Planning car-lite neighborhoods: Examining long-term impacts of accessibility boosts on vehicle ownership

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Planning car-lite neighborhoods: Examining long-term impacts of accessibility boosts on vehicle ownership

A Preprint

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Abstract

Transformative technologies like automated vehicles, and emerging services like mobility-on-demand and ride-sharing, are changing the ecosystem of urban mobility. Land use-transport interaction (LUTI) models provide appropriate platforms to test the impacts of such services on cities. Although these services are purported to have mixed effects on cities, there is a general consensus that these services will increase accessibility. We approach the 'car-lite' policy through this lens of increased accessibility, and base this study in the city-state of Singapore. Different study areas are chosen in a manner similar to the differences-in-differences approach, in order to tease out the effects of initial neighborhood vacancy rate, vehicle-free behavior, and tight markets on policy impacts. We also design different scenarios that represent varying market reactions to the policy, and compare them to a baseline where the car-lite policy is never implemented. Study areas that are initially less 'tight' (i.e., have higher vacancy rates and lower vehicle-free rates) are found to have significantly larger transitions to vehicle-free behavior. Additionally, our finding of accessibility-induced gentrification speaks to the importance of considering the endogeneity in housing and mobility choices while formulating policies that may seemingly feel relevant only to the transportation realm. Providing appropriate mixes of housing typologies with adequate affordable housing, in addition to restricting car use for higher-income car-owning households, are suggested as strategies for designing car-lite neighborhoods.

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

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1 Introduction

Emerging transportation technologies like automated [1] vehicles (AVs), and services like mobility-on-demand (MoD) and micro-mobility (e.g. bikesharing and scooters), are motivating discussions on the future of cities. Combining them under the umbrella term of 'future urban mobility', domain experts agree that there is great uncertainty about their net

[1] Although both important and necessary, a discussion on the distinction between 'automated' and 'autonomous' is perhaps too involved for a research article, and best saved for a seminar or debate panel. It is somewhat unfortunate that the latter term has become ubiquitous in society.

effects on cities. While travel time and cost savings are possible in the short-term, the induced travel demand will likely cancel out those benefits in the long-term (Milakis et al., 2018). There is less uncertainty and more agreement about accessibility benefits, which can increase worker welfare but might also result in larger travel distances and urban sprawl (Zakharenko, 2016). While popular media outlets tend to heavily focus only on the benefits, 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 it is still unclear how the market for private vehicles is going to react to future urban mobility, a paradigm shift in the essence of vehicle ownership is imminent. Mobility-as-a-Service (MaaS) is receiving significant attention from academia and industry alike, especially as the smart city vision becomes more popular (Wong et al., 2019; Goodall et al., 2017). Therefore, it is necessary to think beyond the traditional idea of vehicle ownership, and perhaps begin to conceptualize the concept of *mobility holdings* (Basu, 2019). Building on the spirit of MaaS, *mobility holdings* should include owned vehicles (both motorized and non-motorized), available vehicles (such as rentals or company cars), and passes for different services (such as transit or micro-mobility passes). Correspondingly, we need to think of a different metric for measuring or evaluating mobility holdings. While car ownership rate (share of households owning a private car) was appropriate for the traditional vehicle ownership model, perhaps thinking inversely for the new paradigm is the way forward. We propose that the *vehicle-free rate* (share of households with no private motorized mobility holdings) might be more pertinent for evaluating mobility holdings choice models. Accordingly, we use this metric to highlight some of the findings of this study in later sections.

The vehicle-free rate is relevant for another important reason. Several megacities, particularly Singapore and London, are actively planning strategies to reduce private car ownership and usage [2]. While the specifics of their strategies are culturally and contextually different, their underlying visions of creating 'car-lite' policies and fostering 'car-lite' communities are common (Chng et al., 2019). Examining the vehicle-free rate over time might be useful to evaluate the impact of such car-lite policies on the region. The Singaporean context is particularly interesting, especially since it is a relatively bounded city-state as opposed to a city spilling over into a larger metropolitan region. Active efforts by the government to regulate car ownership and usage date back to the 1970s, starting from traffic regulations to the more recent introduction of the Off-Peak Car scheme [3]. Since vehicle registration and purchasing a Certificate of Entitlement (CoE) are quite expensive, the costs associated with owning a private vehicle in Singapore are significantly high compared to other living expenses (Basu and Ferreira, in press). The OPC scheme allows for lower registration and CoE expenses in exchange for restricting the use of the car to only off-peak hours (7PM to 7AM on weekdays).

Car-lite policies are likely to be piloted at a neighborhood scale instead of the entire city or region because it stands to reason that planning agencies will test out the policy in a limited capacity first before rolling it out to their entire jurisdiction. Drawing from previously discussed automated mobility literature, we use only one specific assumption related to such car-lite programs, i.e., an increase in accessibility. This leads us to consider the following hypotheses.

Hypothesis 1 (Reduced private mobility ownership effect): *Increased accessibility can induce households that live and/or work inside the study area to reduce their privately owned mobility holdings, thereby increasing the vehicle-free rate of the neighborhood.*

Hypothesis 2 (Gentrification side-effect): *Increased accessibility can augment the attractiveness of the study area, thereby causing a net in-migration of high-income households and possible gentrification of the neighborhood. As high-income households are more likely to own private cars, this side-effect can decrease the vehicle-free rate of the neighborhood.*

The aforementioned hypothesized effects clearly work in opposite directions with regard to the net change in the vehicle-free rate, therefore it is unclear as to which effect is more likely to dominate. Certain neighborhoods might experience a stronger reduced private mobility ownership effect, which will result in a rise in the vehicle-free rate over time. To that end, our research objective is to seek out which neighborhoods might be most likely to experience positive long-term impacts of car-lite pilot programs, with an eye towards understanding the structural characteristics that enable them to make a transition to car-lite travel behavior.

In order to maintain the generalizability of our approach, we do not explore the mechanics of accessibility increase in detail, as different cities might choose to pursue different processes in their vision of a car-lite future. The exploration of the impacts of such a policy requires building futuristic scenarios. Therefore, we use an agent-based land use-transport interaction (LUTI) model to simulate different scenarios based on potential market reactions to the policy. This allows us to maintain the link between impacts on land-use and transportation decisions through the inclusion of

[2]https://www.clc.gov.sg/research-publications/publications/urban-systems-studies/view/creating-liveable-cities-through-car-lite-urban-mobility

[3]https://www.lta.gov.sg/content/ltaweb/en/roads-and-motoring/transport-options-for-motorists/revised-off-peak-car-and-opc-and-weekend-car.html

different accessibility measures. Various study areas are selected in order to tease out the effects of initial neighborhood characteristics on policy impacts, which enable us to provide suggestions for study areas that are more likely to experience successful pilots.

The remainder of this paper is structured as follows. We review related literature and discuss the potential contributions of our approach in the following section. Section 3 provides an overview of the research methods that are employed in this study; namely, the simulation framework, design of hypothesized future scenarios, and selection of different study areas. We present our findings from the simulations and discuss their implications in a broader context in Section 4. Finally, concluding remarks are provided along with suggestions for future research efforts in Section 5.

2 Literature Review

We provide a brief discussion of related research in this section. The first sub-section provides a review of long-term impacts of automated mobility on cities. The operationalization of different accessibility measures is discussed in the second sub-section, while the third sub-section focuses on different LUTI models and their applications.

2.1 Long-term impacts of automated mobility

The two long-term impacts of automated mobility that are of primary interest to policy-makers are related to *private vehicle ownership* and *residential relocation*. Researchers have attempted to understand the effect of automated mobility on vehicle ownership using agent-based models and activity-based models. The general approach is to vary the fleet size of autonomous vehicles while trying to match total travel demand and trip generation rates. Evaluation metrics of system performance include vehicle miles traveled (VMT) as a proxy for emissions, and total travel time as a proxy for congestion. Some studies find that private vehicle ownership would not be attractive in a future dominated by 24/7 mobility-on-demand, as current travel patterns could be maintained with a significant reduction in the number of private vehicles (Hörl et al., 2016; Zhang et al., 2018). These results seem to suggest that the paradigm of private vehicle ownership is under threat. However, a critical caveat common to these studies might be the key assumption of total replacement of private vehicles by AVs. A recent review of similar empirical studies reported that there is a general consensus among academics and practitioners that exogenous assumptions (about time or cost savings in particular) and the complete replacement assumption (which is rather unrealistic) limit the use of such studies for policy-making (Soteropoulos et al., 2019).

Another approach towards this research question is to use stated preference surveys to elicit user preferences towards AVs. American households are found to be more likely to give up a private vehicle in lieu of a shared AV, only if they own multiple vehicles (Menon et al., 2019). Results from a German study too indicate that private cars are likely to remain the most preferred mode (Pakusch et al., 2018). While there are undeniable socio-demographic and cultural variations in public opinions and responses to automated mobility, stated preference findings seem to be challenging the aforementioned hypothesis that the ownership model will decrease in popularity with the widespread availability of AVs in the near future (Haboucha et al., 2017). One key aspect of this debate that might end up being the clincher is the cost of ownership. Higher-income households are found to have a higher willingness-to-pay for automated mobility, perhaps due to their higher perceived value of time (Wadud, 2017; Jiang et al., 2018). 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 automated mobility-on-demand (AMoD) services in Singapore found that shared AVs can save around 15,100 USD/year in total mobility costs compared to a privately owned human-driven car (Spieser et al., 2014).

Research on the impacts of automated mobility on location choices has been relatively limited. Studies have suggested that automated mobility would result in an increase in accessibility, along with an increase in population in well-connected outer suburbs and rural regions (Soteropoulos et al., 2019). However, it is worth bearing in mind that these findings of urban sprawl are associated with strong assumptions that automated mobility would reduce travel times, increase roadway capacity, and reduce the travel time penalty (since the rider could engage in other activities besides driving). Assuming a reduction of value of time by 50% for private AVs, Thakur et al. (2016) modeled travel behavior and residential location choices for Melbourne in 2046. Their findings indicate slightly positive out-migration from the inner city to the suburbs. However, their results are inconclusive due to mixed effects when shared AVs are considered. Zhang and Guhathakurta (2018) 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, Meyer et al. (2017) found that shared AVs could curb urban sprawl. While it is difficult to draw generalizable conclusions due to mixed evidence, a common finding of these studies is the increase in accessibility owing to automated mobility. Meyer et al. (2017) goes so far as to call this a ‘quantum leap’ in accessibility. In light of this common finding, this study approaches a similar research question through the lens of increased accessibility stemming from automated mobility.

2.2 Accessibility measures

Urban transportation planning efforts were (and arguably still are, to a great extent) geared towards planning for and around automobiles. However, the emergence of micro-mobility and on-demand mobility services are necessitating a paradigm shift towards planning for accessibility, as opposed to mobility (Basu and Alves, 2019). Although this was suggested by Cervero et al. (1997) more than 20 years ago, cities are responding more actively to this thought now in light of the paradigm shift in urban mobility. The operationalization of accessibility measures in models connecting the built environment and travel demand varies widely across applications. The seminal work by Geurs and Van Wee (2004) discusses the trade-off between complex, disaggregate accessibility measures and more aggregate measures that are easier to interpret. Aggregate accessibility measures like cumulative opportunities or gravity-based decay are easier to calculate, but do not account for the spatio-temporal constraints at the individual level. Activity-based accessibilities (ABA), as expressed by the logsums of activity-based models, can accurately account for different constraints related to infrastructure, location, the individual, and economic utility (Dong et al., 2006). It is worth noting that ABA measures capture demographic effects appropriately since different individuals can have different utilities for the same combination of mobility and location choices.

The above discussion is not to devalue the contribution of other accessibility measures, but to highlight the importance of using ABA measures in land use-transportation models. Alternative accessibility measures, such as the 3Ds (density, diversity, and design), are also useful to characterize the built environment (Cervero and Kockelman, 1997). These have been extended to include distance to transit and destination accessibility as well (Ewing and Cervero, 2010). Along with distance to transit, distances to different amenities such as restaurants, shopping malls, schools, etc. (sometimes collectively termed as 'local accessibilities') can also be informative in creating neighborhood accessibility measures such as WalkScore and BikeScore [4].

2.3 Land use-transport interaction (LUTI) models

Land use-transport interaction (LUTI) models have a reputation of being perhaps "the most promising technique" for representing the complex dynamics of spatial and behavioral patterns in metropolitan regions (Wegener and Fürst, 2004). Despite their promise and potential for aiding decision-making, their use in planning practice has remained relatively limited, perhaps owing to their intense requirements of data and computational resources (Lee Jr, 1973). However, recent advances in information and communication technologies over the last couple of decades have enabled these models to become more easily implementable.

Although the origin of LUTI models can be perhaps traced back to the Lowry model in the 1960s, the number of operational LUTI models has really picked up over the last couple of decades. MUSSA was one of the first applications of the bid-choice theory in urban land markets, and was coupled with the four-stage transport model ESTRAUS in Santiago de Chile (Martinez, 1996). More recently, Hunt and Abraham (2009) proposed PECAS (Production, Exchange and Consumption Allocation System) which combined a regional econometric model with microsimulation of land development at the scale of individual parcels. Researchers in several countries have combined microsimulation of demographic transitions and land development in Paul Waddell's UrbanSim with agent-based transport microsimulation in Kay Axhausen's MATSim (Waddell, 2002; Balmer et al., 2008), primarily motivated by both platforms being released in an open-source capacity for public use. In Europe, Michael Wegener's land use microsimulation model IRPUD was extended by Rolf Moeckel and colleagues, who proposed ILUMASS (Integrated Land-Use Modelling and Transportation System Simulation) which included sub-models for environmental evaluation (Wegener, 1982; Moeckel et al., 2002). Tangentially, Eric Miller's research group in Canada developed the ILUTE (Integrated Land Use, Transportation, Environment) microsimulation modelling system that included an activity-based travel model TASHA (Travel Activity Scheduler for Household Agents) (Salvini and Miller, 2005; Roorda et al., 2008). A more detailed review of these LUTI models can be found in Iacono et al. (2008).

LUTI models use accessibility as a bridge to link the land use and transportation simulation components. While this is theoretically sound, the operationalization of accessibility is found to vary widely. Examples include logsum-based accessibilities only from the mode choice model in SWIM (A Statewide integrated model for Oregon) by Donnelly et al. (2018), time-dependent auto network performance in SimTRAVEL (Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land) by Pendyala et al. (2012), and zone-level accessibility using shortest path-based travel costs on the road network in an UrbanSim - MATSim integration (Nicolai and Nagel, 2012). Although the concept of activity-based accessibility (ABA) proposed by Ben-Akiva and Bowman (1998) has gained significant popularity in

[4] https://www.walkscore.com/

practice-ready implementation of transportation models, we were unable to find LUTI models that use the full economic information represented through the logsum of an activity-based travel demand model for integration. This is one of the key contributions of *SimMobility* (*Simulation of Future Urban Mobility*), which is the LUTI model developed by our research group based on the gaps we identified in the literature.

While the development of LUTI microsimulation platforms still remains an active research area, the capability of these tools to adapt to a changing mobility ecosystem is an important research question. In a recent review of LUTI models with an eye towards their appropriateness for an automated future, Hawkins and Nurul Habib (2019) argue that operational LUTI models were largely developed during a period of relative uniformity in mobility choice sets. Therefore, the new mobility paradigm necessitates reevaluating the capability of these tools, and implementing critical changes that can enable them to remain relevant and useful. Our relatively recent research project (which started in 2010 and is still active) provides us the opportunity to respond to some of these concerns. Accordingly, *SimMobility* was designed with capabilities for simulating future scenarios, and analysing policies that are pertinent to the emerging mobility ecosystem.

3 Research Methods

This section outlines the research methods used in this particular study. First, we provide a brief overview of the simulation platform developed in-house by our research group, followed by a description of the specifics of the framework employed to use the simulation platform for policy analysis. Second, we describe the different scenarios that were designed to model different reactions to the car-lite policy pilot. Finally, the different study areas considered for this pilot are described, and typologies are assigned based on their demographic and housing characteristics.

3.1 SimMobility: An agent-based LUTI microsimulation

SimMobility is a multi-scale agent-based microsimulation platform that incorporates time-scale dependent behavioral modeling through activity-based frameworks (Adnan et al., 2016). The *Long-Term (LT)* component involves creation of a synthetic population, followed by household-level residential location and mobility holdings choices, and individual-level job location choices, at the temporal scale of days to years (Zhu et al., 2018). The *Medium-Term (MT)* component couples a mesoscopic supply simulator with a microscopic demand simulator that involves mode choice, route choice, and activity-travel pattern generation at the temporal scale of minutes up to a day (Basu et al., 2018). The LT and MT components are connected through activity-based accessibility (ABA) measures that are disaggregate utility-based measures of alternative daily activity patterns (*logsums*), which are then used as explanatory variables in LT choice models. It is worth noting that ABA measures are calculated based on a hierarchical medium-term travel behavior decision-making framework that incorporates choices of tours, trips, destinations, modes, and departure times. By definition, the ABA measures derived from the daily activity patterns of individuals are dependent on socio-demographic characteristics (such as income, age, occupation, driving license availability, etc.) and household characteristics (such as residential location, private vehicle ownership and availability, etc.), and are unique to each individual.

The long-term choice models in SimMobility use a variety of the accessibility measures discussed earlier in the literature review section. Along with local accessibilities, we include ABA values that are generated dynamically for each agent (i.e., an individual or a household). There are three sets of ABA values that we generate: (a) *fixed-work varying-home ABAs* that are generated for each household agent keeping the workplace Traffic Analysis Zones (TAZs) of the household members fixed and varying the residential location across all TAZs in the region, (b) *fixed-home varying-work ABAs* that are generated for each individual agent keeping the residential location TAZ for their household fixed and varying the workplace location across all TAZs in the region, and (c) *fixed-home fixed-work varying-mobility ABAs* that are generated for each household agent keeping the residential location TAZ of each household and the workplace location TAZs of their members fixed, and varying the mobility bundle choice across the choice set of mobility holdings. The TAZ-averaged fixed-work varying-home ABAs are used in the household-level residential location choice models, such as the hedonic price model and the willingness-to-pay (WTP) model. The fixed-home varying-work ABAs are used in the individual-level job location choice model, while the varying-mobility ABAs are used in the household-level mobility holdings choice model.

All households in the synthetic population in the base year (2012) are considered to be eligible for the daily bidding process. An 'awakening' model, estimated from a recent mover survey, determines which households begin a period of active housing search each day in the simulation. 'Eligibility' and 'screening' models are then used to build choice sets for determining whether and how much to bid on the housing unit that provides the maximum expected consumer surplus. We use the bid-auction housing model to simulate housing market transactions for the simulation period (considered as one year in this study). At the end of the simulation period, we identify households who had successful bids along with their new residential locations. Households that changed units, i.e., moved during the simulation period, are called *mover households*. Households whose residential locations remained the same in 2013 as in 2012 are called *non-mover households*. Readers interested in the details of the bid-auction housing model should refer to Zhu et al. (2018).

Following a change in residential location, all mover households reconsider their mobility holdings using dynamically calculated logsums based on their new housing unit. In addition, households in the study area who did not move during the simulation period will also re-evaluate their mobility holdings since the accessibility improvements from the car-lite pilot will have improved their logsum accessibility measure. Finally, we categorize the rearranged population at the end of the simulation period (in 2013) into (a) mover households with new residential locations and new mobility holdings, (b) non-mover households inside the study area with unchanged residential locations and new mobility holdings, and (c) non-mover households outside the study area with unchanged residential location and mobility holdings.

Further empirical details about our simulation framework for scenario comparisons can be found in Basu and Ferreira (2020a). For the sake of brevity, we limit the details presented here and highlight three aspects that are key to understanding this paper. First, the synthetic population was created by matching marginal demographic and spatial distributions obtained from Census data, while the choice models are calibrated on observed behavior recorded in travel surveys and real estate transactions. This is likely to cause a mismatch in simulated behavior, especially at the start of the simulation. To account for this inconsistency, we perform a burn-in simulation for one year to reach a quasi-equilibrium. We start off with a synthetic population for 2012, simulate a burn-in for one year, reconstruct the synthetic population using the updated population at the end of the burn-in, and then simulate one year for observing policy impacts (see appendix for details). Second, the ABA values used in the housing market models (i.e., the hedonic price and willingness-to-pay models) for the car-lite scenarios are augmented by k times the standard deviation of the ABA distribution across the population for households that live or work inside the study area. Third, the household-specific 'vehicle-free' logsum used in the household mobility holdings model is augmented by k times the average difference between the 'car-only' logsum and the 'vehicle-free' logsum. The default value of k is set to 0.50 for the simulations as a conservative assumption of accessibility increase stemming from the car-lite pilot. We test the sensitivity of the policy impacts to k by varying the value of k across a grid $[0.25, 0.50, 1.0, 2.0]$ for a particular study area (see sub-section 4.4).

3.2 Scenario design

We design the following scenarios in order to capture different market reactions to the accessibility changes that might result from a car-lite pilot.

- ***Baseline:*** The baseline run simulates the long-term evolution of Singapore, assuming that the car-lite pilot was never introduced. All parameters in the long-term choice models are held constant and equal to the estimated values.
- ***Scenario I (Minimal effect):*** we assume that the car-lite pilot has only an 'awareness' effect. Households are aware of the pilot but do not value the accessibility changes. We model this effect by including at least one housing unit from the study area in the choice set of each household seeking alternative housing, and doubling the likelihood that housing units inside the study area are included in the choice set of an awakened household. Apart from an awareness about the introduction of the pilot, there are no other market effects in this scenario.
- ***Scenario II (Buyer valuation increases):*** In addition to the changes in the previous scenario, we hypothesize that the pilot leads to an increase in housing demand inside the study area. The increased demand can be represented through ABA parameter modifications in the willingness-to-pay (WTP) model that estimates the value of a vacant-for-sale housing unit from the buyer's perspective. This scenario can be thought of as a *short-term 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-term market reaction*, where both consumers and suppliers have reacted to the pilot. The market has had enough time to respond to the increased demand, and sellers increase their asking prices to capture the increased market value from the accessibility improvements. In this case, adjustments are made to the ABA parameters in the market price (hedonic) estimates as well as the WTP estimates that were already adjusted in Scenario II.

3.3 Selection of study areas

It is expected that car-lite pilot impacts will vary by space, as different study areas will react to the pilot differently (Basu and Ferreira, 2020b). Since we are modeling behavioral choices of housing and mobility, we chose pertinent metrics such as *vacancy rate* (share of vacant housing units) and *vehicle-free rate* (share of households without a private vehicle) to characterize a study area. Accordingly, we then consider three different cases to isolate the effect of each metric on car-lite pilot impacts.

Table 1: Characteristics of selected study areas

Case	Study Area	Households [a]	Vacancy rate	Vehicle-free rate	Typology
Vacancy	Bukit Batok	38,427	8.21%	51.64%	Less
	Choa Chu Kang	47,187	10.98%	50.19%	More
Vehicle-free	Bukit Timah	21,707	10.06%	27.31%	Less
	Sembawang	19,465	10.41%	48.1%	More
Tight market	Clementi	34,763	8.33%	55.75%	Less
	Yishun	49,264	7%	65.26%	More
Overall	Singapore	1,148,066	7.1%	54.11%	-

[a] We only consider households whose head is a Singapore citizen or Permanent Resident.

We consider the city-state of Singapore as our region of interest for this study. The Urban Redevelopment Authority distinguishes 55 planning districts in Singapore and we use these to select neighborhoods for consideration as car-lite pilot areas. Table 1 compares several characteristics of six planning districts, while their relative spatial locations are shown in Figure 1. Our first case examines the *effect of vacancy rate on pilot impacts*, which motivates us to select two planning districts of comparable vehicle-free rates but very different vacancy rates. This approach can be thought of as similar to a differences-in-differences (DID) approach in spirit, as we are controlling for one of the metrics (vehicle-free rate, for this particular case). We find that Bukit Batok and Choa Chu Kang match our requirements quite well, with the former being classified as ‘less vacant’ and the latter as ‘more vacant’.

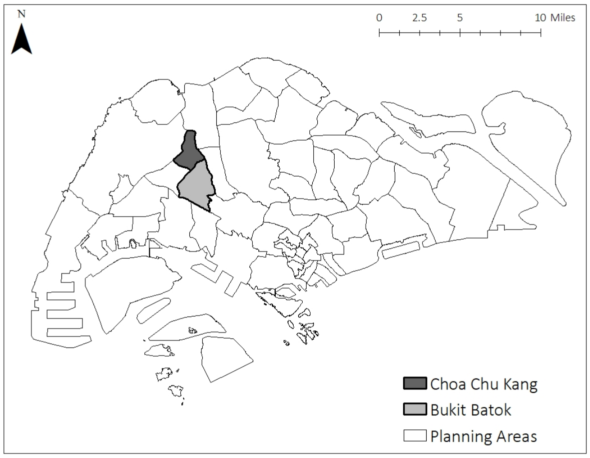
The second case examines the *effect of vehicle-free behavior on pilot impacts*. Arguably, a study area with higher vehicle-free behavior (as evidenced by a higher vehicle-free rate) might be more likely to become even more vehicle-free with the institution of the car-lite pilot. Therefore, Bukit Timah and Sembawang are selected as they have similar vacancy rates but very different vehicle-free rates, with the former being classified as ‘less vehicle-free’ and the latter as ‘more vehicle-free’.

Finally, we combine both metrics to consider the third case that examines the *effect of tight markets on pilot impacts*. A study area with higher vacancy rate is more likely to experience gentrification and a consequent rise in mobility holdings, while that with a higher vehicle-free rate might be induced to become even more vehicle-free. Since these market effects work in a conflicting manner, we select Clementi (high vacancy rate and low vehicle-free rate) and Yishun (low vacancy rate and high vehicle-free rate) as our study areas. They are consequently classified as ‘less tight’ and ‘more tight’ respectively.

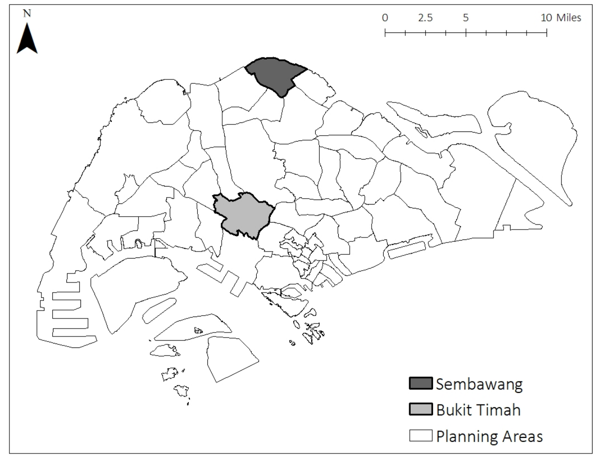
4 Results & Discussion

In this section, we discuss our findings from the three cases outlined in the previous section and the sensitivity analysis to our assumptions regarding accessibility increase. It is worth highlighting at this point that we conducted five simulation runs for each combination of study area and scenario. The five runs are sufficient to estimate the stochasticity across 365-day Monte Carlo simulations using the same parameter settings. Therefore, a total of $(5 * 6 * 4 =)$ 120 simulations were run for the six study areas, and the baseline with three scenarios. The sensitivity analysis involved 45 additional simulations for the selected study area and three scenarios. We represent the mean values in the bar plots, and include error bars to represent the standard deviations across the five runs for each combination of study area and scenario.

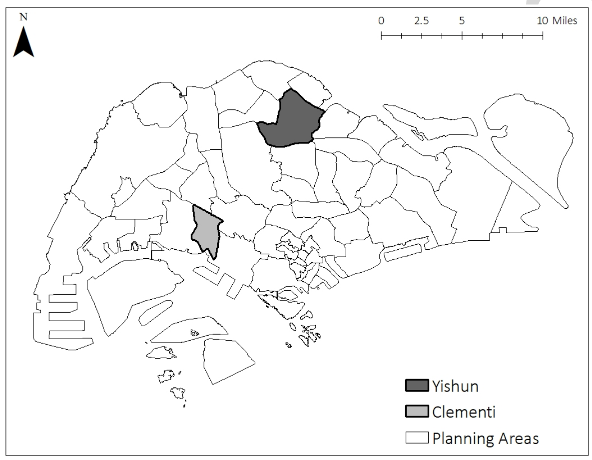
The discussion is oriented around four metrics of neighborhood change through which we measure the impacts of the car-lite pilot on the study area. First, we measure the *net in-migration effect* through the difference in the number of in-mover households and the number of out-mover households. A positive value implies that more households moved into the study area, i.e., there is a net positive in-migration effect. This metric allows us to evaluate the attractiveness of the study area to the population of the entire region, which is Singapore in this application. Second, we measure the *gentrification effect* through the difference between mean household incomes of the mover cohorts and the mean household income of the study area at the beginning of the simulation. A positive value implies that in-movers tend to



(a) Varying vacancy rates



(b) Varying vehicle-free rates



(c) Varying tightness of market

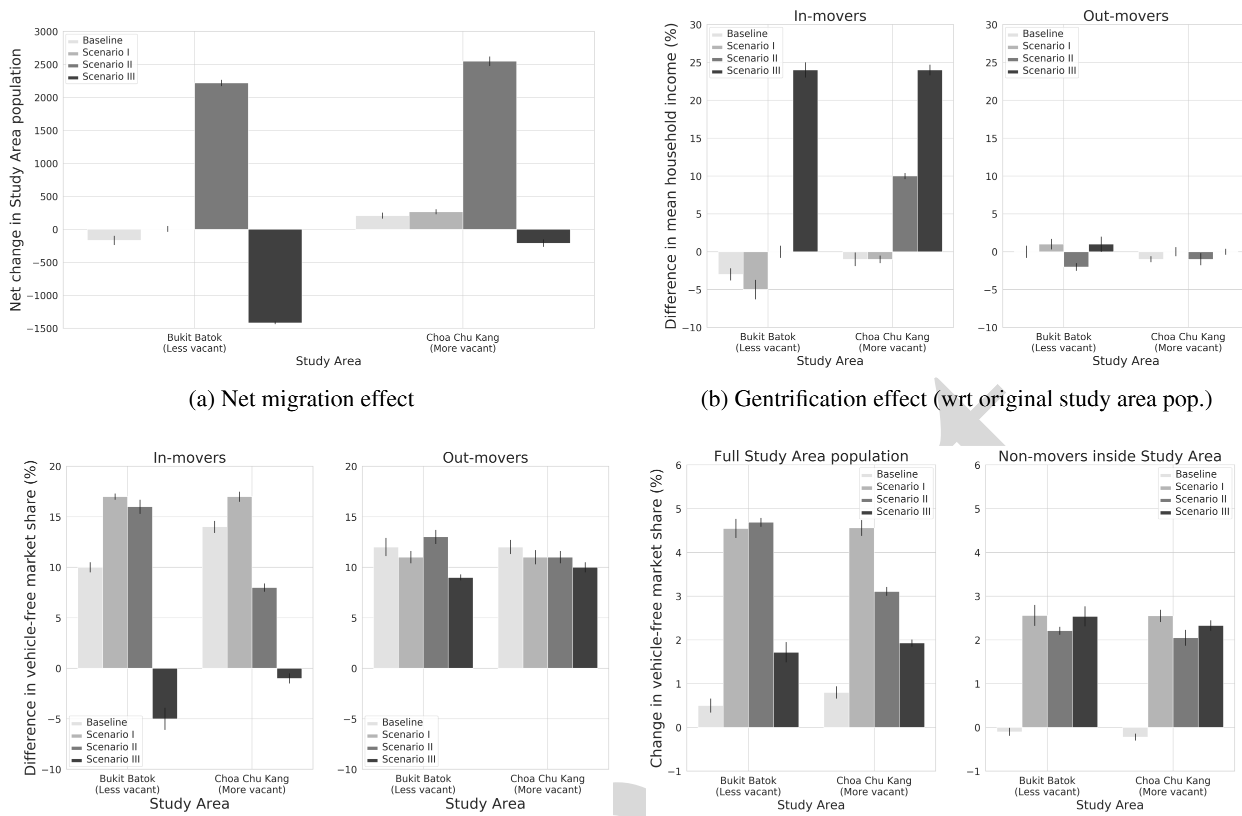
Figure 1: Study areas for three cases of neighborhood characteristics (*lighter color indicates lower value*)

not only be richer than out-movers but also richer than the original study area population, which is one characteristic of a gentrifying neighborhood.

Third, we measure the *vehicle-free effect on mover cohorts* through the difference between the vehicle-free rate of the mover cohorts after residential relocation and the vehicle-free rate of the study area at the beginning of the simulation. A positive value indicates that movers are more vehicle-free than the original study area population. This metric allows us to evaluate the effect of the car-lite pilot on households that move into the study area and households that are being displaced. If in-movers are less vehicle-free and are displacing more vehicle-free households, that is indeed a cause for concern as this phenomenon counteracts the intended outcome of the pilot. Finally, we measure the *net vehicle-free effect on the entire study area* through the difference between the vehicle-free rate of the study area after and before the simulation. A positive value indicates that the study area has become more vehicle-free, i.e., more households are now without vehicles than at the beginning of the simulation. This implies the success of the car-lite pilot in achieving its intended outcome.

4.1 The effect of initial vacancy rates

We will first discuss our findings related to the effect of vacancy rates on policy impacts. For this case, we had selected Bukit Batok and Choa Chu Kang as our study areas. Recall that Bukit Batok had a vacancy rate of 8.21% and was classified as 'less vacant', while Choa Chu Kang was classified as 'more vacant' owing to its much higher vacancy rate of 10.98%. Figure 2a compares the net in-migration effect between the two study areas. We find that both study areas experience low migration levels initially, with Choa Chu Kang proving to be more attractive than Bukit Batok. With



(a) Net migration effect

(b) Gentrification effect (wrt original study area pop.)

(c) Vehicle-free effect (wrt original study area pop.)

(d) Net vehicle-free effect

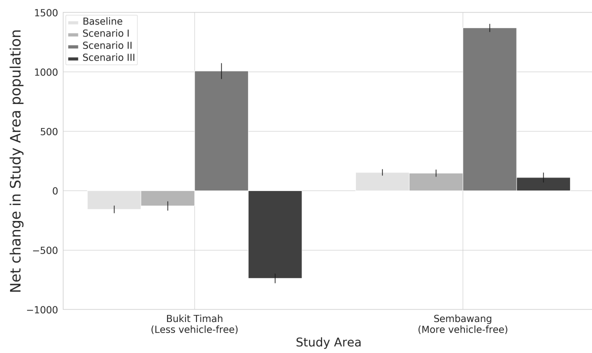
Figure 2: Measuring car-lite policy impacts on study areas with varying vacancy rates

the inclusion of higher demand valuation in Scenario II, the in-migration effect increases significantly for both study areas. However, the seller-side reaction in Scenario III dampens this effect to the extent that the net migratory effect is negative. It is worth noting that Choa Chu Kang is not affected as drastically as Bukit Batok.

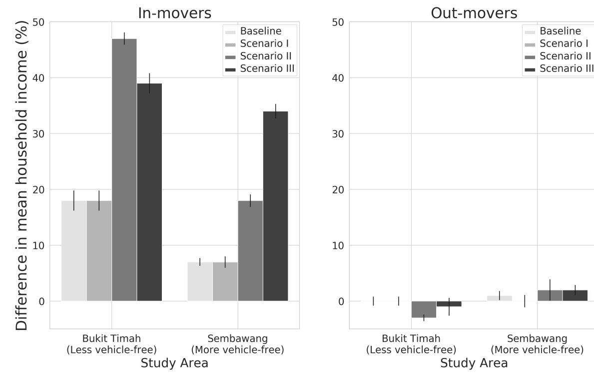
Figure 2b shows that out-movers are relatively similar in terms of household income across scenarios for both study areas. However, in-movers are very different from out-movers. Although in-movers in Bukit Batok have a lower household income on average in the baseline and Scenario I, supply-side reactions in scenario III induce in-movers to be around 25% higher-income than the initial study area population on average. While similar effects are noticed for Choa Chu Kang, in-movers are significantly higher-income even in Scenario II, unlike for Bukit Batok.

The vehicle-free behavior of mover cohorts for the two study areas is presented in Figure 2c. Although the vehicle-free market share may seem counter-intuitive to readers, we chose to use this metric as a representation of vehicle-free household behavior (as discussed earlier). A decrease in the vehicle-free market share implies an increase in private mobility holdings, which consequently means that vehicle-free behavior has decreased. We find that in-movers are slightly less vehicle-free than out-movers in Bukit Batok, while the reverse is true for Choa Chu Kang. Due to the unadulterated accessibility boost to the ‘vehicle-free’ logsum in Scenario I, it is not surprising to see that in-movers are consistently more vehicle-free than out-movers. However, in-movers are drastically affected with the inclusion of market effects. This is most evident in Scenario III, where in-movers are less vehicle-free than the original study area population (in addition to out-movers, of course).

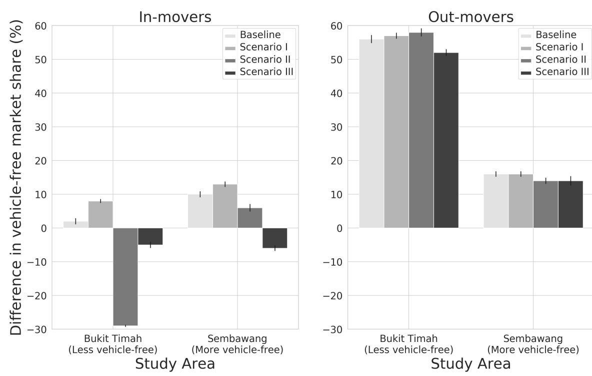
On average, non-movers inside the study area are positively influenced by the car-lite pilot, without significant differences across the two study areas (see Figure 2d). However, we find that the net effect on the study area shows variation when market effects are considered. Although the impact of the pilot remains positive, market effects can significantly dampen potential vehicle-free gains in the study area. In particular, a higher vacancy rate leads to a more dominant gentrification effect in the short-term, and consequently a more muted impact of the pilot. However, in the long-term, we note that the net vehicle-free behavioral outcome does not vary significantly by vacancy rate, even though the constituent processes are impacted with varying magnitudes.



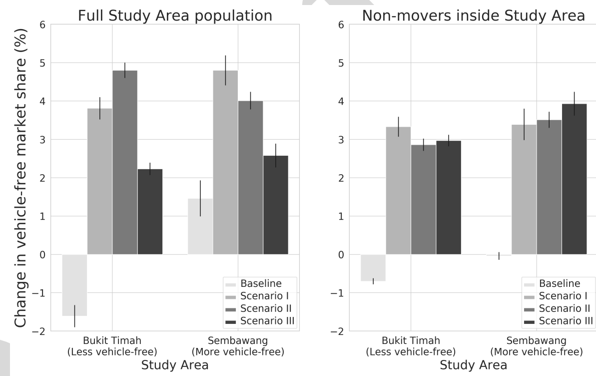
(a) Net migration effect



(b) Gentrification effect (wrt original study area pop.)



(c) Vehicle-free effect (wrt original study area pop.)



(d) Net vehicle-free effect

Figure 3: Measuring car-lite policy impacts on study areas with varying vehicle-free rates

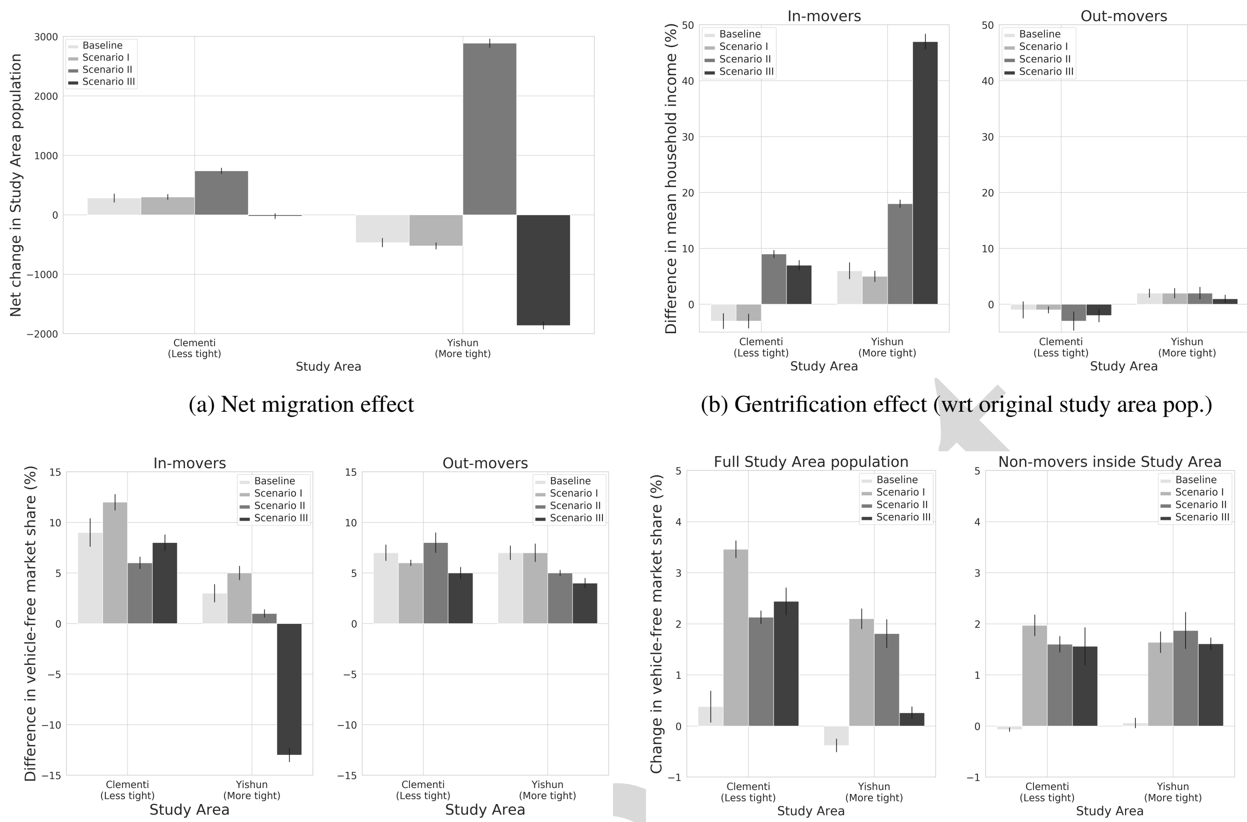
4.2 The effect of initial vehicle-free behavior

We had selected the 'less vehicle-free' Bukit Timah and 'more vehicle-free' Sembawang as our study areas, as their vehicle-free rates were 27.31% and 48.1% respectively. We find from Figure 3a that Sembawang is always more attractive compared to Bukit Timah, although the trends across scenarios are similar for both study areas. As expected, the in-migration effect in Scenario I cannot be statistically differentiated from the baseline effect. Scenario II witnesses a sharp jump in in-migration due to increased demand valuation, which is then substantially moderated through supply-side reactions in Scenario III. It is worth noting that the net in-migration effect in Scenario III is slightly positive for Sembawang, but significantly negative for Bukit Timah.

Figure 3b shows that there is little difference between out-movers and the initial study area population in terms of mean household income. However, in-movers have a significantly larger mean household income than both out-movers and the initial study area population. The less vehicle-free Bukit Timah experiences more gentrification than its more vehicle-free counterpart in the baseline and all three scenarios. While the gentrification effect is more pronounced for Bukit Timah in Scenario II, the Scenario III effects are comparatively more similar.

From Figure 3c, we find that the less vehicle-free Bukit Timah experiences different vehicle-free effects across mover cohorts. The higher-income in-movers have a significantly lower and negative vehicle-free rate, i.e., they have higher mobility holdings. On the other hand, the lower-income out-movers have a much higher and positive vehicle-free rate. This implies that the more vehicle-free households are being displaced by the less vehicle-free and higher-income households that move into the study area. The more vehicle-free Sembawang experiences relatively different effects. Although out-movers are always more vehicle-free than in-movers, the differences between the two mover cohorts are not as drastic as in the case of Bukit Timah.

The non-movers are similar to the original study area population in terms of vehicle-free behavior for both study areas in the baseline. However, we find very different results when we evaluate the entire study area as a whole (see Figure 3d). The unadulterated vehicle-free gains in Scenario I are larger for the more vehicle-free Sembawang. The inclusion



(a) Net migration effect

(b) Gentrification effect (wrt original study area pop.)

(c) Vehicle-free effect (wrt original study area pop.)

(d) Net vehicle-free effect

Figure 4: Measuring car-lite policy impacts on study areas with varying tightness of market

of both demand and supply-side reactions in Scenario III indicate that the moderated long-term effect still remains larger for Sembawang.

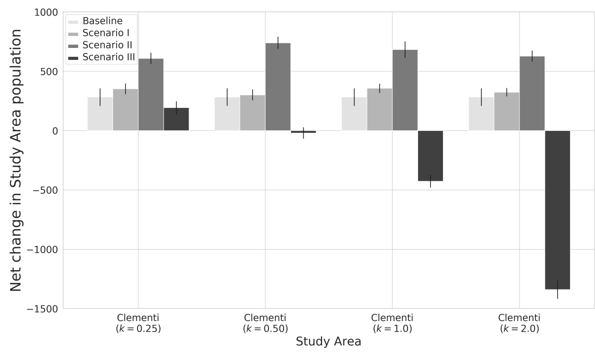
4.3 The effect of initial tight markets

We had selected Clementi as a less tight market because of its higher vacancy rate and lower vehicle-free rate, while Yishun was selected as a more tight market because of its lower vacancy rate and higher vehicle-free rate. Figure 4a shows the net migration effect for the two study areas. As expected, Clementi has a higher migration effect for the baseline, and Scenarios I and III. However, increased demand valuation in Scenario II serves to increase migration for Yishun to the extent that it overshadows the less tight market in Clementi.

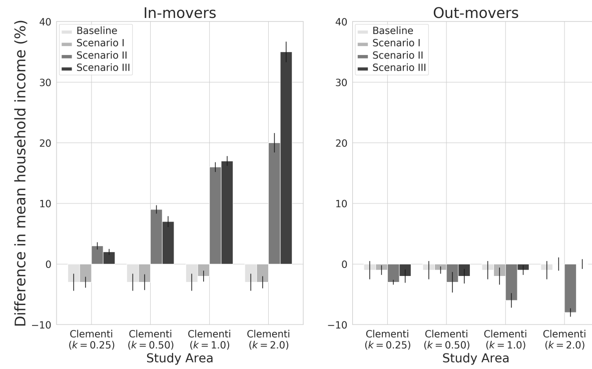
We find from Figure 4b that out-movers are almost always lower-income compared to the in-movers across scenarios for both study areas. In-movers in Clementi are about 10% higher-income than the original population in Clementi when market effects are considered. However, the tighter market in Yishun is subject to more significantly pronounced gentrification effects. In-movers in Yishun are about 20% higher-income than the original Yishun population in Scenario II, which rises to about 47% in Scenario III. Therefore, we find evidence that the tighter housing market (as evidenced through the lower vacancy rate) leads to greater competition for units, especially when market effects are considered, which eventually leads to magnified gentrification effects.

The vehicle-free behavior of mover cohorts is presented in Figure 4c. In-movers in Clementi are more vehicle-free than out-movers for the baseline and Scenario I. However, the trend reverses for Scenario II, when in-movers are also higher-income. On the other hand, out-movers are always more vehicle-free compared to in-movers in Yishun. The largest difference between the mover cohorts is noticed for Scenario III in Yishun, which is also subject to the largest gentrification effect.

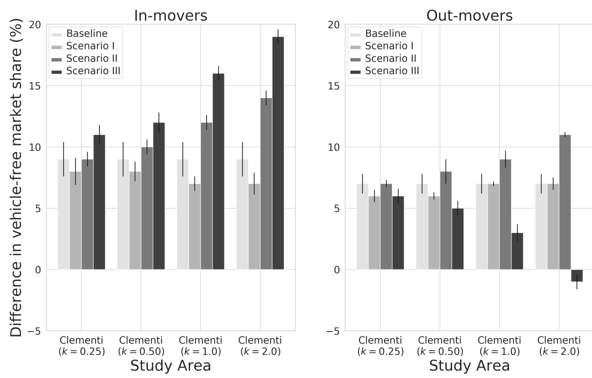
The less tight market in Clementi witnesses significantly larger policy impacts compared to Yishun, especially in Scenario I (see Figure 4d). Despite the dampening effect of housing market reactions, Clementi enjoys more favorable outcomes, particularly in Scenario III where we noticed remarkably high gentrification effects in Yishun. Therefore, we



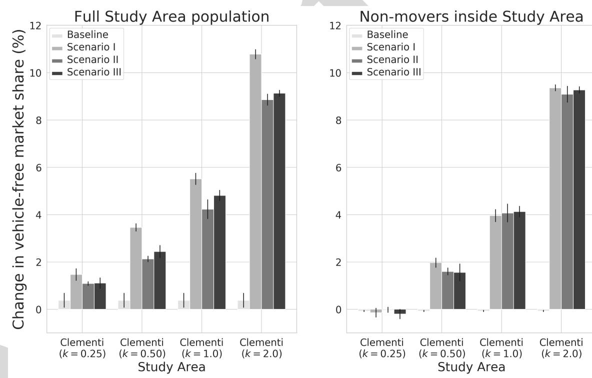
(a) Net migration effect



(b) Gentrification effect (wrt original study area pop.)



(c) Vehicle-free effect (wrt original study area pop.)



(d) Net vehicle-free effect

Figure 5: Measuring sensitivity of car-lite policy impacts to accessibility increase

can conclude that dominant gentrification effects can significantly undermine net vehicle-free gains for the study area through the in-migration of higher-income in-mover households, who are less likely to relinquish their private mobility holdings despite the accessibility boosts from the car-lite pilot.

4.4 Sensitivity analysis

We had assumed that ABA would increase by k (default value = 0.50) times the standard deviation for households living or working inside the study area. We choose Clementi as the study area for the sensitivity analysis since it is a less tight market and experienced the highest positive outcome in Scenario III among all six study areas. We vary k across a grid of values $[0.25, 0.50, 1.0, 2.0]$ and examine the policy impacts for these different magnitudes of accessibility increase.

Figure 5a represents the net migration effect on Clementi relative to the different assumptions of accessibility increase. We find that the migration effect is independent of the accessibility increase for the baseline and Scenario I, which is consistent with expectations. Recall that the baseline does not include the car-lite pilot, while Scenario I only implies a greater awareness but no direct accessibility increase for the long-term choice models. There is a slight positive trend in in-migration relative to the magnitude of accessibility increase (i.e., k) when buyer-side effects are included. However, with the inclusion of seller-side effects, we find that there is a strong inverse non-linear relationship between the net in-migration and k, which can be described as a decay function. A higher value of accessibility increase induces more competition in the housing market, and thus leads to fewer bids being accepted by sellers who have also increased the valuations on their units.

We find that there is a positive linear relationship between the gentrification effect of in-movers and accessibility increase in Scenario II, while the relationship remains positive but becomes heavily non-linear (resembling a power or exponent law) in Scenario III (see Figure 5b). The gentrification effect on out-movers is parabolic for Scenario II, with a flat initial decay which dips more sharply for higher values of k. Consistent with expectations, the out-movers are significantly lower-income relative to in-movers, and the gap between them increases further with an increase in the magnitude of accessibility increase.

Figure 5c shows that the vehicle-free rate for out-movers has a non-linear and non-uniform relationship with accessibility increase. It is apparent that out-movers become more vehicle-free in Scenario II as the accessibility boost increases; however, the reverse holds true in Scenario III. In the case of in-movers, we find a similar but sharper linear increase in Scenario II, while there is a non-linear and more strongly positive increase in Scenario III. It is worth noting that the difference in vehicle-free behavior between in-movers and out-movers is accentuated as the accessibility benefits from the pilot are increased.

Figure 5d indicates that the net policy impact increases rapidly in a non-linear fashion for all three scenarios. However, the dampening effect also increases with an increase in accessibility benefits. Therefore, we conclude that car-lite pilots with larger accessibility benefits can induce more significant car-lite transitions, but also run an increased risk of gentrification that can significantly dampen the possible vehicle-free gains, which could potentially have been achieved in the absence of market effects.

5 Conclusion

Transformative technologies like automated vehicles and emerging services like mobility-on-demand and ride-sharing are changing the ecosystem of urban mobility. Most attempts by municipal governments and planning agencies to manage these transformative changes have been reactive in nature. While this is not necessarily a faulty approach, the unexpected emergence of scooters and dockless bikes in the last couple of years has shown that there is great uncertainty about what the next innovation in the mobility ecosystem might be in the years to come. In order to prepare better for this uncertainty, some megacities like Singapore are trying to shift to a more proactive approach in managing urban mobility services. While there are myriad approaches to design sustainable urban mobility policies, one particularly relevant approach is the formulation of 'car-lite' policies. Despite the differences across spatial contexts, the common underlying thread is that such policies are aimed at reducing private vehicle ownership and usage.

Although automated mobility and emerging mobility services are purported to have mixed effects on the city, there is a general consensus among scholars and practitioners that these services will increase accessibility. We approach the car-lite policy through this lens of increased accessibility, and base this study in the city-state of Singapore. Different study areas are chosen in a manner similar to the differences-in-differences approach, in order to tease out the effects of initial neighborhood vacancy rate, vehicle-free behavior, and tight markets on policy impacts. We also design different scenarios that represent varying market reactions to the policy, and compare them to a baseline where the car-lite policy is never implemented.

The findings of this study reveal a cautionary tale of a well-intentioned policy resulting in unintended negative consequences. The promise of increased accessibility from the car-lite pilot indeed makes the study area significantly more vehicle-free, which corroborates our hypothesis of a reduced private mobility ownership effect. However, the in-mover households are found to be comparatively higher-income than both the households they displace as well as the original study area population. The vision of a car-lite community is adversely impacted as several of these higher-income households, who are more likely to have private mobility holdings, refuse to reduce their mobility holdings and become more vehicle-free. Thus, the gentrification side-effect significantly reduces the potential vehicle-free gains from the car-lite policy, as hypothesized initially. In certain study areas, this market effect-driven reduction to the vehicle-free boost can be as high as 90%, implying that the study area is only marginally more vehicle-free than it was initially without the car-lite pilot.

Our analysis of different neighborhood characteristics can help guide planners in designing similar car-lite policies, in addition to providing suggestions about which neighborhoods might be more likely to have significantly positive vehicle-free transitions. We find that areas with higher vacancy rates are likely to be affected by housing market reactions, especially in the long-term. Areas that are more vehicle-free might intuitively seem like good choices, but the self-selection effect seems to be overshadowed by the gentrification side-effect. Our findings indicate that there is a greater opportunity to induce more vehicle-dependent regions into becoming more vehicle-free, if supply-side effects can be moderated. Finally, we find that tight markets with low vacancy rates and high vehicle-free behavior are more likely to be negatively impacted. The study area of Clementi, which is a less tight market, was found to have the least reduction in the vehicle-free boost, even with the inclusion of market effects. While empirically useful for Singapore, the structural characteristics of Clementi that enabled a successful and significant vehicle-free transition are also useful for planners around the world aiming to design similar car-lite neighborhoods.

The sensitivity analysis in this paper highlights a sharper decay in policy impacts with larger magnitudes of accessibility increase. Our finding of accessibility-induced gentrification, which is perhaps a generalization of previous findings of transit-induced gentrification in the literature (e.g. see Dawkins and Moeckel (2016)), speaks to the importance of designing policies in a holistic manner. Transportation policies are often designed in a silo by transportation planning agencies, without considering the endogeneity between housing and mobility choices. This study provides evidence that calls for greater collaboration between different planning agencies (transportation, housing, and metropolitan or regional, among others) for policy formulation. While the housing and urban development planning agencies can add to the affordable housing stock to make study areas more attractive to lower-income vehicle-free households, the transportation planning agency can consider policies that restrict private car use (e.g. off-peak cars, car-free zones, etc.), especially for higher-income car-owning households living inside the study area.

We would like to note a couple of limitations in this study. First, we considered the overall vacancy rate without examining the housing mix in the neighborhood while selecting study areas. Designing appropriate mixes of housing typologies might help to control the gentrification effect. As mentioned earlier, the vision of car-lite neighborhoods cannot be realized through transportation policies alone; rather, coordinated affordable housing policies need to be synced with mobility restrictions or green nudges. However, such policy designs are outside the scope of this particular study, and are therefore suggested as potential directions for future research efforts. Second, our WTP model (that impacts bids made by interested buyers) uses TAZ-averaged ABA measures, instead of household-specific logsums, as a subset of covariates due to convergence issues during model estimation with the latter. If the accessibility improvements were more attractive to lower-income households and/or housing additions in the car-lite neighborhood were not particularly attractive to wealthier households, then the car-lite policy might not be overwhelmed by the gentrification effect. Of course, it is not easy to thread this needle.

While designing car-lite neighborhoods is by no means an easy task, Singapore offers an opportunity to understand the process better through their proactive approach towards urban mobility management. Our LUTI simulation allows us to examine the market dynamics that occur in response to car-lite policies, along with anticipating (and, thereby, guarding against) unintended consequences of such policies. To that end, this study highlights the importance of considering the endogeneity in housing and mobility choices while formulating policies that may seemingly feel relevant only to the transportation realm. In closing, we hope that this study proves useful to researchers and policy-makers who are actively engaged in the vision of designing car-lite communities for a more sustainable urban future.

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Appendix

Since we could not find evidence of burn-in simulations in literature related to other LUTI models, we present the details of our burn-in simulation in this appendix. The burn-in, or warm-up, is a commonly used approach in simulation studies to shake off the initial effects of the simulation, which may not be reliable. If conducted for a large enough period, the system reaches a quasi-equilibrium that is more reliable as a starting point. Recall that our base year is 2012, as our synthetic population was calibrated with data from travel surveys and census-related sources in 2012. We tested different values of burn-in duration, and found that one year was more than adequate for achieving quasi-equilibrium in the housing market. Therefore, we started off with the calibrated synthetic population in 2012 and simulated 365 housing market days with no changes in the total number of households and housing units. It is worthwhile to note here that the system is treated as a closed system where the 'burn-in' can assign households to different housing units but there is no change in the total demand and supply. For example, housing units that were pre-sold and had move-ins scheduled during 2012 are excluded from the burn-in simulation. We used information related to residential relocation and reevaluation of mobility holdings from the burn-in simulation outputs to reconstruct a modified synthetic population. This modified population was consequently used as a 'reconstructed' starting point for 2012, and we proceeded with a regular one year simulation with the system now kept open for pre-scheduled moves, new construction, and the like.

We report the effect of the burn-in on the population of the different study areas in Table A1. The original study area population is reported in the third column, as obtained from the calibrated synthetic population. After conducting the burn-in simulation for one year, we end up with household counts shown in the fourth column for each study area. Finally, we report in the final column the household counts in each study area after one year 'baseline' simulations that start with the 'burned-in' 2012 population. It can be seen that the number of residential moves are quite high and somewhat implausible during the burn-in, indicating the instability of the simulation on startup and consequent

Table A1: Effect of burn-in on study area population (*number of households*)

Case	**Study Area**	**2012 (*calibrated*)**	**2012 (*after 1-year burn-in*)**	**Burned-in 2012 (*after 1-year baseline simulation*)**
Vacancy	Bukit Batok	39,905	38,427 (*-1,478*)	38,261 (*-166*)
	Choa Chu Kang	46,528	47,187 (*+659*)	47,396 (*+209*)
Vehicle-free	Bukit Timah	21,352	21,707 (*+355*)	21,550 (*-157*)
	Sembawang	19,819	19,465 (*-354*)	19,619 (*+154*)
Tight market	Clementi	33,152	34,763 (*+1,611*)	35,045 (*+282*)
	Yishun	51,208	49,264 (*-1,944*)	48,796 (*-468*)

requirement of a burn-in. The migration effects for the latter simulation (after the burn-in) are more plausible given the one year duration, and are much lower than those observed during the burn-in. This indicates that the system is much more stable after the burn-in.

Table A2: Effect of burn-in on study area vehicle-free rate (*share of households with no vehicles*)

Case	**Study Area**	**2012 (*calibrated*)**	**2012 (*after 1-year burn-in*)**	**Burned-in 2012 (*after 1-year baseline simulation*)**
Vacancy	Bukit Batok	51.52%	51.64% (*+0.11%*)	51.9% (*+0.26%*)
	Choa Chu Kang	49.15%	50.19% (*+1.05%*)	50.59% (*+0.4%*)
Vehicle-free	Bukit Timah	26.35%	27.31% (*+0.96%*)	26.87% (*-0.44%*)
	Sembawang	48.24%	48.1% (*-0.15%*)	48.8% (*-0.7%*)
Tight market	Clementi	54.54%	55.75% (*+1.21%*)	55.96% (*+0.21%*)
	Yishun	65.93%	65.26% (*-0.67%*)	65.01% (*-0.25%*)

The effect of the burn-in on the vehicle-free rate for different study areas is reported in Table A2. Similar to our previous observation, we find that the system is more unstable during the burn-in, which helps stabilize it to a great extent. The magnitude of change, as expressed through the values inside parentheses, is much higher during the burn-in relative to the consequent one year simulation. Thus, the importance of conducting a burn-in is highlighted, and the necessity of doing so is justified, in light of the evidence related to the change in the population and vehicle-free rate for different study areas.