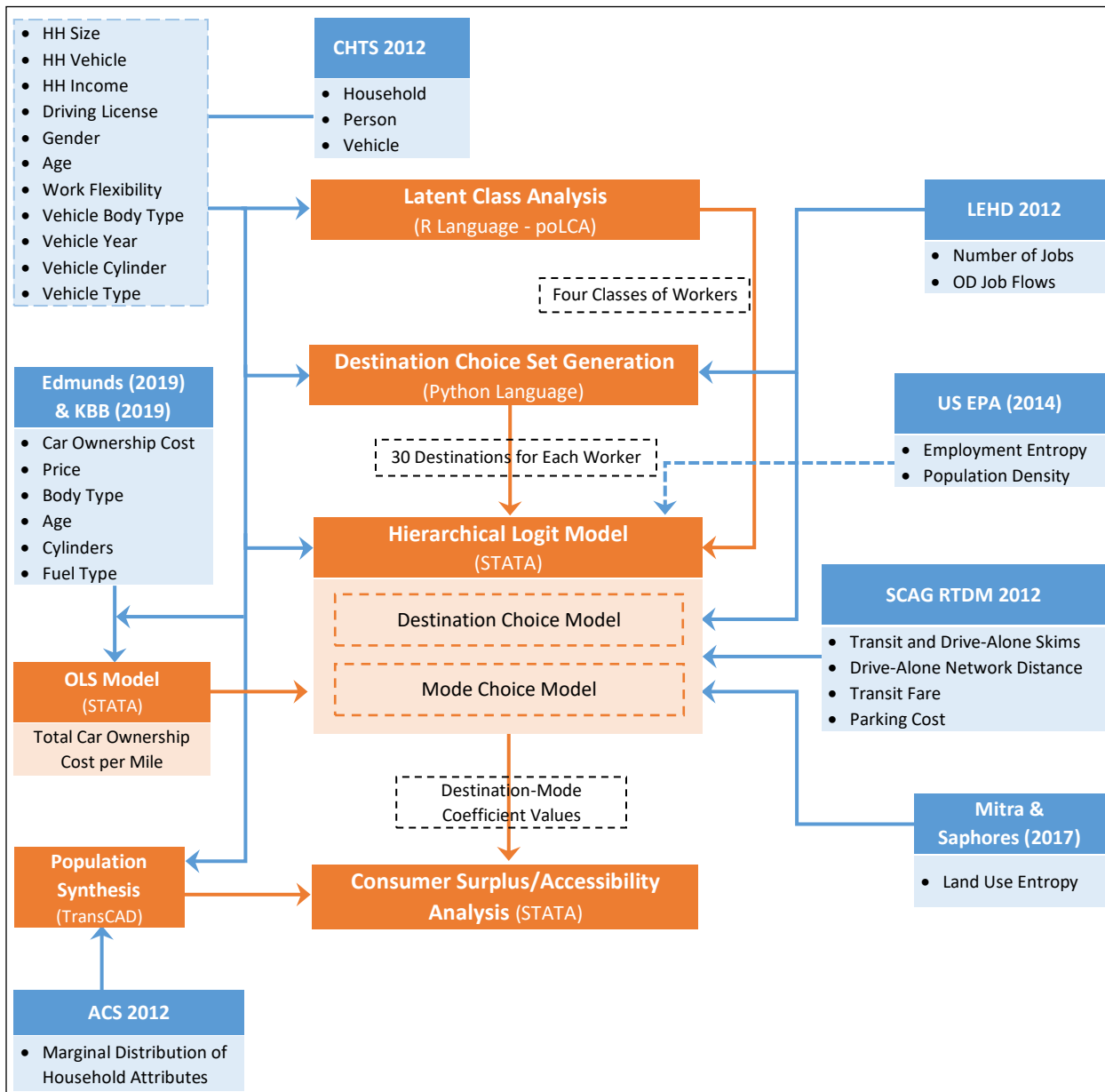
Figure 1. Flowchart Illustrating Methodological Framework

Data

This subsection provides an overview and description of the data sources employed in this study (displayed in Figure 1) as well as information on dataset preparation for different models and calculations. The analysis area is the SCAG region that includes the counties of Imperial, Los Angeles, Orange, Riverside, San Bernardino and Ventura. The analysis (i.e. research methodology) required a variety of data, including:

1. A sample of workers in the SCAG region and data on their commute modes, destination choices, socio-demographics, and other travel and activity characteristics.

2. Distances, mode-dependent travel times (wait, walk, in-vehicle), and transit fares between each pair of Origin-Destination (OD) zones (i.e. home and work census tracts) in the SCAG region, as well as parking costs in each destination zone.
3. Driving costs between OD zones.
4. The number of employment opportunities and employment entropy in destination zones.
5. Population density and land use entropy in OD zones.
6. Marginal distributions of household attributes across census tracts.

A sample of SCAG workers is available in the 2012 California Household Travel Survey (CHTS) (National Renewable Energy Laboratory, 2017) and it contains detailed travel (e.g. commute mode) and activity information (e.g. work location) on 42,116 persons belonging to 15,713 households in the SCAG region. The publicly available version of the CHTS dataset provides location information at the census tract level. Therefore, this study analyzes the impacts of SAMS modes on employment accessibility at the census tract level of spatial aggregation. Since the study focuses on employment accessibility, the final dataset only includes employed persons. The study uses the CHTS data, directly or indirectly, in all six models and calculations in Figure 1.

The travel time, (driving) distance, and transit fare data between OD zones (i.e. OD skim matrices) are available from the SCAG metropolitan planning organization (MPO). The SCAG's regional travel demand model and 2012 model validation report (SCAG, 2016) provides details on the available data. The SCAG dataset includes OD skim matrix information across travel analysis zones (TAZs) that have different spatial boundaries than census tracts. To convert from TAZs to census tracts, this study utilizes the SCAG network data and the information on census tract boundaries. The former includes TAZ IDs for each node in the SCAG network and the latter allows one to convert TAZ IDs to census tract IDs. Finally, as mentioned previously, the study only considers the peak-hour travel times.

Unfortunately, the SCAG dataset does not include an OD skim matrix for walking distance or walking time. Assuming the walking distance for commute trips is similar to driving distance (implicitly assuming workers can and do walk alongside roadways), to calculate walking times between OD zones, this study divides the driving distance by a walking speed of 3 miles per hour – around the average pedestrian walking speed (Fitzpatrick et al., 2006).

This study also assumes the in-vehicle travel times (IVTT) of the SAMS modes are equivalent to the drive-alone mode. However, the SAMS modes include a five-minute wait time at the beginning of the trip. In the SAMS+Transit option, the study assumes the SAMS trip segment would not be greater than 10 miles and not more than 50% of the total travel distance. For simplicity, the study only allows SAMS to be a transit access mode, not a transit egress mode. Additionally, total transfers (including the SAMS to transit transfer) for the SAMS+Transit option will be less than or equal to two. Given these constraints and using the car and transit total travel time OD skim matrices, the transfer point that minimizes overall travel time can be

determined. After determining the transfer point, it is possible to obtain OD skim matrices for total travel, in-vehicle, wait, transfer, and egress travel times for the SAMS+Transit mode.

Driving cost data for different makes and models of cars is not directly available from any source. Therefore, this study estimates driving cost per mile, as a function of vehicle characteristics, using two different sets of data sources. The first is the aforementioned CHTS data that provides information on the vehicle each respondent owns. The second is the five-year cost of car ownership data from Edmunds (2019) and Kelley Blue Book (KBB, 2019). The study estimates the cost per mile for the drive-alone mode for each worker in the CHTS sample by first developing and then applying an ordinary least squares (OLS) regression model based on observations of cost per mile data collected from Edmunds (2019) and Kelley Blue Book (2019). A total of 297 observations of total cost of ownership were drawn from these sources that represented vehicles of different make, model, cylinder type, age, and category. These websites report five- year cost estimates of new and used vehicles assuming the vehicles are driven 15,000 miles per year. The costs include tax credits, insurance, maintenance, repairs, taxes and fees, financing, depreciation, and fuel. Categorical variables in the OLS cost per mile model include: four purchasing price categories, three body types, five cylinder categories, and several vehicle ages. The purpose of the vehicle cost model is to more accurately reflect the actual cost each worker spends while driving alone to work, based on the make, model and age of his/her vehicle, rather than assuming a flat driving cost per mile. To account for the difference in the cost of new versus used vehicles, the cost per mile value is raised by 19.9% if the car was acquired new or is less than or equal to six years old. This rate is based on the average cost difference of five different vehicles with an ownership of 5 years and 15 years (Q, 2019). The car total cost per mile results are shown in Table 7 in the Appendix and they illustrate that there are significant differences in the costs per mile across vehicle types.

Data on the number of employment opportunities, by job category, in each destination zone is available in the 2012 Longitudinal Employer-Household Dynamics (LEHD) database (US Census Bureau, 2012). This study uses the LEHD database to create destination choice sets as well as to characterize the destinations in the work destination choice model. The analysis involves converting the 20 job categories in the LEHD database to eight categories following the classification structure used in the US EPA's Smart Location Database (US EPA, 2014). The Smart Location Database (US EPA, 2014) and Mitra and Saphores (2017) contain data on population density and land use entropy, respectively.

Finally, the marginal distribution of household (HH) attributes (e.g. HH income, HH size, number of HH workers) across census tracts is available in the 2012 American Community Survey (ACS) (US Census Bureau, 2013). This study uses the ACS marginal distributions and the sample of CHTS workers to create a synthetic population of workers in the SCAG region.

Modeling Scope and Assumptions

AVs and SAMS modes are expected to have wide-ranging impacts on transportation systems and land-use in metropolitan regions. Trying to model all the potential impacts simultaneously

is beyond the scope of this study. Hence, this study assumes the introduction of SAMS modes will mainly impact the mode choice and destination choice of workers. Conversely, this study assumes no major changes in the residential locations of workers nor in the workplace locations of employers. Future research can explore these choice dimensions jointly.

This study also assumes no major changes in the road network travel times in a future with AVs and SAMS modes. This assumption is made for several reasons. First, this study aims to provide somewhat conservative estimates of the employment accessibility benefits of SAMS modes. This reasoning is also why the current study does not assume the disutility of IVTT will decrease when workers commute via SAMS models or personal AV modes, unlike other studies in the literature (Vyas et al., 2019). Second, it is not clear what overall impact AVs and SAMS modes will have on network congestion (and whether policy makers will implement congestion pricing mechanisms or other policies to try to mitigate congestion). While AVs are expected to improve the stability and throughput of traffic (Talebpour and Mahmassani, 2016), the benefits (including accessibility benefits) of AVs and SAMS modes are expected to significantly increase demand for vehicle-based travel, thereby pushing congestion levels back toward current levels, if travelers are unwilling to share rides with other travelers (Meyer et al., 2017). Capturing the demand-supply feedback loop between the impact of accessibility benefits and traffic flow benefits of AVs and SAMS modes on travel demand, and the subsequent impact of increased travel demand on network congestion, is left for future research.

Clustering Workers

The first step of the research methodology (see Figure 1) involves clustering workers based on their socio-demographic attributes. The study assumes clustering workers based on socio-demographic attributes can partially capture how different workers value different types of employment opportunities. For instance, a cluster representing high-income, high-education workers may value education jobs significantly more than retail jobs; whereas, the reverse may be true for low-income, young workers. Hence, the LCA model captures socio-demographic differences in order to subsequently capture the fact that a new travel mode that improves travel times/costs to destinations with education jobs will improve accessibility for high-income, high-education workers more than a new travel mode that improves travel times/costs to destinations with retail jobs.

To cluster workers in the CHTS sample, this study employs the LCA clustering approach. In comparison to other clustering methods, LCA provides the advantage of statistically confirming the number of classes as well as incorporating multivariate discrete categorical data (Dean and Raftery, 2010; Greene and Hensher, 2003), the latter property being necessary for the socio-demographic data in this study. The mathematical formulation of the LCA model is provided in Eqn. 7-9 (Linzer and Lewis, 2011).

Let V denote the set of manifest variables, indexed by $v \in V$; and let K_v denote the set of outcomes for each manifest variable $v \in V$, indexed by $k \in K_v$, wherein the subscript v denotes the fact that the number of possible outcomes varies across manifest variables $v \in V$.

Moreover, let C denote set of classes, indexed by $c \in C$; and let N, once again, denote the set of individuals, indexed by $n \in N$. Finally, let Y_{nvk} equal 1, if individual $n \in N$ has outcome $k \in K_v$ on variable $v \in V$, and 0 otherwise. The LCA model approximates the observed joint distribution of the manifest variables as the weighted sum of a finite number, $|C|$, of constituent cross-classification tables, where the analyst sets $|C|$ (Linzer and Lewis, 2011).

The probability an individual $n \in N$ in class $c \in C$ produces a specific set of $|V|$ outcomes on the manifest variables V, assuming conditional independence of the outcomes Y_{nvk} given class memberships, is the product:

$$f(Y_n; \pi_c) = \prod_{v \in V} \prod_{k \in K_v} (\pi_{vck})^{Y_{nvk}} \tag{7}$$

where, π_{vck} is the class-conditional probability a member of class c results in outcome k on variable v. π_{vck} is a model parameter that needs to be estimated and has the property: $\sum_{k \in K_v} \pi_{vck} = 1$ for all $v \in V$ and $c \in C$.

The probability density function across all $|C|$ classes is simply the sum of class-conditional probabilities ($f(Y_n; \pi_c)$) weighted by p_c:

$$P(Y_n | \pi_{vck}, p_c) = \sum_{c \in C} p_c f(Y_n; \pi_c) = \sum_{c \in C} p_c \prod_{v \in V} \prod_{k \in K_v} (\pi_{vck})^{Y_{nvk}} \tag{8}$$

where, p_c is the unconditional probability that an individual will belong to class c before considering the outcomes on the manifest variables (Y_{nvk}). p_c is another model parameter that needs to be estimated. The p_c values are also known as the mixing probabilities and the "prior" probabilities of latent class membership, with property: $\sum_{c \in C} p_c = 1$

The study estimates the LCA models (i.e. p_c and π_{vck}) using the poLCA package in the programming language R, which utilizes Expectation Maximization (EM) and Newton-Raphson algorithms (Linzer and Lewis, 2011). Once parameter estimates for p_c and π_{vck} are obtained, the posterior probability that individual n belongs to a specific class c, can be calculated using Bayes' formula:

$$\hat{P}(c_n | Y_n) = \frac{p_c f(Y_n; \pi_c)}{\sum_{c' \in C} p_{c'} f(Y_n; \pi_{c'})} \tag{9}$$

In addition to choosing the number of clusters $|C|$, the analyst also determines the manifest variables. To find latent classes of workers, this study considered the socio-demographic attributes of the workers in the CHTS. The final model includes four categorical variables, namely, gender, age, education, and household income. The study also considered the number of vehicles per licensed driver in the household, but it was excluded because it did not help meaningfully distinguish between workers in the dataset.

Hierarchical Destination-Mode Choice Model

This section provides an overview of the modeling procedure to obtain parameter estimates for a hierarchical destination-mode choice model. The parameter estimates are necessary inputs to calculate logsum-based measures of accessibility.

Let i_n denote the census tract of worker n's residence (i.e. commute trip origin) and O the set of all origin census tracts, $i_n \in O$. Moreover, let D_n denote the work destination locations worker n considers, indexed by $j \in D_n$, where $D_n \subseteq J$. Additionally, let M_{j_n} denote the commute modes worker n considers when considering work destination j, indexed by $m \in M_{j_n}$. Finally, let $M^0 = \{Car, Transit, Walk\}$ be the set of all commute modes before the introduction of SAMS modes, and let $M^1 = \{Car, Transit, Walk, SAMS, SAMS + Transit\}$ be the set of all commute modes after the introduction of SAMS modes, where $M_{j_n} \subseteq M^0$

Given the nature of the CHTS data (National Renewable Energy Laboratory, 2017), it is not possible to determine the set of work destinations each worker actually considers. Hence, this study generates a random sample of 29 work destination census tracts, along with the destination census track where the worker currently works j_n, to populate the destination choice set for each worker, i.e. $|D_n| = 30$. The study draws the 29 destinations from the LEHD data, which provides job flows between pairs of census tracts. The method does not assume all destinations in the SCAG region can be in D_n; rather, a search distance of 50 miles was imposed around i_n beyond which it seemed unreasonable to commute on a regular basis. Mitra and Saphores (2019) find that only 6.4% of long-distance (50+ mile) trips in California are commute trips. However, this search distance was sometimes extended when the number of destinations was inadequate (e.g. around rural areas where commutes can be quite long). Besides decreasing computational time, limiting the number of alternatives in the choice set also minimizes the risk of overwhelming the model with unreasonable destination locations (Ortúzar and Willumsen, 2011).

It is also necessary to determine the modes available to each worker to commute to each of the destinations in their destination choice set. The walk, car, and transit modes are considered available for each worker for each destination unless (i) the total travel time between the worker's origin, i_n, and a potential destination $j \in D_n$ is greater than three hours for a mode, or (ii) the worker does not own a personal car, in which case, the car is not available in their choice set.

Error! Reference source not found. displays this hierarchical destination-mode choice structure for an example worker n with origin location i_n. This hierarchical structure assumes workers determine their work location before choosing their commute mode; however, it also assumes they consider the attributes of the potential commute modes in each destination, along with the other destination attributes, when determining their work location. The assumption that the mode choice is nested within the employment destination choice is (i) based on the fact that employment location is typically considered to be a more important and longer term

decision than mode choice, (ii) something that can be statistically tested and verified within the hierarchical discrete choice modeling framework, and (iii) consistent with much of the existing literature that assumes and statistically verifies that mode choice is a lower-level choice than work destination choice.
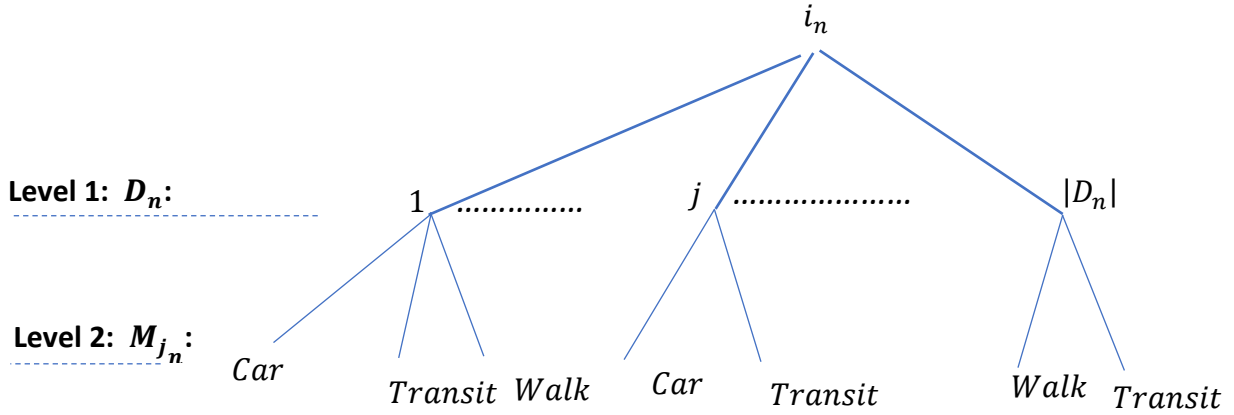

Figure 2. Hierarchical Structure of Destination-Mode Choice Model

Given the MNL assumptions described in Section 2.2, the probability $P_{m|j}^{i_n}$ that worker n residing in origin i_n chooses mode $m \in M_{j_n}$ given the choice of destination $j \in D_n$ can be expressed as (González et al., 2016):

$$P_{m|j}^{i_n} = \frac{e^{V_{m|j}^{i_n}}}{\sum_{m' \in M_{j_n}} e^{V_{m'|j}^{i_n}}} \tag{10}$$

where $V_{m|j}^{i_n}$ is the systematic component of utility that worker n derives from taking mode m to commute between her origin i_n and potential destination j. The term $V_{m|j}^{i_n} = \sum_{a \in A^m} \beta_a X_{a,m|j}^{i_n}$ is the product sum of a vector of coefficients to be estimated (β) and a vector of attributes ($X_{m|j}^{i_n}$) associated with mode m between i_n and j, and worker n, with both vectors having rank $|A^m|$, where A^m is the set of mode choice level attribute indices.

The natural log of the denominator in Eqn. 10 is the mode choice logsum (i.e. inclusive value) that represents the maximum expected utility a worker obtains from all mode options, M_{j_n}, at destination j (Small and Rosen, 1981; Zhao et al., 2012). Equation 11 displays the mode choice logsum $I_j^{i_n}$, which can be used in the upper-level destination choice model as a measurable attribute of potential destination $j \in D_n$ (Ortúzar and Willumsen, 2011).

$$I_j^{i_n} = ln \sum_{m \in M_{j_n}} e^{V_{m|j}^{i_n}} \tag{11}$$

At Level 1, the choice scenario involves a worker selecting a destination considering the attributes of the destination locations (particularly employment opportunities) as well as the distance and mode choice logsum ($I_j^{i_n}$) from i_n to potential destination j. Equation 11 displays the mathematical formulation of the destination choice model, where $P_j^{i_n}$ indicates the probability worker n with origin i_n chooses destination j.

$$P_j^{i_n} = \frac{e^{\mu I_j^{i_n} + \sum_{b \in A^d} \beta_b \cdot X_{bj}}}{\sum_{k \in D_n} e^{\mu I_k^{i_n} + \sum_{b \in A^d} \beta_b \cdot X_{bk}}} \tag{12}$$

In Eqn. 12, X_j is a vector of attributes describing destination j; β is a vector of coefficients, to be estimated, that convert the destination attributes into utility units; and, μ is the parameter coefficient for the mode choice logsum ($I_j^{i_n}$) that verifies the destination-mode choice structure if $\mu < 1$. The term $\mu I_j^{i_n}$ connects the mode choice model in Level 2 with the destination choice model in Level 1. Both β and X_j have rank $|A^d|$ where A^d is the set of destination choice level attribute indices.

Let $P_{mj}^{i_n}$ represent the probability worker n with origin i_n chooses commute mode m and employment destination j. Assuming a hierarchical choice wherein the commute mode choice is nested within the work destination choice, Eqn. 13 shows that $P_{mj}^{i_n}$ is the product of Eqn. 12 and Eqn. 10. The hierarchical choice model can be estimated simultaneously or sequentially. Given the size of the CHTS dataset, this study estimates the hierarchical choice model sequentially.

$$P_{mj}^{i_n} = P_{m|j}^{i_n} \cdot P_j^{i_n} \tag{13}$$

The natural log of the denominator in Eqn. 12 is the destination choice logsum that represents the maximum expected utility a worker obtains from all work destination choice options D_n. Equation 14 shows that multiplying the destination choice logsum by $1/\alpha$, where α is still the marginal utility of income, provides the consumer surplus for the hierarchical destination-mode choice, which is our measure of employment accessibility. Consistent with much of the literature (Ortúzar and Willumsen, 2011; Train, 2009), this study uses the marginal disutility of travel cost parameter from the mode choice model, to obtain the α value.

$$Accessibility_n = CS_n = \frac{1}{\alpha} \ln \sum_{j \in D_n} e^{\mu I_j^{i_n} + \sum_a X_{aj} \beta_a} + C \tag{14}$$

This study estimates one set of mode choice parameter values, β_a, for all workers. However, the study estimates separate destination choice parameter values, β_b, for each separate worker cluster.

Logsum Measure of Employment Accessibility

To apply the estimated hierarchical destination-mode choice model, a 5% representative population was generated for each census tract of the SCAG region. The representativeness of the population was established by using the marginal distribution of four household level variables – household size, household income, number of workers in the household, and number of household vehicles. Values for these four variables come from the 2012 American Community Survey (ACS). Other synthetic population generation inputs include the household and person dataset from the CHTS sample (National Renewable Energy Laboratory, 2017).

The generation of the synthetic population was carried out using the 'Population Synthesis' tool in TransCAD (Caliper, 2019), which employs the Iterative Proportional Fitting (IPF) algorithm to match the marginal distribution of the census tracts with the joint distribution of the household attributes (Beckman et al., 1996). After creating the synthetic population, 44 out of the 3,951 census tracts had missing data, which is mostly due to the absence of households or workers in these census tracts according to the ACS data.

To quantify the employment accessibility benefits of the two SAMS modes, this study defines two sets of commute modes:

- Pre-SAMS Modes, M^0: Walk, Drive Alone and Transit
- Post-SAMS Modes, M^1: Walk, Drive Alone, Transit, SAMS-only, SAMS+Transit

This study assumes that the SAMS-only mode has many of the same modal attributes as the Drive Alone mode, except the SAMS-only mode has zero parking cost, a different cost per mile, and a wait time. The SAMS+Transit mode is treated as a mix between the Drive Alone and Transit modes.

Given the synthetic population, the parameter estimates from the hierarchical destination-mode choice model (and the assumed parameters for the SAMS-only mode and the SAMS+Transit mode), Eqn. 15 displays the formula to determine the increase in employment accessibility as a result of two new SAMS commute modes. The superscripts 1 and 0 represent the model with and without SAMS respectively.

$$\Delta Accessibility = \Delta CS = \frac{1}{\alpha}\left[\ln\left(\sum_{j,m} e^{V_{jm}^1}\right) - \ln\left(\sum_{j,m} e^{V_{jm}^0}\right)\right] \tag{15}$$

Results and Discussion

Characteristics of the Latent Classes

This section presents the LCA model results. To ensure optimality of the classification, this study considered class sizes up to 10 and for each class size the specified model was run 50 separate times with a random set of initial probabilities conditional on the class and manifest variables.

This was required to increase the prospect of reaching a global maximum solution rather than a local maximum. The model with four classes was found to have the lowest cAIC (i.e., consistent AIC) and second lowest BIC.
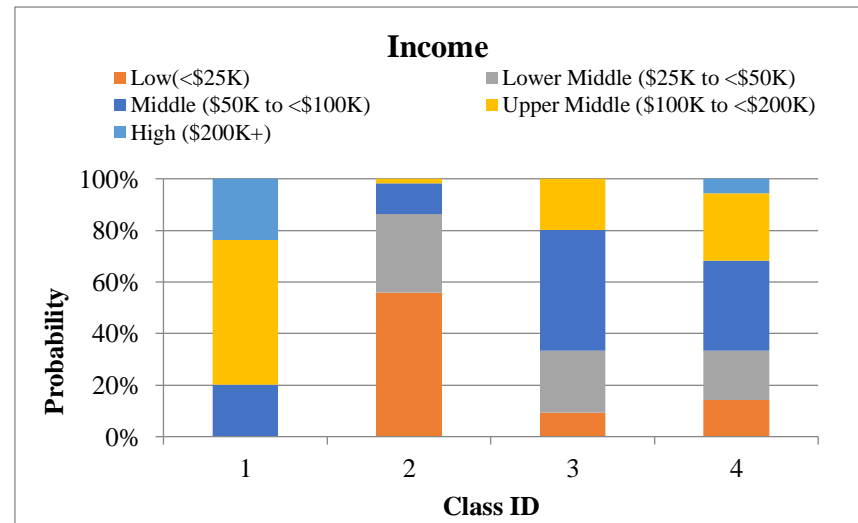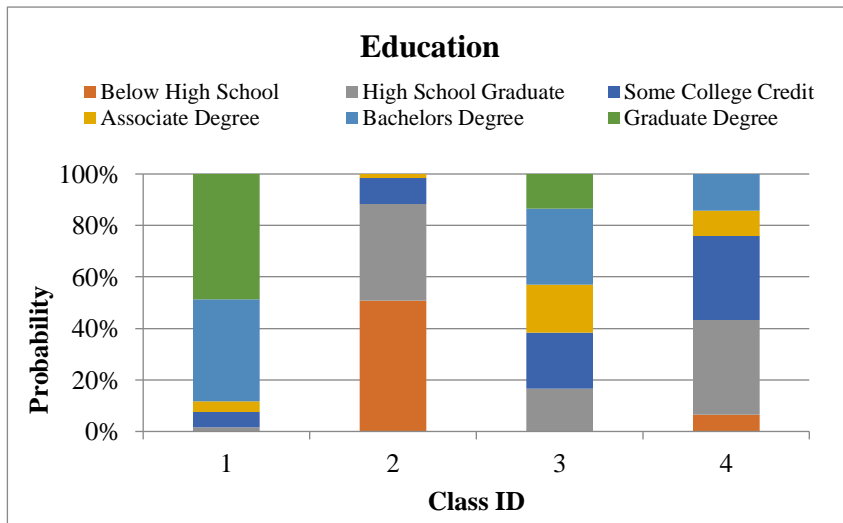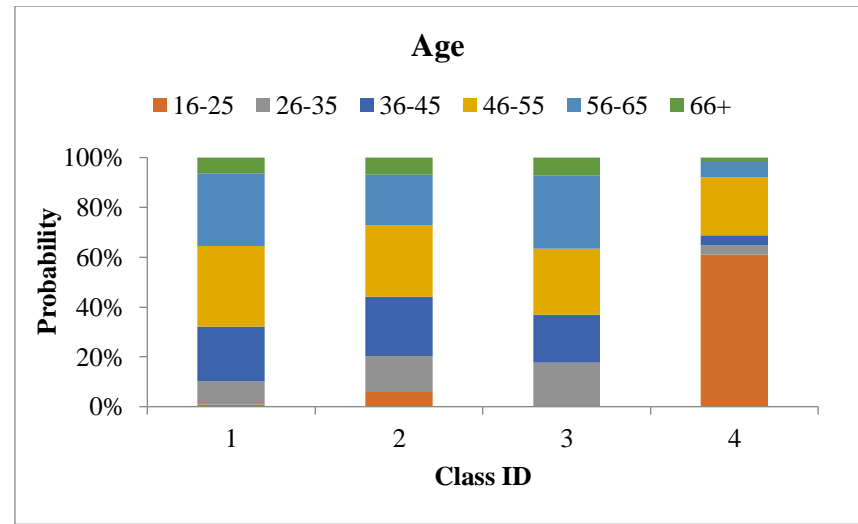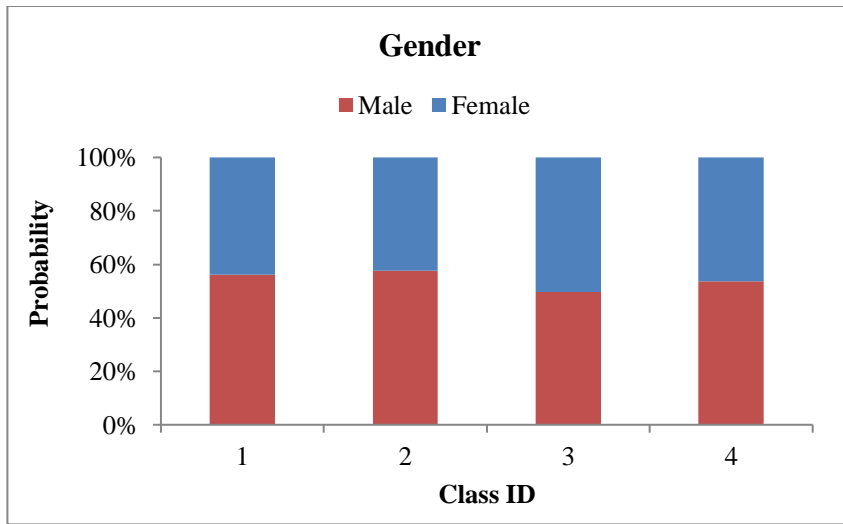
Figure 3. Class-Condition Probabilities

Figure 3 displays the estimates for π_{vck}, the class-conditional probability a member of class c results in outcome k on variable v. Figure 3 shows that the class-conditional probabilities for education and income vary the most across the classes. Conditional on being in Class 1, the probability of having a college degree and making more than $100k per year is the highest across classes. Conversely, conditional on being in Class 2, the probability of not having a college education and making less than $50k per year is the highest across classes. Conditional on being in Class 4, the likelihood of being younger than 25 is much higher than for other worker classes. Figure 3 also shows that there is not much difference in the class-conditional probabilities for gender, with the female probabilities of ranging from 42% to 50%. Other than Class 4, the class-conditional age probabilities are consistent across Classes 1, 2, and 3.

Table 1 labels the classes based on their class-conditional probabilities in the final four columns. The third column displays the estimates for the parameter P_c, the unconditional probability that an individual will belong to class c. The second column displays the results of the assignment of the sample workers to classes considering the posterior probability $\hat{P}(c_n|Y_n)$. Each worker n was assigned to the class c with the highest posterior probability.

The workers in Class 2 have low education attainment levels and live in households with annual incomes below $50k. This class of workers only makes up 8.3% of the sample of CHTS workers. On the other hand, the workers in Class 1 have high education attainment levels and live in households with annual incomes above $50k with most household annual incomes above $100k. This class of workers makes up 32.4% of the CHTS sample. The workers in Class 4 are most notably young, with low education attainment (likely because they are young) and live in households with a wide range of incomes. This class of workers makes up only 9.5% of workers in the CHTS sample. Finally, the workers in Class 3 have a relatively even distribution of ages and education levels. However, their household annual incomes are noticeably in the middle-income levels and this class has a disproportionately high number of female workers. The workers in Class 3 make up 50% of workers in the CHTS sample.

Table 1. Characteristics of the Classes with respect to Four Manifest Variables

Class	Proportion Assign from Post. Prob	Unconditional Class Prob.	Class Representation			
			Gender	Age	Education	Income
1	0.324	0.280	-	-	Graduate/Bachelors	Upper Middle/High
2	0.083	0.140	-	-	Below High School	Low/Lower Middle
3	0.498	0.433	Female	-	-	Middle
4	0.095	0.147	-	16-25	High School/ Some College	-

Table 2 displays the distribution of socio-demographic and travel characteristics across the four worker classes and the significance of their differences with respect to the p-values of chi-square and ANOVA tests. Once again, workers in the CHTS sample were assigned to the class

with the highest posterior probability. The second column of Table 2 also shows the distribution of socio-demographic and travel characteristics for all workers (i.e. without clustering). The first four variables, from the LCA model, verify a statistically (and practically) significant difference between the four classes in terms of the four manifest variables.

In addition to the socio-demographic differences in the classes, there are significant differences in the distribution of variables pertaining to household/person characteristics, travel characteristics, and work location attributes. The most important is the current employment sector of workers because the study assumes that different workers value different employment types differently; hence, in the destination choice model it is valuable to cluster workers based on the type of jobs they are likely to value. As expected, Table 2 illustrates significant differences between the classes in terms of current employment type. Moreover, the crosstab values between employment sector and class (considering the LCA class attributes) are unsurprising. Class 1 workers, who have the highest education and household incomes, have more jobs in education and offices than the other three classes. Class 2 workers, who are predominately male without college degrees and have low household incomes, have a much higher percentage of industrial jobs than the other worker classes. Class 3 workers, who are in medium income households, have the highest percentages of jobs in healthcare and public administration sectors. Finally, Class 4 workers, who are the youngest, are more likely to have jobs in entertainment and retail than the other worker classes.

The employment type results, specifically the statistical significance across clusters, provide some evidence that the LCA method, which used only four socio-demographic manifest variables, clustered workers in a manner that should be effective in terms of differentiating the types of employment opportunities different segments of the working population value.

Table 2. Distribution of Socio-demographic and Travel Characteristics Across Classes

Characteristics	All Class (*N*= 12,733)	Class 1 (*N*= 4,125)	Class 2 (*N*=1,055)	Class 3 (*N*=6,343)	Class 4 (*N*=1,210)	Significance of Difference
Household/Person						
Gender						
Male	52.49	56.56	68.91	47.23	51.82	$Pr(> \chi^2) = 0.00$
Female	47.51	43.44	31.09	52.77	48.18	
Age (years)						
16-25	9.68	0.24	2.94	0.03	98.35	
26-35	13.28	10.06	13.84	17.75	0.33	
36-45	19.33	22.11	29.57	19.50	0.00	$Pr(> \chi^2) = 0.00$
46-55	28.68	34.35	35.36	29.10	1.32	
56-65	23.96	27.78	14.31	27.65	0.00	
66+	5.07	5.45	3.98	5.96	0.00	
Education						
Below High School	5.32	0.00	58.86	0.00	4.63	
High School Graduate	15.58	0.36	38.01	18.45	32.89	
Some College Credit	17.39	1.62	3.13	26.39	36.36	$Pr(> \chi^2) = 0.00$
Associate Degree	11.16	0.68	0.00	20.09	9.83	
Bachelor's Degree	27.57	40.87	0.00	25.67	16.28	
Graduate Degree	22.98	56.46	0.00	9.41	0.00	

Characteristics	All Class (N= 12,733)	Class 1 (N= 4,125)	Class 2 (N=1,055)	Class 3 (N=6,343)	Class 4 (N=1,210)	Significance of Difference
Household Income ($1,000)						
Low (<25)	8.43	0.00	52.61	5.74	12.81	
Lower Middle (25 to <50)	15.43	0.00	35.73	22.21	14.79	
Middle (50 to <100)	35.06	11.22	9.86	54.74	35.12	$Pr(> \chi^2) = 0.00$
Upper Middle (100 to <200)	32.47	64.63	1.80	17.31	29.09	
High (200+)	8.60	24.15	0.00	0.00	8.18	
HH Size	3.19	3.03	3.93	2.99	4.11	$Pr(> F) = 0.00$
HH Vehicle per Driver						
Low (<1 Vehicle)	15.62	9.76	26.35	15.59	27.59	$Pr(> \chi^2) = 0.00$
High (1+ Vehicles)	84.38	90.24	73.65	84.41	72.41	
Employment Sector						
Retail	9.11	3.49	12.70	9.16	24.88	
Office	10.38	12.90	3.03	10.75	6.28	
Industrial	18.70	12.65	42.46	20.05	11.49	
Service	14.29	16.99	14.22	13.07	11.49	$Pr(> \chi^2) = 0.00$
Entertainment	8.60	5.31	13.74	7.20	22.64	
Education	18.43	26.86	3.51	17.01	10.17	
Healthcare	11.66	12.07	8.06	12.42	9.42	
Public Administration	8.83	9.72	2.27	10.33	3.64	
Job Count	1.25	1.20	1.40	1.26	1.24	$Pr(> F) = 0.00$
Work Hour (per week)	37.39	40.34	36.68	37.19	28.60	$Pr(> F) = 0.00$
Work Flexibility						
No	41.98	32.88	53.33	45.65	44.24	
Low	44.39	50.58	35.65	41.49	45.94	$Pr(> \chi^2) = 0.00$
High	13.63	16.54	11.01	12.86	9.82	
Travel						
Commute Distance (miles)	9.68	10.44	8.60	9.78	7.51	$Pr(> F) = 0.00$
Commute Mode						
Walk	3.67	3.49	6.73	2.96	5.29	
Drive Alone	91.51	93.55	79.15	93.08	87.11	$Pr(> \chi^2) = 0.00$
Transit	4.82	2.96	14.12	3.96	7.60	
Work Location						
Population Density	14.75	14.66	15.09	15.00	14.01	$Pr(> F) = 0.28$
Employment Density	7.66	7.94	8.47	6.69	8.97	$Pr(> F) = 0.06$
Land Use Entropy	0.52	0.52	0.53	0.50	0.53	$Pr(> F) = 0.00$
Employment Entropy	0.54	0.54	0.53	0.53	0.54	$Pr(> F) = 0.37$

Note: Data on land use entropy was collected from Mitra & Saphores (Mitra and Saphores, 2017), who created this index based on eight land use categories.

Specification and Estimation Results of the Hierarchical Logit Model

This section presents the final model specification and estimation results of the hierarchical destination-mode choice model. Since the focus of the report is on accessibility analysis, this section does not include a detailed discussion of each parameter estimate. The destination and

mode choice models were specified considering the variables in Table 2. For the lower-level mode choice model, the specification includes household-, person-, mode-, and some destination-specific variables. All destination-specific variables were considered for the destination choice model along with the mode choice logsum. These variables were incorporated in the models in different combinations and the final set of variables for each model were identified based on their significance, impact on the sign and significance of other variables, and the overall goodness-of-fit of the model.

Table 3 shows the mode choice model estimation results for the combined dataset containing all four classes. Among the three alternatives in the mode choice model ('Walk', 'Drive Alone' and 'Transit'), 'Walk' was specified as the base alternative. As the mode choice data was only available at a spatially aggregate level, the mode choice model estimation results were relatively sensitive to changes in the specification of the mode-specific variables. The final model specification of the mode-specific parameters includes only parameters that are consistent with transportation theory (i.e. cost and travel time showing a negative marginal utility). The total travel time includes access time, wait time, transfer time, in-vehicle travel time, and egress time. According to the parameter estimates, the value of total travel time savings (VOTTTS) is $19.7 per hour. Given this baseline, walk time is $14.3 per hour more onerous, resulting in a value of walk time savings of $34.1 per hour. Similarly, wait time is $11.6 per hour more onerous, giving a value of wait time savings of $31.4 per hour. These values are consistent with most value-of-time ranges in the existing literature (Frei et al., 2017; Wardman, 2004). The opposite of the coefficient for 'Total Travel Cost', B_{cost}, is treated as the 'Marginal Utility of Income' parameter to measure consumer surplus/accessibility; i.e. $\alpha = -B_{cost}$.

In terms of the individual-specific variables in the mode choice model, there are several notable results. Relative to males, females prefer driving alone and taking transit to walking to work. Age is only found to be significant for drive-alone and the two positive coefficients indicate that older workers (age 46-55 and 66+) are more likely to choose drive-alone than walk. The coefficients for household income are only significant for transit, where they suggest a consistently decreasing tendency to choose transit over walk when income increases from middle to high. There is a significant negative association between the choice of drive-alone and having some work flexibility. This is also true for transit, which is an indication that an inflexible work schedule requires workers to choose faster commute modes. Also, as expected, tendency to choose drive-alone is positively associated with household size, and negatively associated with high population density at work locations. While in the case of transit, a higher diversity of land uses at work locations tends to increase workers preference for transit as a commute mode.

Table 3. Hierarchical Logit Model (Lower Level: Mode Choice) Estimation Results

Parameters	Coefficients	
Total Access and Egress Time (mins)	-0.021***	
Total Wait Time (mins)	-0.017	
Total Travel Time (mins)	-0.029***	
Total Travel Cost ($)	-0.088***	

Mode (Base: Walk)	Drive Alone	Transit
Constant	-1.004**	-0.088
Gender: female	0.565***	0.581***
Age (base: 16-25)		
Age: 26-35	0.145	-0.432
Age: 36-45	0.141	-0.257
Age: 46-55	0.422*	-0.195
Age: 56-65	0.335	-0.276
Age: 66 and above	0.997***	-0.130
HH Size	0.109*	0.044
HH Vehicle per Driver: high (base: low)	1.201***	0.031
HH Income (base: low)		
HH Income: lower middle	-0.117	-0.334
HH Income: middle	0.282	-0.522*
HH Income: upper middle	0.244	-0.686**
HH Income: high	0.021	-1.488***
Work Flexibility (base: no)		
Work Flexibility: low	-0.587***	-0.455**
Work Flexibility: high	-0.378	-0.408
Land Use Entropy at Destination	1.582	0.961*
Population Density at Destination (persons/acre)	-0.013*	0.001

Model Results		
Log-Likelihood	-3340.284	
Wald χ^2	488.190	
AIC	6756.568	
BIC	7035.680	

Note: Sig. codes: 0.01'***' 0.05'**' 0.10'*'

Table 4 displays the results of the destination choice model which was estimated separately for each of the four classes. The log of distance parameter is statistically significant and negative in all four models, clearly indicating that workers prefer employment locations closer to their residence locations. Except public administration, which is negative for the relatively high-income classes—Class 1 and Class 3—all the job type count variables are positive and have a high statistical significance. The interpretation of the job type count variables (with a positive coefficient) is that workers are more likely to choose a destination location with more jobs of a

specific type. Hence, looking at Class 4, the very young cluster, an additional retail job in a destination is significantly more impactful than an entertainment job, which is significantly more impactful than a health care job, which is significantly more impactful than an office job wherein the office job has no statistically significant value for members of Class 4.

The signs on the percentage of medium and high-income workers in the destination are consistent with the representation of the income levels of the four classes. For example, High (Medium) Wage Worker Percentage is positive (negative) and statistically significant for Class 1, which is the group composed of workers from high-income and upper-middle income households. Employment entropy, which represents the diversity of employment opportunities, is positive and statistically significant for Class 1 and Class 3, which are the two highest income and education attainment classes, indicating diversity in employment opportunities is more valuable for these workers.

The significant differences in the magnitudes of the coefficient estimates for the employment types (as well as employment entropy and wage-levels) across the four classes, confirm that (1) different types of workers value different types of employment opportunities at different levels, and (2) the LCA clustering approach using only age, income, gender, and education variables effectively captures major differences.

Table 4. Hierarchical Logit Model (Upper Level: Destination Choice) Estimation Results

Parameters	Coefficients			
	Class 1 (N=3,766)	Class 2 (N=849)	Class 3 (N=5,663)	Class 4 (N=1,078)
Log of Distance	-0.733***	-0.668***	-0.718***	-0.917***
Retail Jobs	0.143***	0.112*	0.138***	0.356***
Office Jobs	0.029***	---	0.025***	---
Industrial Jobs	0.052***	0.082***	0.055***	0.049***
Service Jobs	0.024**	0.044**	---	---
Entertainment Jobs	0.133***	0.118***	0.162***	0.159***
Education Jobs	0.091***	---	0.080***	0.106***
Health Jobs	0.133***	---	0.104***	0.095***
Public Administration Jobs	-0.022***	0.011*	-0.018***	---
Medium Wage Workers (%)	-0.013***	0.034***	0.011***	---
High Wage Workers (%)	0.026***	---	0.023***	---
Employment Entropy	0.276*	---	0.515***	---
Mode Choice Logsum	0.371***	0.554***	0.427***	0.618***
Log-Likelihood	-8150	-3280	-15632	-4782
Wald χ^2	2480	495.6	2870	765.2
AIC	16327	6576	3128	9579
BIC	16408	6614	31368	9614

Note: Number of jobs are in thousands; Sig. codes: 0.01'***' 0.05'**' 0.10'*'

As expected, the coefficient for the mode choice logsum is positive and significant in all classes, indicating that in addition to distance to destinations, the modal attributes between worker origins and destinations impact the choice of destinations. Moreover, the mode choice logsum coefficient estimates are all less than 1, which verifies the nesting of mode choice under employment destination choice. The relative magnitudes of the mode choice logsum coefficient estimates across the four worker classes provide insight into which groups may benefit the most from the introduction of SAMS. Table 4 indicates that improvements in commute mode choice alternatives may improve accessibility the most for Class 4 followed by Class 2, Class 3, and Class 1. Interestingly, this indicates that the high-income class (Class 1) and the middle-income class (Class 3) may be less sensitive to changes in mode choice alternatives than the low-income class (Class 2) and the young worker class (Class 4).

Employment Accessibility Improvements in the SCAG Region

This section presents the employment accessibility analysis results. The accessibility results were calculated using the parameter estimates presented in Table 3 and Table 4, for workers in the synthetic population. The study assumes that the individual-specific mode choice coefficients (e.g. age, income, work flexibility, population density, etc.) for the SAMS-only mode are the same as the drive-alone mode in Table 3; whereas, for the SAMS+Transit mode, the study assumes the individual-specific mode choice coefficients are an average of the drive-alone mode and transit mode in Table 3. Section 3 describes how the study determines modal attributes for the SAMS-only mode (i.e. the same as drive-alone but with no parking costs and a five-minute wait time at the origin) and the SAMS+Transit mode (i.e. a mix of drive-alone and transit).

Employment Accessibility Benefits across Worker Classes

Table 5 displays summary statistics comparing the consumer surplus/accessibility benefits across the classes. All values correspond to the 5% synthetic working population in the SCAG region. With respect to the total benefit, Class 3 sees the largest increase in accessibility from the introduction of the SAMS modes because Class 3 represents the largest portion of workers in the synthetic population. Considering the median benefit across the workers in each class, Class 4 sees the largest accessibility improvement ($9.09 per work trip), whereas Class 1 sees the smallest ($6.30). A look at the 25th and 75th percentiles in accessibility benefits suggest that most workers would receive a benefit between $5 and $10 per work trip from the introduction of SAMS modes. To provide additional insights, Figure 4 displays a histogram of accessibility benefit values for the synthetic workers in each worker class.

Interestingly, Table 5 shows that the employment accessibility benefits across worker classes are relatively consistent, with the mean and median benefit values ranging between $6.34 and $9.20. Although there is a relatively even distribution of benefits across the four worker classes, the young worker class (Class 4) and the low-income class (Class 2) do benefit the most and second-most respectively from the SAMS modes, respectively. Considering the results in Table 4, the difference in overall benefits from SAMS across the worker classes shown in Table 5 is

coming directly from the sensitivity to changes in mode choice alternatives (i.e. the coefficients for Mode Choice Logsum) in the destination choice model.

Table 5. Employment Accessibility Improvements Across Classes

Statistics	Class			
	1	**2**	**3**	**4**
Total Benefit ($)	504,056	197,000	842,098	246,638
Benefit per Capita ($)				
Minimum	2.70	4.56	3.70	4.30
Maximum	20.53	25.51	22.12	29.91
25th Percentile	5.72	7.87	6.31	8.43
50th Percentile	**6.34**	**8.48**	**6.86**	**9.09**
75th Percentile	7.20	9.18	7.58	9.85
Mean	**6.61**	**8.62**	**7.06**	**9.20**
Std. Deviation	1.35	1.31	1.22	1.39
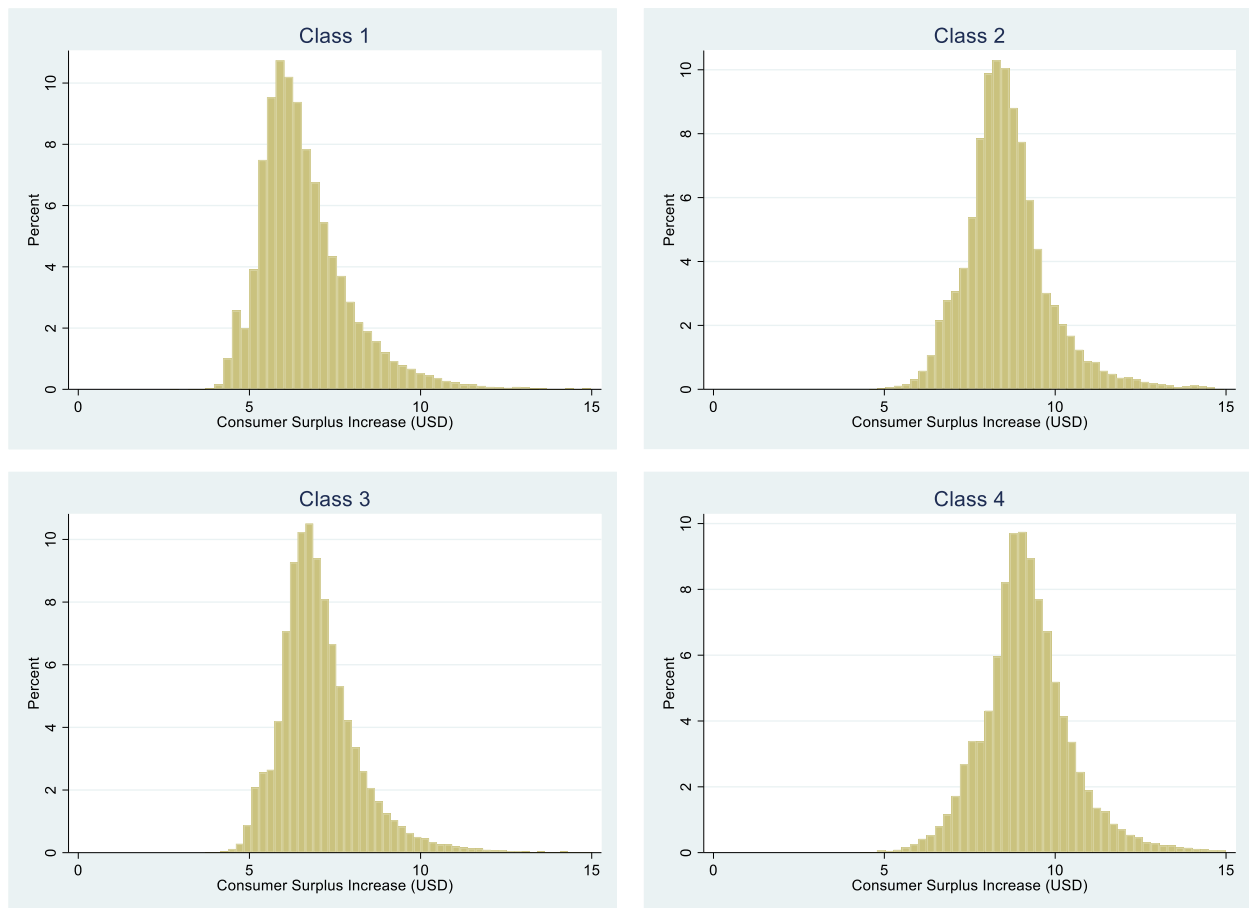
Figure 4. Distribution of Employment Accessibility Benefits in Each Class

Employment Accessibility Benefits from each SAMS Mode

Error! Reference source not found. displays the benefits of adding both the SAMS-only mode and the SAMS+Transit mode to the commute choice set of workers. This section illustrates the percentage of overall SAMS benefits obtainable from each of the two SAMS modes, individually. Let M^S ={SAMS-only, SAMS+Transit} be the set of SAMS modes, indexed by $m^S \in M^S$. Equation 16 displays the formula for determining the percentage of the overall SAMS accessibility benefit that is obtainable from just adding one of the two SAMS modes to the workers' choice sets. It is important to note that $\Delta\ Accessibility_{M^s} \neq \Delta\ Accessibility_{SAMSonly} + \Delta\ Accessibility_{SAMS+Transit}$; therefore, it is necessary to calculate $\Delta\ Accessibility_{m^s}$ for each SAMS mode individually added to the workers mode choice sets.

$$\%Overall\ SAMS\ Benefit_{m^s} = \frac{\Delta\ Accessibility_{m^s}}{\Delta\ Accessibility_{M^s}} \qquad (16)$$

Figure 5 displays the share of the total SAMS accessibility benefits from the two SAMS modes—SAMS-only and SAMS+Transit—obtainable from just incorporating one of the two SAMS modes into each worker's mode choice set. The results suggest that just adding the SAMS-only mode can provide at least 98% of the total accessibility benefits of both SAMS modes for all four classes. Conversely, just adding the SAMS+Transit mode only provides 2-4% of the accessibility benefits of both SAMS modes across the four classes. These results imply that SAMSs may provide very little benefit to workers as a mode to access transit in Southern California. Moreover, SAMS access modes seem unlikely to positively impact transit ridership in a significant way, at least not for commute trips, based on the models developed in this study.
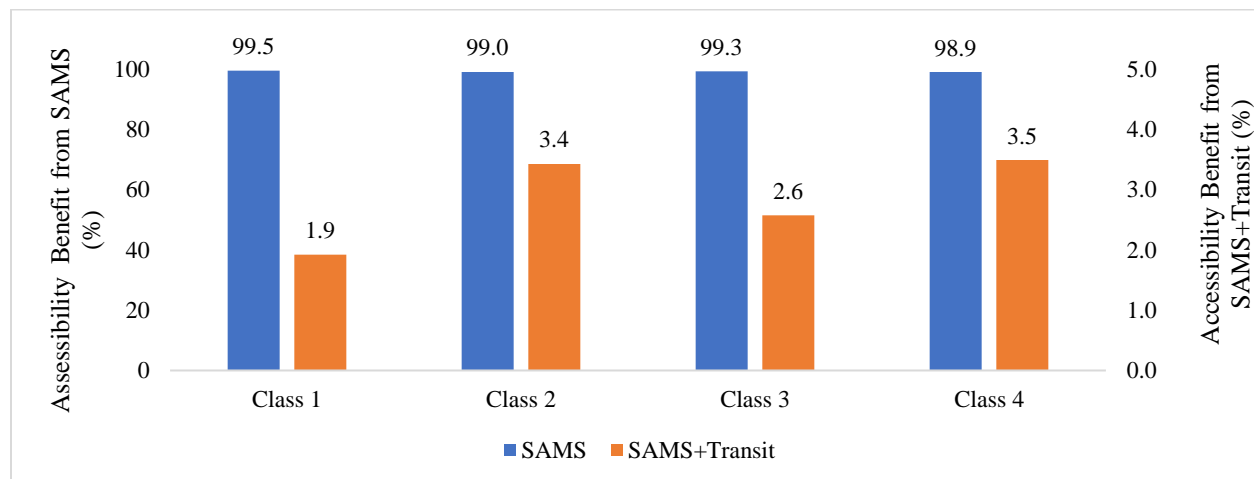

Figure 5. Share of SAMS Employment Accessibility Benefits Obtainable from just One SAMS Mode Alone

Spatial Distribution of Employment Accessibility Benefits

To understand the spatial distribution of accessibility improvements from the SAMS modes, three sets of maps were generated for the SCAG region; the maps illustrate the whole SCAG

region (Figure 6), the City of Los Angeles (Figure 7), and Orange County (Figure 8). Figure 6a, Figure 7a and Figure 8a display the accessibility improvements by census tract in the respective administrative areas, when using the base modal attributes for the SAMS modes. Figure 6b, Figure 7b and Figure 8b display the accessibility improvements by census tract when assuming service quality (i.e. wait time) is a function of population density (see Section 4.3.2 for further analysis). Figure 7c and Figure 8c display the median household income across census tracts; whereas, Figure 7d and Figure 8d display population density across census tracts.

The reason behind choosing the City of Los Angeles (LA) and Orange County is that they have different demographic distributions. For example, household income and population density vary significantly across census tracts in LA; whereas, household income and population density are relatively consistent across Orange County census tracts.

Figure 6 clearly shows that the census tracts that benefit the most from SAMS modes are in the periphery of the SCAG region, where population density is lowest. The same inference can be drawn when looking at the accessibility improvements in LA (Figure 7) and to a lesser extent Orange County (Figure 8). The significant differences in employment accessibility improvements from SAMS modes in low- vs. high-density areas stem from the distances between residential locations and employment opportunities in low- vs. high-density areas and (related to commute distances) the ability to walk or take transit to work in low- vs high-density areas. In low-density areas where employment opportunities are far away from residential locations, walking is unviable, and transit service is usually poor or nonexistent, workers would benefit significantly from a fast and relatively affordable travel mode like the SAMS-only mode. Conversely, in high-density areas where employment opportunities are close to residences, walking is a reasonable option in some cases, and transit service can be good or adequate, the benefit of another commute mode like the SAMS-only mode is not as large as for workers in low-density areas. The low accessibility improvements shown in Downtown LA as well as in the cities of Anaheim, Fullerton and Santa Ana in the northwestern region of Orange County exemplify this effect.

Figure 7 also shows that low-income census tracts seem to receive relatively lower accessibility improvements from SAMS modes than high-income census tracts in LA. As there is nothing in the modeling framework and the parameter estimates to suggest low-income households receive lower accessibility improvements from SAMS modes (in fact the opposite is the case according to the class-dependent results in Table 5), the relationship between income and accessibility improvements in LA shown in Figure 7 is likely coming from the strong relationship between density and income in LA. That is, high-density census tracts are also low-income census tracts, and high-density census tracts see lower accessibility improvements from SAMS modes in general, as discussed in the previous paragraph.

Figure 7 and Figure 8 also display disadvantaged areas that represent vulnerable low-income communities that are unduly subjected to several polluting sources, according to the California Environmental Protection Agency (CalEPA) for Senate Bill 535 (SCAG, 2019). The SCAG

disadvantaged areas in LA experience accessibility benefits that are slightly higher than the other low-income areas but not as high as the high-income areas, which are in less-dense areas.
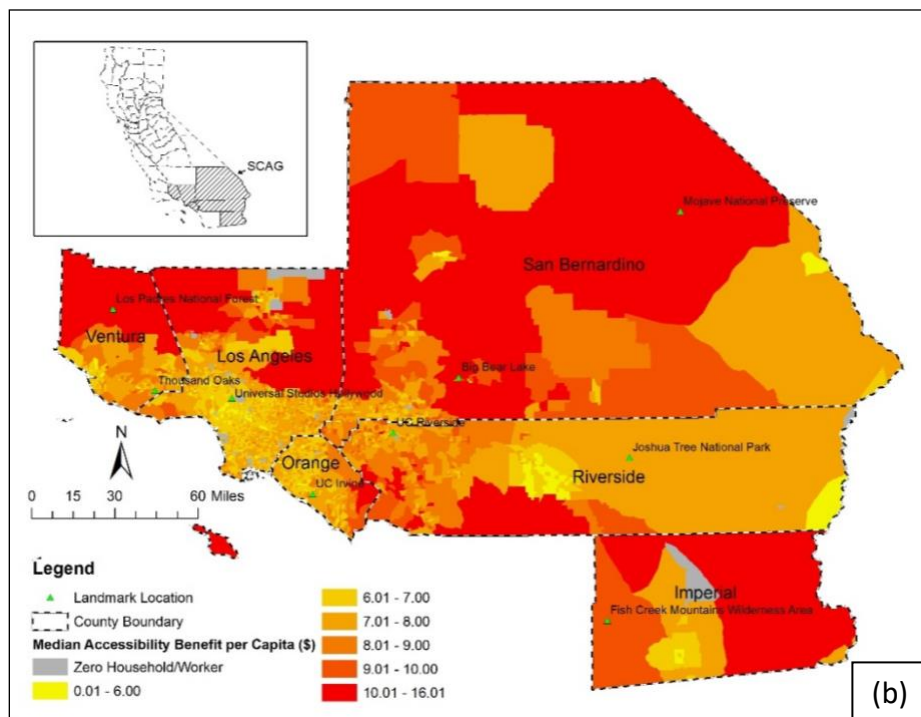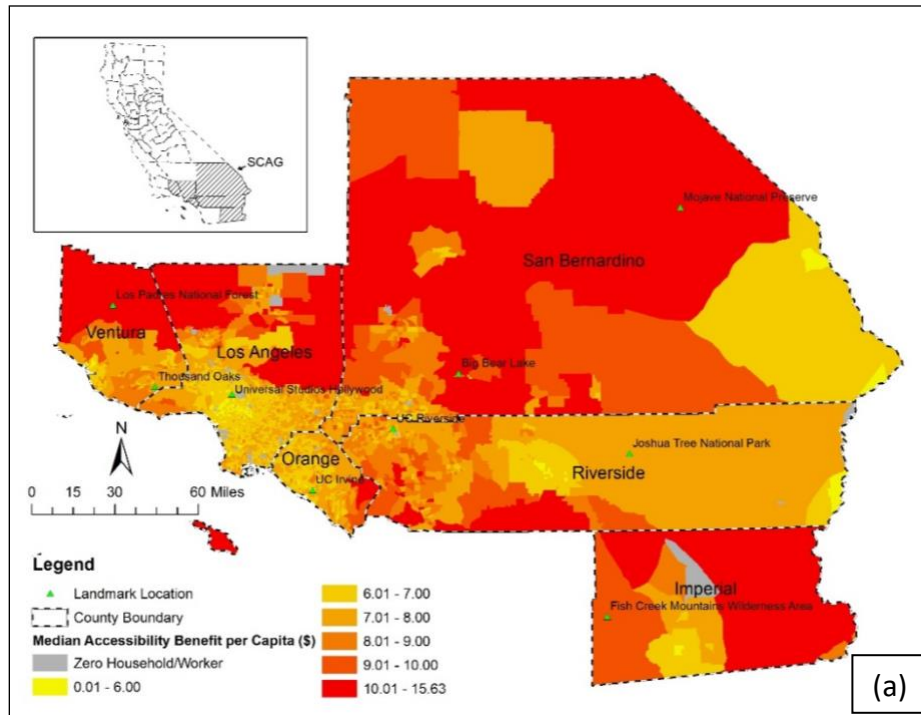

Figure 6. Employment Accessibility Benefits of SAMS modes with (a) Density-independent and (b) Density-dependent, SAMS Wait Times, across the SCAG Region Census Tracts
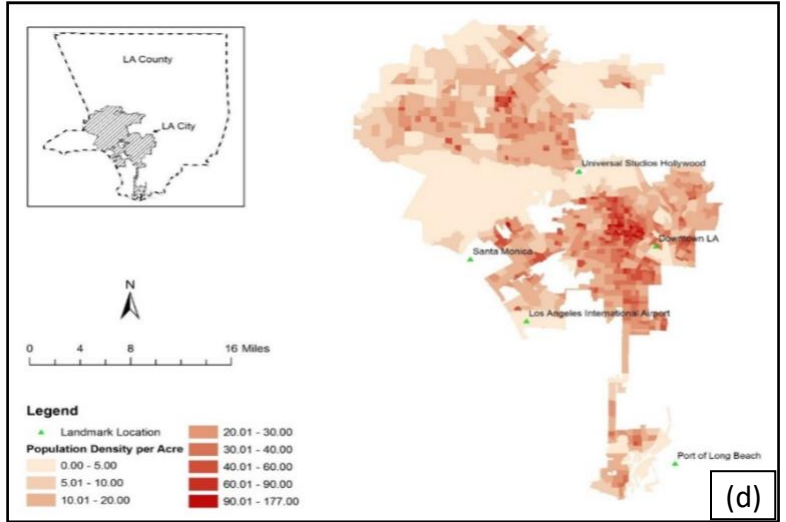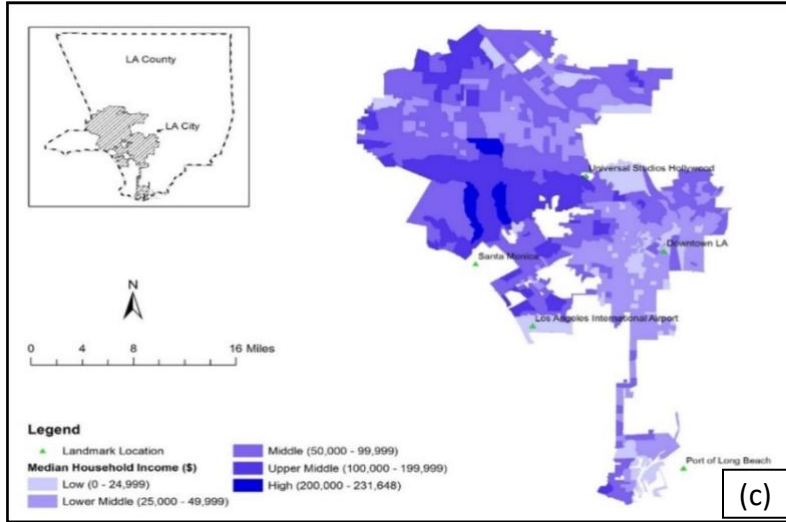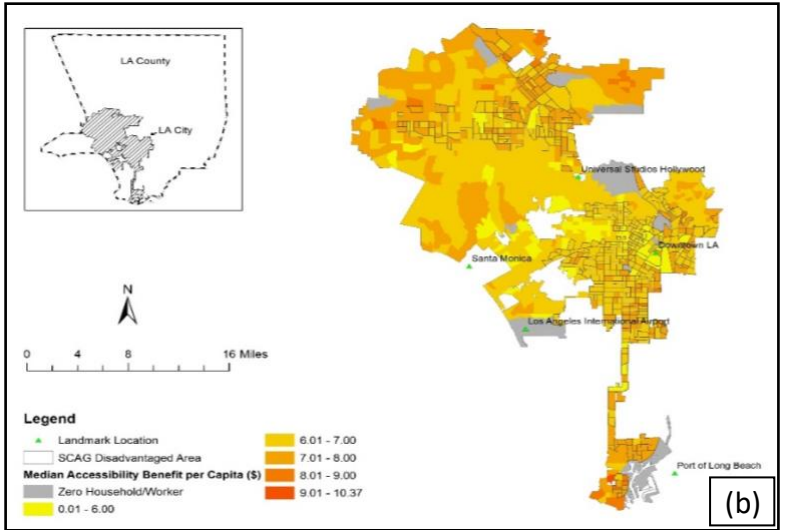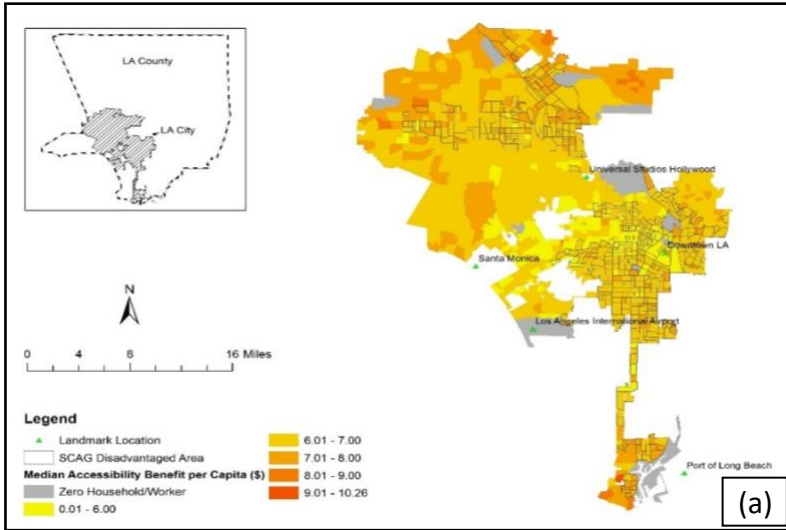
Figure 7. LA City Census Tracts: (a) Baseline Employment Accessibility Benefits; (b) Employment Accessibility Benefits with Density-Dependent SAMS Wait Times; (c) Median Household Income; (d) Population Density
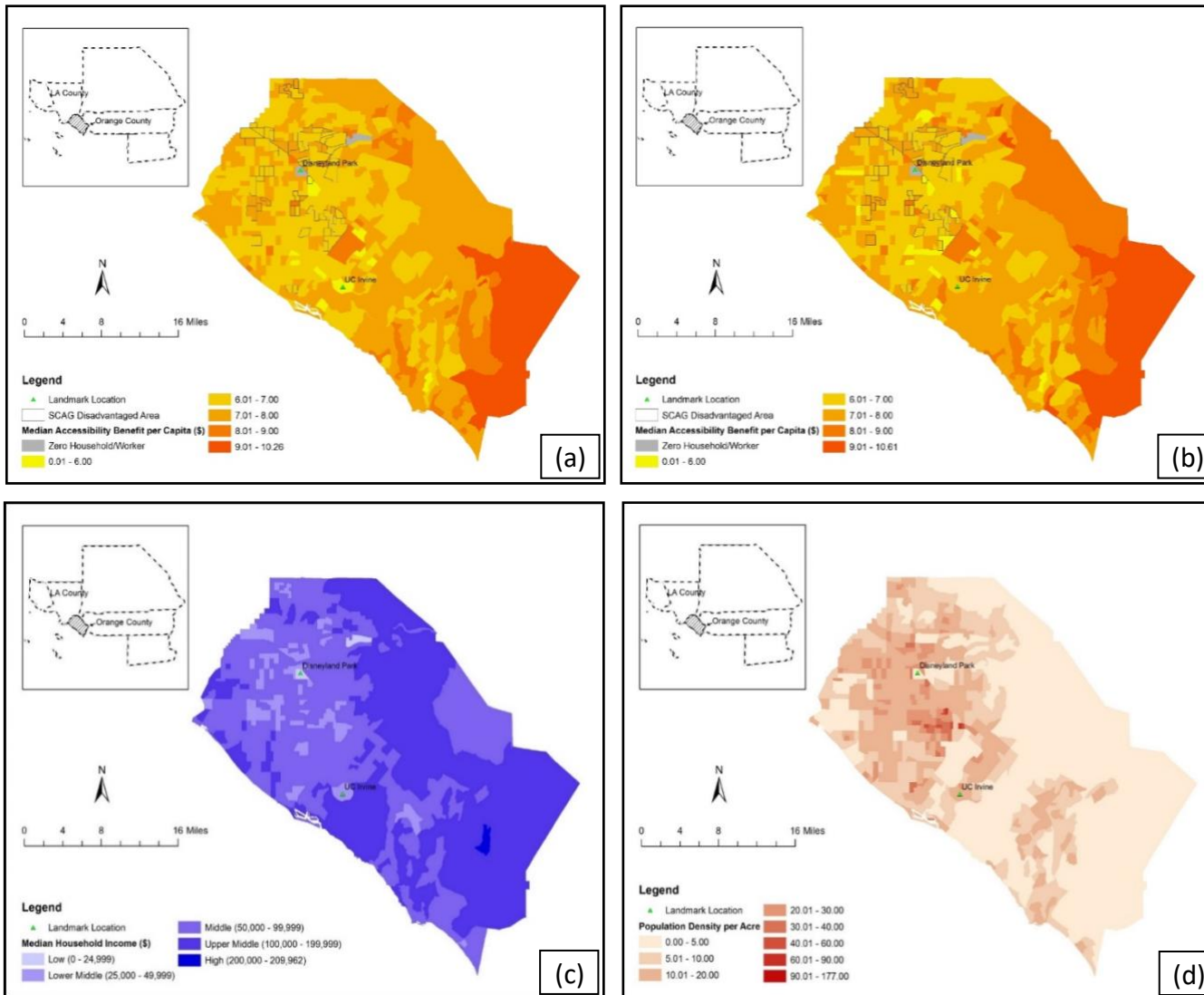
Figure 8. Orange County Census Tracts: (a) Baseline Employment Accessibility Benefits; (b) Employment Accessibility Benefits with Density-Dependent SAMS Wait Times; (c) Median Household Income; (d) Population Density

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Employment Accessibility Benefits with Density-dependent SAMS Wait Times

In the previous analyses, the SAMS wait time attribute value was set to five minutes for all members of the synthetic population. This is an unlikely assumption given the relative ease of having available vehicles near travelers in dense urban areas, and the relative difficulty of having available vehicles near travelers in rural areas, from a SAMS fleet operations perspective (Hyland and Mahmassani, 2018). This subsection analyzes an alternate, possibly more realistic, scenario wherein SAMS wait times are dependent on population density. This section assumes highly dense areas have more available vehicles nearby resulting in low average wait times (Loeb et al., 2018; Zhang and Guhathakurta, 2018). To analyze this scenario, the wait times are apportioned according to the population density. The population density in SCAG, which ranges from 0.01 to 146.79 persons per acre in the census tracts with non-zero households, was divided into quartiles with each origin census tract receiving a wait time between 10 to 3 minutes. The quartiles were further segmented into two for increased resolution of wait times. Hence, the synthetic workers in the lowest density tracts were assigned a 10-minute wait time; whereas, synthetic workers in the highest density tracts were assigned a 3-minute wait time.

Table 6 displays summary statistics of accessibility improvements across classes for the case where SAMS wait times are dependent on population density. Similarly, Figure 6b, Figure 7b, and Figure 8b display the accessibility improvements in the census tracts of SCAG, LA, and Orange County, respectively, for the case with density-dependent SAMS wait times.

Table 6. Employment Accessibility Improvements Across Classes with Density-dependent SAMS Wait Times

Statistics	Class			
	1	2	3	4
Total Benefit ($)	513,974	201,805	860,895	251,710
Benefit per Capita ($)				
Minimum	2.88	4.61	3.76	4.60
Maximum	20.85	26.07	22.56	30.54
25th Percentile	5.83	8.06	6.45	8.56
50th Percentile	6.47	8.68	7.02	9.28
75th Percentile	7.35	9.41	7.75	10.07
Mean	6.74	8.83	7.22	9.39
Std. Deviation	1.39	1.34	1.26	1.43

Comparing the employment accessibility benefits of SAMS in Table 6 with Table 5, there is only a small difference in benefits, with all classes seeing around a 2% increase in accessibility benefits when SAMS wait times depend on population density. The increase in overall benefits suggests that the increase in benefits of SAMS in high density areas (from lower wait times) outweighs the reduction in benefits in low density areas (from higher wait time).

Figure 6 through Figure 8 shed additional light on this effect. In Figure 6, the distribution of benefits appears to be similar, at least in the peripheral low-density areas, in both the density-dependent and density-independent cases. Contrasting with the maps of population density in Figure 7 and Figure 8, a closer look at the high-density tracts of LA (Figure 7) and Orange County (Figure 8) reveal slight increases in the accessibility benefits in most of these tracts. These findings are consistent with the results in Table 6 that indicate slight overall increases in benefits with density-dependent wait times.

Sensitivity Analysis

This section and Figure 9 present the results of a sensitivity analysis on employment accessibility benefits from SAMS modes with respect to changes in the expected SAMS cost per mile attribute value. Conducting the sensitivity analysis simply involves changing the modal attributes for the SAMS modes in the dataset for the synthetic population of workers and recalculating the accessibility/consumer surplus values.

The original cost per mile for the SAMS modes was $0.30/mile; whereas, this section considers cost per mile values of $0.10/mile, $0.20/mile, $0.40/mile and $0.50/mile. Figure 9 presents the median accessibility benefit for all five cost scenarios, across all four clusters. When moving from a higher to lower cost per mile, all four classes experience a constant linear increase in the median accessibility benefit per capita.

The fact that the employment accessibility benefits of SAMS decrease as the expected cost per mile increases is unsurprising. However, it is important to note the magnitude of the decrease in accessibility benefits. According to Figure 9, for Class 4 (Class 1, respectively), accessibility benefits decrease from $10.16 ($7.35) per commute trip, to $8.18 ($5.46) per commute trip, as SAMS cost per mile increases from $0.10 to $0.50; this represents a 19.5% (25.7%) decrease in accessibility benefits. Hence the SAMS cost per mile significantly impacts overall accessibility. However, the SAMS modes can still provide accessibility benefits even at cost values comparable to the current cost per mile of personal vehicle travel in a sedan.
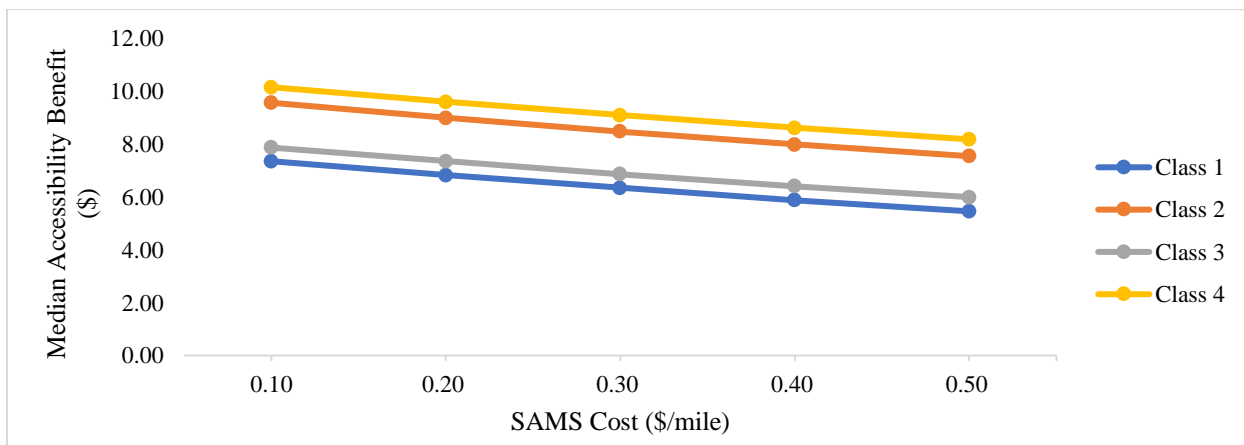

Figure 9. Sensitivity Analysis on Employment Accessibility Benefits with Respect to Changes in SAMS Cost

Conclusion

This study assumes SAMS modes exist in the future and are competitive with existing commute modes. Given this assumption, the study analyzes the potential employment accessibility benefits of adding two new SAMS modes to the mode choice sets of workers—SAMS-only and SAMS+Transit. The main employment accessibility benefits of the SAMS modes captured in this study arise from the ability of SAMS modes to (i) avoid parking costs in dense urban areas that personal car users need to pay and (ii) use the temporally and spatially ubiquitous roadway network to provide transport services that are significantly faster and more reliable than public transit service between many residences and employment locations in Southern California.

To analyze the impact of the SAMS modes on employment accessibility, the study first estimates hierarchical destination-mode choice models using CHTS data. Next, the study applies the parameter estimates from the hierarchical choice models to a 5% synthetic population of workers in Southern California to obtain welfare-based measures of employment accessibility before and after the introduction of SAMS modes. Another important component of the methodology is the clustering of workers based on their socio-demographics before estimating destination choice models. The purpose of clustering workers is to improve the explanatory power of the destination choice models as different clusters value different types of employment opportunities at different levels. The agent-based modeling framework and accessibility analysis methodology is relatively data-intensive; however, this allows analysts to investigate the potential wide-ranging employment accessibility benefits of SAMS in significant detail.

The results of the analysis provide several valuable insights into the potential impacts of SAMS modes on employment accessibility. First, although the difference in magnitudes of accessibility benefits from SAMS are not huge, there are noticeable differences in benefits across the four worker classes. The results indicate that young workers and the workers from low-income households may receive larger employment accessibility benefits from SAMS modes than workers from high- and middle-income households.

Second, results show significantly higher benefits of SAMS in suburban and rural areas than dense urban areas, assuming service prices and service quality are the same everywhere. However, even when assuming service quality is lower in less dense areas, the overall results do not change significantly. This finding implies that the benefits of SAMS modes, from an employment accessibility perspective, will be higher in less-dense suburban areas than higher density urban areas.

A third notable finding is that the magnitude of employment accessibility benefits is heavily dependent on the service price of SAMS. For example, the findings in this study indicate that the employment accessibility benefits decrease by 26% for workers in Class 1 (the high-income, high-education attainment class) as the SAMS service price increases from $0.10/mile to $0.50/mile.

A fourth finding indicates that most of the accessibility advantages from the SAMS modes come from the SAMS-only mode rather than the SAMS+Transit mode. This finding indicates that first-mile SAMS modes are unlikely to (i) provide significant value to commuters and therefore (ii) increase commute-based transit ridership significantly, without major changes and re-designs of transit networks, such as proposed in Pinto et al. (2019).

As far as the authors are aware, this is the first study to provide an in-depth theoretically- and methodological-sound analysis of the potential employment accessibility benefits of SAMS using the logsum-based measure of accessibility. Moreover, the results in this report provide valuable insights into the potential impacts of SAMS on different clusters of the working population and different regions of Southern California. The four insights described above should have immediate value to transport planners and policy makers.

The modeling framework employed in this study has significant potential to provide further insights into the impacts of SAMS modes on employment accessibility. The disaggregate agent-based modeling framework enables the calculation of accessibility/consumer surplus for all workers in the dataset as well as any worker segment or subsegment. For example, the authors are currently using the proposed modeling framework and employment accessibility analysis methodology to explore subsegments of the different worker classes, considering their socio-demographics and residence locations, to gain more insights into the potential impacts of SAMS modes on employment accessibility.

Other areas of future research include (i) capturing spatial competition for jobs (Merlin and Hu, 2017) when measuring employment accessibility using the logsum-based approach; (ii) integrating the hierarchical destination-mode choice model presented in this study with residential location choice (or other activity-based travel demand sub-models), firm location choice, and/or traffic and transit network assignment models to provide more accurate and theoretically sound employment accessibility estimates; (iii) capturing how improvements in employment accessibility from SAMS modes may induce persons currently out of the workforce to enter or re-enter the workforce, which the current study does not do.

This study includes several limitations related to data availability. One example includes the temporal dimension of employment accessibility. This study assumes all commuters travel during the peak commute period. A more realistic model would capture work and commute trip start and end times. Future research that captures off-peak start and end times may find even larger benefits for the SAMS modes which have high availability throughout the day, unlike transit. Another data limitation relates to the aggregate nature of the modal attributes used in the study. Higher resolution modal attribute data between all relevant origin-destination pairs would likely improve the mode choice model parameter estimates. A final limitation of the study is the sequential rather than simultaneous estimation of the hierarchical destination-mode choice model. As the study aims to provide first-order estimates of the employment accessibility benefits of SAMS, more advanced model estimation procedures are left for future research

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Appendix

Table 7. Car Total Cost Per Mile Model Results

Parameter	Coef.	t-value
Intercept/Constant	0.657	15.32
Purchase Price Base = Low		
High	0.306	14.23
Luxury	0.678	14.62
Vehicle Type Base = Truck		
Sedan	-0.095	2.89
SUV	-0.076	2.13
Age Base = 0-1 years		
Age 2-3	-0.108	5.01
Age 4-6	-0.208	9.64
Age 8+	-0.392	3.87
Fuel Type Base = Hybrid		
3-4 Cylinders ICE	0.039	1.98
5-6 Cylinders ICE	0.071	2.15
8+ Cylinders ICE	0.15	1.87
EV	-0.071	1.26
Model Statistics		
Sample Size	297	
F (11,285)	73.16	
Prob > F	0.000	
R-squared	0.8102	
Root MSE	0.14811	
LL (null)	-94.9	
LL (model)	151.904	
Df	12	
AIC	-279.81	
BIC	-235.48	