A LUTI microsimulation framework to evaluate long-term impacts of automated mobility on the choice of housing-mobility bundles

The MIT Faculty has made this article openly available. Please share how this access benefits you. Your story matters.

| Citation | Basu, Rounaq and Joseph Ferreira. "A LUTI microsimulation framework to evaluate long-term impacts of automated mobility on the choice of housing-mobility bundles." Environment and Planning B: Urban Analytics and City Science (May 2020) © SAGE Publications |
| As Published | http://dx.doi.org/10.1177/2399808320925278 |
| Publisher | SAGE Publications |
| Version | Author’s final manuscript |
| Citable link | https://hdl.handle.net/1721.1/126102 |
| Terms of Use | Creative Commons Attribution-Noncommercial-Share Alike |
| Detailed Terms | http://creativecommons.org/licenses/by-nc-sa/4.0/ |
A LUTI microsimulation framework to evaluate long-term impacts of automated mobility on the choice of housing-mobility bundles

ABSTRACT

Land use-transportation interaction (LUTI) models can be useful planning support systems to assess the long-term implications of emerging transportation technologies like mobility-on-demand and automated vehicles. We propose an agent-based simulation framework (SimMobility Long-Term) that uses econometrically robust behavioral models to model the potential impacts of accessibility changes in ‘car-lite’ communities on the choice of housing-mobility bundles. Residential relocation and private mobility holding decisions are jointly considered in a sequential simulation modeling approach. Different types of market responses to the car-lite pilot are modeled through various scenarios via assumptions of changes in model parameters, and compared to a baseline where the car-lite pilot is never implemented. A comparatively vehicle-free study area with a low vacancy rate is chosen to obtain conservative estimates of policy impacts. Our findings indicate that initial awareness of the pilot is quite effective in making the study area more vehicle-free relative to the baseline. However, as market effects start impacting housing prices and bidding results, the vehicle-free gains are significantly reduced due to neighborhood gentrification. In conclusion, we highlight how LUTI models can be used to explore market dynamics to see where market pressures matter, along with the need to align car-lite policies with market conditions regarding vacancy and car ownership rates.

Keywords Automated mobility · Accessibility · Residential location choice · Vehicle ownership choice · Agent-based microsimulation · Land use-transport interaction (LUTI) model

Citation: Basu, R. and Ferreira, J. (2020). A LUTI microsimulation framework to evaluate long-term impacts of automated mobility on the choice of housing-mobility bundles. Environment and Planning B: Urban Analytics and City Science. doi: 10.1177/2399808320925278

1 Introduction

The emergence of open and big data platforms have fueled the rise of urban informatics, which provide city evaluation metrics that can be constructed in an automated and easily accessible manner, e.g. WalkScore and BikeScore. However, the successful integration of such metrics for broader use in Planning Support Systems (PSS) requires the use of modeling efforts to address the increasing uncertainty in urban futures (Deal et al., 2017). Land use-transport interaction (LUTI) models are a particularly promising example of how behavioral models of decision-making under uncertainty can be integrated with simulation dynamics to evaluate possible future scenarios (Batty, 2011). In particular, the raison d’etre of LUTI models is to provide a platform for policy analysis in light of potentially disruptive changes to the spatial socio-economic processes in the city. There is ample evidence that urban mobility will continue to be disrupted by
new technologies and services, while land use strategies need to become more cognizant of rising sea levels and other climate change-related environmental outcomes (Han et al., 2017). Therefore, existing PSS (such as LUTI, among others) must adapt to the changing urban landscape, while concurrent efforts are needed to integrate urban informatics into PSS in a meaningful way for policy-making and evaluation. To that end, this study demonstrates an example of how LUTI models can be used for evaluating a policy intervention in an era of automated mobility, while using different metrics of neighborhood change to evaluate policy impacts.

Emerging transportation technologies like mobility-on-demand (MoD) and automated vehicles (AVs) are motivating discussions on the future of cities. AVs offer several benefits to the transportation system such as reduced day parking locations and per-kilometer commute costs in addition to enhanced consumer experience through lower prices and higher comfort of traveling. While examining city-level impacts, Zakharenko (2016) found that increased AV availability can increase worker welfare, travel distances and city size. Meyer et al. (2017) corroborated this by stating that AVs could cause a quantum leap in accessibilities. However, the net effects of AVs are uncertain, and recent investments by car manufacturers (such as Ford and General Motors) and transportation network companies (like Uber and Lyft) in the AV market have attracted attention from policy-makers with regard to regulation strategies and equity considerations.

While the benefits of AVs are heavily advertised in media outlets, experts hold more nuanced opinions of the impacts of AVs on cities. Using a survey of domain experts, Milakis et al. (2018) reported that there are three major viewpoints about AVs.

- **Uncertain benefits**: The accessibility benefits due to AVs will be highly uncertain, because the induced travel demand will cancel out the travel time and cost savings in the long-term.
- **Changing urban form**: AVs will cause the city center to become denser while the peripheries will expand leading to urban sprawl.
- **Only for the rich**: The benefits of AVs will be enjoyed only by those who can afford them, thereby leading to negative implications for social equity.

A recent review of modeling studies related to the impacts of AVs by Soteropoulos et al. (2019) found that the literature can be broadly segmented into two categories: (a) impacts on travel behavior, such as trip generation rates, mode choice, and vehicle-kilometers traveled (VKT); and (b) impacts on land use, such as location choices and reduction of parking spaces. Long-term effects of AVs on transport-land use interactions are undeniably very complex and are co-determined by exogenous factors like housing supply, area attractiveness and land use policy. Their review indicates a gap in the literature with regard to an integrated treatment of long-term impacts of AVs on urban regions.

LUTI models can be useful tools in addressing this research gap. Hawkins and Nurul Habib (2019) review several LUTI models from the literature, and highlight both their capabilities and shortcomings in undertaking such an exercise. They mention that existing model applications have focused on the discrete addition of new infrastructure or policy at a fixed point in time, an example of which is the oft-considered assumption of all private vehicles being completely replaced by AVs. However, we posit that AV adoption will occur incrementally through time, which is why planning agencies are more likely to pilot such interventions in a ‘micro’ study area at the neighborhood level before implementing the policy metro-wide at a ‘macro’ scale. Therefore, we consider the case of an AV-related policy being implemented as a pilot in a single planning district, and use our LUTI modeling platform, SimMobility, to examine the gradual impact of the pilot on the housing market and neighborhood demographics as well as on car ownership.

The remainder of this paper is structured as follows. Relevant themes in the literature are reviewed and discussed in the next section, following which we detail the elements of our simulation platform. Next, methodological details for this study are provided, and the empirical results of the simulations are discussed. Finally, we provide concluding remarks and suggest areas for future research.

# 2 Literature Review

The two long-term impacts of AVs that are of primary interest to policy-makers are related to (a) private vehicle ownership, and (b) residential relocation. Therefore, we examine recent literature on these fronts in the following sub-sections.

## 2.1 Impact of AVs on private vehicle ownership

Three major threads of inquiry emerge from the literature. The first technique assumes complete replacement of private vehicles by AVs. Two types of methodologies are commonly used in such studies: (a) agent-based models, and (b) activity-based models. Different AV fleet sizes are explored with marginal constraints implemented for matching trip
The third technique employs a cost-based approach by comparing the costs of ownership over the long-term. The second technique uses stated preference surveys to elicit user preferences regarding AVs. Different business models (shared or private AVs), cost structures, travel experience metrics (travel time or cost savings for AVs), and market penetration rates are explored to construct the choices in the stated preference interviews. Examined the impact of shared AVs on the likelihood of relinquishing private vehicles using a sample of university personnel and American Automobile Association (AAA) members. One of their findings highlighted that households are more likely to give up a private vehicle if they own multiple cars, compared to their only car. An online survey conducted in Germany compared current and future travel modes in a pairwise fashion. They too found that private cars would remain the preferred travel mode, thereby challenging the popular hypothesis that the ownership model will decrease in popularity due to availability of AVs. Used a stated preference questionnaire to examine user preferences for currently owned private cars, shared AVs, and privately-owned AVs. They uncovered significant socio-demographic and cultural differences in their combined sample of Israeli and North American residents. Their most substantial finding points to the reluctance in AV adoption, as 25% of their sample were unwilling to use shared AVs even if the service was made completely free. More interestingly, their sample seemed more willing to use AVs to pick up groceries from the supermarket compared to letting them pick up kids from school, which highlights public reluctance and hesitation in embracing complete automation. A more detailed compilation of recent stated preference studies related to AV preferences can be found in Kartzonikas and Gkritza (2019).

The third technique employs a cost-based approach by comparing the costs of ownership over the long-term. Used a cost-benefit analysis to conclude that private vehicle ownership is a cheaper alternative to shared AVs. A similar study in the UK among different income groups reported that high-income households would benefit more from AVs due to their higher perceived value of time. Utilized a cost-based approach to construct an online stated preference survey for car users in Japan. They found that respondents in their sample were willing to pay an additional JPY 402,233 – 793,611 (USD 3,632 – 7,166) to purchase an AV in the future. This has serious implications for social equity, as most households will not be able to afford AVs. However, shared AV fleets offering mobility-on-demand (MoD) services can be more affordable than privately owned vehicles. A financial analysis of AMoD services in Singapore found that shared automated vehicles can save around 15,100 USD/year in total mobility costs compared to a privately owned human-driven car. The key takeaway from our review of existing literature is the challenge associated with influencing people to relinquish currently owned private vehicles. This is rooted in behavioral theory as the endowment effect, which posits that people value ownership of certain commodities more than their willingness-to-pay (WTP) for them. This implies that a shift to AVs will require a boost in utility greater than that expected solely based on the attributes of the alternative modes. Therefore, keeping the link between housing and mobility choices in mind, we believe that neighborhood attributes and locational amenities may have a significant role to play in designing car-lite urban mobility futures.

### 2.2 Impact of AVs on residential relocation

The few studies that have tried to examine the impacts of AVs on location choices of people report an increase in accessibility, along with an increase in population in well-connected outer suburbs and rural regions. Examined travel behavior and residential location choices for Melbourne in 2046. Their findings indicate an out-migration rate of 3% from the inner city to the suburbs. However, their results are inconclusive due to mixed effects when shared AVs are considered. Used an agent-based simulation approach to model changes in residential location choice in a scenario where shared AVs are considered a popular travel mode in the Atlanta Metropolitan Area. Their results indicated that older people moved closer to the inner-city core, while younger people moved out to the suburbs. Additionally, found...
that shared AVs could curb urban sprawl. In summary, these studies find that privately owned AVs could exacerbate urban sprawl, which could possibly be moderated to a certain extent if the AVs were used as shared vehicles.

2.3 Research contributions of this study

We outline our research contributions based on the gaps that emerged from our literature review. First, almost all LUTI models in practice fail to merge agent-based simulation dynamics with behavioral economics in at least one aspect of the land use-transport interactions. We use our LUTI model SimMobility that uses embedded econometric models in an agent-based microsimulation framework to simulate both long-term and medium-term decisions. In particular, the disaggregate manner in which we simulate the dynamics of bidding in the housing market is one of the salient features of SimMobility.

Second, existing literature treats private vehicle ownership and residential relocation as separate decisions while examining the impact of AVs. While some literature exists on jointly considering these decisions, those studies deal with empirical modeling in a past or current setting without the involvement of AVs (Zhang et al., 2014). This is perhaps the first work, to the best of our knowledge, to address this topic by considering them jointly in a sequential simulation framework.

Third, instead of considering complete replacement of private vehicles by AVs, we maintain a more realistic outlook where the planning agency introduces a car-lite policy in a particular neighborhood as a pilot, which enhances accessibility for residents inside the study area. We use our sequential simulation framework to examine the impacts of this pilot on household residential relocation and vehicle availability decisions. Different market reactions to the pilot are modeled through a variety of scenarios, and compared to a baseline where the pilot is never implemented. This allows for a more robust examination of private vehicle substitution patterns as a result of increased accessibility from automated mobility services.

3 Framework

We provide methodological details about our microsimulation platform SimMobility and our proposed framework for policy analysis in this section.

3.1 SimMobility: An overview

SimMobility is a multi-scale agent-based microsimulation platform that incorporates time-scale dependent behavioral modeling through activity-based frameworks (Adnan et al., 2016). Through the consideration of interactions between transportation and land use, SimMobility can be used for a variety of applications ranging from implementation of intelligent transportation systems to evaluation of alternative future scenarios. SimMobility encompasses three major components:

- **Long-Term (LT):** This detailed land use-transport simulator involves the creation of a synthetic population of individuals, households, firms and establishments (Zhu and Ferreira, 2014). This is followed by household-level residential location and vehicle availability choices, and individual-level employment or education location choices. The temporal scale of this component ranges from days to years.

- **Medium-Term (MT):** This component contains a mesoscopic supply simulator coupled with a microscopic demand (daily activity) simulator (Basu et al., 2018). Daily travel decisions like mode choice, route choice, activity-travel patterns, and incident-sensitive (re)scheduling are considered at the temporal scale of minutes to hours, up to a single day.

- **Short-Term (ST):** This microscopic traffic simulator involves lane-changing, gap acceptance, route choice, and acceleration-braking behavior at the temporal scale of seconds to minutes (Azevedo et al., 2017).

The LT and MT components are connected through activity-based accessibility (ABA) measures that are disaggregate utility-based measures of the value of alternative daily activity patterns. Simulation of alternative scenarios in MT enables measurement of individual-level ABAs that would result from participation in those scenarios through logsums. For example, consider an individual living in the $i$th Traffic Analysis Zone (TAZ) and working in the $j$th TAZ. It is crucial to evaluate hypothetical scenarios such as (a) fixed home-variable work, where the individual can choose from all possible TAZs for their work location while keeping the residential location (TAZ $i$) fixed, and (b) variable home-fixed work, where the work location is fixed but the residential location is allowed to vary. For every possible combination of home and work TAZs, MT provides a logsum value for each individual in the synthetic population. These ABAs...
are used as explanatory independent variables in LT models, in the form of TAZ-averaged logsums in the residential location choice and job location choice models, and household-specific logsums in the vehicle availability model.

### 3.2 Behavioral models in SimMobility-Long Term

The LT simulator constitutes a housing market module that simulates daily dynamics in the residential housing market. The synthetic population is constructed prior to the simulation, and assumed to be the state of the system for “day-0”, or \( t = 0 \). Households are assigned particular residential units in specific buildings. While unoccupied units available for sale constitute the housing market supply, we also allow for resales, new sales, and advance purchases. Asking prices are determined by sellers through a hedonic price model, while willingness-to-pay (WTP) of buyers is evaluated through an econometric framework based on expected utility maximization. The hedonic model is specified as a linear-in-parameters function of the following variables:

- **Neighborhood characteristics**, which represent amenities based on spatial location
- **Housing unit attributes**, which represent structural heterogeneity in the housing supply
- **Accessibility measures**, which are captured through ABA measures (i.e., logsum values)

In addition to the variables listed above, we include variables pertaining to household demographics and socio-economics in the WTP model to represent the variability in the WTP of different population cohorts for the same housing unit. A generalized functional form for the WTP of the \( i \)th household for the \( j \)th unit is shown below:

\[
WTP_{ij} = f(Z_{sp}^i, Z_{unit}^i, Z_{hh}^i, Z_{ace}^i)
\]  

(1)

Housing market transactions are modeled through a daily bidding process among active buyers and sellers. This is a salient feature of SimMobility, which (to the best of our knowledge) is the only LUTI microsimulator that uses a daily bid-auction housing model at the metropolitan area scale using econometric frameworks. Potential buyers become active on the market based on explicit probabilistic models for awakening that are calibrated using data from a ‘recent movers’ survey in Singapore. The awakening model determines the likelihood that a currently inactive household will become active and begin searching for alternative residential locations on any given day.

A similar approach is adopted for screening of residential units based on housing and neighborhood type, which results in construction of finite-sample and economically plausible choice sets. This is motivated by the typical search process wherein households tend to narrow their search toward particular neighborhoods and unit types before investing more time and energy to visit and compare individual housing units. Active buyers evaluate each residential unit in their choice set and select a unit to bid on, based on maximization of expected consumer surplus. If a household has a successful bid, they move into the new unit (one month later for resales and when ready for occupancy for new sales), and then reassess the job and school assignments of household members along with their vehicle availability. It should be noted that these moving rates are calibrated to vary by household demographics and current tenure status.

While studies in the past have modeled vehicle ownership choice, we focus our attention on vehicle availability instead of ownership. This is motivated by the growing emergence of mobility-as-a-service (MaaS), where a bundle of different mobility services (commonly referred to as a mobility bundle) is made available to consumers at a fixed daily, weekly, monthly, or annual price. We expect this business model to become even more popular as the mobility landscape keeps expanding with the inclusion of AVs, TNCs, and micro-mobility options, and therefore shift our outcome variable from vehicle ownership to vehicle availability.

Household vehicle availability is modeled through a two-stage framework. The first stage involves estimating a taxi availability model that predicts whether a taxi is available to the household for regular use. We use data from the Household Interview Travel Survey (HITS) in Singapore for model estimation. It is worth noting that the HITS underestimates taxis in 2012 by about 7,500. We impute these 7,500 taxis among the weighted HITS sample using the Synthetic Travel Survey.

The taxi availability model is estimated using the binary logit framework with household socio-demographics as explanatory variables. The model is then used to predict taxi availability as a binary value (taxi owner or not) for households in the synthetic population. A generalized functional form for the probability of the \( i \)th household owning a taxi is expressed below.

\[
V_{\text{taxi}}^i = f(Z_{\text{dem}}^i)
\]  

(2)

\[
P_{\text{taxi}}^i = \exp(V_{\text{taxi}}^i) \cdot \left[ 1 + \exp(V_{\text{taxi}}^i) \right]^{-1}
\]  

(3)
The second stage involves estimating a vehicle availability model that utilizes the results of the first-stage taxi availability model. We combine the HITS data with the taxi availability predictions and local accessibility measures (such as distance to nearest MRT station from residential location) and individual-specific logsum values as explanatory variables. As mentioned earlier, our model considers vehicle availability as a mobility bundle rather than segregated ownership of specific vehicle types. Six vehicle availability categories are considered, which follow a seemingly increasing scale with regard to utilities derived from mobility.

- **C0**: No private vehicles
- **C1**: One or more motorcycles only
- **C2**: One off-peak car w/wo motorcycles
- **C3**: One normal car only
- **C4**: One normal car w/ an off-peak car and/or a motorcycle
- **C5**: Two or more normal cars w/wo an off peak-car and/or a motorcycle

Six logsum values are calculated for each individual keeping their residential and job locations fixed (i.e. one logsum for each of the six aforementioned categories). We aggregate the individual logsums to the household level by considering the highest income-earner as the head of the household. Ties are broken by considering the individual with the highest logsum for the ‘one normal car’ category (C3). Due to the possibility of six choices, the multinomial logit (MNL) framework is used to estimate this model. We also tested the ordinal logit model owing to the manner in which the six alternatives are constructed, but did not find it to be as robust in explanatory power (Basu and Ferreira, 2020a). Finally, we used the estimated MNL model to predict vehicle availability as a categorical variable (with six categories) for households in the synthetic population. We show a generalized functional form for the probability of the $j$th alternative being available to the $i$th household below.

$$V_{ij} = f(Z_{dem}^i, Z_{taxi}^i, Z_{acc}^i, Z_{ABA}^{ij})$$ (4)

$$P_{ij} = \exp (V_{ij}) \cdot \left(\sum_j \exp (V_{ij})\right)^{-1}$$ (5)

We are forced to limit ourselves to a high-level discussion of the framework in this paper for brevity. The reader should refer to Zhu et al. (2018) for further details on SimMobility Long-Term and estimation results of these models.

4 Methodology

First, we provide details about the car-lite pilot we seek to examine. This is followed by the selection of our study area. In subsequent sub-sections, we define various scenarios and outline the assumed behavioral changes due to the pilot.

4.1 Car-lite pilot

We assume that the municipal government (or the planning agency) introduces a car-lite policy in a certain region, which we call the study area, as a pilot. This pilot enhances accessibility due to availability of AVs and AMoD services only in the study area, and nowhere else in the metropolitan region (termed as the spatial setting). Inside the study area, AVs can be used for both ride-hailing (single passenger trips like UberX or JustGrab) and ride-sharing (multi-passenger shared trips like UberPool or GrabShare) services.

We anticipate that the introduction of AVs will lead to a positive perception of the study area in two aspects. First, households living outside the study area may want to move in and enjoy the benefits associated with increased accessibility. Second, households living inside may want to reconsider private vehicle availability due to widespread availability of AVs for trip-making. These anticipated effects are particularly relevant to a region like Singapore, where about 80% of households live in public housing provided by the Housing & Development Board (HDB) and private vehicle ownership is prohibitively expensive. The reader is encouraged to refer to Basu (2019) for further details on vehicle availability in the Singaporean context, such as the requirement of a Certificate of Entitlement (COE) for private vehicle registration. However, it is worth highlighting here that our proposed framework is not limited to Singapore; we merely note the relevance of such a car-lite pilot to the Singaporean context.
4.2 Study area

We consider Singapore as our spatial setting for this paper. Singapore has around 1.15 million households and 1.24 million residential units, leading to an island-wide vacancy rate of 7.1%. There are 55 planning districts in Singapore, among which we choose one as our study area where the car-lite pilot could conceivably be implemented (see Figure 1). Our choice of study area is motivated by considering a plausible albeit somewhat extreme case, i.e. a study area neither in the central business district (CBD) nor in the periphery, and which is already more vehicle-free than Singapore on average. This planning district has 44,028 households (3.83% of total households) and 45,715 residential units (3.70% of total housing stock), implying a vacancy rate of 3.69%. It should be noted that the vacancy rate in the study area is about half that of Singapore.

Moreover, the vehicle availability is also relatively low with a vehicle-free share of 67.02% in the study area compared to 54.11% in Singapore. Therefore, we expect a muted effect of the policy on both residential mobility (due to lower vacancy rate) and private vehicle availability (due to higher vehicle-free share). Our study area selection serves to establish a conservative estimate of the magnitude of policy impacts. Alternative planning districts with less ‘tight’ initial settings would be likely to enjoy more substantial benefits from the car-lite pilot. Interested readers can refer to Basu and Ferreira (2020b) for a discussion on the spatial variation in car-lite pilot impacts on reducing private vehicle ownership.

4.3 Scenario design

To examine the impact of this pilot on household residential relocation and private vehicle availability, we adopt a scenario-based approach:

- **Baseline (No car-lite pilot):** We conduct a baseline run that simulates the long-term evolution of Singapore, assuming that the car-lite pilot was never introduced. All parameters in the long-term behavioral models are held constant and equal to the estimated values.

- **Scenario I (Minimal effect):** The car-lite pilot is now introduced in the study area. This results in an increase in the likelihood that housing units in the study area are included in a household’s choice set through the screening model. It is worth highlighting that there are no other housing market effects in this scenario, apart from an awareness about the policy being introduced in the study area.

- **Scenario II (Buyer valuation increases):** In addition to the change in the previous scenario, we hypothesize that the policy leads to an increase in demand for housing in the study area. The increased demand can be

---

1We do not include construction workers, work permit holders, and other foreigners in our analysis because they do not have full access to the housing market. However, they were included in the daily activity-travel simulator while generating activity-based accessibilities to reflect congestion patterns more accurately.
represented through parameter modifications in the WTP model, which reflects the increased valuation of housing inside the study area from the buyer’s perspective due to increased accessibility. This scenario can be thought of as a short-run market reaction, where only consumers have reacted to the policy.

- **Scenario III (Both buyer & seller valuations increase):** We construct this scenario as a representation of the longer-run market reaction, where both consumers and suppliers have reacted to the policy. The market has had enough time to respond to the increased demand through an increase in the asking price of units inside the study area, which is captured through parameter modifications in the hedonic price model that reflects the valuation of housing from the seller’s perspective. Modifications to the WTP model parameters are made in a fashion similar to the previous scenario.

The aforementioned model parameter modifications are represented through the following behavioral assumptions:

- **Good marketing:** We assume that the screening probability doubles for all residential units inside the study area. This implies that such units are twice as likely to appear in the choice set of any household searching for a new home.\(^2\)

- **Higher buyer valuation:** Recall that ABA is used as an explanatory variable in the WTP model. To reflect increased accessibility stemming from the car-lite pilot, we increase the ABA by \(k\) times the standard deviation of ABA across all TAZs if the household lives or works in the study area. For households living and working in the study area, the ABA is increased by \(2k\) times the standard deviation across all TAZs. We vary \(k\) across a grid of values \([0.25, 0.50, 1.0, 2.0]\) with the intention of measuring the sensitivity of policy impacts to the magnitude of the increase in accessibility.

- **Higher seller valuation:** The hedonic price model also includes ABAs as explanatory variables. Similar to the WTP model, we increase ABAs using the aforementioned technique. These modifications cause an increase in the asking price of units, which is the result of higher seller valuation.

- **Improved vehicle-free accessibility:** Recall that we estimate ABA for the fixed home-fixed work-varying vehicle availability setting, i.e., we calculate six logsum values pertaining to the six vehicle availability categories for each household assuming fixed residential and job locations. This assumption leads us to augment the vehicle-free accessibility (i.e., \(C_0\) logsum) of all households inside the study area by \(k\) times the average difference between the private-car accessibility (i.e., \(C_3\) logsum) and this vehicle-free accessibility. As mentioned earlier, we vary the value of \(k\) to conduct sensitivity analysis. When \(k = 1\), automated mobility boosts vehicle-free accessibility so that it is equivalent to the private-car accessibility (but not exactly equal since the boost is the average difference), i.e., there is no accessibility gain in owning a private car. Other values of \(k\) can be interpreted accordingly.

### 4.4 Sequential simulation framework

In light of the above discussion, it is clear that the car-lite pilot will affect both residential mobility and private vehicle availability decisions. Therefore, we consider the housing-mobility bundle, which combines residential location choices with vehicle availability choices, for joint evaluation. A summary of our proposed framework is illustrated in Figure 2.

All the households in the synthetic population (excluding foreign and low-wage single-individual households, as mentioned earlier) in the base year (2012) are considered to be eligible for the daily bidding process. We use the bid-auction housing model described earlier to simulate housing market transactions for the simulation period (considered as one year in this study). Recall that the baseline scenario does not require any model parameter modifications. Scenario I involves modifying vehicle availability model parameters, but no changes are made to parameters for the housing market models. The ABA and WTP parameters are modified in Scenario II with additional modifications made to the hedonic model for Scenario III. At the end of the simulation period, we are able to identify households who had successful bids along with their new residential locations.

Households that changed their residential location are considered to re-evaluate their vehicle availability based on their new residential location. In addition, households inside the study area re-evaluate their vehicle availability at the end of the simulation using the modified ABA values that reflect the improved vehicle-free accessibility assumption (irrespective of whether they moved or not). New vehicle availability logsums are dynamically calculated for all such households using their new residential location. However, these accessibility modifications are not applicable to

\(^2\)We tested the sensitivity of the policy impacts to this multiplicative factor by varying it across a grid of \([2, 4, 8, 16]\), and did not find any statistically significant change in results that could be separated from the stochastic noise of the simulation. This is certainly plausible as the screening model is used only for the choice set construction, and does not influence the selection of the final unit on which the household eventually bids.
households outside the study area, for whom the only update is the calculation of new vehicle availability logsums, as they cannot enjoy the increased accessibility inside the study area.

New vehicle availability categories are calculated for mover households and all households inside the study area based on the above modifications to the vehicle availability model. Therefore, we obtain a new population after the simulation period in 2013 comprising (a) mover households with new residential locations and new vehicle availabilities, (b) non-mover households inside the study area with new vehicle availabilities and unchanged residential locations, and (c) non-mover households outside the study area with no change to either residential location or vehicle availability.

Recall from our literature review that residential relocation and vehicle availability are often considered as simultaneous decisions. However, we consider them to be sequential decisions in our simulation framework because of computational practicality\(^3\). While considering residential relocation, the choice set of each household comprises 30 alternatives. If we were to consider a simultaneous framework, we would need to calculate at most \((1.15 \text{ million households} \times 30 \text{ residential unit choices} \times 6 \text{ mobility bundle choices}) = 207 \text{ million logsum values in total.}\) Note that all of this has to be done on the fly because each household’s choice set is constructed in a stochastic manner during the simulation due to which these logsum values cannot be pre-computed and stored in a database. Our sequential framework allows us to scale down the computation time significantly as at most \((1.15 \text{ million households} \times 30 \text{ residential unit choices} =) 34.5 \text{ million logsum values are required in the first phase and (1.15 million households} \times 6 \text{ mobility bundle choices =) 6.9 million logsum values are required in the second phase, leading to a total of 41.4 million logsum values.}\) Thus, we obtain computational savings to the tune of \((207 - 41.4) / 207 = 80.5\%\) by using a sequential framework.

5 Results & Discussion

A burn-in simulation of one year was conducted first to achieve a quasi-equilibrium of the housing market under baseline conditions with no change in population or available housing units. We then conducted five simulation runs using the ‘burned-in’ synthetic population for a one-year period, i.e. from 2012 to 2013, related to each of the four scenarios described in the previous section. The results from these simulations are discussed in the following sub-sections. We report both the average values (sample means) and standard deviations across the five runs for relevant indicators of interest.

5.1 Residential mobility & migration

We expect movers in the simulation to exhibit variability in behavior. For example, households that move into the study area do so because they find it to be more utilitarian than their current residential unit, while the converse holds true for those who move out. Therefore, we categorize two types of movers:

\[^3\]There is an additional reason to favor the sequential framework. As our WTP function is not sensitive to household-specific logsums (due to our use of logsums averaged across each TAZ), sequential consideration will lead to the same result as the simultaneous approach. Given this setting, there is no reason to add computational burden by considering the simultaneous framework. That being said, we are exploring heuristics to improve performance for a future scenario when we have a more sensitive WTP model.
- **In-movers:** These households experienced a residential relocation during the simulation period that resulted in them relocating to a unit inside the study area. They could have moved into the study area from outside ($OUT \rightarrow IN$ transition), or could have moved but always remained inside the study area ($IN \rightarrow IN$ transition).

- **Out-movers:** These households were inside the study area in 2012 but moved out during the simulation, and live outside the study area in 2013 ($IN \rightarrow OUT$ transition).

Net migration effects for the four scenarios are shown in Figure 3a. We find that the study area experiences a net out-migration of around 100 households in the baseline scenario. Since Scenario I only introduces policy awareness without any market effects, the migration in this scenario cannot be statistically differentiated from that in the baseline (as expected). When buyer valuation increases in Scenario II, units inside the study area are perceived to be more attractive and households are willing to pay more for such units. This leads to a turn of the tide, evidenced by a net positive in-migration of around 500 households. Finally, when the seller valuation (and market value) rises in Scenario III, only high-income households can afford these more expensive units. Since we account for affordability constraints in the choice set construction, the higher market value (and lower affordability) of units inside the study area reverses the effect noticed in Scenario II and induces a net out-migration.

While the magnitude of accessibility increase does not affect the baseline and Scenario I (as expected), the reported trends for Scenarios II and III are further exacerbated with an increase in the magnitude of $k$. As the magnitude of accessibility increase rises, Scenario II witnesses higher in-migration due to higher perceived valuation of units from the buyers’ perspective. Similarly, asking prices are also higher in Scenario III due to higher boosts to accessibility, which leads to even fewer households being able to afford them, leading to even higher out-migration.
5.2 Gentrification

We also explored variation of socio-demographic variables such as household size, presence of seniors, presence of children, and ethnicity in the study area over time. We found that there are no statistically significant differences among in-movers and out-movers with regard to these socio-demographics. However, significant differences in household income are noticeable across the four scenarios. While there is extensive evidence of transit-induced gentrification present in the literature (see Dawkins and Moeckel (2016) for a related discussion), this study is perhaps the first to uncover gentrification trends through in-migration of high-income households caused by accessibility enhancements that might stem from automated mobility.

We find from Figure 3b that out-movers are indistinguishable from the original study area population in terms of household income, except in Scenario II where significantly lower-income households are displaced. On the other hand, in-movers are always found to be higher-income relative to both the original population and out-movers. In the baseline and Scenario I, both in-movers and out-movers are statistically similar to the original study area population. However, when buyer valuation increases in Scenario II, the mean income of in-movers is about 7% higher than the original study area population even for the most moderate assumption of accessibility increase ($k = 0.25$). The mean income of in-movers drops slightly in Scenario III for this particular $k = 0.25$ assumption, but we witness a widening income gap as the magnitude of accessibility increase rises. For the most impactful assumption ($k = 2.0$), in-movers in Scenario III earn more than twice as much as those in Scenario II. This is consistent with our expectation of higher seller valuation as manifested through higher asking prices.

Apart from obvious long-term gentrification effects, this finding also has implications for the study area in terms of private mobility holdings as high-income households are more likely to own private vehicles. This is particularly relevant in the Singaporean context, where the most important predictor of private vehicle availability is household income (Basu, 2019).

5.3 Vehicle availability transitions

We focus on all households in the study area to examine the transitions that occur between the various mobility bundles as a result of the car-lite pilot. A transition matrix diagram is shown in Figure 4, where the six categories are denoted as $C_0$ (no private vehicles) through $C_6$ (two normal cars w/wo other vehicles). The detailed definition of these six categories can be found in an earlier section in the paper. Owning no vehicles is represented through a green color, while other categories that imply owning at least one vehicle of some sort are represented through increasingly dark shades of red. The left side of the figure denotes the initial vehicle availability category which was assigned to households at the beginning of the simulation in 2012, while the right side of the figure denotes the final vehicle availability category of households at the end of the simulation in 2013 that was re-assessed based on their new residential location. While similar transition matrix diagrams can be constructed for every scenario and $k$, we focus only on Scenario III, which is arguably the most accurate representation of long-term effects. For this particular figure, we chose to highlight $k = 1.0$ as this assumption reflects a future where automated mobility can equate the accessibility of car-owning households with those having no private cars (on average).

We find that the number of households that transition from the private-car alternative to the vehicle-free alternative (i.e., $C_3$ to $C_0$) is higher than the reverse transition. This leads to the study area becoming more vehicle-free by
about 2.5%, relative to the original mobility bundle choices. In addition to this transitional behavior, we examine the aggregate vehicle-free market shares among mover households across scenarios in Figure 5a. As noted earlier, the initial population in the study area owned fewer vehicles than Singapore on average, and in-movers are more likely to own vehicles compared to out-movers. We see from the figure that out-movers are always more vehicle-free than in-movers, even in the baseline case. The inclusion of market effects further decreases the vehicle-free rate among in-movers, which is only exacerbated as the magnitude of accessibility increase rises. As alluded to earlier, this is a result of higher demand causing relatively higher-income households, who are more reluctant to give up their private vehicles, to move into the study area. In Scenario III, where both demand and supply effects are considered, we find that in-movers can be up to 3% less vehicle-free compared to the original population of the study area.

It is worth noting here that the vehicle-free rate of out-movers in Scenario I does not change significantly from the baseline. However, out-movers are comparatively more vehicle-free in Scenario II, which consistently aligns with our observations of the mean incomes of the displaced households. Thus, we find that the gentrification side-effect displaces households whose willingness to be vehicle-free is above the study area average, out of the study area. While there are several other ramifications of gentrifying neighborhoods, this finding is quite significant in terms of understanding the unintended consequences of the car-lite pilot on the neighborhood.
5.4 Aggregate vehicle-free market share

The car-lite pilot certainly increases the attractiveness of the study area, as evidenced by more households moving into the study area than moving out in Scenario II. However, supply effects can hamper migration through higher-than-usual asking prices of units inside the study area. Market-driven effects (including both demand and supply) may dampen the potential of the car-lite pilot in inducing transitions to a vehicle-free lifestyle.

Figure 5b summarizes the aggregate vehicle-free market shares in the study area for the baseline plus three scenarios, and also compares them to the market shares corresponding to non-mover households in the study area. We see that the vehicle-free share slightly decreases in the study area in the baseline scenario when the car-lite pilot was not introduced. However, the accessibility boost in Scenario I (without being marred by market reactions) makes the study area more vehicle-free. Unfortunately, market effects serve to dampen this behavior by lowering the net vehicle-free share. As we increase the magnitude of accessibility boost, the study area becomes comparatively more vehicle-free, although the dampening effects get consecutively larger. When $k = 2$, the potentially unadulterated vehicle-free boost is around 7.5%, which gets lowered to about 6% (i.e., a decrease of 20%) in Scenario III. Our earlier observation about in-migration points to non-movers forming the bulk of the population in the study area, and we see here that some of them are relatively unaffected by market effects. Therefore, we can conclude that non-movers dominate the vehicle-free behavioral changes, which can be moderated (sometimes significantly) by the reluctance of most in-movers to relinquish their privately owned vehicles.

The reluctance of in-movers to give up private vehicles despite enjoying the benefits of the car-lite pilot is reminiscent of what economists refer to as the endowment effect, although we did not explicitly model this effect in our framework. The households that moved in were more likely to own a car in 2012, compared to those that moved out, and even compared to those that remained in the study area. Thus, the in-movers were less vehicle-free to begin with and remained so even after moving in, compared to the highly vehicle-free initial population in the study area. As choice transitions are driven by relative utility gains, our findings indicate that the increase in accessibility is desirable enough to induce residential relocation, but not necessarily enough to motivate becoming vehicle-free.

6 Conclusion

Recent enhancements of mobility options are motivating policy-makers to re-evaluate the very essence of private vehicle ownership. *How will the market for private vehicles get affected when on-demand and shared mobility services become ubiquitous?* Such questions become even more complex with the consideration of automated vehicles in the fleet mix. The research question of AVs substituting private vehicles has started receiving considerable attention in recent times. This study attempts to address this question by combining econometrically robust behavioral models with an agent-based microsimulation framework in our LUTI model *SimMobility*, and then examining the extent to which accessibility changes in ‘car-lite’ communities can influence private vehicle ownership directly, in addition to the mediating effect of residential relocation. At a broader level, this study is an example of how urban informatics and behavioral modeling can be integrated within planning support systems to understand the dynamics through which we design car-lite mobility futures.

A scenario-based design is adopted, wherein different types of market responses to the car-lite pilot are modeled through various assumptions of changes in model parameters. We chose a study area that has a lower market share of private vehicles than the overall metropolitan area to obtain conservative estimates of policy impacts. Our findings indicate that the study area does not undergo substantial changes in demographics over a one-year horizon despite positive in-migration rates. However, we notice that in-movers are richer and initially less vehicle-free than out-movers. The final share of vehicle-free households and the transition rates from private vehicle availability to vehicle-free are not encouraging. While the accessibility boost works as intended, market effects lead to gentrification and significant dampening of the realized vehicle-free behavioral change. Although the study area remains more vehicle-free overall, the dampening effect is exacerbated as the magnitude of accessibility increase rises, which further incentivizes higher-income households to move into the study area without relinquishing their privately owned vehicles.

*In summary, the car-lite pilot can result in unanticipated negative consequences, such as gentrification, that can dampen the potential vehicle-free gains in the study area. It is likely that alternative study areas with less ‘tight’ markets will experience greater success with the pilot.*

Our finding of AV-induced gentrification motivates us to recommend that the private vehicle availability of in-movers needs to be moderated (or perhaps even restricted) through appropriate policy design. Leaving in-mover behavior in the hands of the market results in them “having the cake and eating it too”, as they enjoy the accessibility benefits of the study area in addition to retaining their private vehicles. Paying attention to affordable housing policy regulations and the characteristics of the study area (such as mix of housing stock, vacancy rate, and initial vehicle-free behavior) is
also essential before piloting such a car-lite policy. This is particularly true for megacities in the Global South, several of which are facing crippling traffic congestion and housing affordability crises. Since there are stark socio-economic (particularly income) inequalities in such contexts, it becomes all the more critical to understand the differences in valuation of increased accessibility by various population cohorts, which can lead to unforeseen ripple effects of seemingly well-intentioned policy interventions. Our proposed framework can be easily extended to examine such contexts due to the purposefully context-agnostic design. However, appropriate context-specific data are necessary for calibrating the behavioral models in the LUTI microsimulation. In the absence of such data (which is quite often the case in resource-constrained and data-poor settings), it might be advisable to construct virtual cities as micro-representations of larger metro areas and use them as testbeds for exploring socially relevant policy questions (e.g., see [Basu et al., 2018]).

Our work opens up a couple of avenues for future research. First, exploration of other scenarios that represent different market reactions would be useful in observing variability in policy impacts. We are currently working on including other supply-side reactions such as accelerated housing development behavior leading to an increase in housing stock inside the study area. Second, we could replace our speculative assumptions regarding accessibility improvements with activity-based accessibility measures for individuals that have shared and automated mobility options added to their choice sets. The SimMobility Medium-Term team is working on simulating activity patterns for such scenarios and generating corresponding ABA values, which can then be used directly in our Long-Term models.

There are a few limitations in this study. First, we do not consider the cost of vehicle availability in our framework. The vehicle availability choice model does not contain cost as an explanatory variable due to lack of reliable data. Second, some studies indicate that vehicle availability changes are closely associated with changes in household demographics and life cycle events (such as changing a job or getting married), which we do not consider in their entirety. We are addressing both these issues by conducting a retrospective survey of Singaporean households that tracks all major life cycle and demographic changes over the past three years (2016-2018). Additionally, the survey captures specific details of all vehicles owned by the household, including purchase and transaction costs, frequency and reason of use, and major users, which can help include cost-dependent covariates in our vehicle availability choice model. Third, our WTP model is not conditional on availability of mobility options. While the ideal method would be to estimate a WTP model that considers joint housing-mobility bundles as choices, obtaining relevant data for such a model is quite challenging.

Overall, we hope that this study provides useful contributions to both the academic literature and planning practice by demonstrating how a technically robust LUTI simulation framework (SimMobility Long-Term) can be utilized as a policy analysis tool to anticipate the net effect of various competing forces, depending on the manner in which we introduce new technologies that improve accessibility. The importance of considering market effects and housing policy regulations while evaluating the impacts of automated mobility is highlighted in the study, which speaks to how detailed LUTI models can be integrated into robust PSS that are used to fine-tune policy interventions as they are incrementally rolled out by understanding the dynamics of public acceptance and market reactions.

Acknowledgements

This research was funded in part by the Singapore National Research Foundation through the Future Urban Mobility group at the Singapore-MIT Alliance for Research and Technology Center. We appreciate the contributions of past and present members of the SimMobility team. A preliminary version of this paper was presented in July, 2019 at the 16th Conference on Computers in Urban Planning & Urban Management (CUPUM) in Wuhan, China. We thank the two anonymous referees whose comments helped us improve the presentation of our ideas.

References

M. Adnan, F. C. Pereira, C. M. L. Azevedo, K. Basak, M. Lovric, S. Raveau, Y. Zhu, J. Ferreira, C. Zegras, and M. Ben-Akiva. Simmobility: A multi-scale integrated agent-based simulation platform. In 95th Annual Meeting of the Transportation Research Board, 2016.

C. L. Azevedo, N. M. Deshmukh, B. Marimuthu, S. Oh, K. Marczuk, H. Soh, K. Basak, T. Toledo, L.-S. Peh, and M. E. Ben-Akiva. Simmobility short-term: An integrated microscopic mobility simulator. Transportation Research Record, 2622(1):13–23, 2017.

R. Basu. Reinterpreting vehicle ownership in the era of shared and smart mobility. Master’s thesis, Massachusetts Institute of Technology, 2019. URL https://hdl.handle.net/1721.1/123940

R. Basu and J. Ferreira. Understanding household vehicle ownership in Singapore through a comparison of econometric and machine learning models. Transportation Research Procedia, 2020a.
Evaluating long-term impacts of automated mobility (Pre-print)

R. Basu and J. Ferreira. Can increased accessibility from emerging mobility services create a car-lite future? Evidence from Singapore using LUTI microsimulation. Transportation Letters, 2020b. doi: 10.1080/19427867.2020.1731993.

R. Basu, A. Araldo, A. P. Akkinepally, B. H. N. Biran, K. Basak, T. Seshadri, N. Deshmukh, N. Kumar, C. L. Azvedo, and M. Ben-Akiva. Automated mobility-on-demand vs. mass transit: A multi-modal activity-driven agent-based simulation approach. Transportation Research Record, 2018. doi: 10.1177/0361198118758630.

M. Batty. Modeling and simulation in geographic information science: Integrated models and grand challenges. Procedia-Social and Behavioral Sciences, 21:10–17, 2011.

P. M. Bösch, F. Becker, H. Becker, and K. W. Axhausen. Cost-based analysis of autonomous mobility services. Transport Policy, 64:76–91, 2018.

C. Dawkins and R. Moeckel. Transit-induced gentrification: Who will stay, and who will go? Housing Policy Debate, 26(4-5):801–818, 2016.

B. Deal, H. Pan, V. Pallathucheril, and G. Fulton. Urban resilience and planning support systems: the need for sentience. Journal of Urban Technology, 24(1):29–45, 2017.

C. Gkartzonikas and K. Gkritza. What have we learned? A review of stated preference and choice studies on autonomous vehicles. Transportation Research Part C: Emerging Technologies, 98:323–337, 2019.

C. J. Haboucha, R. Ishaq, and Y. Shiftan. User preferences regarding autonomous vehicles. Transportation Research Part C: Emerging Technologies, 78:37–49, 2017.

Y. Han, P. C. Zegras, V. Rocco, M. Dowd, and M. Murga. When the tides come, where will we go?: Modeling the impacts of sea level rise on the greater boston, massachusetts, transport and land use system. Transportation Research Record, 2653(1):54–64, 2017.

J. Hawkins and K. Nurul Habib. Integrated models of land use and transportation for the autonomous vehicle revolution. Transport reviews, 39(1):66–83, 2019.

S. Hörl, F. Ciari, and K. W. Axhausen. Recent perspectives on the impact of autonomous vehicles. Arbeitsberichte Verkehrs- und Raumplanung, 1216, 2016.

Y. Jiang, J. Zhang, Y. Wang, and W. Wang. Capturing ownership behavior of autonomous vehicles in japan based on a stated preference survey and a mixed logit model with repeated choices. International Journal of Sustainable Transportation, pages 1–14, 2018.

D. Kahneman, J. L. Knetsch, and R. H. Thaler. Experimental tests of the endowment effect and the coase theorem. Journal of Political Economy, 98(6):1325–1348, 1990.

N. Menon, N. Barbour, Y. Zhang, A. R. Pinjari, and F. Manering. Shared autonomous vehicles and their potential impacts on household vehicle ownership: An exploratory empirical assessment. International Journal of Sustainable Transportation, 13(2):111–122, 2019.

J. Meyer, H. Becker, P. M. Bösch, and K. W. Axhausen. Autonomous vehicles: The next jump in accessibilities? Research in Transportation Economics, 62:80–91, 2017.

D. Milakis, M. Kroesen, and B. van Wee. Implications of automated vehicles for accessibility and location choices: Evidence from an expert-based experiment. Journal of Transport Geography, 68:142–148, 2018.

C. Pakusch, G. Stevens, A. Boden, and P. Bossauer. Unintended effects of autonomous driving: A study on mobility preferences in the future. Sustainability, 10(7):2404, 2018.

A. Soteropoulos, M. Berger, and F. Ciari. Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. Transport reviews, 39(1):29–49, 2019.

K. Spieser, K. Treleaven, R. Zhang, E. Frazzoli, D. Morton, and M. Pavone. Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in singapore. In Road vehicle automation, pages 229–245. Springer, 2014.

P. Thakur, R. Kinghorn, and R. Grace. Urban form and function in the autonomous era. In 38th Australasian Transport Research Forum (ATRF), 2016, Melbourne, Victoria, Australia, 2016.

Z. Wadud. Fully automated vehicles: A cost of ownership analysis to inform early adoption. Transportation Research Part A: Policy and Practice, 101:163–176, 2017.

R. Zakareiko. Self-driving cars will change cities. Regional Science and Urban Economics, 61:26–37, 2016.

J. Zhang, B. Yu, and M. Chikaraishi. Interdependences between household residential and car ownership behavior: a life history analysis. Journal of Transport Geography, 34:165–174, 2014.
W. Zhang and S. Guhathakurta. Residential location choice in the era of shared autonomous vehicles. *Journal of Planning Education and Research*, page 0739456X18776062, 2018.

W. Zhang, S. Guhathakurta, and E. B. Khalil. The impact of private autonomous vehicles on vehicle ownership and unoccupied vmt generation. *Transportation Research Part C: Emerging Technologies*, 90:156–165, 2018.

Y. Zhu and J. Ferreira. Synthetic population generation at disaggregated spatial scales for land use and transportation microsimulation. *Transportation Research Record*, 2429(1):168–177, 2014.

Y. Zhu, M. Diao, J. Ferreira, and C. Zegras. An integrated microsimulation approach to land-use and mobility modeling. *Journal of Transport and Land Use*, 11(1), 2018.