Planning sustainable cities: Coordinating accessibility improvements with housing policies

by

Rounaq Basu

B.Tech., Indian Institute of Technology Bombay (2016)
M.S.T., Massachusetts Institute of Technology (2019)
M.C.P., Massachusetts Institute of Technology (2019)

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Author ....
Department of Urban Studies and Planning
August 31, 2022

Certified by ....
Professor Joseph Ferreira
Department of Urban Studies and Planning
Dissertation Supervisor

Accepted by ....
Associate Professor Gabriella Y. Carolini
Chair, PhD Committee
Department of Urban Studies and Planning

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Abstract

Emerging mobility services (such as mobility-on-demand and micromobility) have expanded the range of travel options available to individuals and offered ways to improve access to various opportunities. Unlike mass transit services, emerging mobilities can be implemented and experimented with rather rapidly. As a result, they are also likely to induce relatively rapid changes in travel behavior and location choices. Several cities across the world are experimenting with 'car-lite' policies that aim to reduce auto ownership and use (and emissions) with the help of emerging mobilities, transit improvements, and/or urban design. Therefore, it becomes important to understand the near-term effects of emerging mobilities on neighborhoods through the lenses of vehicle ownership and residential location choice over the first few years of change. This is especially important given the gentrification patterns we have observed in neighborhoods where transit improvements or extensions have been implemented (often referred to as 'transit-induced gentrification'). Will we observe similar patterns of *accessibility-induced gentrification* with emerging mobilities as well? If so, how can we, as planners, seek to mitigate these undesirable but consequential side-effects of car-lite policies?

In my dissertation, I introduced necessary methodological extensions to a state-of-the-art land use-transport interaction (LUTI) model that can enable better modeling of the interdependencies between various choices and tradeoffs of housing and mobility. Applying this improved LUTI model to the city-state of Singapore, I conducted quasi-static analyses and agent-based microsimulations of 'what-if' scenarios regarding how households react to accessibility changes. In addition to looking at neighborhood-level car-lite pilot programs that improve non-auto accessibility, I also explored vehicle restriction policies that seek to ban private vehicles.

I found that private vehicle restrictions alone without complementary non-auto accessibility improvements can reduce accessibility and social welfare, even in a transit-rich place like Singapore. Solely imposing a blanket ban on private automobiles to accelerate the transition to a sustainable mobility future will likely do more harm than good. Evidence of accessibility-induced gentrification, to varying degrees, was found in all of the Singaporean neighborhoods I explored. Lower-income and less auto-dependent neighborhoods seem to be more prone to accessibility-induced gentrification, thereby suggesting that non-accessibility improvements alone may not guarantee equitable outcomes. I then explored two housing

policies – upzoning and parking restrictions – as possible strategies to mitigate the gentrification side-effects. Both policies appeared to have limited value by themselves because, at times, they could accelerate gentrification or reduce social welfare. However, they became much more effective policy instruments when combined with affordability constraints (such as income restrictions and price discounts), so that the accessibility and welfare benefits of car-lite policies could be equitably distributed across residents. I also tested the generalizability and transferability of my findings through various sensitivity analyses, robustness checks, and implementation in a more auto-dependent context separate from Singapore.

This dissertation is expected to contribute to our understanding of the effects of emerging mobilities on three fronts. From a *conceptual* perspective, this study can demonstrate how emerging mobilities can lead to inequitable urban development in the absence of carefully designed market regulations. From a *policy* perspective, we can learn about the effectiveness of some housing and mobility policies in mitigating these undesirable outcomes while enhancing targeted outcomes. From a *methodological* perspective, the study contributes to the creation of a state-of-the-art integrated urban model that can be used to explore near-term market dynamics in reaction to new transportation technologies.

Dissertation Supervisor: Professor Joseph Ferreira

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I would be remiss if I did not thank my parents for their love and support over all the years of my existence. Manjary Guha deserves a special mention for going above and beyond in supporting me through the final phase of this journey. It would not be necessary to use a model to prove that my loved ones have had a strongly positive and statistically significant impact on my life.

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Chapter 1

Introduction

In his memoir 'My Years with General Motors,' long-time president and CEO of General Motors Corporation (and MIT alumnus) Alfred P. Sloan remarked that he would provide "a car for every purse and purpose" (Sloan, 1964). In hindsight, these words are an ominous portent of how auto-dependent our society would become. Newman and Kenworthy (1999) define auto-dependence as "a combination of high car use, high provision for automobiles, and scattered low-density use." Gorham et al. (2002) build on this definition by also emphasizing the role of individual behavior in reproducing and sustaining existing car-oriented social and spatial structures. Attributing auto-dependence to individual behavior can be thought of as a micro-level explanation, while Newman and Kenworthy's position is a macro-level recognition of the attributes of societies as a whole (Mattioli et al., 2016).

With good justification, auto use is heavily implicated in climate change. The transportation sector accounts for more than a quarter of greenhouse gas emissions in developed countries such as the US, and private vehicle use accounts for almost two-thirds of that (EPA, 2020). However, the mobility that autos provide is not easily replaced. Moreover, the pattern of land use that has resulted from the widespread dependence on autos has created a host of pressing societal problems. The need to own, maintain, and use a car can induce significant financial burdens, especially on lower-income households (Blumenberg and Pierce, 2012; Klein, 2020). This need stems from the necessity of auto ownership to access different opportunities, employment in particular (Lucas, 2012; Blumenberg and Pierce, 2014). Living in more auto-dependent areas has been linked to higher likelihoods of obesity, stress, poor mental health, and depression (Pohanka and Fitzgerald, 2004; Lopez-Zetina et al., 2006). Facilitating auto-centric lifestyles also requires significant public investment in road and parking infrastructure, which reduces funding and land that could be used for other, perhaps more important, public sectors. Hence, it is especially important to examine climate-driven efforts to reduce auto ownership and use with detailed attention to the ripple effects on land use patterns and the distributional effects of any transition on accessibility and social welfare. This is especially true when considering emerging mobility options such as mobility-on-demand and micromobility.

My motivation for this dissertation is centered around rethinking auto-oriented policies and planning. To effectively reduce the contributions of the transportation sector to the climate crisis, we will need to find ways to reduce auto-dependence. More fuel-efficient vehicle technologies can help make a dent in greenhouse gas emissions, but will not address the myriad negative consequences of auto-dependence. If current patterns of single-occupancy vehicle travel persist even with more fuel-efficient technologies, we will fail to meaningfully address congestion, auto accidents and injuries, and land allocation to auto-related infrastructure (such as highways and parking). Moreover, different societies are on different development trajectories and undertake diverse policy pathways to ensure the growth of their economies. Cervero (2013) cautions that the progress made by developed countries in reducing greenhouse gas emissions and fuel consumption can be quickly eclipsed if rapidly growing countries like India, China, and Brazil continue to mimic American-style patterns of suburbanization, car ownership, and travel.

Therefore, I argue that the need of the hour is to focus on large-scale systematic changes that force us to challenge the status quo. Among other actions, these involve redesigning our communities to reduce auto-dependence and become more mixed-use and mixed-income. 'Simply' transitioning to electric vehicles will not address all the issues associated with owning, using, and parking vehicles. A successful transition to a sustainable urban mobility future will require high-quality implementation of innovative schemes, and the need to gain public confidence and acceptability to support these measures through active involvement and action (Banister, 2008). The benefits of increasing the use of non-auto modes extend well beyond greenhouse emissions reduction to better public health (Frank et al., 2019), fewer traffic-related injuries and deaths (Mohan, 2002), more life satisfaction (De Vos et al., 2022), and more public space (freed up from roads and parking spaces) available for other land uses such as housing (Millard-Ball, 2022). Reducing auto-dependence is, of course, easier said than done and will require a multi-pronged strategy of improving alternatives to private vehicles, along with making changes to zoning and the built environment that reduce the necessity for auto ownership and use.

Over the last decade, emerging mobilities (such as mobility-on-demand and micromobility) have expanded our comprehension of 'non-auto' options. No longer are the car-less (or car-free) limited to walking, biking, and public transit. Services such as mobility-on-demand (e.g., Uber and Lyft) and micromobility (such as bikesharing and e-scooters) have expanded the mobility choice set and provided those without access to private cars additional options to choose from (Brown, 2019). Unlike mass transit services, emerging mobilities do not require as much additional substantial infrastructure or public investment (beyond the already substantial public investment in road infrastructure), which implies relatively faster implementation of mobility services and programs involving emerging mobilities. These options are more likely to be used by car-deficit (fewer cars than workers) households (Sikder, 2019) and have the potential to reduce auto ownership and use (Basu and Ferreira, 2021; Tirachini, 2020). However, they can also compete with public transit and are held responsible for declining transit ridership (Erhardt et al., 2022). Mobility-on-demand, in particular, has been found to be the largest contributor to growing traffic congestion, likely because most trips are single-passenger, point-to-point trips that closely resemble private auto travel (Erhardt et al., 2019). Emerging mobilities are also critiqued for not providing equal accessibility to all socioeconomic groups (Brown, 2020; Caspi and Noland, 2019). Thus, emerging mobilities hold promise as *one* way to reduce auto-dependence if leveraged appropriately (e.g., to reduce single-occupancy vehicle travel), but leaving it up to the invisible hand of the market has not proven successful in this endeavor thus far.

Emerging mobilities are not the only way to improve non-auto accessibility. An urban design focus on improving sidewalks and bike paths that can enable more walking and biking trips can also yield rich dividends (Boarnet et al., 2001; Buehler and Dill, 2016). Improving the first- and last-mile connections to public transit can reduce the inconvenience associated with using transit and increase transit trip-making (Basu and Ferreira, 2021). Zoning and parking supply are also important policy levers for sustainable metropolitan development (Suzuki et al., 2013; Shoup, 2021). At a more micro-scale, neighborhood planning strategies such as increasing densities or encouraging diverse land uses can encourage more active travel and reduce short auto trips (Cervero and Kockelman, 1997; Sevtsuk et al., 2021).

While both transportation and land use management strategies exist to reduce auto-dependence, which ones are actually implemented are dependent on local (or regional) planning agencies (who make this decision based on residents' needs, available funding, local culture, and political environment). For example, the city-state of Singapore is focusing on a transit-oriented approach to improve non-auto accessibility. Several extensions are planned for the already extensive public transport network, while sidewalks are being widened for better access to and from transit. Minimum parking requirements are also being revised in transit-proximate areas.[1] A little closer to home, the City of Salem is experimenting with an on-demand shared shuttle service (nicknamed the 'Salem Skipper') that provides $2 rides anywhere within the city limits.[2] King County Metro is offering on-demand shared shuttle options for both trips to transit stations as well as direct point-to-point trips.[3] Thus, even though the mechanisms differ, many public entities are trying out 'car-lite' pilots that provide better non-auto accessibility in the hope of reducing private auto ownership and single-occupancy vehicle travel. The motivation behind these car-lite experiments can be traced back to transit-oriented development (TOD) efforts, where public transit extensions were complemented with neighborhood redesign (to create more dense, mixed-use, and compact neighborhoods) such that residents were incentivized to become and remain less auto-dependent. The 'twist' with more modern efforts to create car-lite neighborhoods is that improvements in non-auto accessibility are no longer confined to public transit extensions.

That being said, the manner in which car-lite pilots are rolled out can be key to determining the success of these programs. Perceptions matter, as evidenced by the whirlwind emergence and disappearance of dockless bikes and e-scooters in many cities. Three major dockless bike companies began operations in Singapore in 2017, but all three exited the market by July 2018 citing difficulties in complying with a new licensing regime[4] and proposed regulations pertaining to indiscriminate parking.[5] Many cities in the US have reacted strongly when dockless e-scooter companies deploy vehicles unannounced and operate with-

[1] `https://www.lta.gov.sg/content/ltagov/en/newsroom/2018/11/2/new-parking-standards-for-private-developments-from-february-2019.html`. Last accesssed on August 24, 2022.

[2] `https://www.salemma.gov/mobility-services/pages/salem-skipper`. Last accessed on August 24, 2022.

[3] `https://kingcounty.gov/depts/transportation/metro/travel-options/on-demand.aspx`. Last accessed on August 24, 2022.

[4] `https://www.straitstimes.com/singapore/obike-ceases-operations-in-singapore-citing-difficulty-in-meeting-new-lta-regulations`. Last accesssed on August 24, 2022.

[5] `https://www.straitstimes.com/singapore/transport/new-rules-passed-to-curb-abuse-of-bike-sharing`. Last accessed on August 24, 2022.

out a permit. Residents have raised concerns over improperly parked e-scooters that are an eyesore and impede sidewalk access (Thigpen et al., 2020). Even though auto parking violations vastly surpass those by e-scooters, the much higher frequency with which residents object to the latter highlight that the manner in which car-lite pilots are rolled out will influence how they are perceived and their eventual outcomes (and possible expansion beyond the pilot study areas).

1.1 Research Questions

In this dissertation, I will explore how car-lite policies aiming to reduce auto-dependence can change neighborhoods in the near-term. I measure auto-dependence through the vehicle-free share, i.e., the share of households who do not have access to any private vehicle (or are vehicle-free). A high vehicle-free share indicates lower auto-dependence. As municipalities are likely to pilot car-lite policies in select neighborhoods before considering a city-wide roll out, I frame my dissertation using such a setting. Let us consider a city where a car-lite policy is being piloted within a study area (such as a neighborhood). What are the expected consequences of such a policy on the composition of the neighborhood? Will it succeed in increasing the vehicle-free share within the study area?

I propose a conceptual framework, which forms the crux of this dissertation, to address these questions in Figure 1-1. Pathway 'A' shows that improvements in non-auto accessibility can make auto ownership and use less attractive and, thereby, induce more residents to use non-auto modes (especially where auto ownership, maintenance, and/or use are expensive). Pathway 'B' highlights the link between land use and mobility. Better non-auto accessibility in a neighborhood can increase its attractiveness as a potential residential location, which in turn can cause housing prices to rise as many households may be willing to pay a premium to live in the neighborhood. Pathway 'C' demonstrates how rising housing prices in the neighborhood can tend to attract higher-income households, who are more likely to own and use cars. Thus, pathways 'A' and 'C' work in opposite directions with regard to their influence on neighborhood-wide vehicle-free share.

It remains unclear what the net effect of these opposing forces will be. The intended objective of the car-lite policy is to, of course, reduce auto-dependence by increasing the vehicle-free share. However, the unintended side-effect of increased housing prices (through the land use-mobility link) will dampen the increase in vehicle-free share (from pathway 'A') and, in doing so, could exacerbate concerns about gentrification. This dampening effect may be large enough in some neighborhoods to completely wipe out the benefits from pathway 'A' and result in a net decrease in the vehicle-free share. With this conceptual framework in mind, I ask the following research questions:

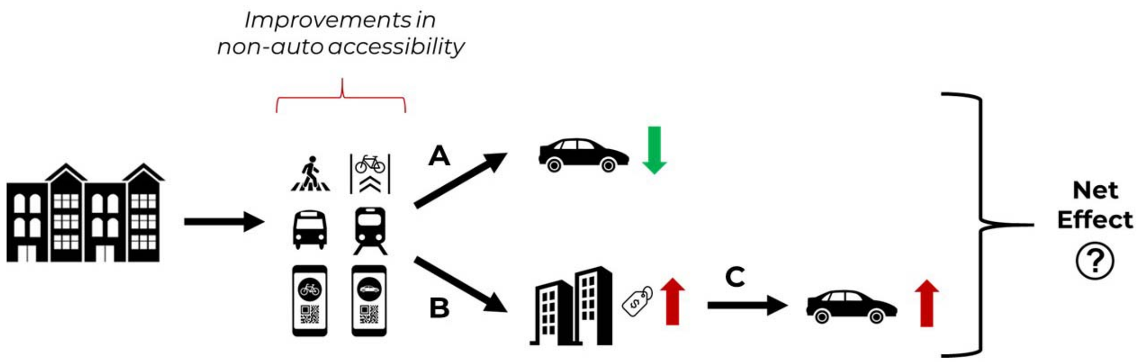

Figure 1-1: Conceptual framework for this dissertation

1. **How might car-lite policies change neighborhoods?**
I explore three types of car-lite policies — restricting private vehicles, non-auto accessibility improvements, and a combination of the two — as pilot experiments in different neighborhoods and examine how they change neighborhoods using both place-based and people-based scenario evaluation measures. These 'car-lite' neighborhoods are motivated by transit-oriented development (TOD) areas, except that I don't consider the 'T' as the only way to reduce auto-dependence. I track changes in the area mean income and vehicle-free share to see if the car-lite policy is successful in reducing auto-dependence, along with the extent to which it might induce gentrification. Pathway 'B' in the conceptual framework I proposed is reminiscent of transit-induced gentrification, where extensions to existing transit lines or construction of new lines have been found to gentrify neighborhoods around the new stations (Padeiro et al., 2019). By examining whether non-auto accessibility improvements may also induce gentrification, I hope to inform a broader narrative centered around accessibility-induced gentrification, of which transit-induced gentrification is a subset. I also look at how car-lite policies affect accessibility and consumer welfare of study area residents. By conducting these explorations in different neighborhoods, I try to relate neighborhood characteristics with car-lite policy outcomes in an effort to understand what types of neigh-

borhoods may be most susceptible to unintended negative side-effects of car-lite policies.

2. **Might housing policies be effective in mitigating gentrification side-effects while enhancing auto-dependence reductions?**
If gentrification side-effects are strong enough to dampen increases in the vehicle-free share, we need to find ways to mitigate them. I take inspiration from recent efforts in some cities to pass regulations related to upzoning near transit and reduced parking minimum requirements, and examine two types of housing policies based on them — (a) new housing supply, and (b) vehicle-restricted housing supply, both without and with affordability constraints. I contend that non-auto accessibility improvements can benefit from coordination with housing policies designed to address the gentrification-driven vehicle-free dampening effect. Designing coordinated housing-mobility policies may be key to ensuring that the benefits of car-lite policies (such as non-auto accessibility improvements) are distributed equitably across socioeconomic groups.

3. **How can integrated urban models be used to examine the near-term effects of car-lite policies on housing-mobility choices?**
Car-lite policies and coordinated housing policies, as described above, can play out in a complex manner. Households will look to respond to these policies by adjusting their housing-mobility choices. In the housing market, buyers and sellers will respond differently to these policies and their consequent changes in accessibility. Keeping track of these housing market effects (and within-market interactions) requires more complex modeling than has been possible thus far. Integrated urban models, such as land use-transport interaction (LUTI) models, provide an appropriate framework but most do not yet possess the necessary capabilities to enable such policy explorations in adequate detail. In this dissertation, I will demonstrate the application of a state-of-the-art LUTI model to explore the near-term effects of these policy scenarios. Unlike standalone choice models, this integrated urban modeling framework integrates various housing-mobility choice models to simulate disaggregate behavior with sufficient detail at different timescales.

1.2 Research Methods

Land use-transport interaction (LUTI) models are important tools that can help us explore complex policy interactions. Integrated LUTI models link the housing and mobility components, and allow us to explore different scenarios of how individuals and households might react to changes in policy and/or infrastructure. Thus far, LUTI model applications have understandably focused on 'long-term' ripple effects of urban (and metropolitan) growth strategies and transportation infrastructure investments (at the timescale of decades). However, emerging mobilities can change accessibility and travel behavior considerably faster than a decade-long subway construction (or development) project. There is a dearth of appropriate modeling tools to model the roll-out of car-lite pilot programs to promote less auto-dependent communities with an eye towards not just travel behavior changes, but also interactions with the residential housing market in adequate detail.

Although agent-based LUTI models are promising candidates and provide appropriate frameworks, most state-of-the-art LUTI models have limited capabilities to explore car-lite policy scenarios with regard to longer-term urban choices such as residential location and private vehicle holdings. These limitations arise from aggregate resolution of representation (e.g., representing space through zones or time through months or years), and/or the land use and mobility components being 'loosely' integrated (e.g., through gravity-based accessibility measures that do not incorporate individuals' utilities). Nevertheless, they are more promising than alternative urban modeling approaches (such as Computable General Equilibrium or CGE models) when it comes to tracking the near-term dynamics of spatiotemporal change.

In this dissertation, I demonstrate the application of a state-of-the-art LUTI model that represents daily transactions in the housing market and is tightly integrated using activity-based accessibility measures. I explore the near-term effects of car-lite pilot programs that seek to reduce auto-dependence by restricting private vehicles and/or improving non-auto accessibility. I also explore the effects of coordinating non-auto accessibility improvements with selected housing policies, such as upzoning and restricted parking supply. These policy scenarios are explored through the lens of disaggregate housing-mobility choices that lead to neighborhood change. Using both place-based and people-based scenario evaluation measures, I compare these scenarios against a baseline reference that shows the natural unperturbed development of the neighborhood in the absence of any policy.

1.3 Contributions

As emerging mobilities become more widespread across the world, understanding their impact on cities is particularly crucial for planners and policy-makers. Research on travel behavior impacts and travel demand modeling of emerging mobilities has received far more attention than research on housing market effects and consequent changes in urban development and land use. Even then, strong exogenous assumptions about emerging mobility impacts (e.g., about time or cost savings, or private vehicles being completely replaced) limit the use of existing studies for policy-making. Although some studies help shed light on the long-term possibilities of emerging mobilities, they say little about the market dynamics along the way. How might neighborhoods change in the near-term when car-lite pilot programs use emerging mobilities to improve non-auto accessibility? This dissertation attempts to contribute to this growing and policy-relevant literature by demonstrating how a LUTI modeling framework can be used for policy analysis to explore the consequent ripple effects in more detail than has been possible thus far. Moreover, LUTI modelers have been critiqued for not exploring social equity concerns (such as gentrification), even though housing and mobility — two fundamental tenets of LUTI models — policies can perpetuate or alleviate inequality (Engelberg et al., 2021). This dissertation aims to demonstrate a policy exploration application which is centered around examining and addressing some equity concerns related to housing markets.

With an eye towards informing the design and evaluation of car-lite pilot programs, I construct and explore various policy scenarios using a state-of-the-art LUTI model. Without any regulation or intervention, improved non-auto accessibility can increase the attractiveness of these pilot neighborhoods and may induce subsequent gentrification. Therefore, understanding which neighborhoods may be most ripe for pilot experimentation without causing undesirable side-effects for the local residents is key to ensuring the long-term success and positive perception of such programs. Additional understanding of housing policy effects is necessary to inform more detailed design of car-lite policies as they are expanded to larger areas beyond the pilot neighborhoods. These scenario analyses are expected to enhance our understanding of how neighborhoods change as a result of non-auto accessibility improvements and what housing policies may be successful in mitigating potentially undesirable side-effects.

In summary, this dissertation can contribute *theoretically* to the LUTI modeling literature by demonstrating different methodological extensions, *practically* towards car-lite housing and mobility policy design by evaluating how car-lite pilot experiments and coordinated housing supply can change neighborhoods, and *conceptually* towards how longer-term urban decisions (such as residential relocation and vehicle holdings) may be impacted by the availability of emerging mobilities. I also note here that the LUTI model I will be using has been developed by a large team (including yours truly) over several years. Part of my work has been in collaboration with my colleagues and will be described with 'we' henceforth, while work that is primarily my own will be described with 'I.'

1.4 Dissertation Outline

The remainder of this dissertation is structured as follows. In the next chapter, I provide a summary of relevant literature surrounding pathways of neighborhood change (including transit-induced gentrification) and the use of LUTI models for housing-mobility policy analysis. Chapter 3 describes the contextual setting of Singapore on which I focus my research and the various data sources I used in this dissertation. I then describe the state-of-the-art LUTI model I used for scenario analysis (SimMobility) along with my proposed methodological extensions in Chapter 4. I present results related to how neighborhoods change in response to private vehicle restrictions, non-auto accessibility improvements, and coordinated housing policies in Chapter 5. In Chapter 6, I discuss whether my findings are sensitive to key simulation parameters and robust to a few core modeling assumptions, as well as the extent to which my findings may be transferable to contexts other than Singapore. Finally, in Chapter 7, I summarize my key findings, discuss the policy implications and limitations of my findings, and outline a few promising avenues for future research efforts to consider.

Chapter 2

Literature Review

In this chapter, I trace the origins of transit-oriented development (TOD) and discuss why, where, and how it has been used as a policy instrument to create car-lite neighborhoods and reduce auto-dependence. New transit infrastructure, which forms the backbone of TOD, can change neighborhood composition by affecting housing prices and travel behavior, which can induce or accelerate gentrification. I discuss the potential of two housing and land use-related policies — upzoning reforms and parking supply regulations — to address gentrification and sustainable mobility concerns in TOD neighborhoods. Next, I make the argument that emerging mobilities, which can also improve non-auto accessibility similar to transit, may induce similar patterns of neighborhood change. To understand these effects before undesirable consequences set in, ex-ante analysis is necessary. Although land use-transport interaction (LUTI) models are quite suitable for such ex-ante analysis, state-of-the-art models are typically not well-equipped to explore the ripple effects of emerging mobilities. I explore the history of land use-transportation interaction (LUTI) modeling and discuss how these models have been used for policy analysis to guide transportation infrastructure investments and zoning reforms. Finally, I summarize by arguing that LUTI models (with better attention to land use and mobility interactions for the modern era) can be useful for not just car-lite policy exploration, but also for examining the near-term effects of coordinated housing policies such as upzoning and parking supply.

2.1 Transit-oriented development (TOD)

Peter Calthorpe is credited with coining the term "transit-oriented development" (TOD), which he described as "a mixed-use community within an average 2,000-foot walking distance of a transit stop and a core commercial area" (Calthorpe, 1993). He envisioned TODs to be car-lite neighborhoods that include a mix of residential, retail, office, open space, and public uses in a pedestrian-friendly environment that made it convenient for residents and employees to travel by non-auto modes such as transit, biking, and walking. Although the use of TOD as a promising tool to restrict urban sprawl and reduce auto-dependence has gained wider support in recent years, the concept itself is not new. Knowles et al. (2020) and Renne and Appleyard (2019) identify three distinct eras of TODs: (a) from the mid-19th century to early 20th century, (b) Planned TOD in the mid-20th century, and (c) TOD for urban regeneration and/or urban expansion since the late 20th century.

Ebenezer Howard's Garden Cities concept heavily influenced the construction of Letchworth and Welwyn Garden Cities in the early 1900s. These two towns, about 30 minutes north of London, contain many of the ideas for the development of a mixed-use, compact, and walkable community centered upon a train station that modern TOD characterizes (Howard, 1965). Additionally, streetcar corridors in several cities across America, Australia, Canada, Europe, and the United Kingdom at the time had land uses, densities, and walkability that would be the envy of modern TOD advocates. In the 1950s and 1960s, the New Town (Planned TOD) Movement grew quite popular in Scandinavia and Japan, and is considered as a prequel to modern TOD. Copenhagen was the pioneer of Planned TOD with its 1947 Finger Plan of five corridors of planned urban development around stations on electrified suburban railway lines. The 1990s marked a turning point in the vicious cycle of freeway-driven sprawl and auto-dependence. Zoning and the building of roads at an enormous scale facilitated ubiquitous, underpriced, and relatively congestion-free driving that further undermined the utility of transit proximity.

Many cities started experimenting with TOD centered around urban rail and bus rapid transit around this time. The goal was to use principles from transport engineering and planning, land use planning, and urban design to make non-auto modes more convenient and desirable, and maximizing the efficiency of mobility services by concentrating urban development around transit stations (Ibraeva et al., 2020). However, TODs are highly context-dependent and can produce different outcomes in different locations. A TOD is relatively easy to implement in a high-density neighborhood near the city center because density and diversity are already high. Moreover, most residents may already be vehicle-free due to good non-auto modal availability, high parking costs, and residential self-selection. However, the picture is not as rosy in low-density suburbs. Most suburban residents are auto-dependent, partly because of the built environment, but also because of an innate preference for the physical characteristics of the suburbs.

Advocates argue that TOD can induce a decrease in auto-dependence as more residents (both original residents and in-movers) start to use transit more frequently compared to people with similar sociodemographics but living elsewhere. Research focusing on TODs in Washington, DC and Baltimore found a significant (21-38%) decrease in driving, as measured by vehicle miles traveled, among TOD residents (Nasri and Zhang, 2014). However, the success of transit corridors in promoting sustainable regional growth hinges on location decisions. Improved transit accessibility may be viewed as an amenity by both buyers and sellers in the housing market, which can attract price premiums on transit-proximate housing in TOD neighborhoods. However, transit proximity (or improved accessibility) alone may not fully explain location preferences.

Most households who choose to relocate to a TOD do not cite access to transit as the reason for their choice (Lund, 2006). A potential explanation for this is that accessibility improvements can result in not only travel time savings, but also what Yan (2021) calls 'destination utility gains', i.e., the additional utility individuals derive from choosing desirable destinations. However, those who were motivated by transit access were found to be more likely to use transit, indicating a strong link between location preferences and travel behavior outcomes. The price premium commanded by station proximity can be significantly higher when TOD neighborhoods have pedestrian-friendly environments, suggesting greater preference for neighborhoods that encourage multimodality and pedestrian accessibility (Duncan, 2011). Thus, improved transit accessibility alone may not ensure the success of TOD. Reforming zoning and development regulations, integrating TOD with affordable housing development, and broadening the focus of TOD beyond 'just' transit to other non-auto modes are recommended to enhance the potential for success of TOD areas (Guthrie and Fan, 2016).

2.2 Transit infrastructure and neighborhood change

Investments in new transit infrastructure have the potential to improve non-auto accessibility and stimulate new housing development in the neighborhoods surrounding these investments. The effects of new infrastructure can transform the urban socioeconomic landscape by inducing changes in neighborhoods. Neighborhood socioeconomic change is a result of shifts in residential sorting of residents reacting to the introduction of a new amenity (e.g., a transit station) which may increase the demand for living in these neighborhoods. Local residents, especially people of color, immigrants, frequent transit riders, and vehicle-free individuals, often perceive the accessibility improvements quite positively (Fan and Guthrie, 2012). However, this increased demand may place an upward pressure on nearby housing values and rents, thus affecting the socioeconomic composition of those willing and able to afford these price premiums, which can, in turn, spur or accelerate gentrification (Delmelle, 2021). Increased land values may also cause the disproportionate exit of lower-income residents who are no longer able to afford the elevated rents or property taxes. The rising real estate valuations can be partially explained by improvements in transit accessibility. However, the amenity-based elements of TOD are also found to play a significant role in urban land markets (Bartholomew and Ewing, 2011).

Over the last two decades, the growing popularity of TOD as a strategy to reduce auto-dependence and stimulate sustainable urban growth has been criticized by community activists who highlight the concern that TOD could induce gentrification and disproportionate displacement of lower-income communities. Additionally, new housing locations are likely to increase the housing cost burdens of displaced households (Baker et al., 2021). Despite these concerns, the evidence supporting this ‘transit-induced gentrification’ hypothesis is mixed.

A review of empirical studies by Rayle (2015) finds little evidence to support that transit-induced gentrification actually causes displacement. Using eviction data, Delmelle et al. (2021) tested the transit-induced displacement hypothesis in four American cities and found evidence of a spike in eviction rates following the opening of a new transit line in only one of the four cities. Despite low-income individuals being more likely to move, Delmelle and Nilsson (2020) do not find significant evidence to suggest that they are more likely to move out of transit neighborhoods. Gentrification seems to be more closely associated with existing local dynamics, built environment attributes, and accompanying policies than transit access itself (Padeiro et al., 2019).

On the other hand, studies focusing on light rail transit (LRT) and bus rapid transit (BRT) have consistently reported evidence of transit-induced gentrification. Using both demographic and economic indicators, Chava and Renne (2022) find signs of gentrification in American cities that expanded LRT systems from 1990 to 2010. They also report a positive correlation of their gentrification index with walkability, density, and diversity variables. The premiums for rail transit accessibility also largely depend on different development phases and can be heavily discounted by the existence of Park-and-Ride facilities (Zhong and Li, 2016). The effect of BRT on property values seems to be more heterogeneous. Multi-family properties nearby BRTs with dedicated lanes were found to experience the most appreciation (Acton et al., 2022). However, BRT-lite systems without dedicated lanes were associated with property appreciation only in relatively dense and congested metropolitan areas with developed transit networks and high ridership.

While TODs can be more expensive places to purchase and rent housing, the lower transportation costs may offset the increased housing costs (Renne et al., 2016). TOD households save money on transportation costs mainly because they own fewer cars than non-TOD households. About two-thirds of the savings can be attributed to built environment characteristics and one-third to improved transit access, suggesting yet again the importance of integrating improved non-auto accessibility with supportive land use planning and neighborhood design (Dong, 2021). Promoting compact land use strategies can have a positive effect on reducing auto use in and of itself, which can be further accentuated by improving non-auto accessibility (Yin et al., 2020). Living in a TOD neighborhood has also been found to increase the use of non-auto modes such as transit and walking, even after accounting for residential self-selection (Nasri et al., 2020; Park et al., 2018).

Despite the reduction in auto-dependence observed in TOD neighborhoods, we might wonder whether the spillover effects cause people to drive more by displacing lower-income households from transit-rich neighborhoods. The higher-income in-movers into TOD neighborhoods are more likely to remain auto-dependent and less likely to transition to vehicle-free lifestyles. Because they do not adjust their preferences according to their surrounding land use patterns and continue their predisposed travel behavior, Schwanen and Mokhtarian (2004) call such individuals 'dissonants' and describe their behavior as 'residential dissonance.' However, this may not be universal as some literature from California do not seem to support this claim. Higher-income households are found to reduce vehicle miles traveled (VMT) more when living in TODs compared to lower-income households, especially in densely populated neighborhoods (Chatman et al., 2019; Boarnet et al., 2020). This suggests that the likely net effect of transit-induced gentrification could be a regional reduction in VMT as long as population and job density are increasing. However, in the absence of densification, VMT will likely increase.

Channeling urban growth in TOD neighborhoods through new housing developments can be an effective strategy to increase density. However, new housing may attract more affluent households who drive more. Boarnet et al. (2020) caution against building transit-proximate housing targeting solely higher-income households and instead advocate for mixed-income housing developments in TODs. Chatman (2013) suggests that transit access might have smaller effects on auto ownership and use than housing tenure and size, parking availability, and the neighborhood and regional built environments. With this possibility in mind, let us examine two types of policies that have been used to constrain the pattern of development within neighborhoods.

2.2.1 Upzoning and the housing market

Zoning reforms that allow higher density (e.g., by reducing or eliminating detached single-family housing zoning restrictions) are known as 'upzoning' policies. Single-family residential zoning zoning has been criticized for exacerbating inequality by making it harder for households to access high-opportunity areas and undermining efficiency by contributing to housing shortages in expensive regions (Manville et al., 2020). Upzoning could be a key policy instrument to stimulate densification and also address the housing affordability crisis. However, many cities fail to provide large-scale regulatory responses even during regional housing shortages, highlighting the contentious nature of reforming single-family zoning (Gabbe, 2019b). Upzoning advocates (often referred to as 'Yes-In-My-Backyard' or YIMBYs) have argued that allowing for denser development can help to lift artificial restrictions on housing supply and lower prices in the long run. However, groups calling for added tenant protection and affordable housing preservation have countered by claiming that upzoning is likely to accelerate gentrification and displacement pressures.

Empirical evidence confirms that these concerns are legitimate. Upzoning activity in

New York City is found to be positively and significantly associated with accelerating gentrification in the short-term (Davis, 2021). In response to the Minneapolis city council approving the city-wide elimination of single-family zoning restrictions, affected housing units experienced an increase in price, which can be attributed to the new development option it offered property owners (Kuhlmann, 2021). The price increases were found to be higher in lower-income neighborhoods and for smaller properties. In a study of recent Chicago upzonings that increased allowed densities and reduced parking requirements, Freemark (2020) found that the short-term, local-level impacts of upzoning are higher property prices but no additional new housing construction.

Blanket changes in zoning, without other supportive policies, are unlikely to improve affordability for lower-income households and may increase gentrification within metropolitan areas (Rodríguez-Pose and Storper, 2020). We need better alignment of zoning, taxes, and subsidies. Supportive policies can include improved non-auto accessibility, reduced parking requirements, and incentives for affordable housing, especially near transit (Gabbe, 2019a). Relaxing zoning restrictions in (both existing and future) transit-proximate neighborhoods increases the probability of parcel-level densification, and the resultant density increase can induce further zoning or plan changes in nearby areas (Kim and Li, 2021). Affordability restrictions targeted to new housing in TODs can be effective tools for promoting housing affordability and improving low-income households' access to transit while simultaneously reducing the extent of transit-induced gentrification (Dawkins and Moeckel, 2016). Although developers may be concerned that placing affordable housing close to transit can increase development costs, the literature does not find any effect of rail proximity on development costs (Palm and Niemeier, 2018). While upzoning in TOD areas may not be a likely solution to addressing the concerns around transit-induced gentrification by itself, upzoning combined with targeted affordability restrictions is a useful housing policy to explore further.

2.2.2 Parking supply and travel behavior

Parking supply remains one of the most neglected land use policies in nudging travel behavior, despite significant evidence linking parking with auto ownership and use. Parking supply can significantly determine household auto ownership decisions, even after controlling for the endogeneity between the two (Christiansen et al., 2017; Guo, 2013a). Its influence is found to outperform household income and demographic characteristics, the often-assumed dominant determinants of auto ownership (Guo, 2013b). The availability of parking and bundled parking regulation increases auto use, even in dense cities (Shoup, 2021). Accessory residential off-street parking (e.g., in a garage or driveway) is found to have a stronger effect on auto commuting than parking in commercial centralized lots (Weinberger et al., 2009). Parking costs are usually much higher in the city center compared to the suburbs. Ostermeijer et al. (2019) estimates that this disparity in parking costs explains around 30 percent of the difference in average auto ownership rates between these areas.

Limiting access to parking at home and at work can be surprisingly effective in reducing auto use. Shoup (1995) estimates how the option to cash out employer-paid parking can reduce commuter parking demand, and recommends a corresponding reduction in minimum parking requirements. Currans et al. (2022) find that constrained on-site residential parking can account for a decrease of 10-23 percentage points in VMT. Using the case of affordable housing lotteries in San Francisco as a natural experiment, Millard-Ball et al. (2022) find that auto ownership and use are significantly affected by essentially random variation in on-site parking availability. The policy that lies at the heart of this issue is known as 'minimum parking requirements.' Parking requirements are the largest predictor of actual parking production (Gabbe et al., 2020). By and large, developers tend to build only the bare minimum of parking required by zoning, suggesting that the minimum parking requirements are binding for developers, as argued by critics, and that developers do not simply build parking out of perceived marked need (McDonnell et al., 2011; Cutter and Franco, 2012). Moreover, residential minimum parking requirements are associated with lower housing and population densities and higher vehicle densities (Manville et al., 2013), thus providing a deterrent to the densification that is needed for TOD success. However, TOD advocates can take heart from the observation that proximity to high quality public transport is associated with lower demand for car parking (De Gruyter et al., 2020).

While reducing (or even eliminating) parking minimums seems like an effective policy instrument to reduce auto-dependence, Antonson et al. (2017) argue that the effects within a single neighborhood may be paradoxically small because of access to parking in neighboring areas. Paid curbside parking to deter non-resident auto trips can instead increase resident auto ownership, especially when resident parking permits are free or inexpensive (Albalate and Gragera, 2020). Therefore, a holistic approach to parking policy is necessary. Introducing more restrictive parking requirements for new developments in parallel with other measures such as raising parking charges and reducing the number of public parking spaces will be key for nudging residents to switch to vehicle-free lifestyles.

2.3 Emerging mobilities and neighborhood change

One of the central arguments in this dissertation is that emerging mobilities (such as mobility-on-demand and micromobility) can also improve non-auto accessibility, similar to public transit. Therefore, it might be possible to observe patterns of neighborhood change similar to transit-oriented development when emerging mobilities are used to provide accessibility benefits (see Figure 1-1). Although emerging mobilities have attracted the attention of researchers and policy-makers alike, the lion's share of attention has been given to the effect of emerging mobilities on short-term activity-travel patterns (e.g., see Basu et al. (2018); Zhu et al. (2018); Hyland and Mahmassani (2020); Hörl et al. (2020)). Relatively few studies have focused on changes in land use and longer-term urban choice behavior, such as choices of residential and job locations (Soteropoulos et al., 2019). Knowles et al. (2020) find in their systematic review that the volume of TOD research is immense but the exploration of TOD with emerging mobilities is still nascent.

The effects of station-based bikesharing on travel behavior and the housing market have received some attention, as bikeshare stations also create a spatially varying accessibility gradient similar to transit stations. Using surveys of bikeshare riders, researchers have reported varying degrees of auto-substitution and associated bikeshare programs with reductions in auto use (Fishman et al., 2014; Shaheen et al., 2013). Living in closer proximity to bikeshare stations predicted increases in biking over time for respondents living in cities with newly implemented bikeshare programs (Hosford et al., 2019). The introduction of new bikeshare programs was also found to increase total active travel time, despite the possibility of some walking trips being substituted by bikeshare trips (Fishman et al., 2015).

In contrast to these fairly straightforward effects, bikeshare has a complex relationship with public transit that can be both complementary and competitive. Urban core residents are more likely to exhibit substitution behavior, while urban periphery residents were found to use bike-share more often as a first-/last-mile connection to mass transit (Martin and Shaheen, 2014). More recent research using longitudinal data and causal inference have confirmed that new bikeshare stations reduce auto ownership, use, and emissions in their vicinity (Basu and Ferreira, 2021). These effects are found to grow stronger in locations where bikeshare can be used to connect to rail transit.

Several studies have empirically confirmed the positive effect of bikesharing on real estate prices. BIXI, the bikeshare system in Montreal, has been found to increase the property value of multi-family housing units (El-Geneidy et al., 2016). Evidence from Pittsburgh, Pennsylvania suggests that housing prices for rental units can also increase, in addition to sale prices (Pelechrinis et al., 2017). Apart from these first-order effects, bikeshare systems can also impact the relationship between real estate prices and distance to transit. However, these results are not always uniform, as illustrated in the case of Nice Ride in Minneapolis, Minnesota. Certain neighborhoods have been shown to witness a decrease in home values after the introduction of a bikeshare station, which may be due to lower-valued homes seeing greater increases in price or a greater share of the value being added to residences of higher-income households (Martin, 2017). There seems to be strong evidence that bikesharing provides a potential opportunity for value capture, which requires a deeper understanding of who benefits most from these infrastructure investments.

Automated mobility has also received immense attention because of its purported capability to improve accessibility. Meyer et al. (2017) goes so far as to call this a quantum leap in accessibility. Researchers have attempted to understand the effect of automated mobility on auto ownership using agent-based models and activity-based models. The general approach is to vary the fleet size of automated vehicles (AVs) while trying to match total travel demand and trip generation rates. Evaluation metrics of system performance include VMT as a proxy for emissions, and total travel time as a proxy for congestion. Some studies find that auto 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 auto 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).

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 in 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. Older people were found to move closer to the inner-city core while younger people moved out to the suburbs. In contrast to these results related to private AVs, shared AVs have been posited to have the potential to curb urban sprawl (Meyer et al., 2017).

The vast majority of these studies have been carried out in a standalone manner, by focusing on only one dimension such as activity-travel patterns or housing market effects. Rarely have studies considered the interactions between land use and mobility, and how they might also be affected by emerging mobilities. Doing so will require more complex modeling than what we have seen thus far. Land use-transport interaction (LUTI) models offer a framework to conduct such modeling efforts but most state-of-the-art models lack the capabilities to explore how car-lite policies can affect housing-mobility choices and change neighborhoods in adequate detail. In the next section, I will provide a brief overview of LUTI modeling and discuss a few key elements of interest within LUTI models that are vital for car-lite policy exploration.

2.4 A brief overview of LUTI modeling

Transportation networks and land use patterns are known to mutually influence each other, and drive spatial socio-economic processes (such as development and migration) in cities. Accessibility, which is the outcome of interactions between transportation and land use, is a crucial element in shaping development patterns and residential relocation (Hansen, 1959; Geurs and Van Wee, 2004; Handy, 2020). Land use-transport interaction (LUTI) models have been developed for many decades to help understand the implications of these interactions.

As automobile use rose drastically in the 1910s in the US, accommodating traffic became the primary goal of administrators and engineers of the time. Rather than disincentivize auto ownership and use by changing the built environment, policy-makers favored widening lanes and adding parking. In 1956, the US Federal Highway Act provided a major impetus towards further auto-oriented infrastructure and planning. Following this, the dice was cast for communities to get stuck in a spiral of auto-dependence. The Highway Trust Fund reinvested gasoline taxes back into car-based infrastructure, which led to a vicious cycle of congestion and road expansion. Understanding auto congestion motivated the development of travel demand models for better highway planning, leading to the use of the four-step travel demand model in Detroit and Chicago in the 1950s. This was one of the first travel demand models that sought to link land use and behavior to inform transport planning. However, its simplistic structure prevented the inclusion of any feedback from the transportation system to land use.

The convenience and low cost of auto travel also contributed to suburbanization, as households began to evaluate the tradeoff between commute time and housing costs in favor of living far from work in more affordable and spacious housing in the suburbs. That led to issues such as urban sprawl, depletion of green spaces, and congestion in the downtown of urban cores. The pressing issue(s) of the day, combined with the computational capabilities and costs of the time, have impacted the approach and scope of LUTI modeling. Since the largely mechanistic operationalization of four-step travel demand forecasting models, technological and theoretical advances have aided significant improvements in LUTI models. In general, there has been a movement towards more disaggregate approaches, higher resolution data, and greater technical sophistication. In the remainder of this section, I will highlight the key elements of LUTI models that are relevant to my approach to examine near-term dynamics of accessibility changes and housing market interactions.

Based on Hansen's seminal work, the first generation of land use-transport interaction (LUTI) models came about in the late 1960s, with an aim to better inform transport models that were designed for exploring ways to reduce congestion. The primary focus was to understand the impact of suburbanization on commuting patterns and city congestion.

Gravity-based measures were used to quantify the trade-off between proximity to work and more affordable and spacious housing in the suburbs. Examples of first-generation LUTI models include the Metropolis model (Lowry, 1964), and ITLUP (Putman, 1974). Unfortunately, these models left a lot to be desired, with their mechanicalness, theoretical shortcomings, data-hungriness, and complexity (among other limitations) being harshly criticized in a review of large-scale models by Lee (1973).

The emergence of new theoretical frameworks in the fields of econometrics and behavioral economics (such as the random utility theory) in the mid-1970s enabled modeling disaggregate behavior by focusing on the prediction of choices among multiple discrete alternatives. Applications such as the choice of travel mode (Lerman, 1976) and residential location (McFadden, 1978) provided the impetus for the second generation of LUTI models. The field branched out into two different directions at this time, based on the method in which spatial processes were represented. The first approach was to use regional economic models that focused on a framework to represent trade flows between different economic sectors along with input/output accounting and economic equilibrium arguments about stable spatial patterns of land use, land price, density, transport costs, and wage differentials that could co-exist within an economically interdependent region. Examples include TRANUS (de la Barra, 1989), MEPLAN (Echenique et al., 1990), and PECAS (Hunt and Abraham, 2005). Contrastingly, the other approach sought to improve the spatial detail and method of representing housing transactions and land markets, as can be seen in MUSSA (Martinez, 1996) and DELTA (Simmonds, 1999).

The third generation of LUTI models was driven by transformative technological advances with significantly greater computational resources and power coupled with more efficient data storage. The improved computational power was put to use for higher-resolution representation of space, time, and agents (i.e., individuals, households, and firms). The improvement in spatial detail was operationalized through either grid-based subdivision or entity-based subdivision (where blocks/buildings/people were the unit of analysis instead of regular grids of land). Cellular automata models (where spatial units themselves are agents) of temporal urban change and spatial evolution, such as SLEUTH (Clarke et al., 1997), came into prominence at this point. At the same time but in a different camp, modelers started representing urban regions at a disaggregate level, wherein individuals, households, firms, and developers were represented as agents instead of land grids.

The early 2000s witnessed the development of four such models — UrbanSim (Waddell et al., 2003), IRPUD (Wegener, 2004), ILUTE (Salvini and Miller, 2005), and ILUMASS (Strauch et al., 2005) — that successfully implemented the agent-based microsimulation approach. Subsequent agent-based microsimulation efforts — SimMobility (Adnan et al., 2016) and SILO (Moeckel, 2017) — improved on the spatiotemporal granularity of representing the land use and mobility systems and the resolution with which agents were being characterized. Many of these models remain active in pursuing improvements to modeling structure and agent representation to the present day. Interested readers may refer to Iacono et al. (2008) and Engelberg et al. (2021) for a more detailed comparative review of these LUTI models. While cellular automata models have also continued to evolve for exploring changes in weather, desertification/deforestation, and urbanization, their focus on regular grids is problematic within metro areas where the decision-making agents (such as individuals, households, developers, and firms) are focused on buildings, infrastructure, and land use that does not match well with regular grids.

Based on the model's level of complexity, different types of accessibility measures have been used in LUTI modeling to connect the land use and transport components. The initial spatial interaction models used simple gravity-based measures to translate transportation into land use outcomes. Lowry's Metropolis model, which was among the first comprehensive models of regional land use change, was never actually integrated with a travel demand model and used Euclidian distances between zones to measure the inconvenience of travel (or travel impedance). Other models in the first generation used estimated network travel times, but still calculated gravity measures, which remained the dominant approach for linking land use simulations with transport models throughout the 1970s and 1980s (Wilson, 1998). The next generation of models, such as MEPLAN and IRPUD, started to include travel time, cost, and parking into their calculations of travel impedance. These impedance measures were used to inversely weight travel forecasts, such that destinations with greater impedance would attract fewer trips. Given that the pressing issue of the time was auto congestion, most of these models focused on auto travel times, and, more specifically, auto commute times. Transit was gradually incorporated into these models with auto and transit commute times being used as impedances to compute their mode shares.

Around the 1990s, LUTI models had started to become comparatively more disaggregate, market-based, and integrated. Although MUSSA (a market-based model) did not integrate fully with the transportation component, both TRANUS and MEPLAN are market-based integrated models. None of these models, however, engaged in microsimulation and modeled space at the higher resolution of zones. IRPUD introduced a stochastic microsimulation for the housing market and used an income group-specific, utility-based measure from the mode choice model. UrbanSim, which is also a microsimulation of the housing market, can be integrated with external transportation models and thus accepts exogenous measures of accessibility. By this time, many modelers had moved from the four-step travel demand model to trip-based travel demand modeling. Aided by econometric modeling advancements in the late 1970s, it was possible to model travel demand at the trip level. Each trip taken by an individual with a particular mode to a specific destination could be included in these frameworks, which could then provide a measure of the utility gained by the individual from conducting the trip(s). With further advancements in the econometric integration of location and travel choices, some modelers have begun to transition from trip-based utilities to activity-based utilities, which are accessibility measures provided by activity-based travel demand models. These models build on their trip-based precursors by considering the activity as the unit of analysis, rather than the trip, which allows for the consideration of trip-chaining and multi-modal travel. SimMobility is a fully integrated LUTI model that uses utilities obtained from the activity-based travel demand framework to model longer-term choices such as residential location, job location, and vehicle availability.

As cities have expanded over time, the focus has shifted from urban development to metropolitan development. Suburban expansion and tradeoffs between commute distance and housing costs still remain important, but polycentricity has brought additional layers of complexity to how we model land use and transport interactions. Additionally, mobility choices have expanded significantly over the last decade. Instead of just ‘planes, trains, and automobiles’ (and biking and walking), multi-modal personalized options are available at affordable cost with modern information and communication technologies enabling efficient transfers and on-demand service. These details of transport modeling as well as the complexity of tradeoffs necessitate LUTI modelers to respond in a timely manner, if the models are to be used for relevant policy analysis. For example, the availability of emerging mobilities make it important for LUTI modelers to address their near-term effects at disaggregate scales.

Microsimulation and activity-based modeling offer promising opportunities for tighter linkages between LUTI model components. By using activity-based travel demand models, we can calculate tour-based accessibilities, which account for the possibility of trip-chaining and represent daily activity schedules of individuals. Moreover, buyer and seller behavior in housing markets can be modeled in detail with microsimulation. Incorporating these disaggregate behaviors is necessary if we want to understand how housing markets react to car-lite policies and/or emerging mobilities. Such richness in resolution, as operationalized in SimMobility, can enable us to simulate policy scenarios, often targeted to specific groups or neighborhoods, and carry out detailed policy analyses within the housing and mobility markets. An overview of the state-of-the-art LUTI models discussed above is provided in Table 2.1.

While agent-based microsimulation models allow for tracking the dynamics of spatiotemporal change, many of the critiques put forth by Lee (1973) still hold to this day despite the improved computational efficiency and significantly larger datasets. These challenges have posed as barriers to the widespread dissemination of agent-based microsimulation models for land use-transport analysis. In contrast, computable general equilibrium (CGE) models have witnessed widespread popularity as a feasible and easily operationalizable alternative (Burfisher, 2021; Dixon and Jorgenson, 2012; Shahraki and Bachmann, 2018). Using microeconomic first principles, such models specify the relationships among key factors (e.g., wages, firm productivity, housing and transportation expenditures, and land prices) that must hold for the land use-transport systems to be in equilibrium. These models have been heavily used in transport appraisal applications, among others related to urban, regional, and environmental economics (Bröcker, 2004; Robson et al., 2018). Despite the numerous benefits offered by CGE models, they are inadequate for tracking the near-term dynamics of spatiotemporal change since they are focused on examining relationships that must exist for each alternative scenario under long-term equilibrium conditions (Tavasszy et al., 2011).

2.5 LUTI models for policy analysis

Despite the existence of a large number of LUTI modeling platforms, the academic literature on the application of LUTI models for policy analysis is sparse. The literature seems to be comparatively richer with papers on methodological advancements of LUTI models. Engelberg et al. (2021) opine that interest in pushing the state-of-the-art has resulted in the

Table 2.1: Overview of state-of-the-art LUTI models

Model	Model type	Units of analysis/agents	Spatial granularity	Temporal granularity	Accessibility used in	Types of accessibility measures
DELTA	Aggregate spatial dynamics; econometric	Zones with households and developed space	Zones (unknown zone size)	Usually 1 or 2 years	Household relocations	Logsums are calculated for each activity type, then summed up
ILUMASS	Activity-based; equilibrium; microsimulation; Random Utility Model (RUM)	Individuals; households; firms	100 meter grids	Traffic and transport demand: seconds to weeks; Land use: months to years	Home and firm location choice	Transport: infrastructure-based; Land use: location-based
ILUTE	Activity-based; disequilibrium; microsimulation; RUM	Individuals; households; ad-hoc “decision-making units”; firms	Variable (census tracts, planning districts, TAZs, and grids)	Variable (typically monthly)	No information available	N/A
IRPUD	Microsimulation; expanded four-step model; RUM; equilibirum; quasi-dynamic	Individuals; households; housing investors; firms	Zones (unknown zone size)	One year or more	Private construction model; housing market model	Gravity-based/location-based (accessibility of jobs, shops, services)
MEPLAN	Spatial interaction; equilibrium; RUM; quasidynamic	Zones with simplified network; household sectors; activity types	Zones (unknown zone size)	5 years	Land market	Infrastructure-based (travel time and cost)
PECAS	Aggregate equilibrium; spatial Input/Output (I/O)	Aggregate commodities; industry categories and households at the zonal level	Zones (preferably correspondent to zones in travel model)	Variable (typically annually)	Land use allocation	Utility-based accessibility
SILO	Microsimulation; heuristics	Individuals and households	Zones (preferably correspondent to zones in travel model)	Annual	Household location choice	Gravity-based access to jobs
UrbanSim	Microsimulation; RUM	Individuals and households	Variable (grids, parcels, zones)	Annual (land use), every 5 years (transport)	Household and employment location models; real estate development model; land price model	Both gravity-based and logsum
SimMobility	*Activity-based; equilibirum; microsimulation; RUM*	*Individuals; households; firms*	*Building level; TAZs*	*Daily (land use), tenths of a second (transport)*	*Residential location choice; job location choice; vehicle availability*	*Logsums / Activity-based accessibility*

Note: This table has been adapted from Engelberg et al. (2021), which the reader is invited to refer to for further detail.

state-of-the-practice being ignored. They report failing to find a comprehensive review of LUTI models currently in use by transportation and planning agencies. In a recent Transport Reviews paper, Thomas et al. (2018) reported that they could find only 21 applied scientific papers, all of which were published after their search period threshold of 1990. This threshold closely corresponds to the ISGLUTI report by Webster and Dasgupta (1991) that compared the LUTI models of the time with an eye towards spatial transferability and replicability.

This is not to say that LUTI models are rarely used for policy analysis. On the contrary, a number of LUTI models have been used to support consulting reports of policy analyses, but these rarely appear in the academic literature. In general, the land use components of LUTI models have not received as much attention as formal planning tools, nor have they been as institutionalized as travel demand models (Engelberg et al., 2021). Additionally, the policy analyses that most LUTI modelers tend to focus on have emphasized long horizons (e.g., 10-30 years) as planning periods, which seems questionable for emerging mobilities that can be quite disruptive within a few years. Very few LUTI models have successfully migrated from development to application. Although few and far between, I will briefly summarize the published applications of three state-of-the-art agent-based LUTI models — UrbanSim, ILUTE, and ILUMASS.

UrbanSim, which was developed in the early 2000s primarily by Paul Waddell while at the University of Washington, has been relatively widely used for a variety of applications across multiple contexts due to the software being available open-source. However, it cannot be viewed as a 'true' LUTI model as it includes only a microsimulation of the housing market. It enjoys widespread use, especially within the US, because it was the first disaggregate land use model with econometric behavioral components that was open-source. Initial UrbanSim applications typically used gravity-based potential accessibility calculated from the transport model. More recent applications have migrated to using utility-based measures. While the flexibility to couple with any existing travel demand model is alluring, it often results in UrbanSim utilizing sparsely informative accessibility measures.

A case study in Austin, Texas evaluated the impact of scenarios such as urban growth and increased transportation cost sensitivity on changes in land use, travel, and energy over a 20-year planning period (Kakaraparthi and Kockelman, 2011). UrbanSim has also been used to evaluate the potential impacts of major transportation infrastructure projects, such as the Light Rail Transit system in Phoenix, Arizona (Joshi et al., 2006) and the BeltLine in Atlanta, Georgia (Wang and Yuan, 2018). A case study of residential location choices in Suwon, Korea by Jin and Lee (2018) stands as an example of the use of UrbanSim even outside the United States. While Kakaraparthi and Kockelman (2011) and Wang and Yuan (2018) used gravity-based accessibility measures using network travel times, Joshi et al. (2006) and Jin and Lee (2018) used utility-based measures derived from travel mode choice models considering auto and public transit as options. These applications highlight that we have yet to embrace the use of disaggregate, activity-based accessibility measures despite widespread recognition of their necessity and value in modeling the complexity of land use and mobility interactions, especially when it comes to incorporating emerging mobilities.

On the other hand, ILUTE, which was developed in the late 2000s by Eric Miller at the University of Toronto in Canada, does not seem to have published case studies of policy applications. Perhaps some of the reasons behind this, as reported from a survey of planners and policy-makers in Canada by Miller himself, are (a) a general disbelief in the usefulness of models for decision-making, and (b) lack of resources for large-scale modelling exercises (Hatzopoulou and Miller, 2009). It is worth mentioning, however, that there are several published papers on methodological advancements of component models within the ILUTE framework, which I do not list here. Although not a direct policy application, a policy-relevant study by Fatmi and Habib (2015) did test the spatial transferability of the residential mobility model in ILUTE from the Greater Toronto and Hamilton Area to Halifax, Nova Scotia. They reported that directly transferring micromodels from one spatial context to another is problematic due to different choice behaviors across contexts.

Developed in the early 2000s in Germany, ILUMASS arguably has the most well-developed models of firm and job location choices. It is still under active development under the purview of Rolf Moeckel at TU Munich. Again, I observe that there are more papers on methodological advancements and model components than on policy applications. A recent policy application of ILUMASS looked at the impact of zoning, transport, and tax-related policies on reducing the urban sprawl of employment in Dortmund, Germany (Moeckel, 2009). Moeckel and his team have also been recently involved in developing SILO, which, like UrbanSim, only models the land use component. They combined SILO with MATSim, a popular open-source activity-based transport modeling framework, to understand the impact of simulation-based traffic noise on rent prices by introducing a feedback loop between transport-related noise emissions and land use (Kuehnel et al., 2021). Similar to some of the UrbanSim applications discussed earlier, they too used coarse accessibility measures derived from a four-step travel demand model.

In summary, I find limited peer-reviewed and published evidence of LUTI models being used for policy analysis, although they have been used as planning support systems for consulting projects with local governments and planning agencies. Despite moving to more theoretically complex frameworks, the use of LUTI models in practice is limited to simpler frameworks. UrbanSim, in particular, is widely being used by many metropolitan planning agencies in the US because of the flexibility with which it can be coupled with existing transport models. However, in addition to a general dearth of case studies, there is also the issue of using appropriate accessibility measures. While accessibility measures that represent individual activity patterns and preferences better represent behavioral realism, LUTI models using simpler accessibility measures (such as gravity-based ones) have seen wider application in practice for policy analysis. Additionally, none of the policy applications of LUTI models have looked at the impacts of emerging mobilities, which I discuss later in this chapter.

2.6 Exploring emerging mobility effects using LUTI models

Survey research and longitudinal data are suitable for exploring the ex-post effects of emerging mobility on travel behavior. However, if we are to detect undesired side-effects and test the effectiveness of potential mitigation measures, then ex-ante analysis will be required. This is where agent-based models can be valuable tools. However, the studies examining automated mobility effects using standalone agent-based models suffer from limitations such as exogenous and often implausible assumptions. Moreover, these standalone models fail to appropriately account for the link between land use and mobility. Thus, LUTI models may be the most pertinent approach to examining how emerging mobilities can change neighborhoods in an ex-ante manner.

However, most state-of-the-art LUTI models have not been designed for the shared mobility era. In their recent review of LUTI models with an eye towards their suitability 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, and are unenthusiastic about the usefulness of such models in the shared mobility era. More general concerns have also been raised about the inability of LUTI frameworks to predict phenomena such as the 'peak car' hypothesis (which claims that car ownership and use have plateaued in some industrial economies) or appropriately model the impact of information and communication technologies (ICTs) on activity-travel patterns (Van Wee, 2015). Two major challenges that plague LUTI models are the integration of activity-based travel demand models and appropriate measures of accessibility (Acheampong and Silva, 2015). Additionally, a recent review by Lopes et al. (2019) highlights how currently operational LUTI models do not adequately recognize all mutual interactions between activities, land use, and transport.

A combined team from MIT and the Singapore-MIT Alliance for Research and Technology (SMART) has been pursuing the development of a state-of-the-art agent-based microsimulation LUTI model (*SimMobility* - Simulation of Future Urban Mobility) built on underlying activity-based discrete choice models of travel behavior. Considering land-use, transportation and communication interactions, *SimMobility* can be used for a variety of applications, including implementation of intelligent transportation systems, estimating vehicular emissions, evaluation of alternative future scenarios, and generation of innovative policy and investment strategies. This project was initiated in 2010, and is still under active development, which gave the team the opportunity to address some of the aforementioned concerns from the LUTI modeling community.

To the best of our knowledge, SimMobility is the only state-of-the-art agent-based LUTI microsimulation model that has been used to examine the effects of automated-mobility-on-demand (AMoD) on travel behavior and residential relocation. Since AMoD is yet to be fully realized, the only alternative to making assumptions about changes in travel behavior is to conduct a stated preference (SP) survey. Oh et al. (2020) is the only study that used 'real-world' SP data to modify travel behavior within a LUTI model framework. They report that the short- and medium-term effects of unregulated AMoD will likely be an increase in network congestion and VMT. Zhou et al. (2021) supplement these findings by suggesting that AMoD can enhance overall accessibility as long as they are introduced as an additional option. If private autos are prohibited to make way for AMoD, then accessibility inequity may be alleviated due to the benefits provided by AMoD being spread non-uniformly across socioeconomic groups.

2.7 Summary

Planning practitioners have turned to transit-oriented development (TOD) in recent times as a car-lite strategy to curb the rise in auto-dependence and urban sprawl. However, community groups have opposed TOD efforts by raising legitimate concerns related to transit-induced gentrification. Not only does transit-induced gentrification deny accessibility benefits to lower-income and transit-dependent groups, higher-income in-movers (who are also more likely to own and use autos) may increase neighborhood-wide auto-dependence. An increase in densification through upzoning regulations has been suggested as a mitigation measure. However, upzoning itself can raise property values without stimulating new housing construction.

Another policy instrument to enhance TOD areas could be the regulation of parking supply. As parking availability is closely tied with auto ownership and use, keeping parking supply in check could be key for reducing auto-dependence. There is consensus in the literature that upzoning and parking restrictions may have limited value on their own. In tandem with supportive policies that seek to improve non-auto accessibility and incentivize the provision of affordable housing, these two policies may be much more effective in mitigating the gentrification side-effects of TOD.

But does TOD need the T? I contend that there are alternative mechanisms to improve accessibility considerably faster than a decade-long subway construction (or development) project, such as emerging mobilities, for example. The exploration of how emerging mobilities can change neighborhoods has been limited by retrospective survey data and often implausible assumptions of behavioral changes. I consider emerging mobilities as *one* particular mechanism of improving non-auto accessibility and instead of focusing only on emerging mobilities, I ask how neighborhoods might change in response to broader non-auto accessibility improvements. Drawing on the transit-induced gentrification literature, I explore whether we observe accessibility-induced gentrification when (more broadly defined) non-auto accessibility improvements are operationalized.

To address these questions with rich, disaggregate spatiotemporal resolution, I use a state-of-the-art land use-transport interaction (LUTI) model. LUTI models have been used by both researchers and planning practitioners to understand how changes in mobility infrastructure and land use can affect urban (and metropolitan) growth. LUTI models are well-suited for policy explorations using scenario analysis to examine both long-term and near-term effects. However, thus far, LUTI models have only focused on traditional transportation modes such as private autos, public transit, and (to a comparatively limited extent) active modes.

Recognizing the limitations of state-of-the-art LUTI models for such explorations, I propose a few methodological improvements to one such model (SimMobility) before using the augmented LUTI model for scenario explorations of neighborhood change. In addition to examining car-lite policies that impose private vehicle restrictions and/or improve non-auto accessibility, I also explore two coordinated housing policies (i.e., upzoning and parking supply restrictions) to see the extent to which they can mitigate gentrification side-effects and enhance the benefits of non-auto accessibility improvements.

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Chapter 3

Context & Data

This chapter describes the contextual setting of the research exploration undertaken in this dissertation. First, I outline the social and spatial contexts of the city-state of Singapore along with discussing relevant policy efforts undertaken by the Singaporean government to design liveable and sustainable communities, provide affordable public housing, and limit private vehicle ownership and use. I then provide an overview of the primary data sources used in this dissertation.

3.1 Contextual setting

The research in this dissertation is contextually and empirically set in Singapore, an island city-state located in South-east Asia that gained independence relatively recently in 1965. Home to over 5.5 million people, the Singaporean economy has continued to grow in strength with an estimated GDP of almost 400 billion USD and the second-highest per capita GDP at purchasing power parity in the world (as of 2021).[1] In this dissertation, I will be using data sources from 2012 to construct a baseline snapshot of Singapore for scenario exploration. Key sociodemographic indicators for the city of Singapore (as of 2012) are summarized in Table 3.1.[2] Singapore's population is made up of two distinct groups — residents and non-residents. The resident population comprises Singapore citizens and per-

[1] `https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=SG`. Last accessed on August 24, 2022.

[2] Data are sourced from the annual '*Population Trends*' documents released by the Singaporean Department of Statistics, also known as Singstat. These documents are archived by the National Library of Singapore, and the 2012 version is available at `https://eresources.nlb.gov.sg/printheritage/detail/2b6dddfe-bdd8-4118-a16c-606e03b12388.aspx`. Last accessed on August 24, 2022.

manent residents (PRs). Permanent residents enjoy most of the same rights and privileges as citizens, but cannot vote or hold public office, and have limited public benefits (such as medical and housing benefits) and lower public school placement priority. Starting in 2010, Singapore set an annual cap on the number of individuals being granted Permanent Residence at approximately 30,000. There is a relatively stable population of just over 500,000 Permanent Residents in Singapore. 'Resident' households are defined as households whose representative or head is a Singapore resident, i.e., a Citizen or Permanent Resident. Most government agencies (such as Singstat) publish detailed data only on resident individuals and households.

In 2012, 1.16 million resident households and 3.818 million residents lived in Singapore. The average resident household size was 3.5, with 1.8 workers within the household. The average monthly household income was SGD 6,886. Close to 1.5 million non-residents also lived in Singapore at the time. These non-residents comprised Work Permit holders (46%), dependants of Singaporean residents (15%), foreign domestic workers (13%), Employment Pass holders (12%), S Pass holders (9%), and international students (6%). Among residents, about a quarter (23.9%) were below 20 years of age, while over one in ten (11.1%) were 65 years or older. As Singapore is a multi-racial and multi-ethnic society, its people have been broadly organised under the CMIO (Chinese–Malay–Indian–Other) system of categorisation since 1965 (Tan, 2004). The ethnicity of the household head (or representative) is assigned to the entire household by government agencies for calculating household ethnic distributions. Ethnic Chinese (74.2%) form the largest group. Ethnic Malays, who are recognized as the indigenous community, are the next-largest group (13.3%), followed by ethnic Indians (9.1%). Other ethnic groups are combined together in government reports and form the smallest category (3.3%), which has been historically dominated by Eurasians.

Mixed-race Singaporeans often take up the race of their father in official documents. However, since 2011, they have the option to provide a double-barrelled race categorisation on their National Registration Identity Cards (NRIC) to signify both ethnicities of their parents.[3] Based on these four ethnic groups, Singapore has four official languages — English (main working language), Malay, Mandarin, and Tamil. Race informs government policies on a variety of issues such as political participation, public housing, and education. The

[3] `https://www.ica.gov.sg/news-and-publications/newsroom/media-release/423`. Last accessed on August 24, 2022.

Ethnic Integration Policy implemented by the Housing and Development Board (HDB) sets a quota on who can reside in a public housing flat in a particular block or neighbourhood. The policy was first introduced in 1989 to prevent the formation of ethnic enclaves and encourage a balanced racial mix in HDB estates.[4]

Singapore is governed as a unitary state without provinces or states. However, for the purposes of administration and urban planning, it has been subdivided in various ways by the Urban Redevelopment Authority (URA). There are five Planning Regions (see Figure 3-1a), with two central and western water-catchment areas. The West Region is the largest in terms of area, while the Central Region is the most populous. These five Planning Regions are further sub-divided into 55 Planning Areas, also known as Development Guide Plan (DGP) areas or DGP zones (see Figure 3-1b). The URA draws up a Development Guide Plan for each planning area, thus providing detailed planning guidelines for every individual plot of land throughout the city-state. Each planning area covers about 14.6 square kilometers (or 5.6 square miles) on average. 43 of the 55 planning areas were populated (with at least 1,000 resident households), as of 2012. There were 26 planning areas with at least 15,000 resident households that were home to 96.6% of the population, while covering only 45.9% of the land-area. Unlike most countries, postcodes in Singapore usually represent individual buildings, except in undeveloped areas where postcodes can refer to a parcel, or low-density areas (i.e., single-family detached housing settings) where several buildings may have the same postcode. There were 116,626 postcodes in Singapore in 2012 (see Figure 3-1c). The transportation planning agency in Singapore (i.e., the Land and Transport Authority, or LTA) uses Traffic Analysis Zones (TAZs) as the unit of geography for transport and traffic planning. There were 1,169 TAZs in Singapore with an average area of 0.73 square kilometers (or 0.3 square miles), as of 2012 (see Figure 3-1d).

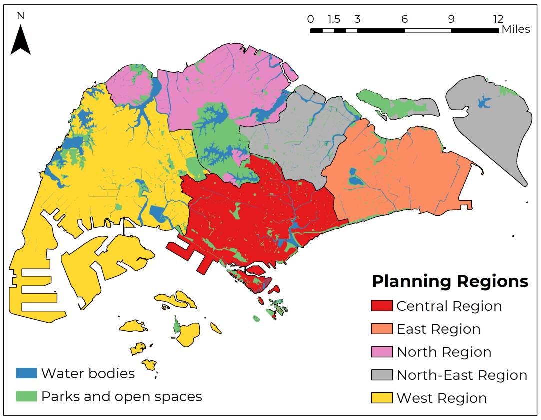
Key indicators of housing and mobility in Singapore (as of 2012) are presented in Table 3.2.[5] Almost nine in ten (89.9%) resident households owned a home. Non-residents make up the majority of renters, while migrant workers are housed in independent workers' dormitories by employers. Public housing in Singapore is provided by the Housing and Development Board (HDB) at cost (estimated based on cost-to-government, including land value) with

[4] `https://www.gov.sg/article/hdbs-ethnic-integration-policy-why-it-still-matters`. Last accessed on August 24, 2022.

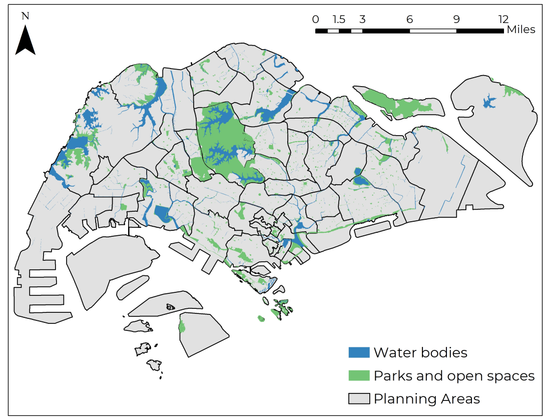
[5] Data are sourced from the '*Population Trends*' documents released by the Department of Statistics, as well as various datasets released by the Land Transport Authority on the Singapore Open Data Portal — `https://data.gov.sg/`. Last accessed on August 24, 2022.

Table 3.1: Sociodemographic summary of Singapore (as of 2012)

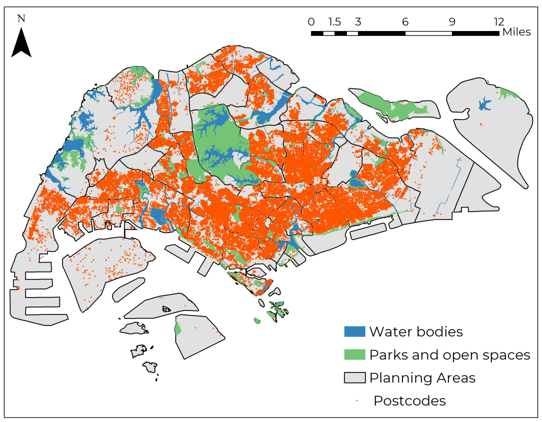
City-level sociodemographic indicators	
Total population (millions)	5.312
Resident population (millions)	3.818
Citizens (millions)	3.285
Permanent Residents (millions)	0.533
Non-Resident population (millions)	1.494
Resident households (millions)	1.160
Density (Population per sq.km. of land-area)	7,399
Sex ratio (Males per 1,000 females)	970
Median age (Years)	38.4
Average worker income (SGD/month)	$4,001
Average household size (pax)	3.5
Average workers in household (pax/hh)	1.8
Average household income (SGD/month)	$6,886
Residents' age	
Below 20 years	23.9%
20 to 64 years	65.0%
65 years or above	11.1%
Household ethnicity	
Chinese	74.2%
Malay	13.3%
Indian	9.1%
Other	3.3%
Administrative divisions	
Planning Regions	5
Planning Areas	55
Traffic Analysis Zones (TAZs)	1,169
Postcodes	116,626



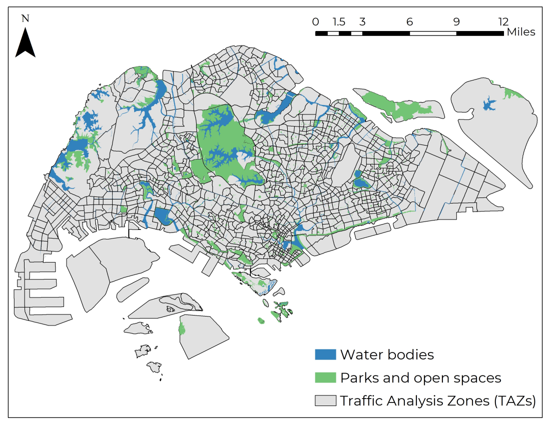
(a) Planning Regions



(b) Planning Areas



(c) Postcodes



(d) Traffic Analysis Zones (TAZs)

Figure 3-1: Administrative divisions in Singapore (as of 2012)

some discounts available to specific groups, e.g., young married couples buying their first HDB unit.[6] Unlike most countries, the overwhelming majority (81.6%) of households in Singapore live in public housing. Various types of flats with different sizes and floor plans are offered by the HDB (see Section 3.1.2 for more details). Close to six in ten (58.1%) resident households lived in the larger 4-room and 5-room HDB flats. Less than a fifth (18.4%) of residents lived in private housing. Among those that do, most (12.4%) lived in condominimums and apartments, while only 6% live in landed properties.[7] With rising

[6] `https://www.hdb.gov.sg/residential/buying-a-flat/flat-and-grant-eligibility/couples-and-families/enhanced-cpf-housing-grant-families`. Last accessed on August 24, 2022.

[7] Landed properties refer to housing built on land that is also owned by the building owner. These are in contrast to 'non-landed' properties that are built on land owned by the government and then leased to the building owner, usually for 99 years. Landed properties can be largely categorised into detached, semi-detached, and non-detached housing. Detached housing are standalone houses such as a bungalow. Semi-detached housing are usually conjoined buildings with a common wall in-between. Terraced housing are usually a row of houses, of at least three units, with two corners and are characterised by shared common

incomes in recent years, more and more households are opting out of HDB flats and moving to private housing. As of 2020, 78.7% of Singapore residents lived in public housing, which is still impressive (compared to other countries) but down from a high of 88.0% in 2000.[8]

Public transit is the backbone of Singapore's transportation system. As of 2012, there were 120 rail stations spread over 177.7 kilometers of rail network. Rail transport in Singapore comprises a heavy-rail rapid transit system (known as the Mass Rapid Transit, or MRT) and several Light Rail Transit (LRT) rubber-tyred automated guideway transit lines. The MRT network in 2012 consisted of four main lines — North South Line, East West Line, North East Line, and Circle Line (see Figure 3-2d). Since then, the rail network has been expanded with the opening of the Thomson-East Coast Line and the Downtown Line to now span 216 kilometers and 127 stations. Two more lines, the Jurong Region Line and the Cross Island Line, are slated to open in 2027 and 2030 respectively. Buses also form a significant part of public transport in Singapore. There were around 350 scheduled bus services operating along almost 4,800 bus stops in 2012.

In addition to creating a well-connected public transit system, there are several measures in place to reduce private vehicle ownership and use in Singapore (see Section 3.1.3 for more details). These measures make private cars a luxury good in Singapore, with most car models pinching the pocket just as much as a smaller-sized HDB flat. Thus, only 42.1% of Singaporean households owned a car in 2012, with a per-capita car ownership rate of 12 cars per 100 people (which is significantly low compared to roughly 80% in the US and 50% in Europe). This has been reported to drop to 35.3% in 2017 by the LTA. As a result of private vehicles being expensive to own and a well-developed public transit system, only about a third (32.7%) of daily journeys in 2012 were made with private vehicles. Over half (52.4%) of daily journeys in Singapore were completed using public transit and active modes (such as biking and walking). The mode share of public transit was 57% in 2012, and increased to 62% in 2016, keeping the LTA on track to meet their goal of 75% public transit peak mode share by 2030.[9]

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walls between houses. These properties have different title deeds and usually different owners.

[8] Data are sourced from the 2021 version of the '*Population Trends*' document released annually by the Department of Statistics, which is available at `https://www.singstat.gov.sg/publications/population/population-trends`. Last accessed on August 24, 2022.

[9] Data are sourced from the '*Public Consultation on the Land Transport Master Plan 2040*' document available at `https://www.lta.gov.sg/content/ltagov/en/newsroom/2018/8/2/public-consultations-commence-for-the-next-land-transport-master-plan.html`. The LTA combines bus, MRT / LRT, and taxi for reporting public transit mode shares. I do not consider taxi to be a public transit option, which is why my estimates are slightly lower than theirs. Last accessed on August 24, 2022.

Table 3.2: Housing and mobility summary of Singapore (as of 2012)

City-level housing and mobility indicators	
Home ownership	89.9%
Household car ownership	42.1%
Rail (MRT + LRT) network length (kms)	177.7
Rail (MRT + LRT) stations	120
Bus stops	4,793
Housing type (%)	
Public housing (HDB)	81.6%
1- and 2-room flats (HDB12)	4.7%
3-room flats (HDB3)	18.6%
4-room flats (HDB4)	32.6%
5-room flats (HDB5)	25.5%
Private housing	18.4%
Condos & Apartments	12.4%
Landed properties	6.0%
Daily journeys (millions, %)	
Private vehicles	4.8 (32.7%)
Taxi	0.8 (5.4%)
Bus	3.2 (21.8%)
MRT / LRT	2.3 (15.6%)
Active Mobility	2.2 (15.0%)
Goods vehicles	1.4 (9.5%)
Peak period mode share (%)	
Private vehicles	37%
Taxi	6%
Bus	30%
MRT / LRT	27%

3.1.1 Land use policies

Urban planning in Singapore is carried out through a three-tiered planning framework: (a) a Concept Plan that serves as a macro-level blueprint envisioning Singapore's development over a long-term planning horizon, (b) a Master Plan for the medium-term, which translates the vision of the Concept Plan into detailed guidelines, and (c) short-term plans. The Concept Plan and the Master Plan are under the purview of the Urban Redevelopment Authority (URA), while short-term plans are prepared by multiple agencies.

Urban planning began in Singapore in the 1820s when the Raffles Town Plan (also known as the Jackson Plan) was implemented (Dale, 1999). Singapore was divided into multiple ethnic areas along with the establishment of a commercial and administrative center (now known as Raffles Place). However, Singapore's growth was haphazard and largely unregulated for most of the 19th century and the first half of the 20th century (Khublall and Yuen, 1991). The British established the Singapore Improvement Trust (SIT) in 1927 in response to congestion and squatter settlements. SIT was charged with responsibilities such as carrying out improvement works, condemning unsanitary buildings, and rehousing people rendered homeless by improvement works. However, it was provided limited powers and, hence, had limited initial impact. Detailed urban planning for Singapore eventually started in the 1950s, with the goal of providing Singapore a meatier economic role in the Federation of Malaya. As a result, the 1958 Master Plan was produced, heavily influenced by British planning practices and assumptions. This plan regulated the type and intensity of development by specifying the land use zoning and the maximum density or plot ratio for each site. It also reserved land for infrastructural uses, community facilities, and open spaces.

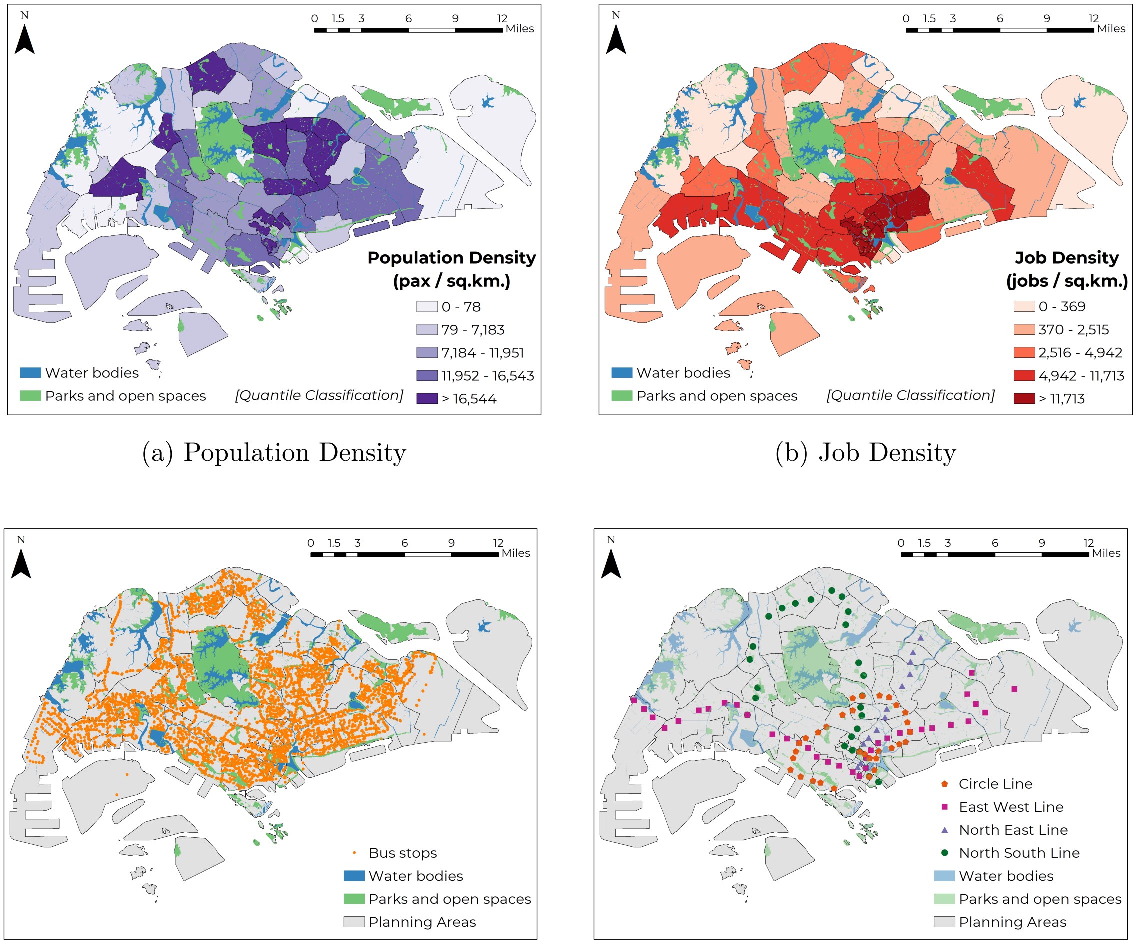
Following Singapore's independence in 1965, the State and City Planning Project (SCP) was initiated to produce a long-range plan to guide the country's physical development for the next 20 years, which led to the 1971 Concept Plan. Land use planning at the time had to address the two priorities of a newly independent Singapore — (a) the provision of adequate housing, and (b) the generation of employment opportunities for the people. Unlike the Master Plan, which provided detailed zoning and density parameters, the Concept Plan showed only the broad direction of the government's land allocation and transportation policies. This plan laid out the basic infrastructure for Singapore's development and brought about the integrated planning process used ever since. The Concept Plan envisioned the development of high- and low-density residential estates, industrial areas, and commercial centres in a ring formation around the central water catchment area, as well as a network of expressways and a mass rapid transit (MRT) system to provide island-wide connectivity. Additionally, the Concept Plan set aside land for the Singapore Changi Airport.

The Land Acquisition Act was passed in 1966 to address the pressing need for an adequate supply of land to carry out developmental projects at the time, especially resettlement and industrialization. This act enabled the compulsory acquisition of private land for public purposes, such as the building of transportation infrastructure and public housing. Between 1959 and 1984, the government acquired a total of 177 square kilometers (about one-third of the total land-area of Singapore then), with the majority occurring after 1967 (Wong and Yeh, 1985). The government became the largest landowner by 1985, owning 76.2% of the land compared to 31% in 1949. This has since increased to almost 90% (Haila, 2015). This act was instrumental in keeping the costs of building housing and industrial premises affordable, as well as facilitating urban renewal efforts in the central area of Singapore.

Planning in Singapore began to incorporate additional priorities from the 1980s, such as quality of life and conservation, while the 1991 revision of the Concept Plan introduced the concept of regional centres to promote decentralisation. Instead of the ring layout adopted in the 1971 plan, the updated plan divided Singapore into five regions (central, north, northeast, east, and west) and proposed the development of four regional centres outside the central region to reduce congestion in the city center. To improve the implementation of the Concept Plan's strategies, Singapore was divided into multiple planning areas in the 1990s, and comprehensive plans for each area's development were produced and compiled into a new plan (Yuen, 1998). These tasks were undertaken by the Urban Redevelopment Authority (URA), which has been designated as the national planning and conservation agency since 1989. The population and job densities for the 55 Planning Areas (as of 2012) are shown in Figures 3-2a and 3-2b respectively.

In the 2001 and 2011 Concept Plans, Singapore's urban planners began to incorporate public feedback and opinions into the planning process, shifting towards liveability and sustainability, while prioritising economic development as the powerhouse of each plan's success. The 2011 Concept Plan also featured a distinct focus on sustainability and conservation.[10]

[10] `https://www.ura.gov.sg/Corporate/Media-Room/Media-Releases/pr10-55`. Last accessed on August



(a) Population Density

(b) Job Density

(c) Bus stops

(d) Mass Rapid Transit (MRT) stations

Figure 3-2: Spatial distributions of people, jobs, and transit infrastructure in Singapore (as of 2012)

The 2014 Master Plan was aimed at creating an inclusive, highly liveable, economically vibrant and green environment for all Singaporeans, focusing on six areas — housing, transport, economy, recreation, identity, and public spaces.[11] The most recent plan is the 2019 Master Plan, which details Singapore's increasing consideration towards sustainability, cultural preservation, building communities, and closing resource loops.[12] This recent focus on liveability and sustainability over the last decade has emphasized 'car-lite' strategies such as improved sidewalks and bike paths connecting to public transit, and extending the transit network such that public housing residents can access at least one bus stop and/or one

24, 2022.

[11] `https://www.ura.gov.sg/maps/?service=mp&year=2014`. Last accessed on August 24, 2022.

[12] `https://www.ura.gov.sg/Corporate/Planning/Master-Plan/Introduction`. Last accessed on August 24, 2022.

MRT station within 400 meters. Singapore has also invested heavily in research collaborations such as the Future Urban Mobility (FM) program with MIT and the Future Cities Laboratory (FCL) with ETH Zurich to explore how disruptive mobility technologies (such as automated vehicles, mobility-on-demand, and micromobility) can be harnessed to create a more sustainable mobility future for Singapore.

3.1.2 Housing policies

The national public housing agency of Singapore is the Housing and Development Board (HDB), which was formed shortly after attaining full self-governance in 1960. Although its goal at the time was to alleviate the severe housing shortage, the emphasis of its housing programs has shifted from quantity of housing to quality of life (Wong and Yeh, 1985). Since 1985, over 80 percent of Singapore's resident population have been living in HDB flats (Tan and Phang, 1992). HDB plans have largely tracked top-down government policies on urban growth and social policy. For example, new HDB estates, with large subsidies for young families, have been used in recent times to promote urban growth in the periphery.

HDB was conceptualized as a successor to the SIT with the primary task of building and managing housing units for lower-income residents. Although the SIT had started building flats from the 1930s onward, the housing problem had worsened significantly by the time HDB replaced the SIT in 1960. SIT's housing programs had fallen far short of what was required to keep pace with the fast-growing population (Field and Ofori, 1989). By 1965, HDB had completed its first Five-Year Building Program with a total of 54,430 units built (Phang, 2001). By the end of 1970, 36 percent of the total population was living in HDB flats (Ching and Tyabji, 1991). Over the next two decades, sustained efforts by the HDB ensured that HDB flats housed more than 80 percent of Singaporean residents. However, racial divisions within HDB estates became increasingly pronounced, which led to the introduction of the Ethnic Integration Policy in 1989 with the aim of capping the racial proportions of residents in HDB estates (Sim et al., 2003).

Since its inception, HDB has focused on designing comprehensive housing programs that include the provision of not only residential units but also supportive facilities (such as kindergartens, community halls, homes for the elderly, and recreational spaces) in the housing estates (Dale, 1999). While the initial focus was on the mass production of affordable, standardized housing for lower-income residents, it has constantly evolved to adapt to the changing housing needs of the population. In recent times, HDB has introduced new schemes for not only nuclear households, but also single individuals, the elderly, and multi-generational households.

The initial flats HDB built were available only as rentals. In 1964, HDB began selling flats under a home ownership scheme. The government implemented another scheme in 1968 that allowed residents to use their mandatory retirement fund — Central Provident Fund (CPF) — accounts to finance their purchase of HDB flats instead of relying solely on after-tax income. These two schemes have been largely responsible for the steady rise in HDB home ownership rates, which was estimated to stand at 92 percent as of 2015 (Phang and Helble, 2016). Housing grants have also been provided to married couples since 1994 to subsidize the purchase of their first HDB flat from the resale market (Phang, 2007).

HDB has also been relaxing its eligibility criteria to give more residents a chance at home ownership (Hui et al., 2009). The citizenship requirement was relaxed in 1989 to allow permanent residents in Singapore to own HDB flats. Starting from 1991, single citizens who were at least 35 years old could finally purchase HDB flats on their own, although their options were limited to only three-room or smaller flats outside the central area. Subsequent revisions to this scheme in 2001 and 2004 ensured that eligible singles can now purchase HDB flats of any type in any location. Additional subsidies are also provided for young individuals if they choose to live near their parents so elder care is easier.[13]

In 2001, HDB launched the Build-To-Order (BTO) system of selling new flats in non-mature estates as an alternative to the Registration for Flats System (RFS) which had resulted in a large stock of unsold flats. Under the BTO system, applications are invited for the flats to be built on the proposed sites and construction begins only if the majority of units are booked. This allows HDB to adjust its supply of flats according to demand. RFS was permanently suspended in 2002 and the BTO system is now the main mechanism for sale of new flats (Phang et al., 2014). The Design, Build, and Sell Scheme (DBSS) was also introduced in 2005 to enhance the variety of public housing. Under DBSS, designated sites are sold to private developers, who are then responsible for designing, building, and selling the flats (Deng et al., 2013).

During its first decade of operation, HDB built only one- to four-room flats. Five-room

[13] `https://www.hdb.gov.sg/residential/buying-a-flat/flat-and-grant-eligibility/couples-and-families/proximity-housing-grant-families`. Last accessed on August 24, 2022.

flats were then introduced in the 1970s, followed by executive apartments in the 1980s in response to the demand for bigger flats. Over time, HDB has also made improvements to each flat type in terms of design and size. In response to the needs of Singapore's ageing population, HDB released a special range of flats known as studio apartments in 1997. Smaller than three-room flats, these homes are partially furnished and fitted with elderly-friendly features such as emergency pull cords linked to an alert system for summoning help. Executive condominiums (i.e., an intermediate unit type bridging the gap between HDB flats and private condominiums) were introduced in 1995. Even though they are built and sold by private developers, these units offer the standard of private condominium living but are not as expensive.

Various types of subsidies are offered by HDB to help couples and families purchase their first HDB flat. For example, there were five BTO projects released in 2012 in Choa Chu Kang — Sunshine Gardens,[14] Keat Hong Pride,[15] Keat Hong Axis,[16] Keat Hong Quad,[17] and Keat Hong Mirage.[18] Across these BTO projects, 3-room HDB units were offered at $138,000 - $165,000, HDB4 units at $223,000 - $265,000, and HDB5 units at $284,000 - $345,000. Eligible households could apply for Additional CPF Housing Grants of around $30,000 (HDB3), $15,000 (HDB4), or $10,000 (HDB5) in 2012. An additional subsidy of $5,000 could also be availed for HDB3 units through the Special CPF Housing Grant. These reflect the maximum subsidy amounts; the actual grant amounts provided to households vary based on income and choice of flat. In 2012, the median resale prices of HDB units in Choa Chu Kang were around $329,000 (HDB3), $420,000 (HDB4), and $486,000 (HDB5).[19] As of 2022, couples or families who are first-time applicants buying a new or resale HDB flat could qualify for an Enhanced CPF Housing Grant of up to $80,000.[20] CPF Housing Grants of up to $50,000 are also available to first-timer couples or families looking to purchase an

[14] `https://singpromos.com/housing/hdb-launches-jan-2012-bto-with-five-projects-11-17-jan-2012-23714/`. Last accessed on August 24, 2022.

[15] `https://singpromos.com/housing/hdb-launches-six-bto-projects-30-may-5-jun-2012-33527/` Last accessed on August 24, 2022.

[16] `https://singpromos.com/housing/hdb-launches-seven-bto-projects-31-jul-6-aug-2012-38789/` Last accessed on August 24, 2022.

[17] `https://singpromos.com/housing/hdb-launches-sep-2012-sobf-exercise-seven-bto-projects-27-sep-3-oct-2012-43672/` Last accessed on August 24, 2022.

[18] `https://singpromos.com/housing/hdb-launches-seven-nov-2012-bto-projects-21-27-nov-2012-49548/` Last accessed on August 24, 2022.

[19] Calculated by the author using detailed HDB resale transaction data (see Section 3.2.2)

[20] `https://www.hdb.gov.sg/residential/buying-a-flat/flat-and-grant-eligibility/couples-and-families/enhanced-cpf-housing-grant-families`. Last accessed on August 24, 2022.

HDB resale flat.[21] Second-time applicants are eligible for the Step-Up Housing Grant of \$15,000 for both new and resale flat purchases.[22]

HDB estates are located in 'new towns' — communities that are intended to be self-contained with services and amenities located close to the housing blocks. New towns built from the late 1970s adopted a 'checkerboard model', alternating residential and non-residential areas throughout the town (Hee and Ooi, 2003). However, since the 1990s, newly built new towns contain densely built developments integrating both public housing and amenities. Since the 1990s, HDB has adopted the Estate Renewal Strategy, which aims to improve the living environment of HDB estate residents through various upgrading programs (Tu, 1999). The Main Upgrading Program was launched by the HDB in 1990 to carry out improvements within the flat and at the block and precinct levels. The Selective En-bloc Redevelopment Scheme was launched five years later, where entire blocks were demolished for redevelopment. Smaller-scale upgrading programs (such as the Home Improvement Program) have also been developed since then to benefit more residents. This shift towards redevelopment has been primarily driven by the recognition that the oldest HDB estates are two generations old and need improvements to reflect changing incomes and housing preferences.

Most public housing in Singapore is owner-occupied (estimated to be 92% in 2015, as mentioned earlier). Owner-occupied public housing is sold on a 99-year leasehold to residents who meet certain income, citizenship, and property ownership requirements. These units can also be sold on the private resale market subject to some restrictions. Rental public housing consists of smaller-sized units (such as one- and two-room flats) and is targeted towards lower-income households who are also eligible for housing grants for flat purchases. These units have lower income requirements than owner-occupied public housing and are distinct from for-own units being purchased and offered for short-term rentals on the rental market (Phang, 2007). Flats with shorter leases and lease monetisation schemes are also available as options for elderly homeowners.

[21] `https://www.hdb.gov.sg/residential/buying-a-flat/flat-and-grant-eligibility/couples-and-families/cpf-housing-grants-for-resale-flats-families`. Last accessed on August 24, 2022.

[22] `https://www.hdb.gov.sg/residential/buying-a-flat/flat-and-grant-eligibility/couples-and-families/step-up-cpf-housing-grant-families`. Last accessed on August 24, 2022.

3.1.3 Mobility policies

Transport planning in Singapore consists of the Land Transport Master Plan, which is revised every five years, and development plans for the rail and bus system. Built upon a spoke-hub distribution paradigm, Singapore's transport planning focuses on the objectives of increased connectivity, improved public transport provision, and increasing the proportion of commuters using public transport (Soon Looi et al., 2018). Responding to population changes in the 2000s, the Land Transport Authority (LTA) called for a significant expansion of the rail network and the integration of the bus and rail systems in a hub-and-spoke network in the 2008 Land Transport Master Plan.[23] The 2013 follow-up called for more sheltered walkways and cycling path networks within new towns to improve pedestrian and cycling access.[24]

Proactive efforts in providing affordable and accessible transportation to residents has resulted in Singapore's public transport system being ranked as one of the best and the most affordable in a study by McKinsey comparing public transit systems in 24 cities using more than 80 indicators over five main dimensions — availability, affordability, efficiency, convenience and sustainability.[25] Using buses, Mass Rapid Transit (MRT), and Light Rail Transit (LRT) systems, the public transport network in Singapore is quite extensive and, accounts for over 50% of daily trips (including active mobility). Almost all HDB estates have at least one bus stop within a walking distance of 400 meters, with the goal being to have eight in ten households living within 10 minutes' walk of a train station by 2030, as outlined in the 2013 Land Transport Master Plan. Significant investment towards betterment and extension of public transport infrastructure is a key characteristic of government policy, as Singapore aims to reach a public transport peak mode share of 75% by 2030. The bus and MRT networks are shown in Figures 3-2c and 3-2d respectively. The MRT network has undergone significant expansion since 2012, with the Downtown Line and Thomson-East Coast Line being new additions in 2013 and 2020 respectively. In addition to planning for better public transport, Singapore is also well-known for its restrictive policies that seek to limit private vehicle ownership and use, which I will describe briefly below.

[23] https://www.lta.gov.sg/content/dam/ltagov/who_we_are/statistics_and_publications/master-plans/pdf/LTMP-Report.pdf. Last accessed on August 24, 2022.

[24] https://www.lta.gov.sg/content/dam/ltagov/who_we_are/statistics_and_publications/master-plans/pdf/LTMP2013Report.pdf. Last accessed on August 24, 2022.

[25] https://www.mckinsey.com/business-functions/sustainability/our-insights/elements-of-success-urban-transportation-systems-of-24-global-cities. Last accessed on August 24, 2022.

Private vehicle ownership policies

The Singaporean government seeks to restrict private vehicle ownership through two major policies: (a) the Additional Registration Fee (ARF), and (b) the Vehicle Quota System (VQS). While the former increases the cost of vehicle ownership, the latter scheme controls the total number of active vehicles on an annual basis.

The Additional Registration Fee (ARF) was instituted as a share of the Open Market Value (OMV) of the vehicle in 1972. The ARF grew from 15% in 1972 to 150% in 1980 and 175% in 1983. The current tax structure is even more steep.[26] Cars registered on or after September 1, 1998 are subject to a registration fee of 220 SGD. The ARF is imposed on top of this registration fee using the following tiered scheme:

- First 20,000 SGD of OMV: 100% ARF rate
- Next 30,000 SGD of OMV: 140% ARF rate
- Above 50,000 SGD of OMV: 180% ARF rate

As an example, the ARF payable for a car with an OMV of 75,000 SGD stands at $\left[(100\% * 20,000) + (140\% * 30,000) + (180\% * 25,000) = \right]$ 107,000 SGD. Thus, we can see how the ARF can easily exceed the OMV for most vehicle models. Road taxes are also levied based on engine and fuel types, while rebates are offered for older cars and differential amounts of vehicular CO_2 emissions. In a recent push to increase the adoption of electric vehicles, residents are being offered a rebate of up to 45% off the ARF, capped at 20,000 SGD, through the Electric Vehicle Early Adoption Incentive Program.

While the ARF influences vehicle ownership levels through the registration fee, the government more directly controls the overall private vehicle fleet size through an auction scheme. Registration of every new vehicle must be preceded by the acquisition of a Certificate of Entitlement (COE), which represents the right to own and use a vehicle for 10 years. At the end of the 10-year period, vehicle owners can de-register their vehicle or choose to renew their COE for another 5- or 10-year period by paying the Prevailing Quota Premium. If the vehicle is de-registered before the expiration of its COE, a rebate is prorated to the number of days remaining on the COE. Users can apply for five categories of COE — small

[26] `https://onemotoring.lta.gov.sg/content/onemotoring/home/buying/upfront-vehicle-costs/tax-structure.html`. Last accessed on August 24, 2022.

cars, large cars, goods vehicles and buses, motorcycles, and an open category.[27] COEs are allocated through an open bidding process, which is conducted twice a month. The number of available COEs is dependent on the limits set by the Vehicle Quota System. As the supply of COEs is highly regulated, prices are extremely volatile depending on the current levels of demand. COE prices have varied between 25,000 - 100,000 SGD for cars and 2,000 - 10,000 SGD for motorcycles over the past decade, as shown in Figure 3-3. COEs are also transferable along with the vehicle in the case of private vehicle transactions between individuals.

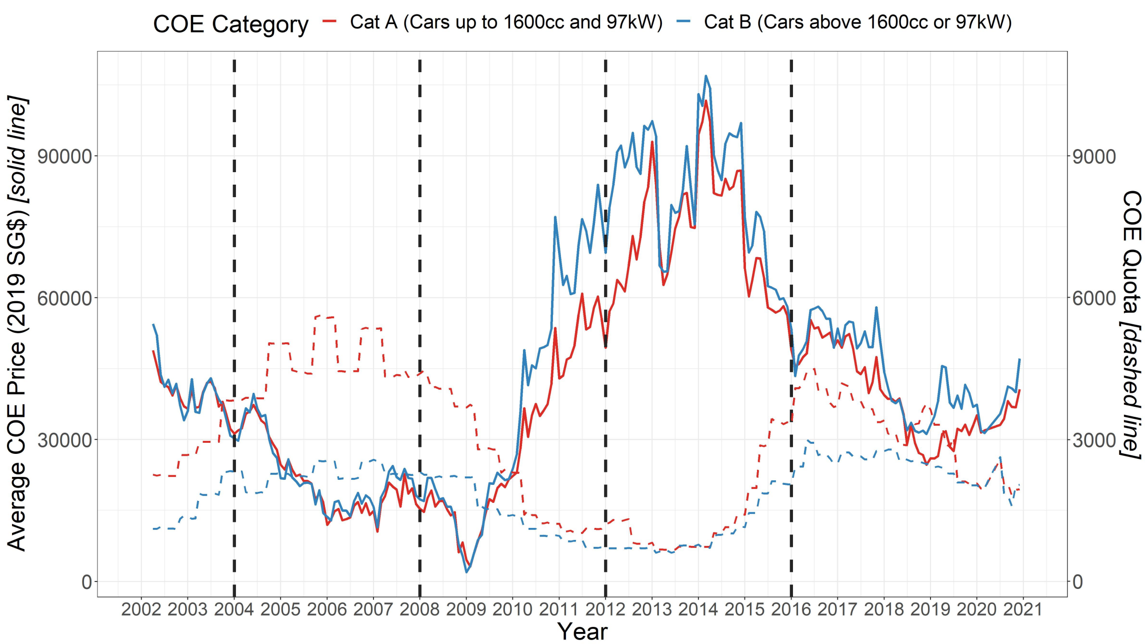


Figure 3-3: Certificate of Entitlement (COE) prices and quotas

Introduced in May 1990, the Vehicle Quota System regulates the rate of growth of vehicles on Singaporean roads, at a rate that can be sustained by developments in the land transport infrastructure. Calculation of the vehicle quota is carried out every three months, and is determined by the number of vehicles de-registered, an allowable growth rate in vehicle population (set by the government), and certain adjustments to account for changes in taxi population, replacements, and expired or cancelled temporary COEs. The allowable growth rate is set to be very restrictive. Starting out at 3% per annum in 1990, it was gradually trimmed until it hit a meager 0.25% per annum in 2015. A landmark announcement in

[27] `https://onemotoring.lta.gov.sg/content/onemotoring/home/buying/upfront-vehicle-costs/certificate-of-entitlement--coe-.html`. Last accessed on August 24, 2022.

2018 set the annual growth rate to 0%, essentially freezing the number of private cars and motorcycles in Singapore.[28]

Policies under the Vehicle Quota System have been effective in controlling the overall number of vehicles added to the national fleet. Moreover, high taxes and financial regulations have transformed car ownership into a luxury good in Singapore. Apart from the COE and the ARF, users also have to pay a registration fee, a 20% excise duty on the OMV, and a 7% Goods & Services Tax in addition to operating costs. For example, a new Toyota Corolla Altis, whose OMV is currently 137,888 SGD (inclusive of a COE price of 78,889 SGD) as of July 2022, is estimated to cost 206,991 SGD over a 10-year period.[29] Annual operating costs would include an average of 1,500 SGD on car insurance, 1,000 SGD for servicing and maintenance costs, 742 SGD in road tax, and 3,480 SGD in parking, tolls, and petrol costs.[30] It is estimated that gross monthly household income has to be north of 8,850 SGD (while the mean income is 6,886 SGD) to be able to afford a regular sedan.[31]

Private vehicle use policies

The LTA aims to reduce on-road congestion by harnessing technological advances and adopting a 'pay-as-you-use' principle on road usage. The Area Licensing Scheme (ALS) was introduced in 1975 as a mechanism to charge drivers entering the Central Business District (CBD). However, the initial success of this policy could not be sustained over time as employment opportunities expanded beyond the CBD. The ALS was then extended to major expressways outside the CBD in 1995 through the Road Pricing Scheme (RPS). Finally, the Electronic Road Pricing (ERP) scheme, which integrated the ALS and RPS strategies in an automated manner, was introduced in 1998. Motorists are charged when they use certain roads during peak hours according to the ERP scheme. ERP rates vary according to the location of the road and time period, and are dependent on local traffic conditions. These rates are determined by a quarterly review of traffic speeds of priced roads, and during the June and December school holidays. These calculations are based on an optimal speed range of 20-30 kmph on arterial roads and 45-65 kmph on expressways.[32]

[28] https://www.straitstimes.com/singapore/transport/government-adopts-zero-growth-stance-for-car-motorcycle-populations. Last accessed on August 24, 2022.

[29] https://dollarsandsense.sg/cost-owning-car-singapore/. Last accessed on August 24, 2022.

[30] https://www.valuechampion.sg/costs-car-ownership-singapore. Last accessed on August 24, 2022.

[31] https://blog.seedly.sg/buy-car-how-much-should-be-earning/. Last accessed on August 24, 2022.

[32] https://onemotoring.lta.gov.sg/content/onemotoring/home/driving/ERP/ERP.html. Last accessed on August 24, 2022.

The Off-Peak Car (OPC) scheme was introduced in 1994 by the LTA to curb rush hour traffic by allowing the purchase of a car that can only be used during weekday off-peak hours (7PM - 7AM) at a reduced price. The use of the OPC is unrestricted during weekends and public holidays. Additional incentives are provided in the form of reduced toll costs and road taxes, and lower COE charges. While the original scheme is no longer available for registration or conversion, car owners can register for or convert to the Revised Off-Peak Car (ROPC) scheme that was implemented in 2009. New cars registered under the ROPC scheme can enjoy up to a 17,000 SGD rebate on the Quota Premium for a COE and the ARF. Moreover, there is a flat discount of up to 500 SGD on annual road tax, and off-peak cars tend to have lower insurance premiums as well.[33] There were around 34,000 OPCs in Singapore (as of July 2015), which accounted for only 5.8% of all private cars.[34] One of the reasons behind the low uptake may be the temporal restriction that prohibits drivers from using it as a commute mode for day-shifts. Workers with night-shift jobs (such as blue-collar workers in certain professions) and households that use this car as a second vehicle for recreational weekend trips may be more likely to avail of this scheme.

3.1.4 Housing and mobility policy effects

The Singapore model shows how a range of well-coordinated mobility policies to control both private vehicle ownership and use, and, at the same time, increase the availability and ridership of public transit can contribute to a sustainable mobility future. The three pillars of Singapore's approach to sustainable mobility are reducing auto-dependence, promoting public transport, and integrated land use and transport planning. In a recent policy review paper, Diao (2019) reports that government policies have been successful in constraining auto-dependence, promoting public transit use, mitigating road congestion, and maintaining affordable transit fares.

The tightening of vehicle quota control and improved rail transit accessibility over the last couple of decades have been found to reduce households' desire to purchase cars in the long-term (Song et al., 2021). By constraining vehicle ownership, the vehicle quota control has a significant influence on vehicle use as well. However, this mitigation effect

[33] 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. Last accessed on August 24, 2022.

[34] https://www.straitstimes.com/singapore/transport/more-drawn-to-off-peak-cars. Last accessed on August 24, 2022.

can be partially offset by higher car use among car owners who want to make more out of their investment in private cars, which Song et al. (2020) characterize as a 'sunk cost' effect. Although expressway network expansion does not affect vehicle ownership, it has been found to increase vehicle use (Song et al., 2020). In addition to reducing vehicle ownership, the expansion of the rail transit network reduced vehicle use as well despite the sunk cost effect. Using the opening of the Circle Line as a case study, Dai et al. (2020) explored how travel mode choices can change in response to improved rail transit accessibility using difference-in-differences models. They found an increase in rail transit mode share and a reduction in private car mode share, but bus mode share and trip generation remained unchanged. These results from Singapore highlight how an integrated approach combining pricing measures to discourage vehicle ownership and use, and public transport investment to provide alternatives to driving can be effective in accelerating our journey towards a sustainable mobility future.

The key pillars of the Singaporean housing policy approach have been land acquisition, the HDB-CPF system of government-provided housing that can be purchased using retirement funds, housing market interventions, and the Ethnic Integration Policy. In particular, the Ethnic Integration Policy has facilitated the creation of divergent resale housing markets for different ethnic groups, while reducing the intensity of ethnic enclaves and increasing social integration (Sim et al., 2003). The national housing program aims for universal provision of 99-year leasehold homeownership for all Singaporean residents. The motivation behind public housing provision was to serve development strategies and nation-building processes, rather than creating entitlement to social rights (Heo, 2014). People who purchased public housing recognized the benefits from housing policies as available assets and readily mobilized them over time. However, this almost universal provision system generated a set of perennial competing demands. Homeowners need to be enabled to monetized their public housing property to finance their post-retirement period. In order to facilitate this funding, public housing units need to be allowed to increase in asset value, to keep up with inflation and rising costs of living. At the same time, new public housing units have to be kept affordable for new entrants into the housing market. Chua (2014) argues for monitoring and intervention by the State for the management of these competing demands.

The unusually high levels of State intervention in the public housing market and mobility sector make Singapore quite unique. This is quite evident when we see a home ownership rate of close to 90% (with almost 80% residents living in public housing) and a per-capita car ownership rate of 12%. Singapore bridges the quality of life usually observed in the global North with cultural ideals and aspirations that closely resemble what we find in other Asian countries (especially Southeast Asia, South Asia, and East Asia). Despite these apparent challenges to generalizability, some land use-transport phenomena play out in an expected manner. Using the opening of the Circle Line as a case study, Diao et al. (2017) find evidence of increasing values of non-landed private housing units proximate to the new stations, even after controlling for heterogeneities in housing attributes and local amenities. 'Anticipation' effects are detected as early as one year prior to the opening of the new transit line, but they diminish closer to the actual opening date. More generally, private developers, who act mainly in response to the market, are found to intentionally place housing units in developments close to MRT stations (Zhu and Diao, 2016). As a result, more higher-income households who can afford private housing are accommodated in areas with greater accessibility to MRT.

These trends of transit-induced gentrification and inequitable access to high-accessibility neighborhoods are not unlike what we observe in other countries, as I discussed earlier in Chapter 2. Should we expect similar trends of accessibility-induced gentrification when non-auto accessibility is increased in a more general manner (compared with a specific mechanism, such as the opening of a new transit line)? Will higher-income households out-bid their lower-income counterparts for neighborhoods with better accessibility even in the public housing market? To address these questions, I conduct scenario explorations of how neighborhoods change in response to accessibility improvements and coordinated housing policies in Singapore. My findings from this dissertation can inform integrated land use and transport planning not just in Singapore, but can also provide valuable insights for other cities (or municipalities) aiming to reduce auto-dependence through similar mechanisms.

3.2 Data sources

I used four major data sources in this dissertation, which are described below. The Land Transport Authority (LTA) provided household travel survey data as well as travel skims that describe travel times between zones by different modes. I obtained detailed time-series data on housing transactions from the Urban Redevelopment Authority (URA) and the

Housing and Development Board (HDB). The URA also provided land use and geospatial data that I used to construct various descriptive measures related to the built environment.

3.2.1 Household Information Travel Survey (HITS)

The Household Information Travel Survey (HITS) is a pen-and-paper personal interview (PAPI) retrospective travel survey (as of 2012) that is carried out once every four years and is used to collect data about households, individuals and their travel patterns for one observed working day.[35] The survey contains three sections — household particulars, individual particulars, and trip particulars. Only resident households (i.e., households whose representative or head is a Singapore citizen or Permanent Resident) are targeted and a random one percent of resident households are selected for surveying (with some stratification to ensure adequate representation). For HITS 2012, sociodemographic characteristics of about 10,000 resident households and almost 36,000 individuals were recorded in the first two sections. However, individual data were not recorded for children of ages six or below. The final section contains data about each stage of a trip that each individual (aged above six years) undertook on the day of observation with trip details such as point of origin/destination, travel time, mode, purpose, etc. Data on active (non-motorized) trips and short trips (below 15 minutes) are comparatively limited because of the nature of these questions. The HITS questionnaire is summarized in Table 3.3. The LTA also provided sampling weights at three levels — household, individual, and trip — along with the HITS data, although the procedure they used to compute these weights is unknown to us.

Key sociodemographics of resident households sampled in HITS 2012 are summarized in Table 3.4.[36] The average household size is 3.7, with one child. Each household has almost two workers, while four in ten households have a senior member (aged 60 years or above). Almost one in five (18.1%) households have access to a bike, while over four in ten (41.1%) households have access to a private car. Access to taxis, motorcycles, and off-peak cars are much more limited with fewer than 6% of households reporting affirmatively for each. Around four in five (77.5%) households reported living in public housing, with the majority (53.2%) living in 4-room and 5-room HDB flats. Consistent with other government agencies, the LTA also assigns the ethnicity of the household head to the entire household,

[35] The LTA experimented with a combination of PAPI and computer assisted web interviewing (CAWI) for recording week-long travel diaries in 2016, before transitioning completely to CAWI in 2021.

[36] Reported values are weighted by household sampling weights.

Table 3.3: Description of HITS questionnaire

Section	Variable	Original Encoding	Examples
Household	Dwelling type	Categorical	HDB 1-room, private flat, etc.
	Dwelling location	Categorical	Postcode, if available
	Ethnicity	Categorical	Chinese, Malay, Indian, etc.
	Household size	Continuous	1, 2, etc.
	Available vehicles	Categorical	Normal car, Taxi, Bike, etc.
	Vehicle properties	Categorical	Registered, Rental, etc.
	Sampling weight	Continuous	50, 100, etc. (can be fractional)
Individual	Age	Categorical	6-9 years, 10-14 years, etc.
	Resident status	Categorical	Citizen, Permanent resident, etc.
	Gender	Categorical	Male, Female
	Driving license	Categorical	Car, Motorcycle, etc.
	Employment status	Categorical	Employed full-time, Student, etc.
	Occupation	Categorical	Professional, Service and sales, etc.
	Industry	Categorical	Manufacturing, Construction, etc.
	Job location	Categorical	Postcode, if available
	Monthly income	Categorical	No income, \$1-\$1000, Refused, etc.
	Sampling weight	Continuous	50, 100, etc. (can be fractional)
Trip	Origin	Categorical	Postcode, if available
	Destination	Categorical	Postcode, if available
	Start time	Continuous	0001-2400
	End time	Continuous	0001-2400
	Mode	Categorical	Car, Bus, MRT, etc.
	Purpose	Continuous	Work, Pick-up/drop-off, etc.
	Sampling weight	Continuous	50, 100, etc. (can be fractional)

thereby recording ethnicity as a household-level variables in HITS. Over two in three (67.9%) households reported being ethnic Chinese, while ethnic Malays and Indians accounted for 15.6% and 8.7% of the sampled resident households. All of the household sociodemographic indicators obtained from HITS 2012 are largely consistent with those reported by Singstat.

Table 3.4: Summary of HITS household data

Household sociodemographics	
Average household size	3.7
Average number of children (<19 years old)	1.0
Average number of seniors (>60 years old)	0.4
Average number of workers	1.7
Average household income (SGD / month)	\$6,759
Private mobility holdings	
Households with bikes (%)	18.1%
Households with taxis (%)	1.5%
Households with motorcycles (%)	5.6%
Households with off-peak cars (%)	2.1%
Households with 'normal' cars (%)	41.1%
Unit type	
Public housing (HDB)	77.5%
1-room and 2-room flats (HDB12)	5.5%
3-room flats (HDB3)	18.8%
4-room flats (HDB4)	29.2%
5-room flats (HDB5)	24.0%
Private housing	22.3%
Condos & Apartments	15.8%
Landed properties	6.5%
Ethnicity	
Chinese	67.9%
Malay	15.6%
Indian	8.7%
Other	7.8%

Key sociodemographics of the individual members of resident households sampled in

HITS 2012 are summarized in Table 3.5.[37] One in four (25.1%) of individuals recorded in HITS are below 20 years old. The gender spilt is almost equal, with a slight skew in favor of males. Six in ten (60.9%) individuals are employed, while two in ten (20.9%) are full-time students. A third of recorded individuals have completed at most primary school, while almost a quarter (22.2%) have obtained a degree from some college or university. All of the individual sociodemographic indicators obtained from HITS 2012 are largely consistent with those reported by Singstat.

I used data from the HITS 2012 sample to estimate several long-term urban choice models, such as the screening model, willingness-to-pay model, and vehicle availability model (see Section 4.3 for further details). Having used the 2012 dataset in previous research (Basu, 2019), I did not have to redo a couple of important data processing steps — imputing missing or unknown incomes and generating continuous income values, and adjusting taxi counts.

A significant share (19.3%) of individuals (aged six years or above) in the HITS 2012 sample had missing incomes, which could be because they refused to report their income or the respondent for the household did not know the income of that particular individual. Moreover, individual income was reported as a categorical variable. Therefore, I had to impute the missing incomes and then convert all the categorical values to continuous values. First, I predicted income categories for the missing income cases using a supervised classification (random forest) model calibrated on individual and household characteristics. Then, I created a log-normal distribution for income and randomly sampled from this distribution to obtain a continuous income value for each individual. I constrained the sampling procedure to ensure that the randomly picked value corresponded to the income category reported in HITS. Finally, I summed the individual incomes across households to obtain continuous income estimates for each household. Average household and individual incomes for the HITS 2012 sample are reported in Tables 3.4 and 3.5 respectively.

Taxi counts were underestimated in the HITS 2012 sample, and required adjustment as households with a taxi are unlikely to own an additional private car. The total taxi count in the weighted HITS sample was around 18,500, while the actual taxi count in Singapore in 2012 was close to 28,000.[38] Therefore, I identified households that would be most likely to

[37]Reported values are weighted by individual sampling weights. Except for age, other indicators are computed only for individuals aged six years or above, as detailed data on children below six years of age are not recorded.

[38]`https://data.gov.sg/dataset/annual-motor-vehicle-population-by-vehicle-type`. Last accessed on August 24, 2022.

Table 3.5: Summary of HITS individual data

Individual sociodemographics	
Average worker income (SGD / month)	$3,929
Age	
Below 20 years	25.1%
20 to 64 years	67.0%
65 years or above	8.0%
Gender	
Male	50.6%
Female	49.4%
Employment status	
Employed	60.9%
Unemployed	0.8%
Full-time student	20.9%
Homemaker	6.1%
Retired	6.7%
Domestic worker	4.7%
Highest educational qualification	
Less than primary school	3.7%
Primary school	33.1%
Secondary school	41.0%
Some college	15.9%
University	6.3%

own a taxi based on individual characteristics such as employment status, occupation type, and industry sector. I then used an imputation method to randomly assign taxis to a subset of these selected households through a weighted iterative proportional fitting procedure such that the total taxi count reached close to 28,000. Following this adjustment, 2.3% of sampled households had access to a taxi, instead of the reported 1.5%.

3.2.2 Housing transactions

The URA provides detailed data on private housing transactions since 1995 through their Real Estate Information System (REALIS) platform. Data are sourced from 'caveats' lodged with the Singapore Land Authority (SLA). A caveat is a legal document usually lodged by the buyer with the SLA to protect their legal interest soon after an option to purchase a property is exercised or a sale and purchase agreement is signed. The reported price is the agreed purchase price of the property between the buyer and the seller as entered in the contract. This dataset contains both new sale and resale transactions. Available data fields include the address (which can be geolocated since the postcode is part of the address), unit type (i.e., apartment, condominium, landed property, etc.), unit size, construction date, transaction date, sale price, and type of sale (i.e., new sale or resale).

As mentioned earlier, the HDB has been building new public housing projects through the BTO program for several years now. These BTOs are sold at fixed and published prices before applying household-specific subsidies. My scenario analyses exclude BTOs because I consider the city as a closed system in my simulations (see Section 5.2.1), so I need detailed data only for HDB flats that were resold on the open market. HDB has an interactive platform where one may search for the resale price of any HDB unit by specifying the address and unit type. My colleagues have scraped this website to create a time-series dataset of HDB resale transactions. Available data fields include the address (which has to be geocoded since the postcode is absent), unit type (depending on the number of rooms in the unit), unit size, construction date, transaction date, and sale price.

As I chose 2012 as my reference year due to the availability of the HITS sample data, I extracted data on HDB resale transactions and all private housing transactions from the aforementioned datasets between January 1, 2011 and December 31, 2014. I included buffer years around 2012 to guard against the possibility of the sale prices being influenced by particular macroeconomic phenomena that I may not be able to control for. Including data from a multi-year period also provides a comparatively better understanding of stable housing market trends such as the relationship of market value and proximity to amenities. I adjusted the sale prices for inflation and used these data to estimate housing models such as the hedonic price model and the willingness-to-pay model (described in Section 4.3).

I summarize the housing transaction data for the different unit types in the two housing markets (public and private) in Table 3.6. Data for HDB3, HDB4, HDB5, and condominiums and apartments are quite voluminous, with at least 20,000 transactions recorded over the four-year period (i.e., 2011 to 2014). Average sale prices of HDB units increase with the number of rooms in the unit, but 1-room and 2-room HDB flats are the most expensive after the sale prices are adjusted for flat area. Condominiums and apartments cost more than twice the price of a 5-room HDB flat on average, while the area-adjusted sale price is almost thrice as high. Landed properties cost close to 4.5 million SGD on average, although the area-adjusted sale price is similar to that of a condo or apartment.

Table 3.6: Summary of housing transaction data

Housing market	*Sale type*	*Unit type*	*Number of transactions (2011-14)*	*Average sale price (2012-SGD)*	*Avg. sale price per unit area (2012-SGD / sq.ft.)*
Public	Resales only	HDB12	844	\$ 265,713	\$ 559 / sq.ft.
		HDB3	21,949	\$ 347,130	\$ 475 / sq.ft.
		HDB4	28,962	\$ 452,871	\$ 441 / sq.ft.
		HDB5	23,996	\$ 563,131	\$ 420 / sq.ft.
Private	Both new sales and resales	Condos & Apts.	90,926	\$ 1,346,933	\$ 1,199 / sq.ft.
		Landed properties	4,685	\$ 4,402,903	\$ 1,131 / sq.ft.

3.2.3 Built environment and land use

Since the residential location of each household and job location of each worker (in HITS) and the location of each housing unit (in REALIS) are recorded as postcodes, it is possible to geolocate each individual, household, and housing unit at the building level. We used this fine-grained detail to construct various geospatial measures related to the built environment and land use. First, we incorporated built environment data by calculating Euclidian distances to various amenities like bus stops, MRT stations, primary schools, shopping malls, and expressway (on/off access) ramps from each postcode. Second, I constructed land use descriptors of the area around each postcode using the 2008 Master Plan provided by the URA. I computed densities of housing and jobs in a 500 meter (Euclidian distance) circular buffer around each postcode. I also constructed similar buffers of 1000 meter radii around each postcode and computed the shares of area covered by seven different land use categories (i.e., residential, commercial, industrial, office, institutional, infrastructural, and undeveloped). Additionally, I combined these land use area shares to construct a Generalized Land Use Diversity Index (GLUDI) using the following formula:

$$GLUDI = 1 - \left[\frac{\sum_{j=1}^{N} \left| \frac{A_j}{T} - \frac{1}{N} \right|}{2\left(1 - \frac{1}{N}\right)} \right] \tag{3.1}$$

where there are $N(=7)$ different types of land uses, A_j represents the area occupied by the jth land use type in the 1000 meter buffer around the postcode, and $T = \sum_{j=1}^{N} A_j$ represents the total land area in the buffer. This index captures the mix of land uses relative to a perfectly equal distribution of uses. When the land in the buffer has a single use, the index achieves a value of zero. On the other hand, a value of one indicates perfectly equal mixing among the $N(=7)$ different land uses. These postcode-level geospatial variables are summarized in Table 3.7.

3.2.4 Travel skims

The LTA also provided travel skims that include estimates of travel time and cost for every possible origin-destination (OD) pair at the Traffic Analysis Zone (TAZ) level differentiated by direction (i.e., TAZ $i \rightarrow$ TAZ j is recorded separately from TAZ $j \rightarrow$ TAZ i), mode (i.e., car and public transit), and peak period (i.e., AM peak, off-peak, and PM peak). While the travel time using car was directly reported for each OD, I calculated total public transit travel time by adding up the in-vehicle travel time, walking time, and waiting time estimates provided in the skims. I used the public transit commute times and commute time differences (between transit and car) as explanatory variables in the long-term behavioral models described in Section 4.3. Although I used the commute time for the household head to explain residential location and private vehicle holding choices, I summarize the weighted average travel times to all jobs using car and public transit for each postcode in Table 3.7. There is a difference of over 30 minutes between public transit and car travel times to all jobs on average.

3.3 Summary

In this chapter, I provided an overview of the contextual setting of this dissertation — the city-state of Singapore. I discussed how the Singaporean government has pursued a top-down approach towards land use planning, public housing provision, and private vehicle ownership

Table 3.7: Summary of postcode-level spatial data

	Mean	***Std. Dev.***
Distances to amenities (kms)		
Distance to bus stop	0.21	0.34
Distance to MRT station	1.16	0.90
Distance to primary school	1.74	1.56
Distance to shopping mall	1.15	1.10
Distance to expressway ramp	1.26	0.95
Land Use indicators		
Housing density in 500-m buffer (units / sq.km.)	4,971	3,499
Job density in 500-m buffer (jobs / sq.km.)	11,103	33,631
Residential area in 1-km buffer (%)	43.0%	18.3%
Commercial area in 1-km buffer (%)	3.4%	5.7%
Industrial area in 1-km buffer (%)	6.2%	13.4%
Office area in 1-km buffer (%)	3.0%	5.3%
Institutional area in 1-km buffer (%)	8.2%	5.6%
Infrastructural area in 1-km buffer (%)	18.9%	5.0%
Undeveloped area in 1-km buffer (%)	15.3%	13.7%
Generalized Land Use Diversity Index	0.46	0.11
Commute time indicators		
Travel time to jobs using car (mins)	25.2	7.6
Travel time to jobs using public transit (mins)	57.1	11.3

and use regulation. The public agencies overlooking these objectives (URA, HDB, and LTA) were our partners on the Future Urban Mobility (FM) research program and assisted us by providing us with relevant data sources and invaluable contextual information. I also briefly described the various data sources I used for this dissertation, namely a household travel survey, housing transactions for both public and private housing, built environment and land use, and travel skims. The next chapter discusses the LUTI model we have been developing in-house at FM (SimMobility). I will also present estimation results for various long-term behavioral models using the data sources mentioned above.

Chapter 4

SimMobility: A LUTI model for the emerging mobility era

SimMobility is a multi-scale agent-based integrated microsimulation platform that incorporates time-scale dependent behavioral modeling through an activity-based travel demand framework (Adnan et al., 2016). It has been developed by the Future Urban Mobility (FM) research group under the Singapore-MIT Alliance for Research and Technology (SMART) program. 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 (such as mobility-on-demand and automated vehicles) to evaluation of alternative future scenarios of land use, infrastructure, and behavioral change. Our recent efforts demonstrate how SimMobility can be used to understand the impact of automated mobility on housing-mobility choices (Basu and Ferreira, 2020a; Zhou et al., 2021), private vehicle holdings (Basu and Ferreira, 2020b), and the future of mass transit (Basu et al., 2018), in addition to highlighting the potential for sustainable mobility futures (Oke et al., 2019). *SimMobility* encompasses three major components:

- **Long-Term (LT):** This detailed land use-transport simulator is used to simulate changes in location (e.g., residential, job, and school) and private vehicle holdings using a synthetic population of households (Zhu and Ferreira Jr, 2014), firms and establishments (Le et al., 2016), and built environment with sufficient spatial and demographic detail to enable estimation and calibration of various choice models such as household-level residential location and vehicle availability choices, and individual-level job and school 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 (Lu et al., 2015; 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).

Across different timescales, SimMobility follows an event-driven, activity-based paradigm, simulating both demand and supply at each level and the interactions between different levels. As shown in Figure 4-1, LT provides (household and firm) population characteristics (including locations) and land-use configurations to MT, which transmits trip chains to ST. In the other direction, ST provides traffic performance measures to MT, which feeds activity-based accessibility measures back to LT.

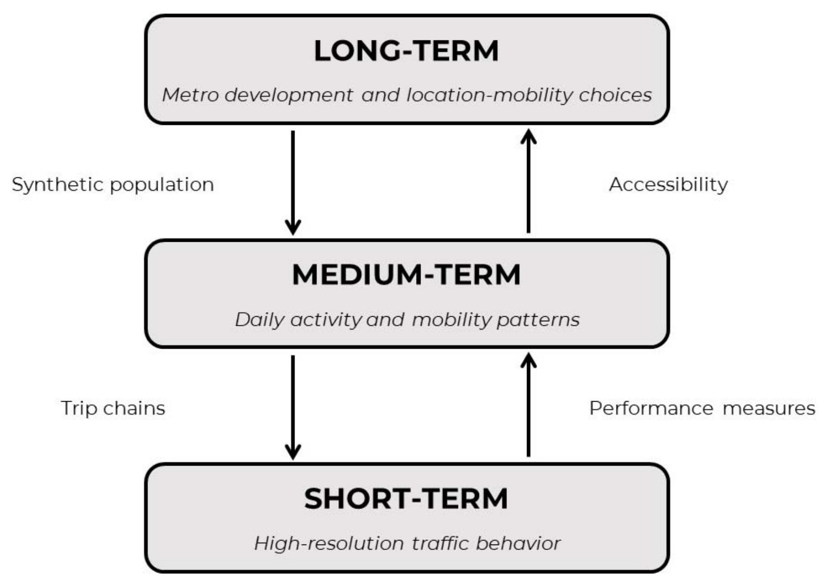


Figure 4-1: SimMobility framework

4.1 Activity-based accessibility (ABA)

The LT and MT components are connected through activity-based accessibility (ABA) measures that represent the expected maximum utility (or 'logsum') values of individuals' daily activity patterns (i.e., combinations of activities, destinations, and modes), as shown in Figure 4-2. In addition to reflecting individual preferences based on actual choices made, ABA measures are also directly linked to traditional measures of consumer surplus (Small and Rosen, 1981).

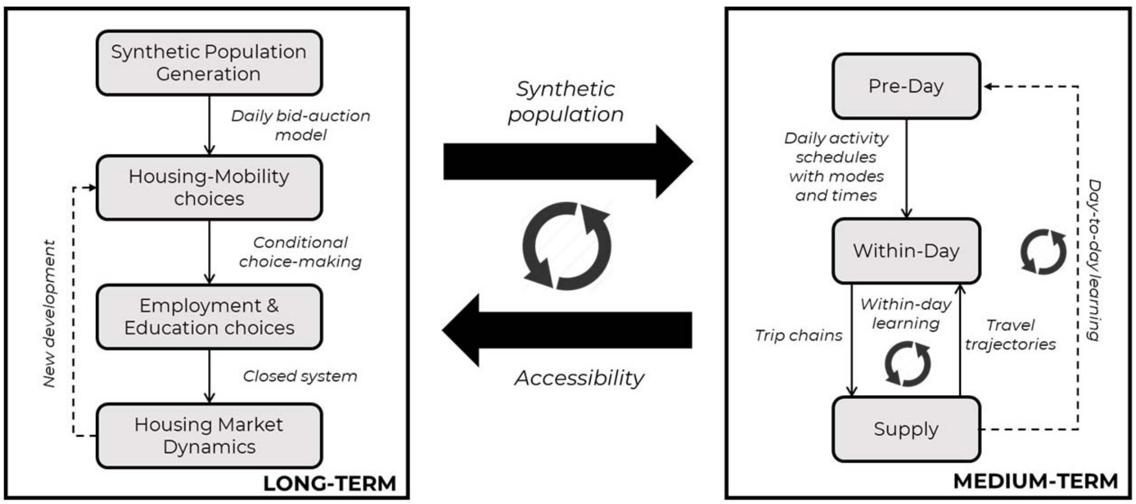


Figure 4-2: Integration between SimMobility Long-Term and Medium-Term

In the disaggregate discrete choice modeling framework, the utility of an alternative is defined as:

$$U_{jn} \ = \ V(X_{jn}, Z_n, \beta) \ + \ \epsilon_{jn} \tag{4.1}$$

where V represents a systematic utility function, X_{jn} is a vector of attributes of the alternatives j for decision-maker n, Z_n is a vector of sociodemographic characteristics of the decision-maker, β is a vector of unknown parameters that need to be estimated, and ϵ_{jn} represents the random, unobservable, unknown component (or the error term) of utility. In logit choice models, the error term is assumed to follow an independent and identical (i.i.d.) Gumbel distribution with a scale parameter μ. The choice probability of each alternative can be written as:

$$P_n(i) = \frac{\exp(\mu V_{in})}{\sum_{j=1}^{J} \exp(\mu V_{jn})} \tag{4.2}$$

The denominator of this probability expression constitutes the expected maximum utility (or 'logsum') from the set of relevant alternatives. This logsum value represents the value of the decision-maker's entire choice set.

$$E\Big(\max_{i \,\in\, C_n} U_{in}\Big) = \frac{1}{\mu} \ln \left(\sum_{i \,\in\, C_n} \exp(\mu V_{in}) \right) \tag{4.3}$$

where V_{in} is the systematic component of utility U_{in} for decision-maker n choosing one alternative from the choice set C_n. This 'logsum' term serves as a summary measure of the utility of the entire choice set, and has been characterized as a reasonable measure of accessibility by Ben-Akiva and Lerman (1985). In the case of the more general nested logit model, the logsums pass up the choice chain, whereby the logsums from the lower-level choices (e.g., mode choice) are included in the systematic utility component of higher levels (e.g., destination choice) up to the highest level (e.g., activity pattern choice). The logsum calculated for the highest level represents the expected value of the full choice set (e.g., of activity-travel patterns) to the decision-maker.

Ben-Akiva and Bowman (1998) build on this framework to demonstrate how activity-based travel demand models can be integrated with residential location choices. In their case study, activity-based accessibility (ABA) represents an individual's maximum utility from their available activity schedules (i.e., combinations of activities, destinations, and modes), given a residential location. This approach allows for individuals to have different accessibilities at different residential locations. In addition to reflecting individual differences in preferences for activity schedules (including destinations and modes), the ABA measure also incorporates the possibilities for activity substitution, trip chaining, and other behaviors that might be influenced by variations in location choices (Ben-Akiva and Bowman, 1998). Thus, the ABA is a disaggregate, behaviorally rooted way of representing the interactions between an individual's long-term choices (such as residential location) and their preferred activity schedules.

In SimMobility Medium-Term (MT), we have extended this approach to other long-term choices such as job location and private vehicle holdings as well. The activity-based travel demand modeling framework used in MT is presented in Figure 4-3. It has been applied by my colleagues to model travel demand in both Singapore and Greater Boston (Siyu, 2015; Viegas de Lima et al., 2018). The framework uses a sequence of discrete choice models, which are functions of different personal characteristics and transport system attributes, divided into three sections — (a) the Day Pattern Level, (b) the Tour Level, and (c) the Intermediate Stop Level. Each of these levels is conditional on the one(s) above and are linked via logsum values.

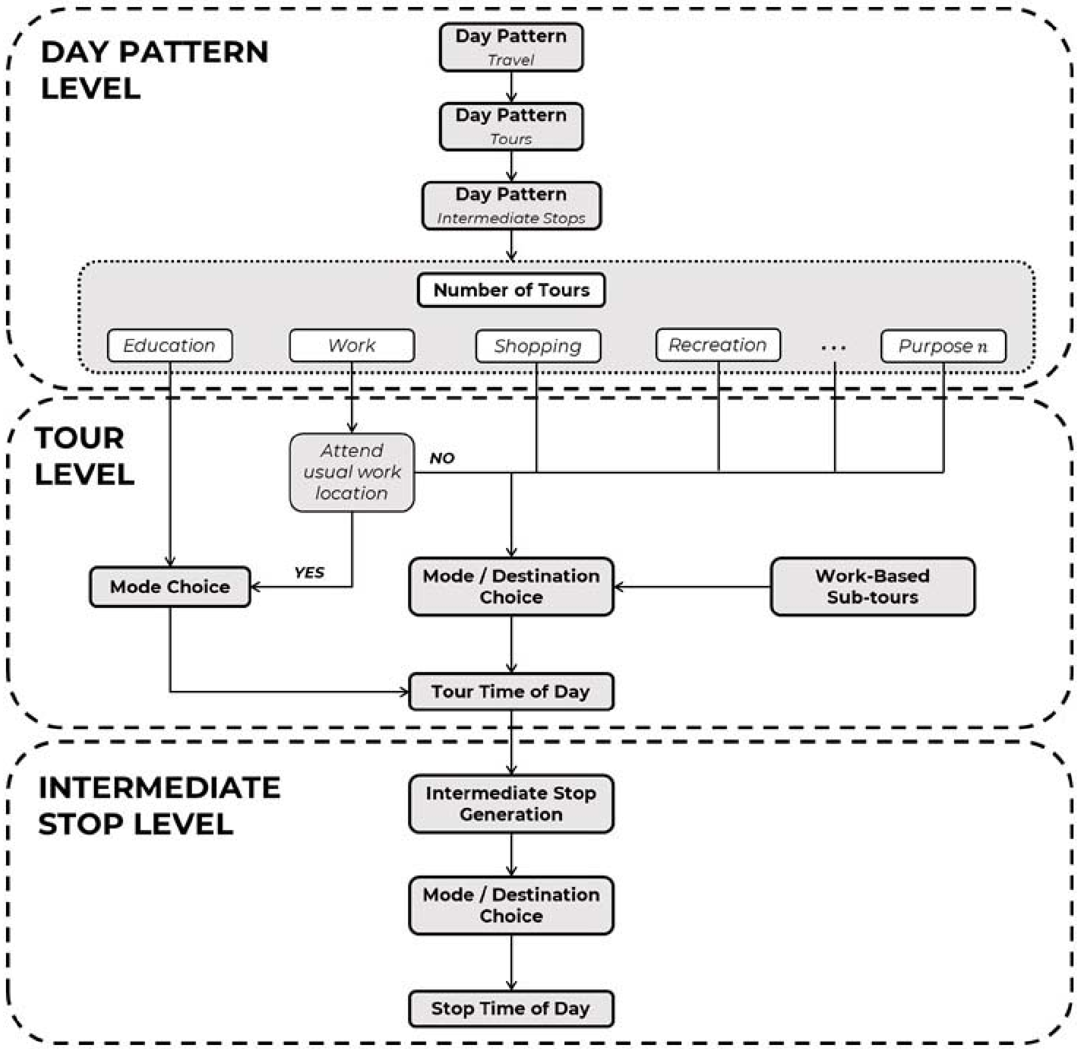


Figure 4-3: Activity-based travel demand modeling framework in SimMobility Medium-Term

First, the Day Pattern Level determines whether the individual will choose to travel on the given day, and if they do, what activity purposes their tours may have, and what types of intermediate stops those tours may contain. It also determines how many tours of each chosen tour purpose the individual will chose to participate in. Then, the Tour Level is executed for each chosen tour. It determines the mode, destination, and start and end times for each activity. For work tours, work-based sub-tours (i.e., originating and ending at work during the duration of the work activity) may also be included. The mode, destination, and time-of-day for these sub-tours are modeled as well. Finally, the Intermediate Stop Level generates stops for trips to and from the primary activity. Purpose, mode, destination, and time-of-day are all modeled for each intermediate stop. To represent the nested nature of the decision-making process, expected utilities (or logsums) from the lower-level models are included in the higher-level models. Additional details on each of these models can be found in Viegas de Lima et al. (2018).

Using this framework, we can compute different individual-level ABAs conditional on different long-term choices (such as residential location, job location, and private vehicle holdings) using MT. For example, let us consider an individual living in the ith Traffic Analysis Zone (TAZ) and working in the jth TAZ. We can obtain different ABAs for each individual pertaining to cases such as (a) *fixed home - variable work - fixed vehicle holdings*, where the individual can choose from all possible TAZs for their work location while keeping the residential location (TAZ i) and private vehicle holdings fixed, (b) *variable home - fixed work - fixed vehicle holdings*, where the work location (TAZ j) and private vehicle holdings are fixed but the residential location is allowed to vary, and (c) *fixed home - fixed work - varying vehicle holdings*, where the individual considers different private vehicle options while keeping their home and work locations fixed. For every possible combination of home TAZ, work TAZ, and vehicle holding option, we can use MT to generate a distinct logsum value representing the activity-based accessibility of each individual in the synthetic population.

These ABAs are used as explanatory independent variables in LT behavioral choice models such as residential location choice, job location choice, and vehicle availability choice. Since both residential location choice and vehicle availability choice are household-level decisions, we need a household-level accessibility measure that can be provided as input to these two models. However, a 'true' household-level ABA would require the incorporation of intra-household interactions as well as scaling the logsum to 'real' units (e.g., dollars or minutes). Unfortunately, intra-household interactions (e.g., how members share the use of one car, or how members of a multi-worker household jointly decide on a residential location) are not provided in the data sources I am using (nor in standard household travel surveys used across the world). Moreover, we have not yet developed satisfactory time- or cost-based scaling factors for the logsum accessibility measures (see Dong et al. (2006)). Therefore, we approximate a household's accessibility by using that of its highest income worker (or, if the household has no worker, the ABA of the oldest member).

I estimated two of the LT sub-models (willigness-to-pay and private vehicle availability) using household-level ABAs as accessibility measures (see Sections 4.3.4 and 4.3.5). To test whether a 'simpler' accessibility measure would provide similar scenario analysis results, I also estimated these two models separately using public transit commute times for the household head (or average transit times from the home location to all jobs, if the household head was not a worker), instead of the more behaviorally rooted and disaggregate ABA (see Tables A.5 and A.7), and used them to conduct a scenario analysis robustness check (see Section 6.2.3). In related research, my colleagues have found disaggregate, utility-based accessibility measures to better represent vehicle ownership decisions and property valuations compared with more aggregate, potential-based measures such as gravity-based accessibility (He et al., 2019).

4.2 SimMobility Long-Term (LT) framework

The SimMobility Long-Term (LT) component is designed to simulate how the interrelationships between the transportation and land-use systems manifest themselves in the housing and commercial real estate markets, household and firm location choices, school and workplace choices, and private vehicle availability choices. In this section, I will describe the demand dynamics of the residential housing market implementation as this is the main focus of the dissertation. The following section will provide further details on the specification and estimation results of different LT sub-models. The reader is invited to refer to Zhu et al. (2018) for additional details on the LT framework (such as real estate supply dynamics).

Using external data sources, a 'day-0' synthetic population of individuals, households, housing units, firms, establishments, and commercial spaces is created in a manner that richly represents their characteristics and spatial locations (Zhu and Ferreira Jr, 2014; Zhou et al., 2022). The 2012 Singapore synthetic population includes around 5.2 million individuals[1], 1.15 million households, 1.4 million housing units, and 170,000 establishments. Most

[1]Although MT simulates activity-travel patterns for all 5.2 million individuals, we exclude 1.16 million construction workers, work permit holders, and other foreigners from the housing market simulation in LT because only resident households with at least one citizen or permanent resident have access to the housing market in Singapore.

LUTI models assign individuals to home and, if applicable, work TAZs, but we go beyond that by assigning each household to a particular housing unit in a specific building. Unoccupied units available for sale constitute the majority of the housing market supply, where both resales and new sales (including units available for advance purchase) are modeled. Sellers set asking prices slightly higher than the perceived market prices that are determined through the *hedonic price model*. Instead of modeling sales and price adjustments as quarterly or annual events (as in UrbanSim and ILUTE), the LT framework models housing market transactions as a daily bidding process among those buyers and sellers estimated to be actively engaged in searching for housing and negotiating sales (see Figure 4-4).

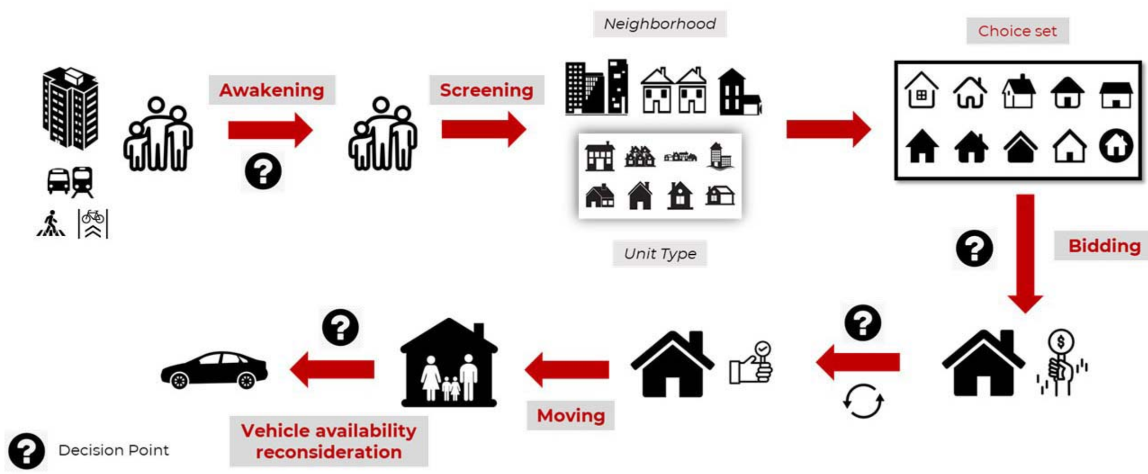


Figure 4-4: Bidding process in SimMobility Long-Term

Potential buyers are drawn from the entire pool of households in the synthetic population based on an explicit probabilistic *awakening model*. The total number of households awakened each day is a modeler-defined parameter (which we estimate based on annual sales and rough estimates of search time and bidding success rates). The awakening likelihoods are multiplied by the overall daily awakening rate to determine the probability that a dormant household will be awakened on any particular day. When a household is awakened, we determine probabilistically whether it will switch tenure type (own or rent). After determining a desired tenure type, a household will continue searching until it bids successfully on a housing unit, or gives up after a number of unsuccessful attempts. Certain households are prevented from being awakened, e.g., all successful bids take at least 30 days to close and advance purchase of unfinished units might delay occupancy by up to four years. Households with such pending sales cannot be (re)awakened. Similarly, unsuccessful bidders have a ‘cooling off’ period and successful bidders have a ‘settling in’ period before they are allowed to return to the pool of potentially awakened households.

The *screening model* determines how awakened households shortlist potential units for consideration based on their preferences for unit type and neighborhood. On any given day, a household’s choice set is formed by drawing 30+ units probabilistically from all available-for-occupancy housing units of the same tenure status as the household’s desired tenure type. The likelihood that a housing unit is included in the choice set of an awakened household is proportional to the screening probabilities that estimate the odds of that household choosing to live in the planning region and unit type that match the candidate housing unit. This approach attempts to mimic the typical search process whereby households tend to narrow their search to particular zones (or neighborhoods) and housing types. We also include ‘affordability’ and ‘eligibility’ constraints that help in the construction of plausible choice sets for all active households by guarding against the inclusion of unlikely candidates in the choice sets and allowing for consideration of government subsidies that are available only to eligible households. The maximum price the household can afford to pay is based on their monthly income, number and age of workers, and the market or rental value of their current residential unit.

Active buyers then evaluate each housing unit in their choice set by determining their *willingness-to-pay* for the unit and the optimal bid that would maximize the expected utility of the unit (including the likelihood that the offer is accepted by the seller). This approach follows Rocco (2014) who builds upon Lerman and Kern (1983). Households are heterogeneous in their valuation of housing bundle characteristics, and the market prices represent some amalgamation of the preferences of those types of households that tend to win the bidding for particular types of locations and housing units. Among units in the choice set, a household bids for the unit that maximizes the expected consumer surplus, provided it is higher than the surplus for their current housing unit. If no unit in the choice set provides positive surplus or the currently occupied unit provides the maximum surplus, the household does not bid that day. Simply placing a bid does not guarantee success. If the seller rejects the buyer’s bid (e.g., for being lower than another bidder or their target price), the buyer will consider forgoing some utility surplus if re-bidding for the same unit on a subsequent day with an improved offer remains promising. The number of days buyers remain actively searching for housing is capped at a few months out of every year and households may forgo surplus or choose to stop searching if, even after several weeks of searching, they remain unsuccessful in bidding for suitable housing.

After successful buyers move into their new housing units, they reassess the job and school assignments of their household members, and reconsider *private vehicle availability*. This reconsideration is based on the location characteristics (such as transport infrastructure and supply, commute distance, and distances to amenities) of the new housing unit. As private vehicle availability is reconsidered after the household has moved into their new unit, this housing-mobility choice framework can be termed as '*sequential*.' I also describe a *simultaneous* choice framework in Section 4.4.3 as a methodological extension which considers both residential location and private vehicle availability together in the bidding process.

4.3 Long-Term (LT) sub-models

In this section, I will provide details on the specification and estimation of the five major sub-models within the Long-Term (LT) framework — (a) the awakening model, (b) the screening model, (c) the hedonic price model, (d) the willingness-to-pay model, and (e) the private vehicle availability model. The LT framework also includes job and school location choice models but I do not describe them here as they are not used in this dissertation.

4.3.1 Awakening model

The awakening model is an external probabilistic model that was calibrated using Singapore census data in addition to a 'recent mover' survey of 6,000 households (including 1,000 who had moved at least once in the prior three years) conducted in 2017 (Shaw, 2018). I report the awakening probabilities (or moving rates) and tenure transition probabilities used for the awakening model in Table 4.1. These probabilities are based on the age of the household head (which is a proxy for where the household is in their life course) and their current tenure status (own or rent). Each day, a weighted Monte Carlo coin flip is used to select households to be awakened from the pool of households that are not 'off market' (because of a recent failed or successful search). Once a household is awakened, the tenure transition rate is used to determine whether their search is to purchase a housing unit or find a rental. This second weighted Monte Carlo coin flip determines, for the duration of their search period, whether they attempt to buy a housing unit or get a rental.

Regardless of the age of household head, renters are twice as likely to move than owners reflecting a greater degree of churn in the rental market. The probability of moving also reduces with an increase in the age of the household head. For example, younger households headed by an individual aged less than 35 years have a 20% annual likelihood of moving if they currently own their unit. However, the same likelihood for older households headed by an individual aged more than 65 years drops to only 4%.

Table 4.1: Estimated awakening and tenure transition probabilities for households

Age of household head	**Current tenure**	**Future tenure**	**Awakening probability**	**Transition probability**
Less than 35 years	Own	Own	0.20	0.94
	Own	Rent	0.20	0.06
	Rent	Own	0.40	0.20
	Rent	Rent	0.40	0.80
35 to 49 years	Own	Own	0.10	0.95
	Own	Rent	0.10	0.05
	Rent	Own	0.20	0.07
	Rent	Rent	0.20	0.93
50 to 64 years	Own	Own	0.05	0.93
	Own	Rent	0.05	0.07
	Rent	Own	0.10	0.13
	Rent	Rent	0.10	0.87
More than 65 years	Own	Own	0.04	0.89
	Own	Rent	0.04	0.11
	Rent	Own	0.08	0.29
	Rent	Rent	0.08	0.71

After a household has been awakened, they are always much more likely to retain their tenure status than switch. Younger owners have a 94% likelihood to remain owners, while older owners have a 89% likelihood to do the same. The rent-to-own transition probabilities are comparatively larger for the youngest age group (20%) and the oldest age group (29%), reflecting rising household incomes (and an aspiration for home ownership) and wealth accumulation respectively. The own-to-rent transition is most likely (11%) for older homeowners, whose decision may be influenced by a loss of income (stemming from retirement or inability to work) or a reduction in household size (e.g., through becoming empty nesters or losing a partner). For implementation in SimMobility LT, we assume tenure transition probabilities to be independent of the decision to move (i.e., awakening probabilities).

4.3.2 Screening model

The screening model is estimated from the 2012 HITS sample data which reported the location (at the postcode level) and housing unit type of each household along with their sociodemographics. I constructed a choice set for each household where every combination of zone (at the planning region level) and housing unit type was included as an alternative to the planning region-unit type combination they reported as having actually chosen. I then estimated a multinomial logit choice model of household preferences for location and housing type jointly. The data are summarized in Table A.1 and the estimation results are reported in Table 4.2.

Three groups of variables were used to explain household preferences for location and housing type. The first group describes the characteristics of the zone (planning region). All else equal, zones that are located far from amenities such as MRT stations and primary schools or require long transit commute times on average are less likely to be chosen as desirable residential locations. Households display an inclination for zones that have diverse land use with an affinity for residential and undeveloped land uses (the latter may reflect proximity to green spaces and water bodies) and a relative aversion for living in areas dominated by commercial land use.

The second group of variables relates to the behavior proposed by Schelling's segregation model where people have in-group preference towards their own group (Schelling, 1971). Based on this assumption, I interacted household characteristics with zonal sociodemographics. Households are found to choose zone-unit type categories that reflect similar income levels and household sizes. I also detect ethnic biases in zonal preferences among house-hunters, which are especially strong for minority non-Chinese groups such as Indians and Malays. Additionally, I find that households with children, teenagers, or seniors prefer zones where similar types of households have an established presence. This may reflect the mediating influence of urban design oriented towards special groups such as children and seniors (e.g., parks, playgrounds, community centers, wider sidewalks, etc.), or desired social networks.

Finally, the third group of variables I constructed tries to capture household preferences for certain types of housing units. For example, bigger households (with more than 3 members) prefer neighborhoods with a higher share of comparatively larger-sized public housing

Table 4.2: Estimation results for household-level screening model

	β	*S.E.*
Average distance to MRT station (weighted average of postcodes in zone)	-0.158	0.121
Average distance to top-30 primary school (weighted average of postcodes in zone)	-0.171***	0.0337
Average transit travel time to all jobs (weighted average of postcodes in zone)	-0.392	0.295
Land Use Diversity (weighted average of postcodes in zone)	5.94***	0.835
Share of total housing units in zone-unit type category (%)	2.91***	0.0639
% of residential area (weighted average of postcodes in zone)	3.78***	0.554
% of commercial area (weighted average of postcodes in zone)	-8.01***	0.779
% of undeveloped area (weighted average of postcodes in zone)	3.2***	0.707
Income difference of household and zone-unit type category average	-1.23***	0.0338
Size difference of household and zone-unit type category average	-0.337***	0.0248
% of Chinese households in zone * Household is Chinese	1.57***	0.168
% of Indian households in zone * Household is Indian	5.9***	0.482
% of Malay households in zone * Household is Malay	8.53***	0.537
% of households with children in zone * Household has a child	1.79***	0.29
% of households with teenagers in zone * Household has a teenager	1.51***	0.292
% of households with seniors in zone * Household has a senior	1.84***	0.224
% of HDB4 and HDB5 units in zone * Household size > 3	1.3***	0.358
% of apartments and condos in zone * Household per-capita income > $3,500	3.57***	0.219
% of landed properties in zone * Household per-capita income > $3,500	3.88***	0.333
% of detached and semi-detached private units in zone * Household per-capita income > $3,500	1.04	0.746

Note: The model was estimated on 9,569 observations and achieved an adjusted McFadden's rho-squared value of 0.158. Coefficient estimates (β) and robust standard errors (*S.E.*) are reported with *** denoting $p < 0.001$, ** denoting $p < 0.01$, and * denoting $p < 0.1$.

units. Additionally, I observe higher-income households to exhibit a preference for zones with larger shares of private housing units such as apartments, condominiums, and landed properties.

4.3.3 Hedonic price model

The hedonic price model describes how the market value of housing units can be explained by unit and location characteristics. It is specified as a linear-in-parameters ordinary least squares (OLS) regression where the dependent variable is the natural logarithm of the area-adjusted sale price (SGD per sq.ft.). I estimated hedonic price models separately for the public housing (HDB) and private housing sub-markets using housing transaction data from HDB and URA respectively (see Section 3.2.2). Within each housing sub-market, I estimated separate models based on the unit type as the sizes of the effects are expected to differ by unit type. I used the Chow Test to confirm that the estimated effect sizes were indeed distinct for the different unit types (Chow, 1960).

I report the data summary and the estimation results for the public housing sub-market in Tables A.2 and 4.3 respectively. Unit types include 1- and 2-room HDB units (HDB12), 3-room HDB units (HDB3), 4-room HDB units (HDB4), 5-room HDB units (HDB5), and executive HDB units. As most HDB12 units are offered as rentals, the number of reported HDB12 resales is relatively low compared to other HDB unit types but the model fit still remains reasonable. I detect a premium on older units located at higher storeys in the buildings, but there are diminishing returns as evidenced by the negative effect sizes of the squared variables. HDB defines planning areas as 'mature' estates (more than 20 years old) or 'non-mature' estates (less than 20 years old). Typically, mature estates are more developed and equipped with better amenities and public transport infrastructure, which can place a premium on HDB units located there. I confirm this through positive effect sizes for 'mature' and 'other-mature' HDB estates relative to the reference category of 'non-mature.' HDB units located close to MRT stations can also attract a premium, although not for HDB12. Being located in primarily residential neighborhoods can also drive up the market value of HDB units. We also see the negative influence of poor connectivity (as measured through long transit commute times) on housing prices of HDB units.

I report the data summary and the estimation results for the private housing sub-market in Tables A.3 and 4.4 respectively. Unit types include condominiums, apartments, executive condominiums, terraced houses, and detached and semi-detached houses. I further subdivided condominium and apartment sales based on unit area as I expected effect sizes to differ. The area thresholds used to define the categories (e.g., 60 sq.m. and 100 sq.m. for condos) were based on the distribution of unit sizes in the sample. Market values for landed properties (such as detached and semi-detached houses) were comparatively harder to explain using the set of variables available. Better data on unit characteristics (e.g., the number of bedrooms, bathrooms, garages, and other amenities such as backyards) could

Table 4.3: Estimation results for hedonic price model of public housing (HDB) units

	HDB12		**HDB3**		**HDB4**		**HDB5**		**Executive HDB**	
	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*
(Intercept)	6.453***	0.118	6.463***	0.033	6.410***	0.021	6.217***	0.031	5.041***	0.094
ln(Age of unit)			0.322***	0.095	1.072***	0.048	1.731***	0.095	6.828***	0.404
$ln(\text{Age}^2)$			-0.198***	0.044	-0.560***	0.022	-0.881***	0.044	-3.279***	0.191
ln(Storey)	0.216	0.284	0.864***	0.046	0.857***	0.035	1.125***	0.044	0.688***	0.085
$ln(\text{Storey}^2)$	-0.084	0.123	-0.358***	0.020	-0.350***	0.015	-0.465***	0.019	-0.279***	0.037
In 'mature' HDB estate			0.041***	0.002	0.087***	0.001	0.120***	0.002	0.097***	0.003
In 'other-mature' HDB estate			0.240***	0.005	0.357***	0.007	0.414***	0.008	0.386***	0.021
MRT station within 400 meters	-0.048***	0.009	0.033***	0.002	0.019***	0.002	-0.004	0.002		
MRT station between 400 and 800 meters	-0.060***	0.009	0.014***	0.001	-0.004***	0.001	-0.008***	0.002		
% of residential area in 1km buffer	0.039	0.028	0.040***	0.006	0.024***	0.005	0.017***	0.006	0.044***	0.011
% of HDB units in planning area	0.619***	0.046	-0.059***	0.010	-0.074***	0.008	-0.248***	0.011	-0.167***	0.018
Avg. transit travel time to all jobs	-0.007***	0.001	-0.009***	0.001	-0.012***	0.001	-0.013***	0.001	-0.009***	0.001
Observations	844		21,949		28,962		17,828		6,168	
Adjusted R^2	0.368		0.565		0.759		0.722		0.501	

Note: The model was estimated on HDB resale data using ln(Sale price / Unit area) as the dependent variable. Coefficient estimates (β) and robust standard errors (*S.E.*) are reported with *** denoting $p < 0.001$, ** denoting $p < 0.01$, and * denoting $p < 0.1$.

help improve this particular sub-model.

As I included both new sales and resales for the private housing sub-market, I confirmed that new sales were indeed comparatively more expensive (all else equal) except for small apartments. Although older condos and apartments are perceived to be more valuable with diminishing returns, very old units (where the age of the building is unknown) are deemed to be much less attractive. While apartments located on higher storeys attract a premium, condo units located on lower storeys seem preferable. Smaller condos are the only private unit type where proximity to the MRT adds market value. Rather than an indication of market preference, the relative location of private housing projects far from public transit is a more likely explanation. Apartments located in areas characterized by diverse land use are preferable, but the opposite is true for all other private housing units. Finally, similar to the public housing sub-market, poor connectivity has a negative influence on housing prices. I find it interesting that private housing residents also value good connectivity to jobs but not necessarily through transit.

4.3.4 Willingness-to-pay (WTP) model

The willingness-to-pay (WTP) model describes the maximum perceived value of a housing unit to a household, or the maximum value a household is willing to pay for a housing unit. The WTP depends on both housing and housing unit characteristics (including location). Without conducting a separate survey specifically focused on extracting WTP, it can be challenging to estimate using secondary data sources such as household travel surveys and housing transactions. Households recorded in HITS report the (aggregated) housing type and location of their currently occupied housing unit, but information regarding purchase price or rent is not available. This necessitates the use of a 'matching' procedure where I expanded the HITS sample using household sampling weights and matched each household to a randomly drawn unit of the same unit type in the same neighborhood (planning area) that was successfully sold. Although this still does not address the fact that the dependent variable is observed transaction price instead of WTP, we can capture the variation in transaction prices (even after holding location and housing type fixed) and introduce that as an error term in the model.

I used an economic method called Stochastic Frontier Analysis (SFA) to estimate the WTP model (Aigner et al., 1977; Meeusen and van Den Broeck, 1977). The stochastic

Table 4.4: Estimation results for hedonic price model of private housing units

	Condo (< 60 sq.m.)		**Condo (60 - 100 sq.m.)**		**Condo (> 100 sq.m.)**		**Apt. (< 70 sq.m.)**		**Apt. (70 - 130 sq.m.)**		**Apt. (> 130 sq.m.)**		**Exec. Condo**		**Terrace**		**Detached & Semi-Detached**	
	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*
(Intercept)	7.856***	0.020	7.993***	0.020	8.040***	0.018	7.420***	0.033	7.780***	0.031	8.117***	0.073	6.847***	0.024	7.529***	0.069	7.646***	0.080
New sale	0.008	0.007	0.003	0.005	0.093***	0.005	-0.034***	0.007	0.094***	0.009	0.213***	0.017						
Freehold	0.208***	0.005	0.208***	0.004	0.203***	0.003	0.056***	0.005	0.094***	0.005	0.154***	0.013			0.199***	0.012	0.092***	0.017
Unknown age	-0.055***	0.012	-0.071***	0.008	-0.149***	0.007	-0.036***	0.009	-0.062***	0.013	0.018	0.031			0.049	0.036	-0.157***	0.035
ln(Age of unit)	0.230***	0.044	0.098***	0.026	0.237***	0.021	-0.041	0.029	0.235***	0.036	0.555***	0.091			-0.556***	0.126	-0.022	0.121
ln(Age^2)	-0.139***	0.022	-0.086***	0.012	-0.161***	0.010	-0.002	0.014	-0.168***	0.017	-0.301***	0.042			0.254***	0.060	-0.026	0.058
ln(Storey)	-0.210***	0.031	-0.120***	0.037	-0.020	0.028	1.189***	0.060	0.313***	0.038	0.128*	0.069	-0.181***	0.051				
ln(Storey^2)	0.119***	0.014	0.074***	0.017	0.036***	0.013	-0.493***	0.027	-0.098***	0.017	-0.025	0.033	0.099***	0.022				
Large unit (area > 75^{th} %ile)													-0.022***	0.002	-0.385***	0.016	-0.002	0.020
MRT station within 400 meters	0.039***	0.005	-0.050***	0.003	-0.103***	0.004	-0.056***	0.006	-0.057***	0.007	-0.220***	0.018	0.022***	0.006	-0.042	0.031	0.071**	0.036
MRT station between 400 and 800 meters	0.019***	0.005	-0.043***	0.003	-0.058***	0.003	-0.174***	0.005	-0.157***	0.006	-0.183***	0.014	-0.006***	0.002	-0.064***	0.017	-0.053***	0.019
Land Use Diversity	-0.033**	0.016	-0.039***	0.012	-0.197***	0.013	0.289***	0.019	0.144***	0.024	0.350***	0.058	-0.002	0.010	-0.539***	0.062	-0.636***	0.086
Avg. transit travel time to all jobs	-0.012***	0.001	-0.016***	0.001	-0.017***	0.001	-0.014***	0.001	-0.018***	0.001	-0.029***	0.001	-0.004***	0.001	-0.004***	0.001	-0.003***	0.001
Observations	5,979		18,641		30,405		11,405		10,848		3,129		9,511		2,409		1,812	
Adjusted R^2	0.656		0.555		0.522		0.468		0.561		0.525		0.219		0.359		0.098	

Note: The model was estimated on private housing transaction data (both new sales and resales) using ln(Sale price / Unit area) as the dependent variable. Coefficient estimates (β) and robust standard errors (*S.E.*) are reported with *** denoting $p < 0.001$, ** denoting $p < 0.01$, and * denoting $p < 0.1$.

production frontier model can be written as:

$$y_i = f(x_i; \beta) \; . \; TE_i \; . \; exp(v_i) \tag{4.4}$$

where y_i is the observed transaction price of household i, x_i is a vector of explanatory variables such as household and housing unit characteristics, β is a vector of parameters to be estimated, TE_i is the technical efficiency (i.e., the ratio of observed price to the maximum feasible price or willingness-to-pay), and $exp(v_i)$ is a stochastic component describing a random shock. Although each household is facing a different shock, I assumed the shocks are random and can be described by a common distribution. Since $TE_i \leq 1$, we can also write it as an exponential $TE_i = exp(-u_i)$ where $u_i \geq 0$. This leads to:

$$y_i = f(x_i; \beta) \; . \exp(-u_i) \; . \exp(v_i) \tag{4.5}$$

I assumed that $f(x_i; \beta)$ takes the log-linear Cobb-Douglas form, following which the model decomposes to:

$$ln(y_i) = \beta_0 \; + \; \sum_n \beta_n . ln(x_{ni}) \; + \; v_i \; - u_i \tag{4.6}$$

where v_i is the 'noise' component and u_i is the non-negative technical inefficiency component. We can consider $(v_i - u_i)$ to constitute a compound error term with a specific distribution. I assumed this variable to be two-sided normally distributed with a mean value of zero and standard deviation determined from observed transaction data summarized by location and housing type. Since the HITS sample only provides aggregate housing types, we cannot use more detailed unit categories such as those used in the hedonic price model. Therefore, I estimated WTP using a stochastic frontier model on the 'matched' data of HITS households (expanded by sampling weights) and housing transactions. Based on the aggregate unit types (i.e., HDB12, HDB3, HDB4, HDB5, apartments and condos, and landed properties), I estimated different sub-models as preferences and WTP values are expected to differ across unit types.

Along with household and housing unit characteristics, I also included an accessibility measure. I report WTP estimation results using household-specific activity-based accessibility (ABA) measures in Table 4.5 below (with the data summarized in Table A.4). These

ABAs are calculated using the *variable home - fixed work - fixed vehicle holdings* approach I described earlier in Section 4.1. The simulation computes the relevant ABA measures for each of the 30+ housing units in that day's choice set for each awakened household using the activity-based framework in MT and plugged them into the WTP model specification. Estimation results using the same specification but switching out ABA for transit commute time of the household head (or transit travel time from the home location to all jobs, if the household head is not employed) are reported in Table A.5 in Appendix A.

I find that zero-worker households (comprising retired seniors) have a higher willingness-to-pay for HDB studios and larger HDB units located in areas that provide them with better accessibility, as well as private housing units but in less accessible locations. For households with at least one worker, moderately sized HDB units and private units both attract higher WTP as long as they are located in areas providing better accessibility. Poor connectivity to job locations (as measured by average transit travel time) reduces WTP across the board. Housing unit characteristics (such as the size and age of the unit, and the storey on which it is located) also influence WTP. All else equal, larger-sized units command higher WTP.

Households are found to have higher WTP for older (with diminishing returns) HDB4 and HDB5 units, along with apartments and condominiums. However, the reverse is true for HDB12 and HDB3 units, and landed properties. Households seem to prefer newer units when it comes to smaller public housing and landed private housing. Units located in 'mature' or 'other-mature' HDB estates command higher WTP compared to 'non-mature' estates. Higher-income households have a preference for landed properties, while larger households prefer paying more for apartments and condos. Households with children and seniors prefer to pay more for small- and medium-sized HDB units. Households with a higher share of workers (and presumably higher combined income) have higher WTP for apartments and condos, while households with a higher share of young professional workers (employed in white-collar jobs) are willing to pay more for landed properties.

4.3.5 Private vehicle availability model

The private vehicle availability model describes what types of private vehicles are available to each household through ownership, rental, and company-provided access pathways. I created six categories of private vehicle holdings — (a) not having access to any private vehicles (or being '*vehicle-free*'), (b) one motorcycle available, (c) one off-peak car (see

Table 4.5: Estimation results for household-level willingness-to-pay (WTP) model with activity-based accessibility as accessibility measure

	HDB12		HDB3		HDB4		HDB5		Apt. & Condo		Landed property	
	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*
(Intercept)	10.245***	0.251	9.717***	0.059	11.855***	0.047	8.511***	0.061	10.537***	0.029	10.296***	0.127
Activity-Based Accessibility * At least one worker	0.011***	0.003	-0.001**	0.001	0.001***	0.001	-0.003***	0.001	0.003***	0.001	0.005***	0.002
Activity-Based Accessibility * No workers	0.104***	0.022	0.007	0.007	0.007	0.004	0.069***	0.009	-0.089***	0.006	-0.133***	0.039
Avg. transit travel time to all jobs	-0.229***	0.027	-0.560***	0.005	-0.661***	0.004	-0.669***	0.006	-0.742***	0.006	-0.455***	0.026
ln(Area of unit)	0.523***	0.021	0.815***	0.006	0.537***	0.006	0.953***	0.007	0.912***	0.002	0.812***	0.006
ln(Age of unit)	-0.911**	0.411	-0.576***	0.091	0.323***	0.042	1.694***	0.089	0.291***	0.012	-0.294***	0.046
ln(Age^2)	0.409**	0.192	0.216***	0.043	-0.211***	0.020	-0.858***	0.042	-0.180***	0.006	0.139***	0.023
ln(Storey)	0.118	0.233	0.776***	0.045	0.663***	0.031	0.992***	0.038	0.157***	0.017	-0.359***	0.043
ln(Storey^2)	-0.039	0.101	-0.320***	0.020	-0.268***	0.014	-0.409***	0.017	-0.042***	0.008		
In ‘mature’ HDB estate	0.075***	0.010	0.038***	0.001	0.098***	0.001	0.114***	0.002				
In ‘other-mature’ HDB estate	0.116***	0.032	0.280***	0.005	0.342***	0.006	0.453***	0.007				
Freehold									0.195***	0.002	0.188***	0.007
ln(Household income)	0.001	0.003	0.002***	0.001	0.002***	0.001	0.008***	0.001	-0.021***	0.001	0.014***	0.004
Marginal effect of household size	0.050***	0.013	-0.001	0.002	-0.005***	0.002	-0.010***	0.002	0.071***	0.003	-0.053***	0.014
Marginal effect of children	0.003	0.010	-0.001	0.001	-0.003***	0.001	-0.009***	0.001	-0.043***	0.002	-0.033***	0.008
Marginal effect of seniors	0.015**	0.007	0.005***	0.001	0.005***	0.001	-0.005***	0.001	-0.010***	0.003	0.001	0.007
% of adults who are workers	0.025	0.018	0.015***	0.003	-0.006**	0.002	-0.015***	0.003	0.074***	0.005	-0.162***	0.016
% of adults who are young professional workers	0.016	0.014	-0.001	0.002	0.001	0.002	-0.008***	0.002	0.004	0.003	0.098***	0.020
Observations	856		22,081		29,214		24,075		55,536		7,456	
Technical efficiency (TE)	0.84		0.87		0.88		0.88		0.82		0.89	
Adjusted R^2	0.474		0.623		0.774		0.719		0.798		0.722	

Note: The model was estimated using ln(WTP) as the dependent variable. Coefficient estimates (β) and robust standard errors (*S.E.*) are reported with *** denoting $p < 0.001$, ** denoting $p < 0.01$, and * denoting $p < 0.1$. Marginal effects are modeled using a log-function to represent diminishing marginal returns of each additional unit. For example, the marginal effect of children is modeled as zero, if there are no children in the household, or $(1 + \frac{ln(n_{child})}{n_{household}})$, if there is at least one child. In this equation, n_{child} represents the number of children and $n_{household}$ represents the household size.

Section 3.1.3) available, (d) one ‘normal’ car available, (e) one ‘normal’ car coupled with a motorcycle, and (f) multiple ‘normal’ cars. I estimated household private vehicle availability using a multinomial logit choice model on HITS sample data.

In addition to household sociodemographics and location characteristics, I also used an accessibility measure as an explanatory variable. I report private vehicle availability estimation results using household-specific activity-based accessibility (ABA) measures in Table 4.6 below (with the data summarized in Table A.6). These ABAs are calculated using the *fixed home - fixed work - variable vehicle holdings* approach I described earlier in Section 4.1. The simulation computes different ABA measures for each of the six private vehicle holding options in a household’s choice set using the activity-based framework in MT, which are then used in the vehicle availability model estimation. Estimation results using the same specification but switching out ABA for transit commute time of the household head (or transit travel time from the home location to all jobs, if the household head is not employed) are reported in Table A.7 in Appendix A.

I find that household-specific vehicle holdings-specific ABA always has a positive influence on vehicle availability choice. An essentially constant (and close to one) ABA coefficient across options means that vehicle availability preferences do indeed depend directly on the ABA (logsum) differences across options. Therefore, we can confirm that the odds of picking various vehicle holding options depend directly on ABA differences, in addition to adjustments for sociodemographic factors and location attributes. As expected, taxi ownership reduces the likelihood of having access to a ‘normal’ car. I also detect a relationship between ethnicity and vehicle availability choices. Chinese households are much more likely to choose a ‘normal’ car, while minority non-Chinese households (especially Malays) are more likely to choose a motorcycle. This could be due to systemic class differences not captured in other parts of the model, or due to cultural differences, although I suspect the former is more likely. As household size increases, the likelihood of choosing multiple private vehicles also increases. Given the high cost of vehicle ownership in Singapore, it comes as no surprise that income has a strong and significant effect of car availability, even for the off-peak car option. The income effect grows stronger as vehicle holdings increase.

Households with children are more likely to own one off-peak car or one normal car, but not multiple normal cars. This is in contrast to the U.S. where such households are observed to own multiple cars. Households with seniors prefer to have access to a normal car and

Table 4.6: Estimation results for household-level vehicle availability model with activity-based accessibility as accessibility measure

	Vehicle-free		Motorcycle		Off-Peak car		Normal car		Normal car & Motorcycle		Multiple normal cars	
	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*
Alternative-Specific Constant (ASC)											-3.69***	0.864
Activity-Based Accessibility (ABA)	0.856***	0.145	0.896***	0.137	0.919***	0.144	0.934***	0.142	0.808***	0.159	0.923***	0.15
Taxi ownership							-1.10***	0.227				
Chinese ethnicity					-0.792***	0.165	0.906***	0.071			1.37***	0.187
Indian ethnicity			0.285*	0.152								
Malay ethnicity			1.11***	0.124								
Household size			0.225***	0.038			0.293***	0.025	0.644***	0.07	0.921***	0.061
Marginal effect of per-capita income					3.29***	1.00	6.43***	0.578	4.81***	1.14	8.71***	0.766
Marginal effect of children					0.643***	0.155	0.235***	0.062			-0.482***	0.147
Marginal effect of teenagers											-0.431***	0.149
Marginal effect of seniors							-0.114**	0.058	0.451*	0.254		
% of male adults			1.42***	0.248			0.327**	0.137	0.99*	0.551		
% of adults who are workers							-0.895***	0.135			-0.667*	0.356
% of adults who are young professional workers							-0.294***	0.12	0.66*	0.382		
% of adults who are retired									-1.52*	0.889		
% of adults who are blue-collar workers			0.782***	0.192								
% of adults who are white-collar workers							0.191*	0.116			0.609**	0.302
Lives in HDB2 unit					-1.38*	0.724						
Lives in HDB3 unit					-1.02***	0.249	-0.244*	0.139	-0.66*	0.356	-1.93***	0.395
Lives in HDB4 unit							0.416***	0.128			-1.14***	0.201
Lives in HDB5 unit							0.963***	0.13				
Lives in private apartment or condo			-2.45***	1.00			1.28***	0.169			1.12***	0.215
Lives on landed property							1.98***	0.268			2.74***	0.328
Bus stop within 200 meters (home)			-4.84***	0.234	-3.89***	0.243	-3.31***	0.299	-7.14***	0.575	-5.03***	0.729
Bus stop between 200 and 400 meters (home)			-4.73***	0.283	-3.82***	0.35	-3.21***	0.304	-7.21***	0.675	-4.55***	0.738
MRT station within 400 meters (home)			-0.388***	0.147			-0.124	0.077			-0.34*	0.194
MRT station between 400 and 800 meters (home)							-0.144**	0.061			-0.262*	0.149
Land Use Diversity							-0.82***	0.332				
Housing density							-0.371***	0.121	-1.20***	0.424	-0.523**	0.274

Note: The model was estimated on 8,718 observations and achieved an adjusted McFadden's rho-squared value of 0.513. Coefficient estimates (β) and robust standard errors (*S.E.*) are reported with *** denoting $p < 0.001$, ** denoting $p < 0.01$, and * denoting $p < 0.1$. Marginal effects are modeled using a log-function to represent diminishing marginal returns of each additional unit. For example, the marginal effect of children is modeled as zero, if there are no children in the household, or $(1 + \frac{ln(n_{child})}{n_{household}})$, if there is at least one child. In this equation, n_{child} represents the number of children and $n_{household}$ represents the household size.

a motorcycle, presumably for varied mobility needs of the younger and older household members in multi-generational households. Male-dominated households have an increased preference for access to motorcycles, all else equal. Households with a larger share of workers do not seem to prefer normal cars, suggesting that multi-worker households are in a more precarious financial situation. Households with a larger share of blue-collar workers are much more likely to choose motorcycles, while households with more white-collar workers gravitate towards one or multiple normal cars.

Looking at location characteristics, I start to detect possible wealth effects through the mediating influence of housing unit type. There could be other omitted variables (such as parking availability and pricing) at play here as well. Households living in larger HDB units or private housing are much more likely to prefer one or multiple normal cars. The wealth effect is especially pronounced for households living on landed properties. Proximity to public transit (both bus stops and MRT stations) reduce the likelihood of any form of private vehicle holding, incentivizing households to choose to become vehicle-free. A 'better' ABA measure (with more informative parking and convenience measures for actual trips) might be able to capture all of this, so that no additional location effects show up in the estimation. I also find that households living in denser and more diverse neighborhoods are less likely to choose normal cars, implying that those who do so live in less dense and less diverse neighborhoods which are located in suburban areas with comparatively poor transit connectivity. While this would usually imply car ownership to be a necessity rather than a pure choice (e.g., in the U.S. context), the high cost of car ownership in Singapore implies that the vehicle holding decision may be less driven by necessity and is likely coupled with purchasing power, attitudinal desire, and residential location choice.

4.4 Methodological extensions

As part of this dissertation, I developed three key methodological extensions to SimMobility Long-Term that have been operationalized in the current version of the open-source code. These extensions allow for more granular modeling of housing-mobility choices in the daily housing market by incorporating transitions and interactions between agents. First, separate housing market dynamics for owners and renters were created, while allowing both households and housing units to transition between the two sub-markets. Second, various types of market feedback effects that reflect realistic interactions of buyers and sellers were included. Finally, I implemented a 'simultaneous' housing-mobility choice framework where households consider both housing units and private vehicle holdings at the same time in the bidding process. I will describe these three extensions in further detail in the following sub-sections.

4.4.1 Separate markets for owners and renters

Although both households and housing units created during the synthetic population generation process had assigned tenure status values (own or rent), a realistic rental housing market model had not yet been implemented (Zhu et al., 2018). If the desired search during the daily bidding process was for a rental unit, households were randomly assigned to an available rental unit, following which they would stop searching and be taken off the market. Moreover, while households can transition between owning and renting as part of the awakening model, housing units could not. I addressed these limitations in my effort to extend our housing market model to cover renters and rentals as well.

I used the following equation to calculate plausible monthly rents for housing units:

$$R_i = O_i \ * \ r_i \ / \ (12 \ * \ (1 \ - \ t_i \ - \ u_i)) \tag{4.7}$$

where R_i is the monthly rental price (or WTP) for housing unit i, O_i is the for-own price (or WTP) for housing unit i, r_i is the rental return rate, t_i is the tax rate, and u_i is the utility rate. Using REALIS data on median rents by location (planning area) and (aggregated) housing types, I estimated rental return rates (r_i) that varied by planning area and unit type. I also assumed the tax rate (t_i) and utility rate (u_i) to be a constant 2% and 1% respectively for all unit types. Using this equation, we can amortize the hedonic price and WTP values for all rental units and renter households accordingly.

I also allowed for sellers to change the tenure status of their housing units based on market conditions. If a for-own unit has not received any bids for several weeks despite asking price adjustments, it could imply that the housing unit is not desirable to owners. Sellers may then opt to transfer the unit to the rental market, amortize the asking price with an additional discount (to reflect the unit not being desirable at the current asking price), and offer it for rent. On the other hand, some sellers may choose to take advantage of 'hot' neighborhoods where demand for owner-occupied housing is growing. These neighborhoods (and unit types) can be identified based on the number of bids they receive from potential buyers. If this number crosses a modeler-specified threshold, some sellers probabilistically choose to transfer their units to the owner market, reverse-amortize the current rents to asking prices, include an additional mark-up to reflect the increased demand in the 'hot' market, and then offer the units for sale. These tenure status transitions are shown in Figure 4-5. The bold lines indicate that most tenure status transitions are within the same category (i.e., most owners choose to remain owners when searching for new housing); cross-tenure transitions are comparatively less likely.

Figure 4-5: Tenure status transitions of households and housing units

4.4.2 Market feedback effects

The daily bidding process in the housing market involves bids made by potential buyers that are dependent on their WTP and asking prices of units set by sellers. Both the asking prices and bid values can be adjusted based on market feedback effects, as I outline in Figure 4-6. For example, if a seller does not receive any bid on their offered unit for several weeks and the unit remains unsold, the seller will revise the asking price and offer the unit at a slightly reduced asking price. On the other hand, sellers can take advantage of high buyer interest by raising asking prices, which can spark off a bidding war. If a unit receives multiple bids where the bid count crosses a modeler-defined threshold on a given day, the seller can refuse all of that day's bids, increase the asking price, and offer the unit at a more expensive rate the next day.

Bidders and sellers can also negotiate between themselves in certain circumstances. If a unit receives only one bid but the bid value is lower than the target price (i.e., the minimum

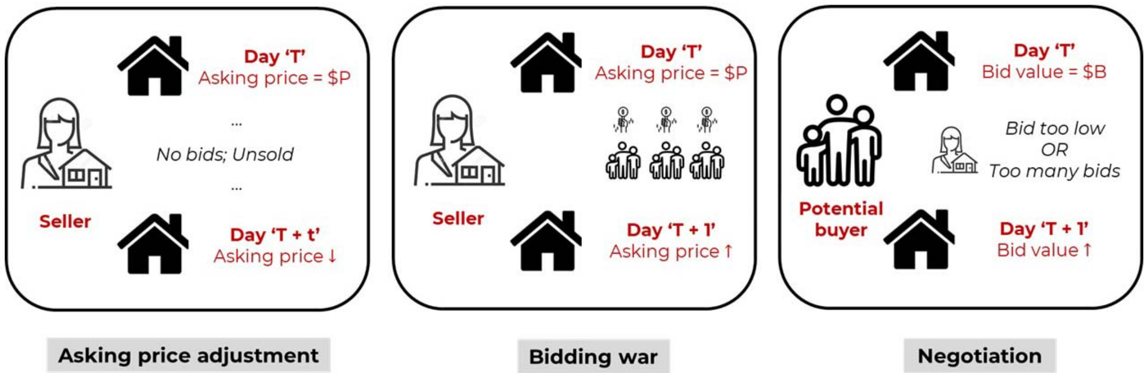


Figure 4-6: Examples of market feedback effects

price the seller is willing to accept for this unit), the seller will reject the bid but also invite the buyer to submit an improved offer the next day. When a unit receives multiple bids (that do not exceed the bid count threshold for increasing the asking price), the seller will capitalize on this high demand by rejecting all bids with an invitation to bidders to submit improved offers the next day. In such circumstances, buyers will evaluate whether submitting a better offer on this unit the next day still provides them with the maximum expected consumer surplus within their next-day's choice set (that is newly re-constructed but retains the current housing unit and any rejected bids accompanied by bid-too-low messages). If it does, they will re-bid with a higher bid value; if it does not, they will not bid on this unit again that day. They could bid on it during some future day if it were still available, perhaps at a reduced price.

4.4.3 Simultaneous housing-mobility choice with vehicle costs

As an extension to the sequential consideration of residential location and private vehicle holdings, I designed a simultaneous choice framework through which households consider both residential location and private vehicle holdings at the same time during the bidding process (see Figure 4-7). This framework also allows for the inclusion of mobility costs in the bidding process as the WTP for housing in a particular location can decrease if the location also requires owning a car, as household expenses for housing and mobility are subject to budget constraints. Not only does my motivation to develop this framework stem from the high cost of vehicle ownership in Singapore, but also a need to better reflect rising auto expenses that invariably influence residential location choices. However, my approach differs from the estimation of joint choices of residential location and auto ownership used (comparatively sparingly) in the literature (see, e.g., Lerman (1976) and Salon (2009)).

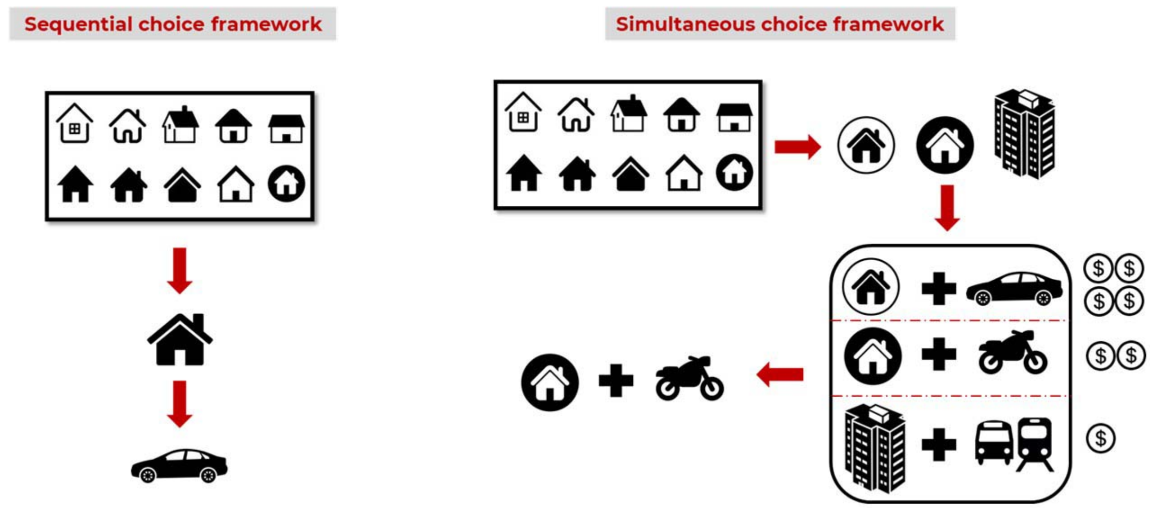


Figure 4-7: Housing-mobility choice frameworks

Under the simultaneous choice framework, households shortlist the top 'l' (set to 3) housing units ranked by expected consumer surplus and evaluate their vehicle holding probabilities if they were to live in those units. The top 'v' (set to 2) vehicle availability categories ranked by probability (among the six outlined in Section 4.3.5) for each of the 'l' housing units are selected, leading to a new housing-mobility choice set of $(l * v)$ alternatives. The vehicle costs associated with each alternative are subtracted from the WTP for housing, and expected consumer surplus is recomputed using these revised WTP values. Finally, the household chooses to bid on the housing-mobility option that provides them with the maximum expected consumer surplus, provided it is higher than their current choice of housing unit and vehicle holdings. This framework is more complex and requires the computation of $(l * 6)$ logsum values to reflect the accessibility of households if they were to live in one of the 'l' units and choose one of the six vehicle availability categories, in addition to the 30+ consumer surplus computations done in the first stage evaluation of that day's choice set. In contrast, the sequential choice framework requires the evaluation of only 6 logsum values for the single unit which was chosen to bid on (and the same 30+ consumer surplus computations). As the evaluation of 12 additional logsums per potential buyer is time-consuming, this slows down the simulation considerably to the point that the simultaneous choice framework takes almost twice as long as the sequential choice framework.

Vehicle costs for each household are generated based on a survey of households who changed vehicle holdings in the prior three years conducted in 2019. Using a supervised classification (random forest) model, I related (categorical) total vehicle costs (including COE prices) to household sociodemographics for three private vehicle categories (i.e., motorcycle, off-peak car, and 'normal' car). I then used this model to predict total vehicle costs for the six vehicle holdings categories in the vehicle availability model for every household in the synthetic population. After obtaining predicted cost categories, I imputed continuous values by drawing from a log-normal distribution that was constrained around the cost category thresholds, similar to my approach for imputing continuous values from income categories. Although I had data available on the age, make, and model of the vehicle, I did not include them in my model as my objective was to obtain total vehicle cost estimates that were reflective of household sociodemographics. The median total vehicle costs are around SGD 30,000 for a motorcycle, SGD 50,000 for an off-peak car, and SGD 100,000 for a normal car. More sophisticated vehicle cost modeling can be pursued in future efforts.

4.5 Calibration

The SimMobility LT framework includes several housing market parameters that require calibration. For example, the simulation length and daily awakening rates influence overall bidding activity and, consequently, total successful transactions. I shortlisted parameters to which simulation results were more sensitive and selected a set of plausible values for each parameter (see Table 4.7). I carried out both single-perturbation (where one parameter is varied holding others constant) and multi-perturbation (where a few representative parameter combinations are selected from the multi-dimensional parameter space using Latent Hypercube Sampling) explorations, and compared simulation results to observed housing transaction data from 2011 to 2014. My final choices of parameter values were based on both objectivity (i.e., which settings tended to most closely approximate ground truth) as well as subjectivity (i.e., expert knowledge on interactions between multiple parameters that cannot be captured in a purely objective calibration exercise).

As I am interested in observing near-term neighborhood changes, I chose a simulation length of 720 days which roughly corresponds to three calendar years based on our observation that the real estate market is less active on holidays, Sundays, and the like. After tuning other parameters, a two-year simulation generated three years of transactions, sug-

Table 4.7: Calibration of housing market parameters

Parameters	**Set of plausible values**	**Selected value**
Simulation length in days	< 182 ; 365 ; 548 ; 730 >	730
Households awakened daily	< 250 ; 400 ; 500 ; 750 ; 1,000 >	400
Ratio of asking price to hedonic price	< 100% ; 105% ; 110% ; 115% >	110%
Standard deviation of WTP error distribution	< $20,000 ; $40,000 ; $60,000 ; $80,000 >	$60,000
Days without bids after which sellers reduce asking prices	< 7 ; 14 ; 21 ; 28 >	21
Reduced asking price % after zero-bid period	< 91% ; 93% ; 95% ; 97% >	97%
Bid count threshold after which sellers increase asking prices	< 5 ; 7 ; 10 ; 15 >	15
Increased asking price % after bid count crosses threshold	<101% ; 102% ; 105% ; 110% >	110%
Increased bid % after seller request to improve offer	< 101% ; 102% ; 105% ; 110% >	110%

gesting a plausible average bidding intensity of four bidding evaluations every six days. 400 households are awakened and enter the housing market daily. The asking price of housing units is set to 10% above the hedonic price (calculated by the hedonic price model) by sellers. The standard deviation of the WTP (normal) error distribution is set to $60,000 (recall that the mean is zero). Sellers reduce their asking price by 3% if they do not receive a single bid for three weeks. If sellers receive more than 15 bids in a single day, then they increase the asking price by 10%. Bidders who are invited to improve their offer remain on the market the next day and evaluate that day's choice set, including this unit, after increasing their bid value for this particular unit by 10%.

We have an additional parameter known as the '*WTP offset*' that is used to adjust WTP values such that the median WTP value is roughly 10% above the median hedonic price for each unit type. This ensures that WTP and asking price values are of the same magnitude, with differences being attributable to variation in preferences. We compute the 'actual' WTP using the following equation:

$$WTP \;=\; (WTP_m \;*\; (\;1 \;+\; wtp_o)) \;+\; wtp_e \tag{4.8}$$

where WTP is the 'actual' WTP, WTP_m is the estimate provided by the WTP model, wtp_o is the WTP offset, and wtp_e is the error randomly drawn from a normal distribution characterized by zero mean and standard deviation of $60,000. We make an initial simulation run using the selected parameter settings without using any WTP offset (i.e., setting $wtp_o = 0$). The simulated bids are analyzed to estimate WTP offset values for each housing unit type. These offset values (see Table A.8 in Appendix A) are then used in subsequent simulation runs.

Finally, as is common in Monte-Carlo Markov Chain (MCMC) simulations, it is necessary to conduct a '*burn-in*' (or warm-up) 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. I tested different values of burn-in duration, and found that one simulation year was more than adequate for achieving quasi-equilibrium in the housing market. Therefore, I started off with the calibrated synthetic population in 2012 and simulated 365 days with no changes in the total number of households and housing units. Essentially, the metro area 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. I used information related to residential relocation and reevaluation of vehicle 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 for all simulation runs made henceforth.

I conducted two separate burn-ins, one excluding vehicle costs (i.e., with the sequential choice framework) and one including vehicle costs (i.e., the simultaneous choice framework), so that we have distinct starting points based on how households make housing-mobility choices. I report summary statistics of the burn-in results in Table 4.8. As I conducted closed-system simulation runs, the vacancy rate and mean household income are not expected to change during the burn-in, which I confirm. However, the inclusion of vehicle costs in the bidding process induces most movers to choose locations that do not require owning a private vehicle, which in turns significantly increases the aggregate vehicle-free share by four percentage points.

Data limitations prevented us from including vehicle holding costs directly in the private vehicle availability model. Therefore, the initial synthetic population assignments of households to housing units used the vehicle availability model without vehicle costs to probabilistically select vehicle holding options that, overall, averaged 51.8% across Singapore. However, when awakened households considered vehicle costs while evaluating relocation options, they tended to move to places that are relatively more attractive without a car.

Table 4.8: Effect of burn-in on the full synthetic population

	2012 (calibrated)	**2012 (after 1-year burn-in)**	
		w/o vehicle costs	***w/ vehicle costs***
Vacancy rate (%)	5.8%	5.8%	5.8%
Mean household income (SGD)	\$6,886	\$6,886	\$6,886
Vehicle-free rate (%)	51.9%	51.8%	55.8%

Hence, the overall vehicle-free share increased by 4% points. If appropriate data were available, a vehicle availability model including costs directly would allow the original assignment to match the observed vehicle-free share of 51.8% in Singapore in a way that would remain unchanged during the burn-in. However, this is beyond the scope of this dissertation and my approach is still appropriate for comparing the effects of car-lite policy scenarios against a reference baseline.

4.6 Simulation

The simulation is coded in C++ because of the computational benefit and power of C compared with, for example, Java and Python, in addition to the ease with which we can implement object-oriented programming (OOP). OOP is particularly effective for agent-based simulations owing to the modular nature with which components can be written (that can communicate with each other), and how code can be easily reused through inheritance. We store data on the synthetic population and sub-model coefficients in PostgreSQL databases and pass simulation parameters (such as those discussed above) to the simulation through Extensible Markup Language (XML) files. When the executable is run, the code initializes parameters based on XML inputs and communicates with the PostgreSQL database to read in necessary tables. The methodological extensions I discussed earlier in this chapter were implemented in the C++ code and also required the addition of some configuration tables in the PostgreSQL database. We have developed SimMobility using a modular architecture that enables us to switch out model estimates and configuration values as needed. However, any changes to model specifications or agent behavior will require changes to the C++ code.

4.7 Summary

In this chapter, I provided an overview of the agent-based land use-transport interaction (LUTI) microsimulation model we have developed in-house — *SimMobility* — and how we compute and use activity-based accessibility (ABA) measures in SimMobility. As I am interested in exploring near-term neighborhood changes in response to changes in non-auto accessibility, I focused on the Long-Term (LT) component of SimMobility which can be used to simulate longer-term urban behavior such as residential location choice and private vehicle availability choice. Despite the detailed nature in which SimMobility LT models the housing market (compared to other state-of-the-art LUTI models), it needs a few methodological extensions to be better equipped for scenario explorations of neighborhood change, which I presented as well. After calibrating the necessary simulation parameters, the LT framework is ready to be used for scenario explorations. In the next chapter, I will demonstrate both city-wide and neighborhood-level effects of accessibility changes such as private vehicle restrictions and non-auto accessibility improvements. Additionally, I will discuss the extent to which coordinated housing policies may be effective in mitigating undesirable side-effects such as gentrification.

Chapter 5

Car-lite policies and neighborhood change

In this chapter, I use SimMobility Long-Term (LT) to explore in detail how neighborhoods might change in response to car-lite policies that seek to restrict private vehicles and/or improve non-auto accessibility, as well as coordinated housing policies. First, I conduct quasi-static analyses of city-wide private vehicle restrictions and non-auto accessibility improvements (i.e., accessibility provided by mobility options other than privately owned automobiles) to understand their effects on residents' accessibility and welfare. Then, I construct various scenarios using these car-lite policy mechanisms and present simulation results of housing and mobility responses to these policies in multiple Singaporean neighborhoods. Subsequently, I propose two types of coordinated housing policies (i.e., new housing supply and vehicle-restricted housing supply) that can enhance the benefits of non-auto accessibility improvements while mitigating unintended negative consequences and explore their impacts on neighborhood change.

5.1 Quasi-static analyses of city-wide car-lite policies

Non-auto accessibility improvements can be operationalized through better urban design (e.g., for pedestrians and cyclists), extensions of public transit lines, better first- and last-mile connections to transit, or emerging mobility services such as mobility-on-demand or micromobility. All of these mechanisms require time and public investment. Therefore, if we want to accelerate our path to a sustainable mobility future, could we 'simply' en-force restrictions on private vehicles? Would banning private vehicles serve as an adequate substitute for comparatively more expensive non-auto accessibility improvements?

Answering this question would ideally involve running what is known as a 'full-loop' simulation of SimMobility. We would remove private vehicles from the choice sets in the private vehicle holdings and mode choice sub-models in LT and MT respectively. In the absence of private vehicles, individuals are expected to adjust their daily activity-travel patterns, which would affect their accessibility, and that, in turn, would affect their location choices. Thus, banning private vehicles is likely to affect both long-term and medium-term choices made by individuals and create a new equilibrium that wouldn't settle down until the supply and pricing of residential and commercial facilities had fully responded to the substantial shock to the system. However, going through the process of doing 'full-loop' simulations for the entire city-state of Singapore can be both cumbersome and time-consuming. Moreover, as a recent effort by Zhou et al. (2021) highlights, in the absence of real data on how individuals respond to a ban on private vehicles, we will have to make multiple assumptions related to how the choice models might need to be adjusted to reflect changes in behavioral preferences.

As I am particularly interested in observing the near-term effects of car-lite policies, it may not be necessary to obtain the new 'actual' accessibilities stemming from changes in activity-travel patterns. To obtain estimates of boundary effects of car-lite policies (i.e., the maximum possible effects which are likely to be reduced in magnitude when individuals have had the chance to adjust their activity-travel patterns in response to the new policies), it is sufficient to assume a certain magnitude of change in accessibility. For example, if a car-lite policy that improved non-auto accessibility were to be piloted in a neighborhood, we could assume that the vehicle-free accessibility of current and future neighborhood residents would increase by a certain amount.

The baseline ABA measures are 'equilibrium' ABA values from MT for the transportation network performance and daily activity patterns that result at the start of the simulation. One might like to rerun MT after a year or two of shifting locations to generate new activity patterns and ABA values, but that was not done for this dissertation because my focus is on first understanding near-term effects before enough households changed their activity patterns so that the network performance became substantially different. Using equilibrium ABA values (obtained from MT) in the baseline and appropriate adjustments to model the effects of car-lite policies, I conducted several scenario explorations of changes in housing-mobility choices through the LT framework as part of this dissertation. I discuss these in further detail in subsequent sections. But before getting into extensive development and simulation regarding the relatively longer-term effects of these big shocks, in this section, let us examine some quasi-static analyses (without simulation) of the very near-term changes in accessibility and consumer surplus that would result from city-wide car-lite policies.

I operationalized the city-wide private vehicle restriction policy through two adjustments to all households in the 'day-0' synthetic population:

- **Activity-based accessibility:** Since all vehicles are restricted island-wide, the accessibility of every household now becomes equal to their 'vehicle-free' ABA value obtained through the *fixed home - fixed work - variable vehicle holdings* approach described earlier.

- **Public transit travel time:** As all individuals are now forced to use public transit, the immediate effect would be an increase in transit travel times due to longer waiting times and overcrowding (unless headways are reduced and supply is increased). To reflect this new reality, I increased public transit travel times by 25% (which is the weighted ratio of mean AM peak travel time to mean off-peak travel time for all workers).

These adjustments are indicative of the quasi-static (or very near-term) effects of a city-wide vehicle restriction policy. Of course, other adjustments will emerge over time (such as households moving to places with better transit accessibility), but this quasi-static analysis is valuable in providing a sense of the direction of changes in accessibility and welfare due to this policy. Now, what if we were to combine this city-wide vehicle ban with non-auto accessibility improvements? Could these city-wide improvements make up for the likely negative effects of the vehicle ban? I operationalized non-auto accessibility improvements through two adjustments. These adjustments are purposely designed to improve non-auto accessibility by a significant (and likely implausible) amount because I am interested in exploring whether removing the need to own a car purely from an accessibility perspective is enough to offset the detrimental effects of a city-wide private vehicle ban.

- **Activity-based accessibility:** I added the mean difference between the ABA with one normal car and the vehicle-free ABA (across all households) to the vehicle-free

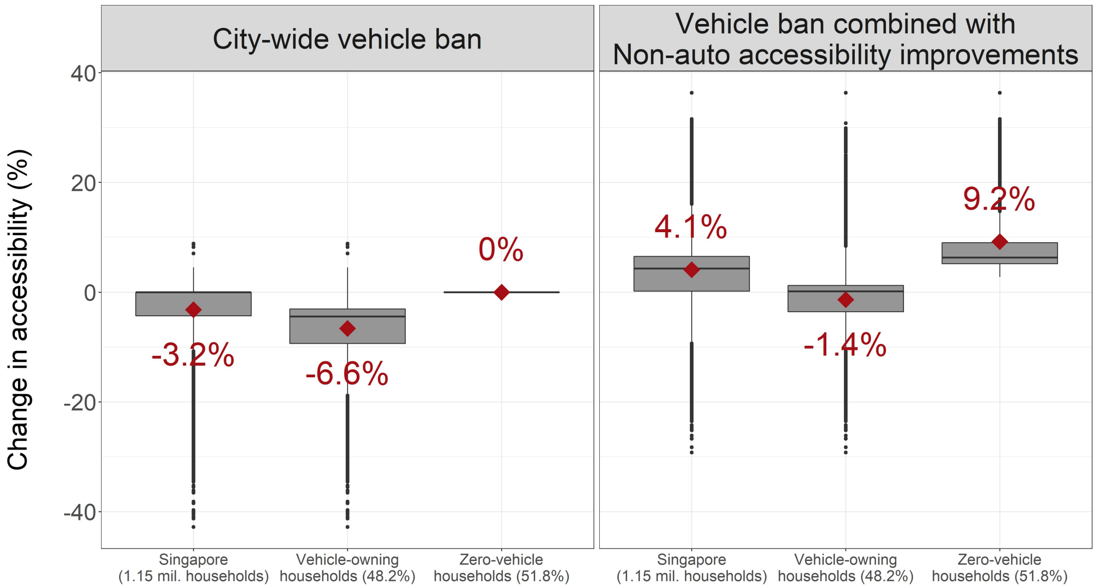
ABA of every household, such that not having access to a private vehicle provides equal accessibility to having one normal car available (on average).

- **Public transit travel time:** I decreased public transit travel time by the weighted mean difference between transit and car travel times (30 minutes), with a floor of 5 minutes, such that revised transit travel times are equal to car travel times on average.

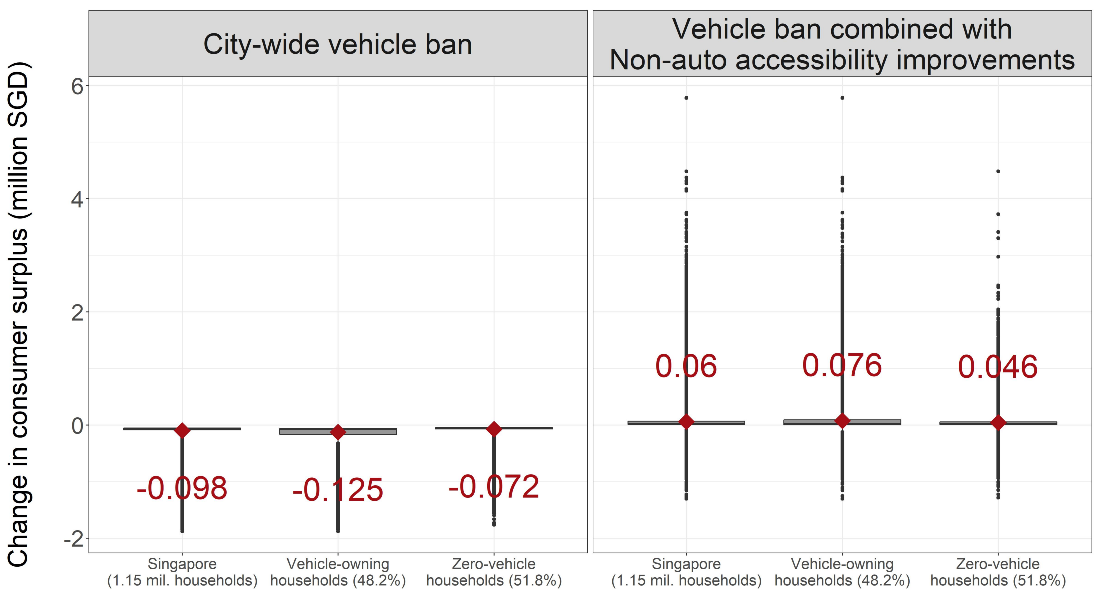
I conducted quasi-static analyses of these accessibility adjustments (without any simulations) to examine changes in residents' accessibility and welfare. I tracked accessibility change using each household's ABA before (i.e., on day-0) and after the two car-lite policies are implemented. Similarly, I tracked welfare change using each household's consumer surplus before and after policy implementation. As I did not conduct any simulations here, households' residential locations did not change but the market prices of housing units and willingness-to-pay for housing did change as both are dependent on accessibility. I plugged the adjusted accessibility values for the two policies into the hedonic price and WTP submodels to obtain revised estimates of market price and WTP for the same housing unit each household lived in on day-0. The difference between WTP and market price provides consumer surplus in the housing market, which I used as a measure of welfare. Thus, I recorded changes in accessibility and consumer surplus for each household stemming from the two car-lite policies (i.e., a city-wide private vehicle ban, and the vehicle ban combined with non-auto accessibility improvements) using quasi-static analyses.

I report these changes separately for vehicle-owning households and zero-vehicle (or vehicle-free) households in Figure 5-1 (where the red diamonds and labels correspond to the mean values). I find that banning private vehicles will decrease accessibility (ABA) by 6.6% for vehicle-owning households. Consumer surplus in the housing market will decrease by an average of SGD 98,000 per household in the city, with vehicle-owning households losing out on an additional SGD 27,000, as both market prices and WTP decrease for locations with comparatively poorer vehicle-free accessibility. As vehicle-owning households predominantly reside in such locations, it is expected that they will experience a greater loss of consumer surplus.

The effects of the vehicle restriction policy combined with non-auto accessibility improvements are shown in Figure 5-1 as well. I find that vehicle-free households receive an almost 10% boost in their accessibility. While vehicle-owning households also experience an increase



(a) Change in accessibility from day-0



(b) Change in consumer surplus from day-0

Figure 5-1: Quasi-static effects of city-wide car-lite policies

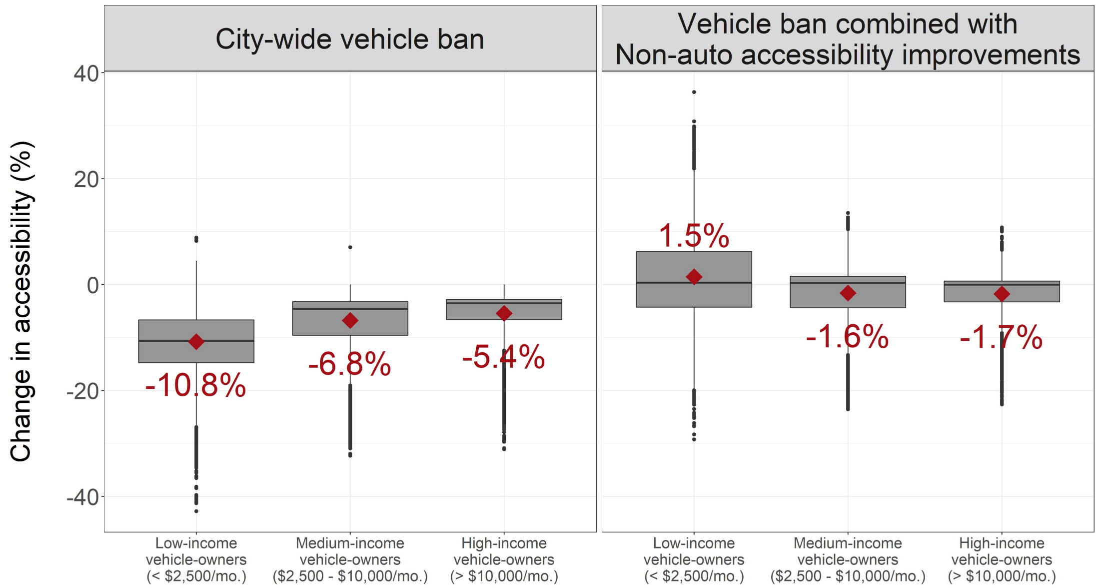
in accessibility, it is not enough to completely offset the negative effects of the vehicle ban. Vehicle-owning households remain below their day-0 accessibility levels (on average) despite the non-auto accessibility improvements. However, consumer surplus for these households increases by SGD 76,000 on average, which is SGD 30,000 higher than the average increase for vehicle-free households. Thus, we see that our very significant improvement in non-auto accessibility may not be enough to offset the detriment in accessibility of vehicle-owning households caused by a city-wide vehicle ban, although they can attract housing premiums large enough to improve consumer surplus in the housing market.

I also examined the distributional effects of these policies across different income groups of households with access to private vehicles on day-0 (see Figure 5-2). I find evidence of non-uniform effects, whereby lower-income vehicle-owning households experience the largest decrease in accessibility due to the vehicle ban policy and consequently the largest increase in accessibility when the ban is combined with non-auto accessibility improvements. However, this trend is reversed when we examine the effects on consumer surplus. As higher-income vehicle-owning households live in locations with comparatively poorer vehicle-free accessibility, banning vehicles reduces their consumer surplus the most and introducing non-auto accessibility improvements improves their consumer surplus to the largest extent.

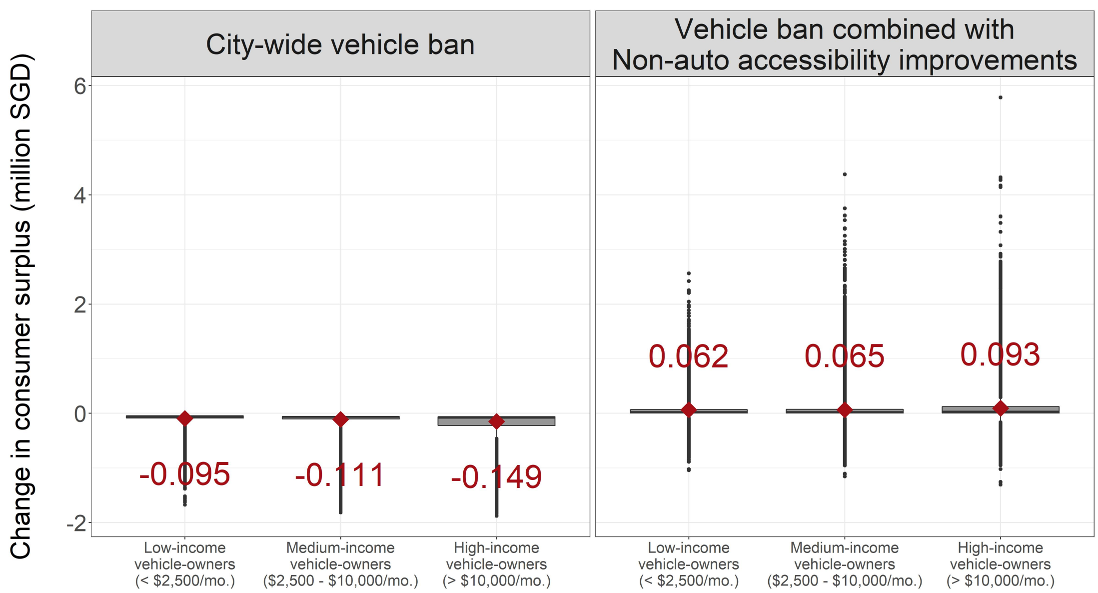
Through these quasi-static analyses, I conclude that introducing city-wide vehicle restrictions in the hope of sharp reductions in vehicular emissions can end up hurting residents unless supplementary policies that improve non-auto accessibility are also put in place. Residents' accessibility and welfare are likely to suffer, which they may try to offset by changing activity patterns and residential locations that, in turn, may drive up housing prices in transit-accessible neighborhoods. I also find evidence of non-uniform effects of these policies across income groups, with lower-income households likely to experience the greatest loss in accessibility. While acknowledging that this is by no means a fully fleshed out analysis, these preliminary results suggest that banning private vehicles outright can have detrimental effects on residents, especially those from lower-income households, even in comparatively less auto-dependent contexts like Singapore.

5.2 Simulation design of neighborhood-wide car-lite policies

Having established that private vehicle restrictions cannot readily substitute for non-auto accessibility improvements, it is thus important to understand the near-term effects of these car-lite policies on neighborhoods. How will they influence housing-mobility choices and thereby change neighborhoods? To examine this question in complete detail, we would have to resort to doing a 'full-loop' simulation of both housing-mobility and activity-travel choices. However, it is both possible and plausible to examine only housing and mobility



(a) Change in accessibility among vehicle-owning households



(b) Change in consumer surplus among vehicle-owning households

Figure 5-2: Quasi-static effects of city-wide car-lite policies on vehicle-owning households by household income

choices under certain assumptions, especially if we are interested in understanding near-term neighborhood-level changes. As mentioned earlier, municipalities are likely to implement car-lite policies (such as a ban on private vehicles and/or non-auto accessibility improvements) at a neighborhood level first before rolling them out city- or metro-wide. Therefore, I can isolate one planning area (interchangeably referred to as a neighborhood henceforth) as a candidate study area for this car-lite policy pilot (see Figure 5-3), implement the necessary accessibility adjustments due to the policy, and simulate the entire city-state of Singapore using only the LT framework plus the MT activity-based travel demand framework that allows us to compute day-0 activity-based accessibilities for each household if they were to relocate or change their private vehicle availability. Simulation results can then be compared across different policy scenarios (and against a reference case) using a mix of place-based and people-based scenario evaluation measures (such as accessibility and welfare, as shown earlier).

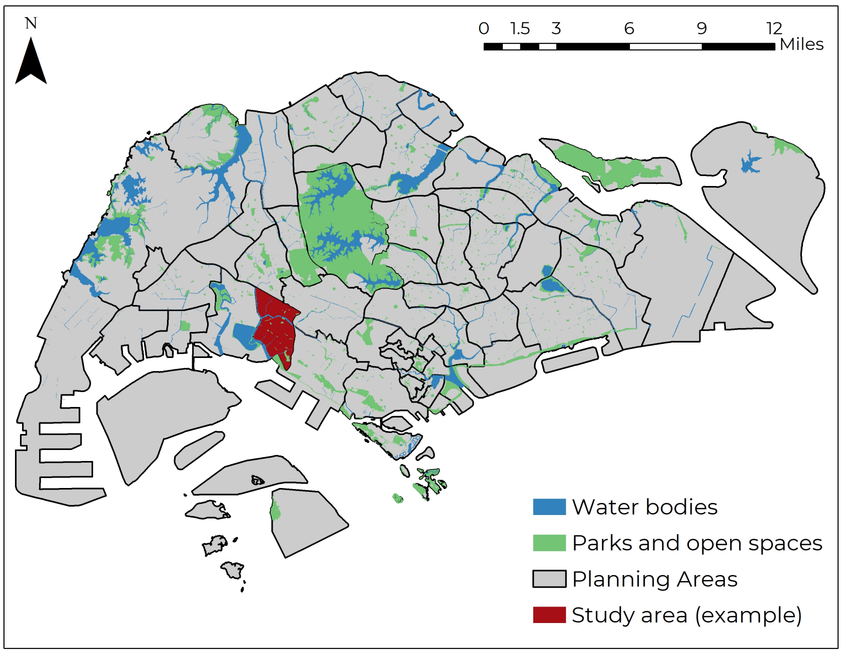


Figure 5-3: An example planning area (Clementi) that could be selected for piloting a car-lite policy

5.2.1 Design of car-lite policy scenarios

In keeping with the city-wide car-lite policies I explored using quasi-static analyses, I designed the following five scenarios which I simulated over two simulation years (roughly equivalent to three calendar years, as discussed in Section 4.5) to examine near-term changes in neighborhoods. As mentioned earlier, the key difference between these policy scenarios and the previous quasi-static analyses is that these car-lite policies are implemented in a particular neighborhood (and the entire city is simulated), while the quasi-static analyses looked at policies that were implemented city-wide (without any household relocation or change in vehicle availability, other than the ban on private vehicles).

- **Baseline:** This describes the baseline (or 'business-as-usual') development of the study area where the car-lite pilot was never trialed and accessibility changes were never implemented.

- **Neighborhood-wide private vehicle ban:** This scenario is similar to the baseline except that households currently living or considering living in the study area are restricted from owning private vehicles. Unlike the quasi-static analysis reported in Section 5.1, this is a simulated scenario but using only the LT framework. I include this scenario to explore whether my findings from the quasi-static analysis hold true even with simulated outcomes where households can respond to the policy by changing their housing-mobility choices (but not their activity-travel patterns).

- **Neighborhood-wide accessibility improvement (without housing market response):** This scenario is again similar to the baseline except that non-auto accessibility improvements are now implemented within the study area and households are aware of the accessibility improvements. However, the housing market response is largely absent except for buyers being aware of the pilot and more willing to include study area units in their choice sets (without any change in the likelihood to bid on them). Operationally, this means that the improved accessibility is only considered in the private vehicle availability and screening models, but disregarded in the hedonic price and WTP models.

- **Neighborhood-wide accessibility improvement (with housing market response):** This scenario builds on the previous scenario by including both the demand-side and supply-side response to non-auto accessibility improvements. Buyers become more likely to choose units from the study area for inclusion in their choice sets as well as pay higher prices to live within the study area, which can be replicated by plugging the improved accessibilities into the WTP model when computing WTP for units in the study area. At the same time, sellers will raise asking prices in an effort to capitalize on the increased demand for housing within the study area, which is reflected by plugging the improved accessibilities into the hedonic price model when computing market prices for units in the study area. This and the previous scenario are separated specifically to demonstrate the significant effect of housing market response to accessibility improvements on neighborhood change.

- **Neighborhood-wide private vehicle ban combined with accessibility improvement:** This scenario combines two of the earlier scenarios by restricting private vehicle ownership and improving non-auto accessibility within the study area at the same time. Both buyers and sellers are allowed to respond to these accessibility changes through changes in the WTP and market prices in the housing market. The motivation here is to explore the extent to which (and where) accessibility improvements can offset the detrimental effects of the neighborhood-wide vehicle ban.

Using the 'baseline' scenario as the reference and every other policy scenario as a counterfactual, we can attribute the simulated changes between a non-baseline policy scenario and the baseline scenario directly to the particular car-lite policy being implemented (excluding stochastic variation, of course). I operationalized accessibility changes stemming from the different car-lite policies in a similar manner to my approach in Section 5.1, which is summarized in Table 5.1. Using these assumed accessibility adjustments only within the study area where the car-lite policy is being piloted, I simulated Singapore-wide changes as a closed system (i.e., by keeping the total counts of households and housing units constant) over two simulation years (three calendar years).

Table 5.1: Assumed accessibility changes for different car-lite policies

Car-lite policy	**Activity-based accessibility**	**Public transit travel time**
Private vehicle ban	ABA becomes vehicle-free ABA	Increased by 25%
Non-auto accessibility improvement	Vehicle-free ABA increased by mean difference between vehicle-free and one-car ABAs	Decreased by 30 minutes
Both ban and improvement	ABA becomes vehicle-free ABA, which is then increased by mean difference	Increased by 25%, then decreased by 30 minutes

5.2.2 Scenario evaluation measures

I used a mix of place-based and people-based measures to evaluate the simulation results of these policy scenarios. Place-based measures track how the study area evolves in response to the car-lite policy intervention, while people-based measures track temporal changes in households' experiences and/or behavior.

- **Place-based measures:**
  - ***Vacancy rate:*** This measure provides a sense of how popular the study area is by tracking the extent to which housing units in the study area are occupied (i.e., being owned or rented).
  - ***Area mean income:*** By tracking changes in area mean income, we can understand which income groups are moving into the study area and which income groups are being displaced. Observing changes in area mean income between in-movers and out-movers can provide insights into the extent of gentrification of the study area.
  - ***Vehicle-free share:*** This measure records what share of households within the study area are vehicle-free, i.e., do not have access to any private vehicles. Increasing the neighborhood vehicle-free share is the key objective of a car-lite policy pilot.
- **People-based measures:**
  - ***Accessibility:*** Using this measure, we can understand how different car-lite policies (such as vehicle restrictions and/or accessibility improvements) and coordinated housing policies can affect the overall accessibility of study area residents. This is useful for comparing activity-based accessibility changes (from day-0) for all households that end up living in the study area, especially in-movers.
  - ***Consumer surplus:*** As our simulation sub-models can track both the market prices of housing and each household's WTP for any unit, we can estimate the net welfare gain or loss that results after the housing relocation, price changes, and vehicle availability changes have affected household welfare during the initial

three years of the car-lite pilot. I use consumer surplus as a measure of welfare, and as mentioned earlier, consumer surplus in the housing market is the difference between the willingness-to-pay of a household for a housing unit and the market price of that unit.

5.3 How might car-lite policies change neighborhoods?

In this section, I first discuss how I expect households to react to the different car-lite policy scenarios I described earlier. The implications of changes in long-term urban choices for neighborhood-level changes are presented. Then, I select 26 planning areas (with at least 15,000 housing units) in Singapore and simulate the car-lite policy scenarios in order to extract the housing market effects on area mean income and vehicle-free share. Observing the variation in these effects, I select four planning areas for detailed analysis. I then track changes in the five scenario evaluation measures proposed earlier for the different car-lite policy scenarios within these four planning areas over two simulation years (three calendar years). I also explore the extent to which these neighborhood-level changes translate to changes at the city scale. Finally, I discuss how neighborhood characteristics affect the manner in which housing market effects play out with an eye towards identifying what types of neighborhoods may be more susceptible to negative side-effects of accessibility improvements such as gentrification.

5.3.1 Hypothesized effects

Before presenting simulation results, I would like to discuss my hypotheses on how car-lite policy scenarios (such as vehicle restrictions and/or accessibility improvements) can change neighborhoods through the four non-baseline policy scenarios I outlined earlier (see Figure 5-4). When the neighborhood-wide vehicle ban is instituted, I do not expect any change in the composition of the study area compared to the baseline except for the vehicle-free share to shoot up to 100%. When non-auto accessibility improvements are provided within the study area, in the absence of housing effects, I expect a slight decrease in vacancy rate as buyers are now more willing to choose study area units within their choice sets. At the same time, area mean income is likely to remain the same while vehicle-free share is expected to increase (compared to the baseline) as some households will forgo private vehicles in the presence of improved non-auto accessibility. When the housing market response to accessibility improvement is considered, the increased demand is expected to drive down the vacancy rate even further. However, increased WTP and asking prices are expected to result in higher-income movers, which will raise the area mean income and reduce the vehicle-free share (compared to the same policy scenario but without housing market response).

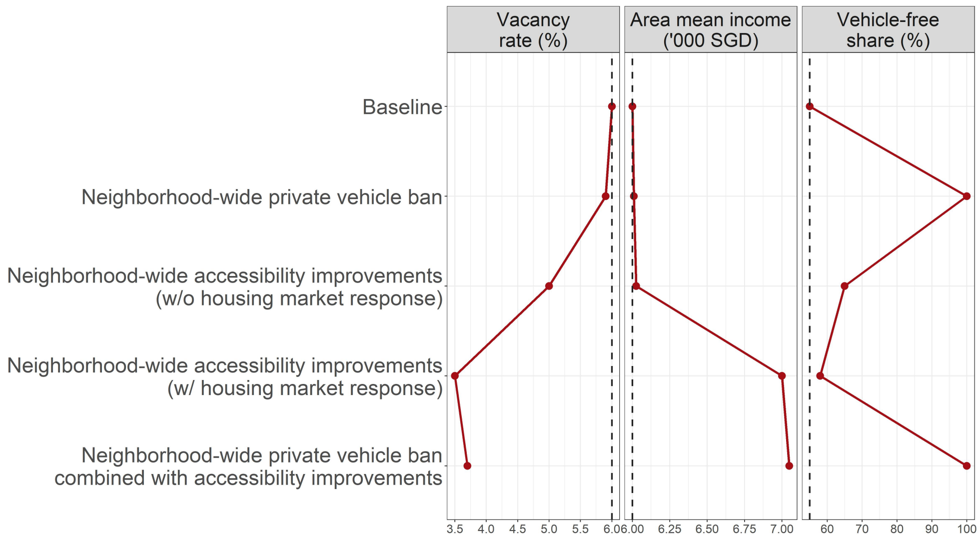


Figure 5-4: Hypothesized effects of neighborhood-wide car-lite policies

When the private vehicle ban is combined with accessibility improvements, I do not expect any significant change in the vacancy rate and area mean income compared with the accessibility improvement only scenario (with housing market response). However, as a result of the vehicle ban, the vehicle-free share in the neighborhood will go up to 100%. Housing market effects on these three place-based measures of neighborhood change can be extracted by comparing the accessibility improvement only scenario without housing market response against the scenario where both buyers and sellers react to accessibility improvements. Neighborhood characteristics will, of course, influence the magnitudes of neighborhood changes and housing market effects.

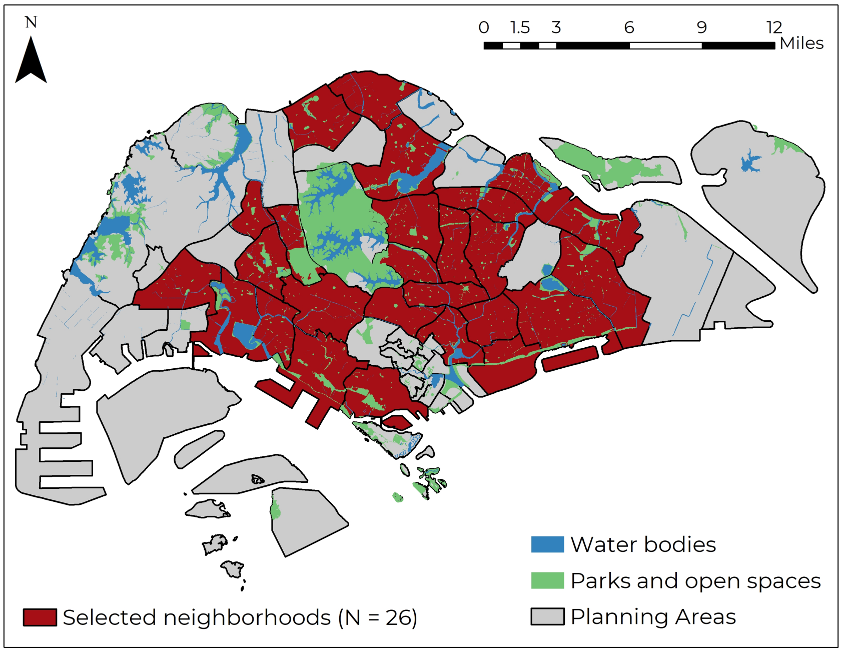
5.3.2 Simulated effects

Having set up the five scenarios (i.e., baseline and four car-lite policies), I selected 26 different planning areas (each having at least 15,000 housing units) as candidate neighborhoods for the car-lite pilot, as shown in Figure 5-5a. These 26 planning areas are home to 96.6%

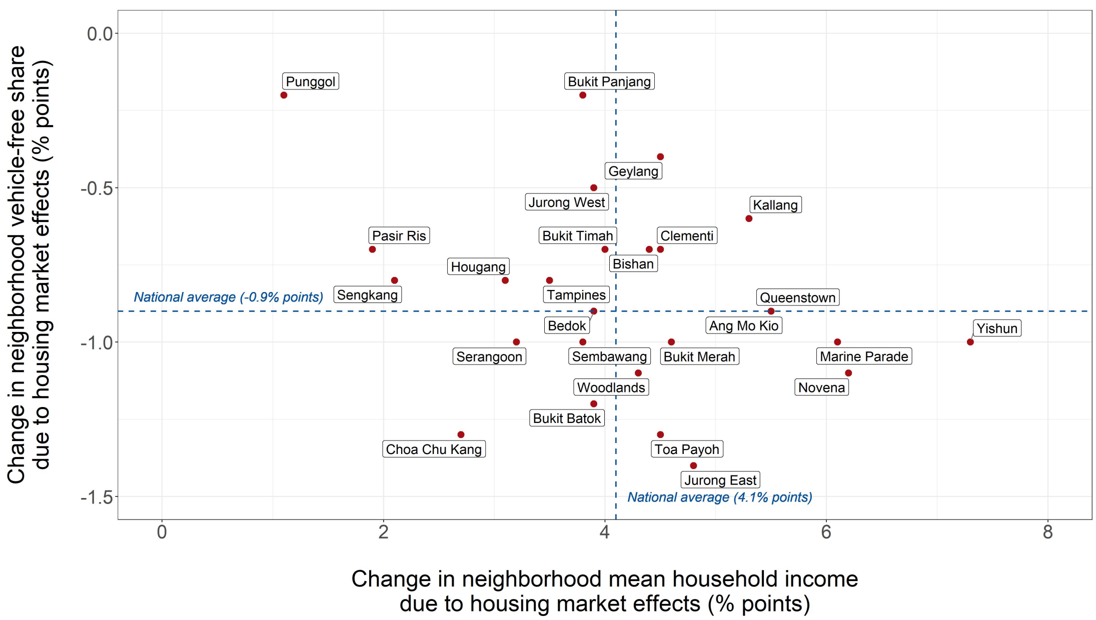
of the population, while covering only 45.9% of the land-area. I then conducted city-wide simulations with the five scenarios for each of these 26 study areas, where only one planning area experiences the car-lite policy. I present the simulated housing market effects on area mean income and vehicle-free share for these 26 planning areas in Figure 5-5b. As mentioned earlier, these housing market effects are extracted by comparing simulated outcomes of the accessibility improvement only scenario with housing market response against the previous scenario (i.e., accessibility improvement only but without housing market response).

I find that the housing market effects on area mean income are always positive, implying that buyer and seller responses to accessibility improvements always drive up the area mean income by attracting higher-income in-mover households. This suggests that accessibility-induced gentrification is likely to occur in all of the selected Singaporean neighborhoods, but to different extents. I also find that the housing market effects on vehicle-free share are always negative, implying that the neighborhood becomes less vehicle-free despite the accessibility improvements as a result of higher-income households (who are also less likely to be vehicle-free) moving in. Thus, accessibility-induced gentrification is likely to lead to the dampening of the increase in vehicle-free share that would otherwise have occurred in the absence of housing market effects.

I then placed the planning areas into four quadrants based on how the housing market effects on area mean income and vehicle-free share compared with the national averages. This helped me look at four distinct cases — (a) small income increase and small vehicle-free decrease (e.g., Punggol), (b) small income increase and large vehicle-free decrease (e.g., Choa Chu Kang), (c) large income increase and small vehicle-free decrease (e.g., Kallang), and (d) large income increase and large vehicle-free decrease (e.g., Yishun). I selected the four outliers (i.e., Punggol, Choa Chu Kang, Kallang, and Yishun) from these four quadrants for a more detailed examination of neighborhood changes. The spatial locations of these four selected planning areas are presented in Figure 5-6. We can see that Kallang is located close to the CBD, Punggol is to the north-east, Yishun is in the north, and Choa Chu Kang is a north-western suburb. Thus, the four planning areas selected for detailed analysis are well distributed across Singapore.



(a) Selecting 26 different planning areas as candidate neighborhoods for piloting car-lite policies



(b) Change in income and vehicle-free share due to housing market effects

Figure 5-5: Simulated housing market effects on neighborhood outcomes in Singapore

Detailed analysis of selected neighborhoods

I first present the vacancy effect of accessibility changes in the four selected planning areas in Figure 5-7. The simulated trends closely resemble my hypothesized effects, even if the

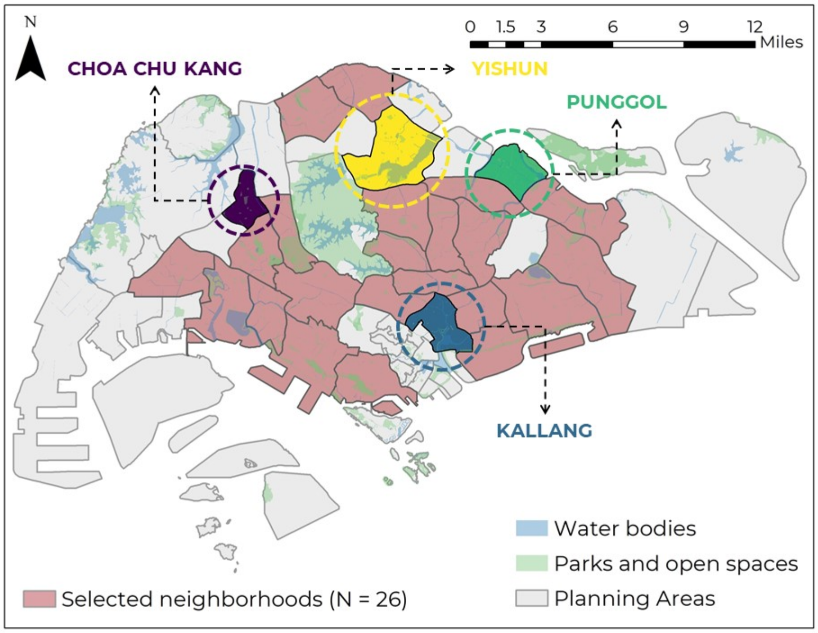


Figure 5-6: Selecting four planning areas (quadrant outliers) for detailed analysis

magnitudes vary across the planning areas. The neighborhood-wide vehicle ban does not affect vacancy rate compared to the baseline. I observe that accessibility improvements, even without housing market effects, make the study area a more attractive residential location by increasing the number of resident households and driving down the vacancy rate. The attractiveness of the area is further accentuated when the housing market response is taken into consideration. There is no further difference between this scenario and the final policy scenario where the vehicle ban is combined with the accessibility improvements. The only difference is seen for Punggol, where vacancy rate increases slightly with the additional imposition of the vehicle ban. This is likely because Pungool is comparatively more auto-dependent (with a vehicle-free share of only 39.5%, compared with the national average of 51.8% — see Table 5.3). In such neighborhoods, the imposition of a vehicle ban, even when combined with accessibility improvements, can reduce the attractiveness of housing location and disincentive potential in-movers.

Figure 5-8 first presents changes in area mean income for the four selected planning areas, followed by a more detailed comparison of mean incomes of in-movers and out-movers. I find confirmation of my hypothesized trends from Figure 5-8a. When accessibility changes are implemented without the inclusion of housing market effects, area mean income does not seem to differ from the baseline value. As expected, the area mean income rises with

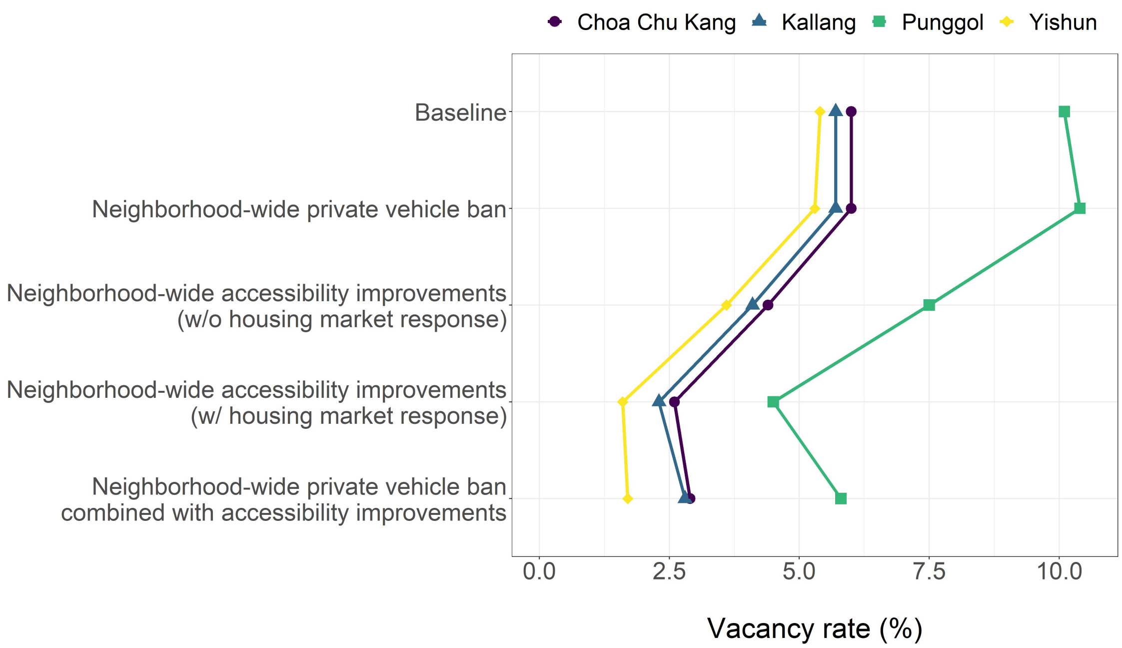
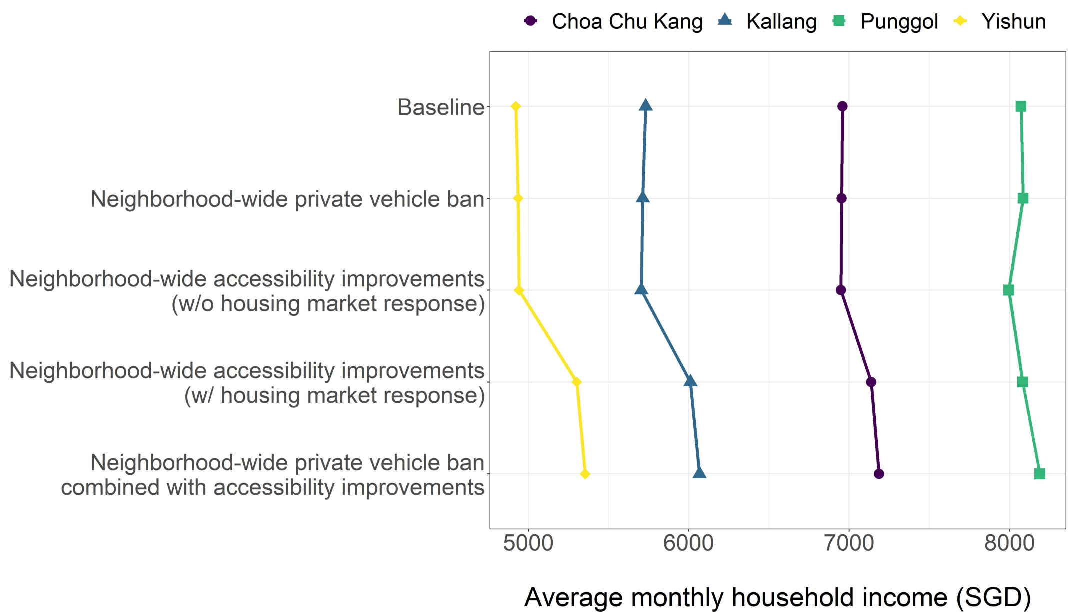


Figure 5-7: Vacancy effect of car-lite policies in selected Singaporean neighborhoods

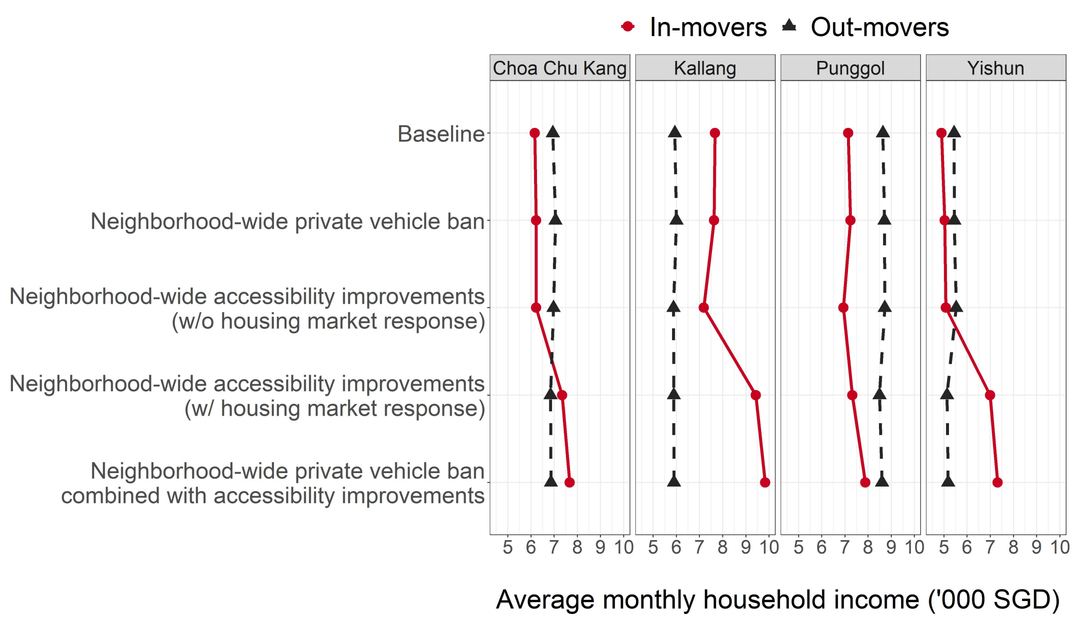
increased demand for housing and higher asking prices for units in the study area. The positive effect of housing market responses on area mean income suggests that in-movers are higher-income compared to original neighborhood residents, when accessibility is improved and the housing market is allowed to subsequently respond.

From Figure 5-8b, I confirm that the average income of in-movers always increases when housing market effects are considered. In neighborhoods like Choa Chu Kang and Yishun (where the housing market effect on vehicle-free share reduction is larger), we see evidence implying accessibility-induced gentrification. In-movers were lower-income compared to out-movers in the absence of housing market response, but higher-income in-movers start displacing lower-income out-movers with the inclusion of housing market response. Although the housing market effects are noticeable for Kallang and Punggol as well, their trajectories are different. Kallang was gentrifying even in the baseline, the extent of which is accelerated by housing market effects. Punggol, on the other hand, does not gentrify in any of the five scenarios.

I then examine changes in the neighborhood-wide vehicle-free share and compare the vehicle-free shares of in-movers against non-movers in Figure 5-9. When the car-lite policy includes a neighborhood-wide vehicle ban (on its own or combined with accessibility improvements), the neighborhood vehicle-free share is always 100%. In Figure 5-9a, vehicle-



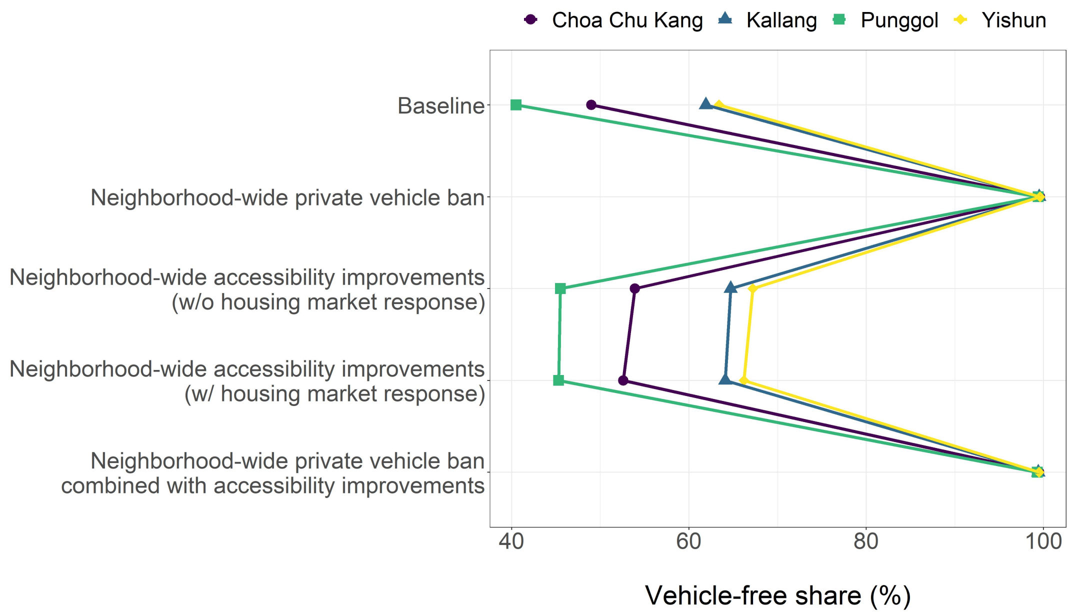
(a) Change in average neighborhood income



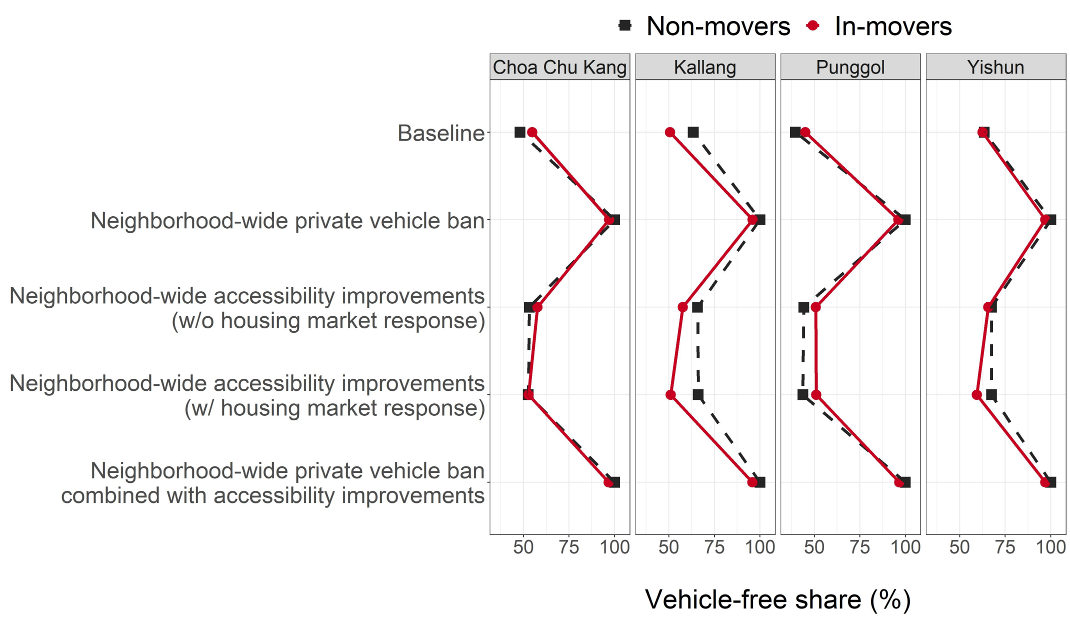
(b) Change in average income of movers

Figure 5-8: Income effect of car-lite policies in selected Singaporean neighborhoods

free share is found to increase by 3-5% points when accessibility is improved in the absence of housing market effects (compared to the baseline). However, as buyers and sellers start responding, the unintended gentrification side-effect of the car-lite policy dampens the increase in vehicle-free share. While the dampening effect is more pronounced for Choa Chu Kang and Yishun, the dampened vehicle-free share still remains higher than the baseline value.



(a) Change in neighborhood-wide vehicle-free share



(b) Change in vehicle-free share of movers

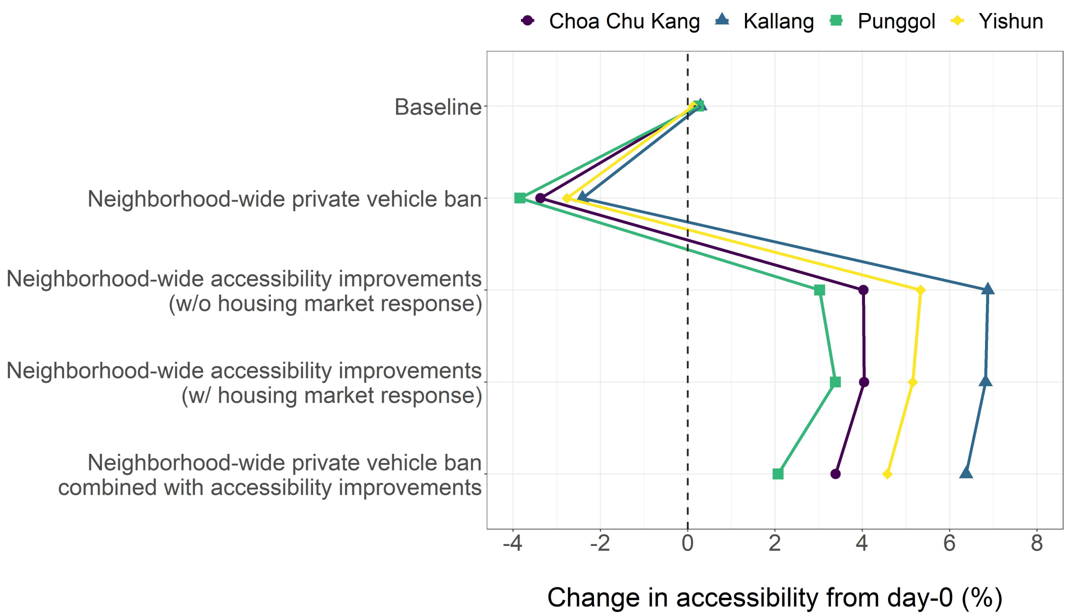
Figure 5-9: Vehicle-free effect of car-lite policies in selected Singaporean neighborhoods

Examining in-movers more closely in Figure 5-9b confirms the consequences of the gentrification side-effect. While in-movers are just as vehicle-free as non-movers (if not more) in the baseline and housing effect-absent accessibility improvement scenarios, they become less vehicle-free in comparison when the housing market response is considered. In Choa Chu Kang, in-movers were more vehicle-free than non-movers in the baseline, but that difference disappears over scenarios. In-movers in Yishun become less vehicle-free than non-movers, driving down the overall vehicle-free share. Despite experiencing these shifts in vehicle-free share, in-movers in Kallang are always less vehicle-free and in-movers in Punggol are always more vehicle-free than non-movers.

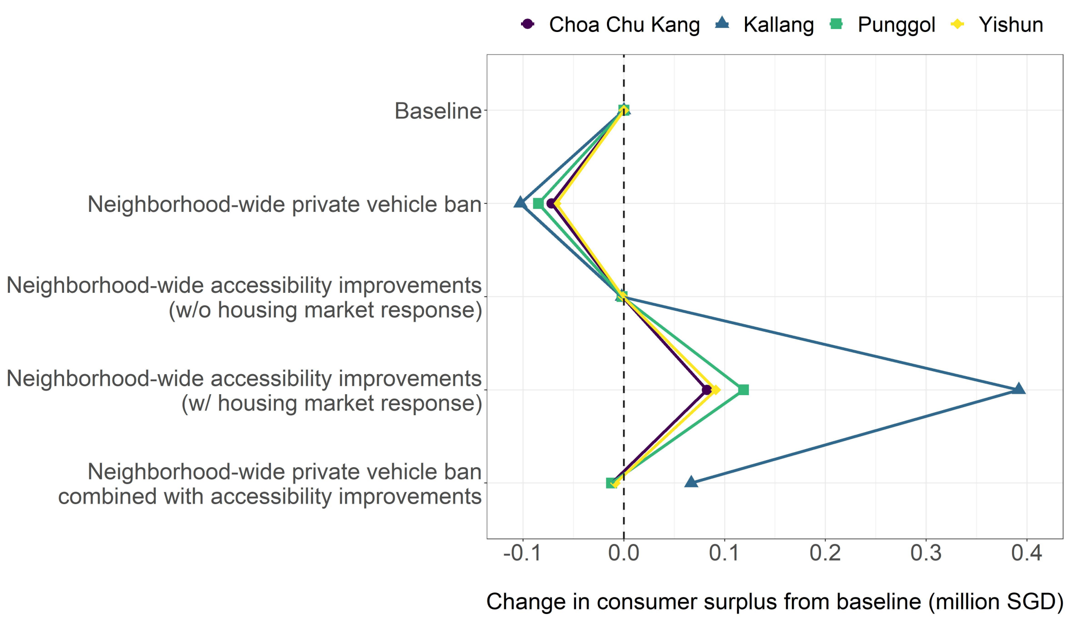
Finally, I present changes in people-based scenario evaluation measures in Figure 5-10. As expected, a neighborhood-wide vehicle ban is found to reduce accessibility of study area residents by 2-4% on average. When accessibility improvements are introduced, then study area residents experience a 2.5-6.5% increase in average accessibility. In addition to reducing accessibility, the vehicle ban policy also reduces consumer surplus by SGD 80,000 - 100,000 per household. When the housing market response is considered, consumer surplus (in the housing market) increases to about SGD 80,000 - 120,000 over baseline values with Kallang being an outlier. When accessibility improvements are combined with the vehicle ban, these significant welfare gains largely disappear. For three of the four planning areas, the resulting surplus becomes slightly lower than the baseline values. The surplus of residents in Kallang remains positive but significantly lower than what they experienced without the vehicle ban. These trends suggest that a vehicle ban will negatively affect both the accessibility and welfare of residents, but non-auto accessibility improvements can provide better accessibility and welfare even after accounting for accessibility-induced gentrification caused by housing market effects. Instead of implementing a neighborhood-wide vehicle ban, it may be more prudent to impose the ban partially, e.g., on new housing developments.

From neighborhood outcomes to city-wide outcomes

As we have been looking only at changes within the neighborhood where the car-lite policy is piloted thus far, one might wonder about the extent to which changes in a single neighborhood affect the wider city or metro area. One question of particular concern might be to see if lower-income (and more vehicle-free) out-movers are being displaced to other neighborhoods where they become less vehicle-free (by choice or by being forced to purchase a car). Therefore, I looked at changes in the Singapore-wide vehicle-free share when accessibility is improved in the four selected neighborhoods. I report these results in Table 5.2, where the post-simulation city-wide vehicle-free share is found to be at least that observed on day-0.



(a) Change in neighborhood-wide activity-based accessibility



(b) Change in neighborhood-wide consumer surplus

Figure 5-10: Accessibility and welfare effects of car-lite policies in selected Singaporean neighborhoods

In most cases, neighborhood-level vehicle-free share increases translate to a minor city-wide increase. This is a promising observation which suggests that expanding accessibility improvements to cover multiple neighborhoods has the potential to increase vehicle-free share not only within the study area but throughout the city or metro area as a whole. For the scenarios where the car-lite policy includes a vehicle ban, the vehicle-free share in the study area goes up to 100%, which will obviously translate into a larger increase in the city-wide vehicle-free share but at the cost of reducing accessibility and welfare.

Table 5.2: Change in Singapore-wide vehicle-free share due to neighborhood changes

Study Area	**Scenario** (***Accessibility improvement***)	**Singapore-wide vehicle-free share (%)**		
		Simulation start (day-0)	*Simulation end*	*Change (% points)*
-	Baseline	51.8%	51.7%	-0.1
Choa Chu Kang	w/o housing market response		51.9%	+0.1
	w/ housing market response		51.9%	+0.1
Kallang	w/o housing market response		51.9%	+0.1
	w/ housing market response		51.9%	+0.1
Punggol	w/o housing market response		51.8%	0.0
	w/ housing market response		51.8%	0.0
Yishun	w/o housing market response		51.9%	+0.1
	w/ housing market response		52.0%	+0.2

Although I do not report it here, city-wide consumer surplus is also likely to increase when the car-lite policy includes accessibility improvements but not a private vehicle ban. We found earlier that consumer surplus in the study area increases as a result of accessibility improvements, even after accounting for housing market effects. As non-movers outside the study area do not experience any welfare changes and out-movers choose locations that provide better surplus than their current locations (as do all movers in our bidding process), surplus increases within the study area are likely to translate to city-wide welfare improvements, although the magnitudes may be more muted.

5.3.3 The role of neighborhood characteristics

In an effort to better understand which neighborhoods are more susceptible to accessibility-induced gentrification, I examined how neighborhood characteristics relate to housing market effects (i.e., changes due to accessibility improvements with and without housing market response). I describe the four selected planning areas and their simulated housing market effects in Table 5.3. Kallang and Punggol, which are significantly lower-income compared to not just the national average but the other two neighborhoods as well, experienced higher increases in area mean income. They were also less vacant (implying a 'tight' housing market) and significantly more vehicle-free. This suggests that non-auto accessibility improvements made in lower-income neighborhoods can produce unintended consequences such as gentrification, which can make these initially more vehicle-free neighborhoods more auto-dependent. This outcome goes against the very intention of the car-lite policy, thus highlighting the need to guard against unintended consequences through supportive coordinated policies.

Table 5.3: Characterizing selected Singaporean neighborhoods by housing market effects

	Singapore	**Punggol**	**Choa Chu Kang**	**Kallang**	**Yishun**
Quadrant in Fig. 5-5b	-	Top left	Bottom left	Top right	Bottom right
Increase in area mean income	-	Small	Small	Large	Large
Decrease in vehicle-free share	-	Small	Large	Small	Large
Units	*1,219,394*	21,050	51,244	36,977	53,373
Vacancy rate (%)	*5.8%*	11.0%	6.1%	4.7%	4.6%
Mean household income (SGD)	*$6,886*	$8,327	$7,060	$5,534	$4,994
Vehicle-free share (%)	*51.8%*	39.5%	49.0%	63.0%	63.7%

One may wonder whether my observations are influenced by my choice of the outlier in each quadrant (see Figure 5-5b). To address this concern, I also compared neighborhood characteristics across quadrants instead of selecting just the four outlier neighborhoods. I did not find evidence of any quadrant-based spatial clustering that would suggest a spatial effect, and my observations about lower-income and more vehicle-free neighborhoods being more susceptible to accessibility-induced gentrification holds true at the quadrant level as well (see Figure A-1 and Table A.9 in Appendix A).

5.4 Coordinated housing policies to support accessibility improvements

I made the case in the previous section that improving non-auto accessibility alone may not be enough to achieve the intended outcomes of car-lite policies in some neighborhoods because of unintended side-effects such as accessibility-induced gentrification. Moreover, a neighborhood-wide vehicle ban is likely to reduce both accessibility and welfare of residents, to an extent that even significant accessibility improvements may be unable to offset. Thus, neither a blanket ban on private vehicles nor accessibility improvements alone are effective car-lite policies when considering outcomes beyond just the vehicle-free share.

In this section, I propose two types of housing policies that, in coordination with accessibility improvements, can enhance the potential benefits of car-lite policies by mitigating some of the negative side-effects such as gentrification. First, I examine how increasing housing supply with accessibility improvements can change neighborhoods. This policy is motivated by upzoning efforts in TOD areas. In addition to direct upzoning by adding new housing supply, I also explore whether affordability constraints (based on income thresholds for eligibility and discounts on asking prices) can improve neighborhood outcomes and distribute the accessibility benefits across socioeconomic groups more equitably.

Building on this, the second housing policy I examine is providing new housing but with restrictions on private vehicle holdings (i.e., a private vehicle ban) for residents of these new units. This is motivated by my previous discussion of reduced minimum parking requirements. Since we are aware of the strong link between parking availability and auto ownership, this policy is conceptualized as upzoning with parking constraints for the new units. Thus, households choosing to reside in these new units are, in a way, restricted from holding private vehicles. My objective here is not to find the optimal coordinated housing policy but to understand how different housing policy instruments (e.g., upzoning, affordability constraints, parking restrictions) can be effective in addressing concerns around accessibility-induced gentrification.

5.4.1 New housing supply

Table 5.4 presents the distribution of housing units by unit type within the four selected neighborhoods. 81-92% of the units in these neighborhoods are public housing (HDB) units. The HDB units in Kallang and Yishun are predominantly smaller units with at most 3 rooms, while about 90% of HDB units in Choa Chu Kang and Punggol are larger with 4 or 5 rooms. Punggol does not have any HDB units with 3 rooms, while only 6% of HDB units in Yishun with at most 3 rooms are small studios or 2-room units. I describe this distribution here because I operationalized the new housing supply policy by doubling the number of HDB units in each of these four neighborhoods. Doubling the entire public housing stock in a neighborhood might seem like overkill but, as mentioned earlier, I am interested in boundary effects. 'Actual' policies will likely be implemented at a smaller scale, which is why this exploration is useful for us to understand the potential maximum benefits of particular policies. The reason for choosing public housing to operationalize this policy is simple. Housing supply in Singapore is primarily driven by the HDB, and four in five households live in HDB units. Therefore, new housing supply policies in Singapore must be designed keeping these nuances in mind.

Table 5.4: Distribution of housing units by unit type in selected Singaporean neighborhoods

Study Area	**Total units**	**HDB units**		**HDB123 units**		**HDB12 units**	
		Count	***% of total***	***Count***	***% of HDB***	***Count***	***% of HDB123***
Choa Chu Kang	51,244	47,167	92%	2,592	11%	1,106	43%
Kallang	36,977	29,887	81%	16,660	77%	5,896	35%
Punggol	21,050	18,567	88%	1,146	9%	1,146	100%
Yishun	53,373	49,231	92%	14,420	58%	805	6%

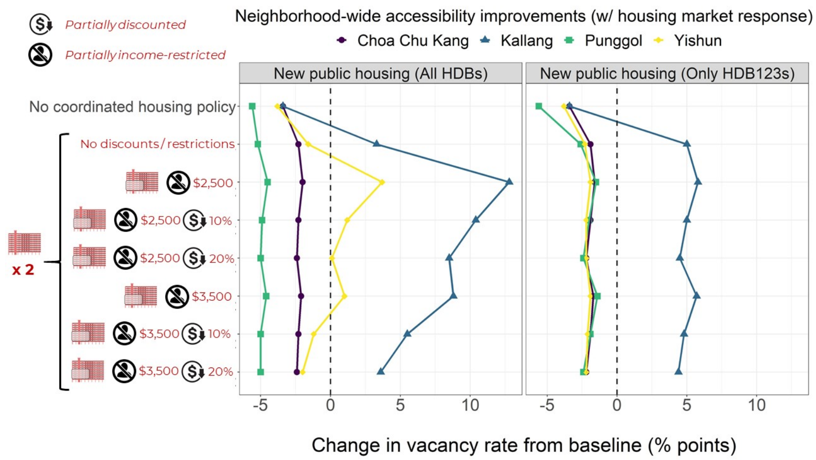
I considered two distinct cases — (a) doubling the entire public housing stock ('*All HDBs*'), and (b) doubling only the smaller public housing stock ('*Only HDB123s*'). I separated out these two cases because households living in HDB4 and HDB5 units tend to be higher-income and are comparatively less likely to be vehicle-free. Since the objective of the car-lite policy is to make the neighborhood more vehicle-free, perhaps targeting the new housing supply towards households who are more likely to become and/or remain vehicle-free can be more fruitful. In addition to 'simply' doubling the public housing stock to provide new housing supply, I created additional scenarios where the new housing units are subject to affordability constraints. These include income restrictions (i.e., only households with incomes below a certain threshold are eligible to bid or rent) and/or discounts (i.e., the asking price is discounted by a certain amount). I selected a subset of HDB units for these affordability constraints based on the unit type. When the new housing supply includes all HDB units, only HDB12 and HDB3 units can be income-restricted and/or discounted. Similarly, when HDB12 and HDB3 units are offered as new housing, only HDB12 units can be income-restricted and/or discounted. I tried out two values for the income-restriction threshold — SGD 2,500 (the 25th percentile of household incomes in the synthetic population) and SGD 3,500 (the 35th percentile). Concurrently, I tried out 10% and 20% as two possible discount values for the asking price. I provided these discounts only for those units which were income-restricted in an effort to make the new housing supply more affordable for lower-income households.

The effects of these new housing supply scenarios on neighborhood outcomes are presented in Figure 5-11. I retain the scenario where both buyers and sellers react to accessibility improvements without any coordinated housing policy as a reference, and then show the results of the additional scenarios with new housing supply (first, without any affordability constraints, and then with varying values of income-restriction thresholds and asking price discounts). Doubling the entire public housing stock is found to increase the vacancy rate in neighborhoods like Kallang and Yishun, which had experienced stronger gentrification effects without this coordinated housing policy. This is because these neighborhoods have a larger share of HDB123 units (56% in Kallang and 29% in Yishun).

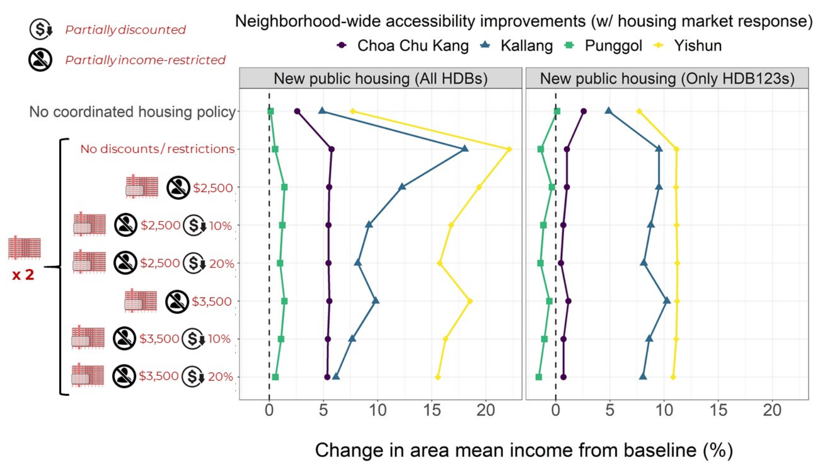
When new HDBs are offered with the same unit type distribution, in-movers rush in to occupy the larger HDB4 and HDB5 units but most of the smaller HDB units remain unattractive at current asking prices. We find confirmatory evidence of this explanation by observing the significant rise in the area mean income. Having seen earlier that higher-income households are less likely to become vehicle-free despite the non-auto accessibility improvements, it comes as no surprise that the neighborhood-wide vehicle-free share drops sharply with this flood of in-movers. What is surprising is that this decrease is so large that the vehicle-free share drops to lower than the baseline value. This implies that, in neighborhoods like Kallang and Yishun, providing new housing supply (of all HDB units) can be worse than not coordinating the accessibility improvements with any upzoning policy.

These concerning trends can, however, be tempered with the help of affordability constraints on the new housing supply that make these units seem more attractive to lower-income households. These additional policy instruments help reduce the vacancy rate by attracting lower-income and more vehicle-free households who reduce the area mean income and increase the aggregate vehicle-free share. For the other two neighborhoods (Choa Chu Kang and Punggol), the effects of upzoning are comparatively muted without significant change in the vacancy rate or area mean income. I find that the vehicle-free shares do increase, but not by much, despite additional affordability constraints to improve the attractiveness of the new housing supply.

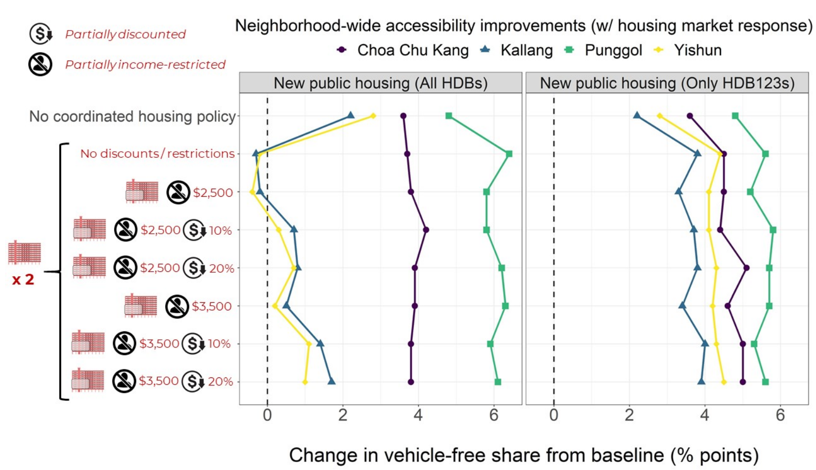
Examining the case where I implemented upzoning by doubling only the smaller HDB



(a) Change in vacancy rate



(b) Change in area mean income



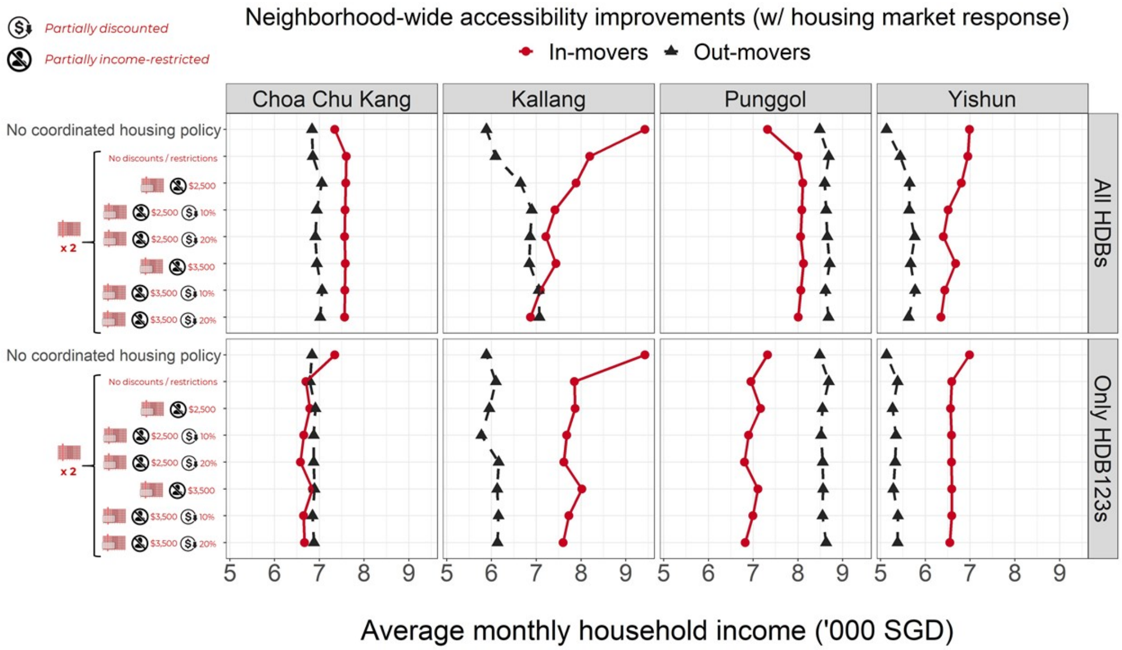
(c) Change in vehicle-free share

Figure 5-11: Neighborhood outcomes of coordinated new housing supply in selected Singaporean neighborhoods units, I observe different trends. Kallang is the only planning area which experiences an increase in vacancy rate due to the upzoning policy. This is because 35% of the HDB123 units in Kallang are smaller HDB12 units, which are not attractive to most households. Despite the various affordability constraints used to offer a better deal on these units, the vacancy rate does not decrease. Both Kallang and Yishun experience about 10% increase in area mean income across the various new housing policy scenarios. However, unlike the previous policy case (with all HDBs), I find that the vehicle-free share increases for all neighborhoods with the supply of new smaller public housing units, which is the intended outcome of the car-lite policy. These results seem to suggest that coordinated housing policies will benefit from being tailored to the neighborhood; one housing policy does not fit all neighborhoods.

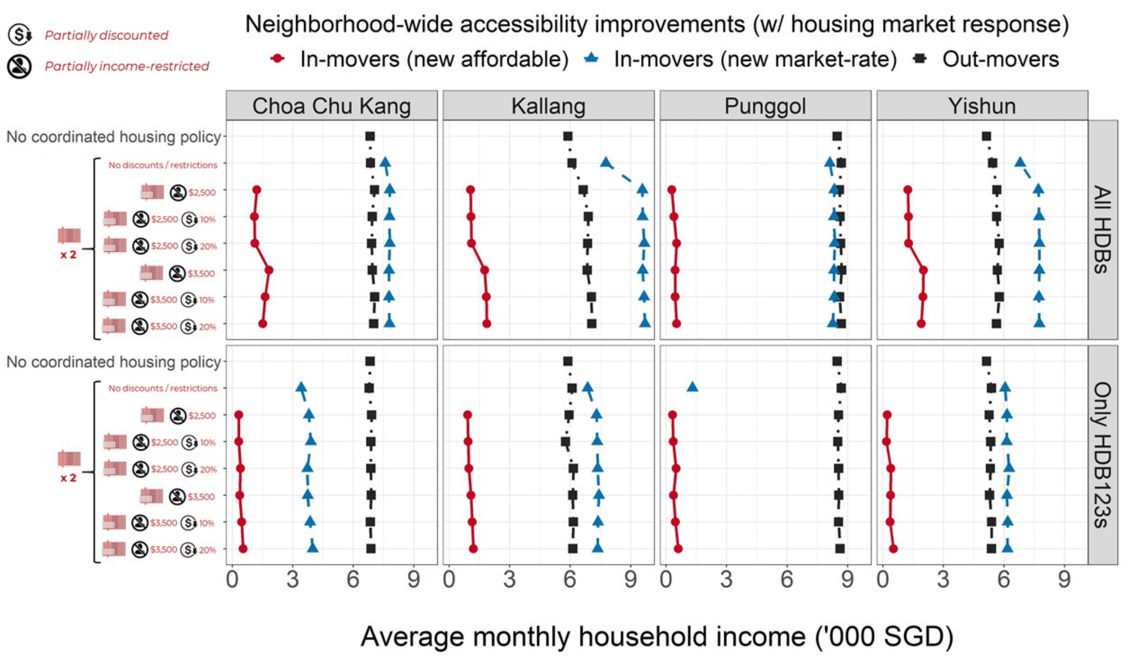
Next, I compare the incomes of in-movers and out-movers, and separate out the residents of new housing units based on whether they moved into new affordable (i.e., income-restricted and/or discounted) units or new market-rate units (see Figure 5-12). When all HDBs are doubled, in-movers are always higher-income than out-movers (except for Punggol) but coordinated upzoning policies can reduce the income difference. My observation for the case where only smaller HDBs are doubled is similar but only Choa Chu Kang and Punggol have relative success in reducing the income difference. Out-movers are much more lower-income in Kallang, which is why, despite the reduction in income of in-movers with the help of income-restrictions and discounts, they remain higher-income than out-movers.

Separating out the in-movers into these new units based on the unit type (affordable or market-rate) yields further insights. As expected, in-movers occupying new affordable units have significantly lower incomes, implying the success of the affordability constraints (i.e., income restrictions and discounts) in increasing the attractiveness of new housing supply in the study area. The extent of gentrification, thus, seems to be driven purely by households who move into the new market-rate units. Lower-income neighborhoods such as Kallang and Yishun remain at risk of further gentrification because the in-movers into new market-rate units are higher-income than not just other in-movers but also the out-movers they displace.

Similar to the detailed income exploration, I examined the vehicle-free shares of movers in greater detail as well (see Figure 5-13). In-movers appear to be less vehicle-free than out-movers in lower-income neighborhoods like Kallang and Yishun when all HDBs are upzoned. However, the additional affordability constraints on part of these new housing units increase the vehicle-share of in-movers to some extent. When only smaller HDB units are provided



(a) Change in average income of all movers



(b) Change in average income of movers into new housing units

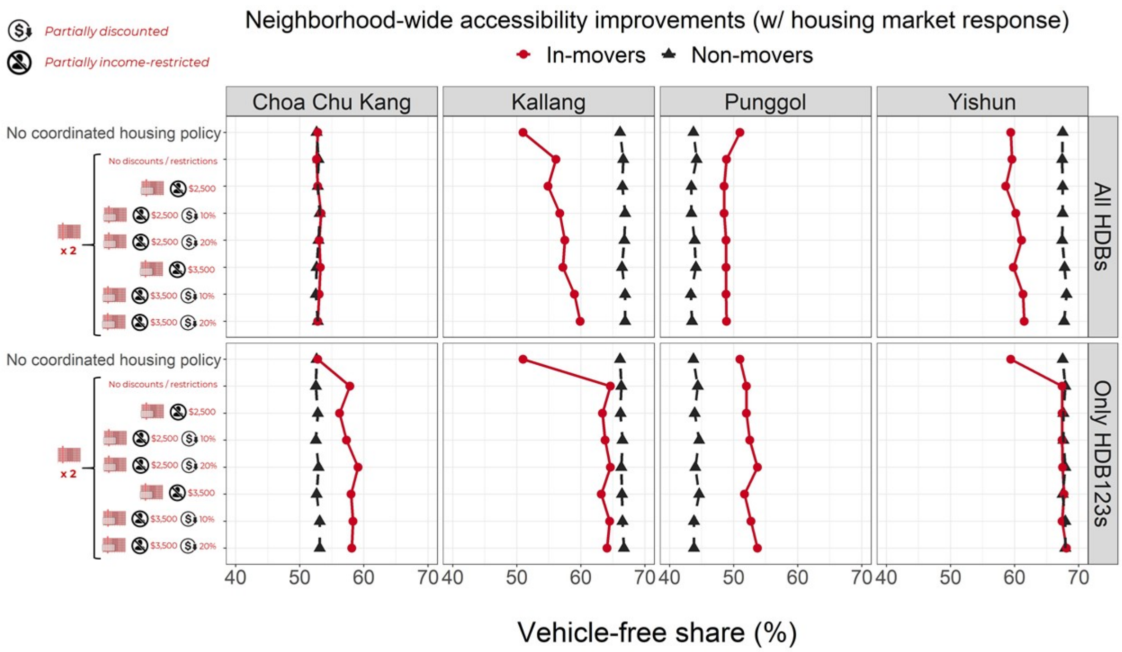
Figure 5-12: Income effect of coordinated new housing supply in selected Singaporean neighborhoods

as part of the new housing supply, there is an increase in the vehicle-free share of in-movers in all four neighborhoods. However, no further benefits are observed despite the addition of supplementary affordability constraints. As expected, in-movers in new affordable units are mostly vehicle-free with vehicle-free shares close to 90%. Therefore, the vehicle-free transitions of households moving into new market-rate units seem to guide the eventual change in neighborhood-wide vehicle-free share. If they are less vehicle-free as in Kallang and Punggol with the doubling of all HDBs, the neighborhoods will not be able to experience the maximum potential benefits of the car-lite policy.

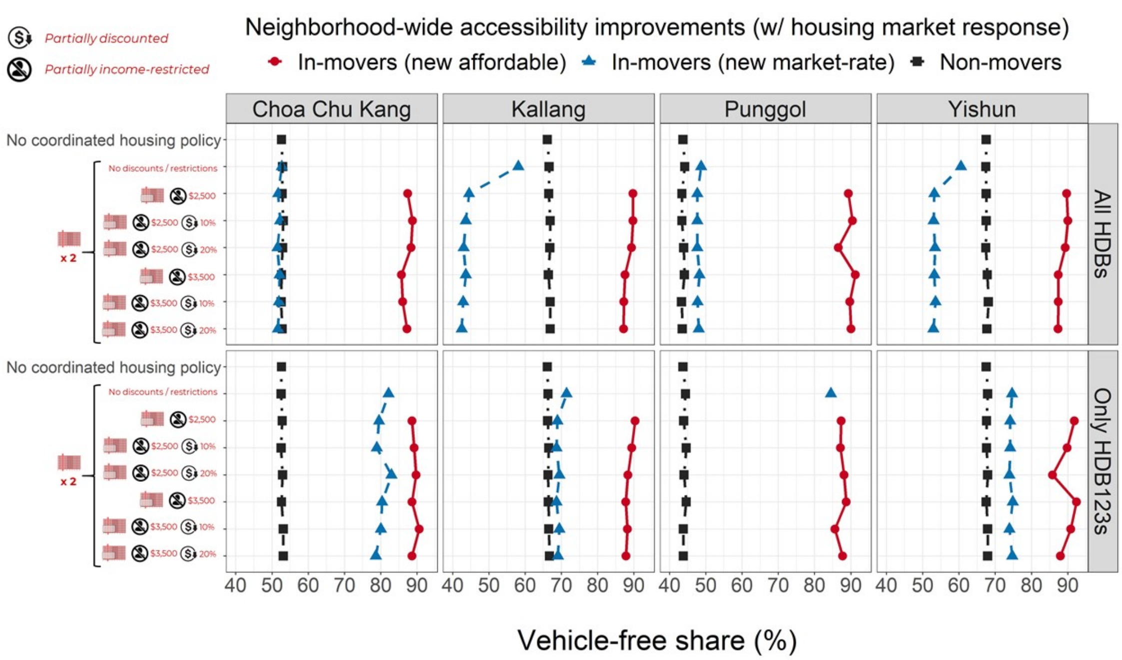
Finally, I present changes in people-based scenario evaluation measures in Figure 5-14. Accessibility appears to decrease marginally with the introduction of upzoning (see Figure 5-14a). This may be explained by the in-migration of higher-income households who experienced greater accessibility in their former residential locations (with private vehicle holdings) than they do now in the study area, despite improvements in non-auto accessibility. However, in neighborhoods like Kallang and Yishun, affordability constraints can be effective in reducing the extent of this accessibility decrease. Overall, accessibility with upzoning remains quite close to accessibility without upzoning and much larger than initial day-0 levels. Consumer surplus with upzoning is found to be better than that without upzoning in all neighborhoods, although the magnitudes obviously differ (see Figure 5-14b). Similar trends are observed across neighborhoods, but the scale of the x-axis in the figure masks close observation of the trends in neighborhoods other than Kallang. The increase in consumer surplus due to upzoning can be further accentuated by income restrictions and discounts, suggesting that upzoning with affordability constraints can be an effective mechanism to equitably distribute improvements in accessibility and welfare across socioeconomic groups.

5.4.2 Vehicle-restricted housing supply

My findings from providing new housing supply suggested more attention towards incentivizing households who move into new market-rate units to become more vehicle-free. Such a transition could be influenced by incentives such as discounts on the asking prices of housing units or disincentives such as more expensive parking or parking restrictions (or even elimination). As different municipalities are likely to pursue different mechanisms, I operationalized this policy in a manner that is agnostic to the particular mechanism through which the vehicle-free transition is influenced. Same as earlier, I provided new housing supply by doubling the public housing units in the neighborhood (both with all HDBs and only HDB123s) with the key difference being that all new housing units are now vehicle-restricted. This policy restricts households who move into these new units from any private



(a) Change in vehicle-free share of all movers

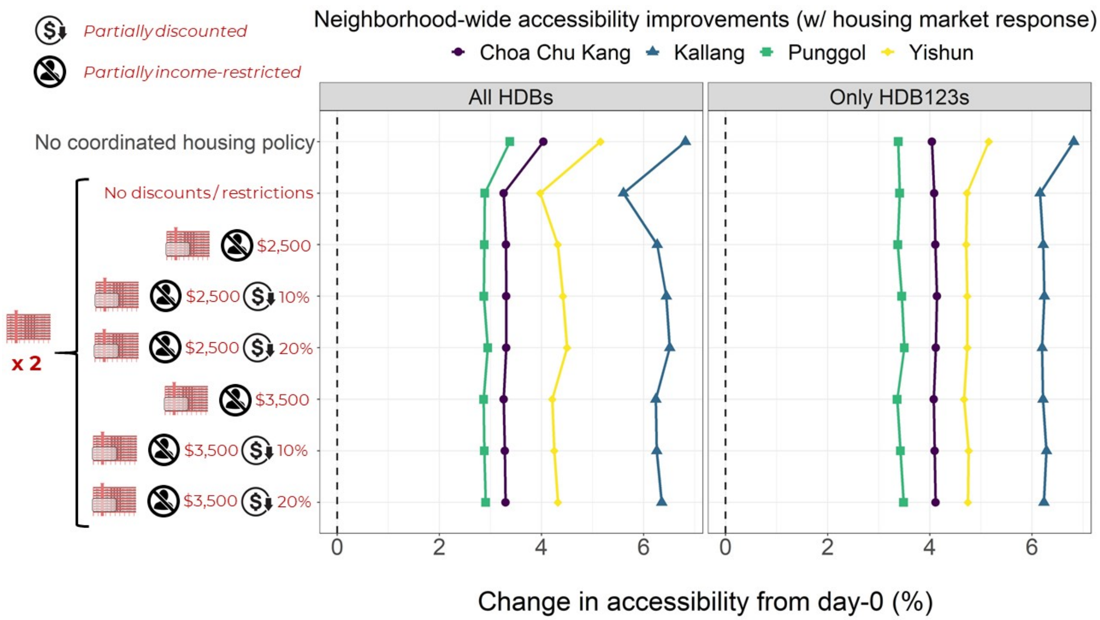


(b) Change in vehicle-free share of movers into new housing units

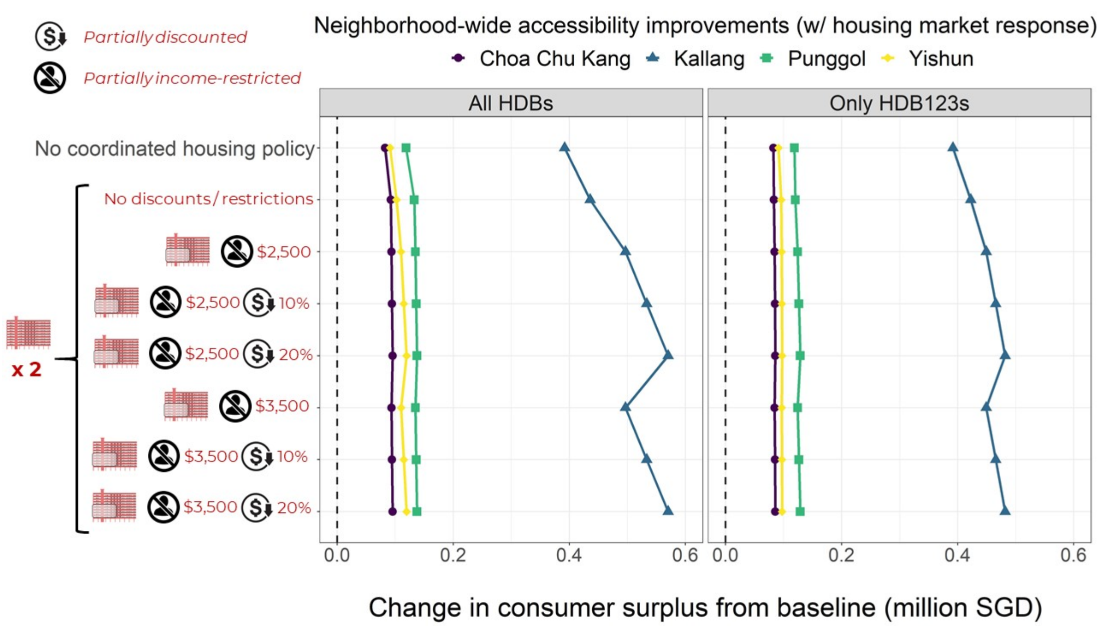
Figure 5-13: Vehicle-free effect of coordinated new housing supply in selected Singaporean neighborhoods

vehicle holdings and forces them to become vehicle-free.

I ran several simulations of this vehicle-restricted upzoning policy, first without any affordability constraints, and then with varying values of income restrictions (set at SGD



(a) Change in neighborhood-wide activity-based accessibility



(b) Change in neighborhood-wide consumer surplus

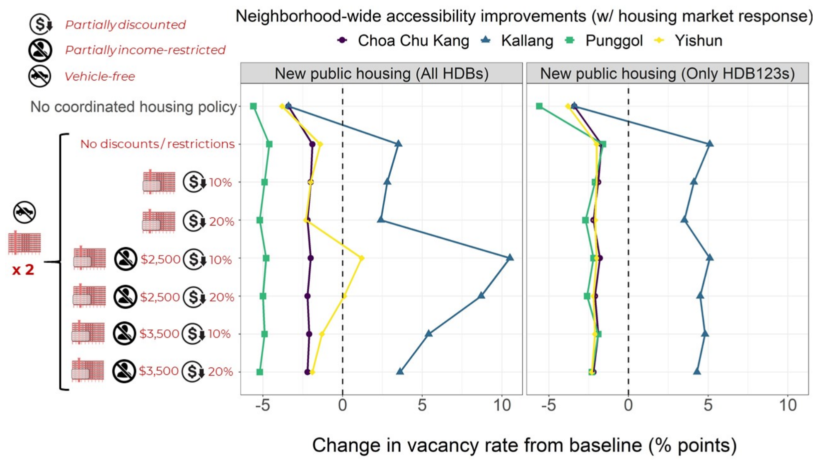
Figure 5-14: Accessibility and consumer surplus effects of coordinated new housing supply in selected Singaporean neighborhoods

2,500 or SGD 3,500) and discounts (set at 10% or 20%). The only difference between these scenarios and those in the previous sub-section is that, except for one, every scenario with vehicle-restricted housing supply includes a discount on the asking price. I did not include any scenario with only income restrictions, unlike with new housing supply, because I am interested in examining whether lower asking prices can make up for the inconvenience caused by the restriction on vehicle holdings even though non-accessibility improvements are provided.

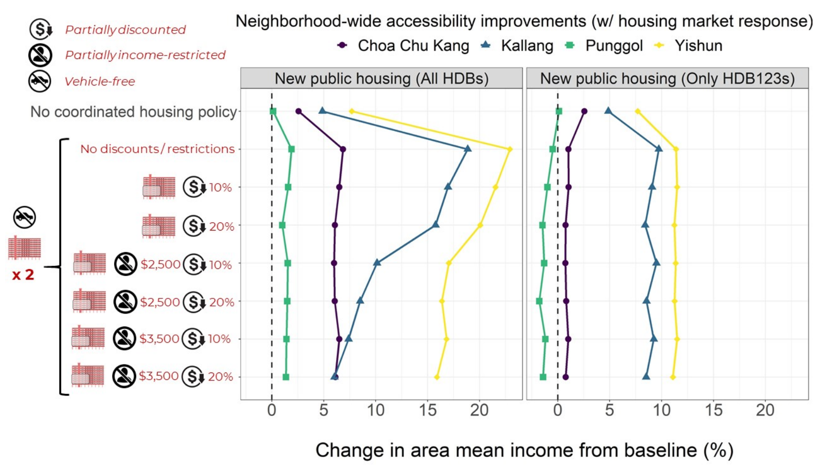
Figure 5-15 reports changes in neighborhood outcomes. Lower-income neighborhoods that are more susceptible to accessibility-induced gentrification (such as Kallang and Yishun) experience more changes due to the coordinated vehicle-restricted upzoning policy. When all HDB units are doubled but with restrictions on vehicle holdings, the lack of affordability constraints make neighborhoods like Kallang and Yishun less attractive as evidenced by the increase in vacancy rate. At the same time, area mean income increases drastically, suggesting that fewer households move into the study area (compared to when coordinated housing policies were absent) and those that do are significantly higher-income. However, as a result of the vehicle-restricted clause associated with new housing supply, these higher-income households are forced to become vehicle-free and the neighborhood-wide vehicle-free rate increases by at least 15% points. Introducing income-restrictions and discounts seems successful in making these new vehicle-restricted housing units more attractive to lower-income households as area mean income reduces. Despite mitigating the gentrification side-effect, no additional vehicle-free benefits are realized. Similar trends are observed when only HDB123s are offered as new vehicle-restricted housing, although the increases in vehicle-free share are comparatively more modest and do not exceed 10% points.

Examining the incomes of in-movers in further detail in Figure 5-16 confirms these findings and yields some new insights. When income restrictions are put in place on the new vehicle-restricted housing units, the average income of households who move into the new market-rate units increase, especially in Kallang and Yishun. As the income restrictions reduce the pool of new housing units for which middle-income households are eligible, the reduced supply sparks off a bidding war. Many middle-income households who were moving into these new vehicle-restricted units are now ineligible for the affordable units and cannot afford the market-rate units as higher-income households bid up the asking prices. This increases the neighborhood vacancy rate as well. However, the vehicle-free share is not affected because all households, regardless of income or preference, have to become vehicle-free after moving into the new housing units offered through the vehicle-restricted upzoning policy.

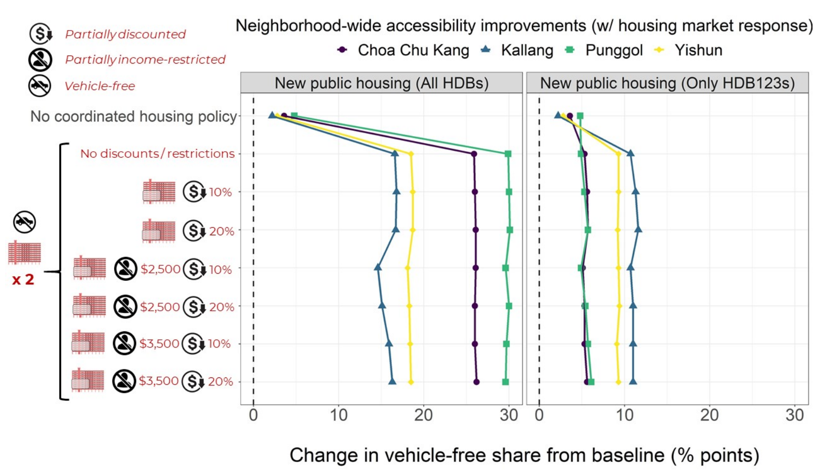
Finally, I present changes in people-based scenario evaluation measures in Figure 5-17. Accessibility appears to decrease by 1-2% points with the introduction of vehicle-restricted



(a) Change in vacancy rate

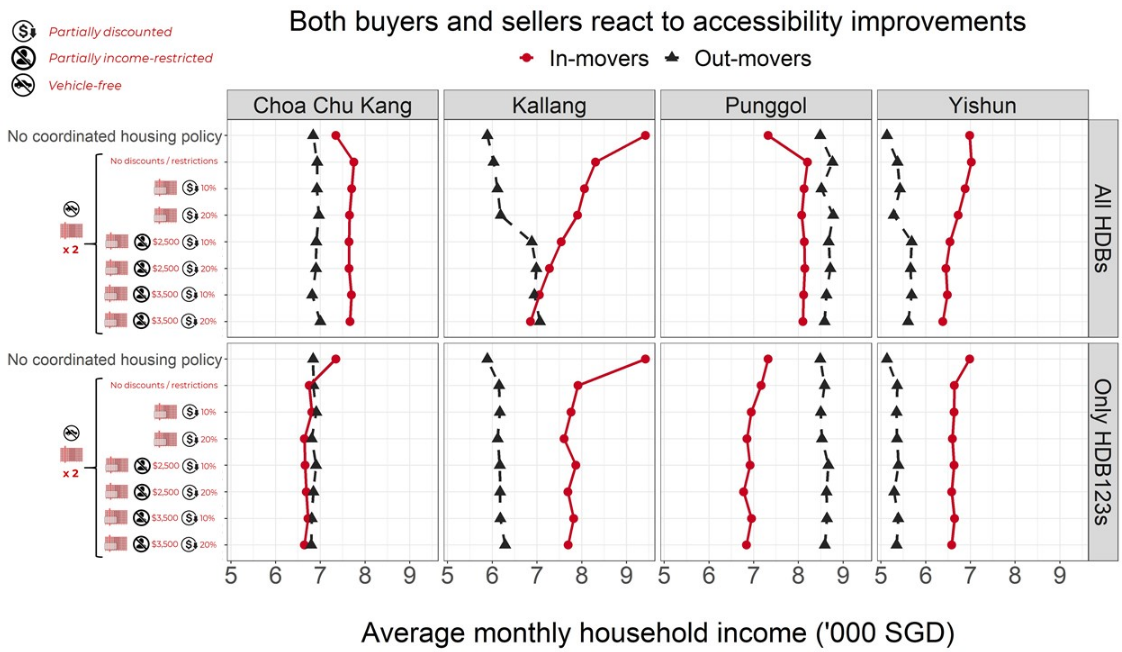


(b) Change in area mean income

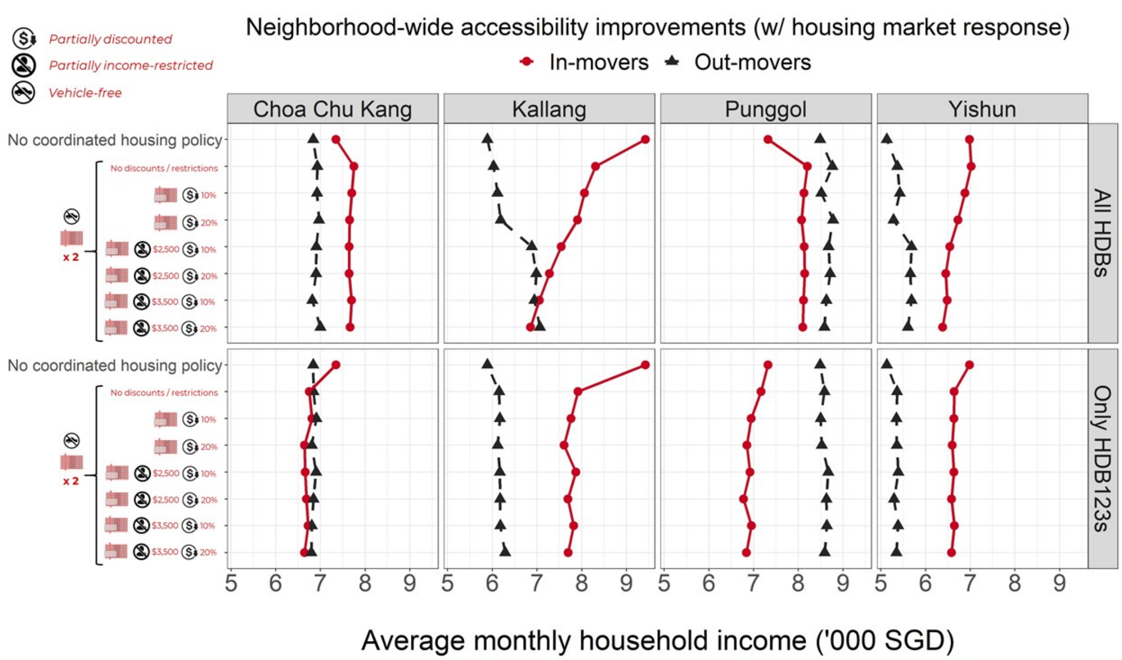


(c) Change in vehicle-free share

Figure 5-15: Neighborhood outcomes of coordinated vehicle-restricted housing supply in selected Singaporean neighborhoods



(a) Change in average income of all movers



(b) Change in average income of movers into new housing units

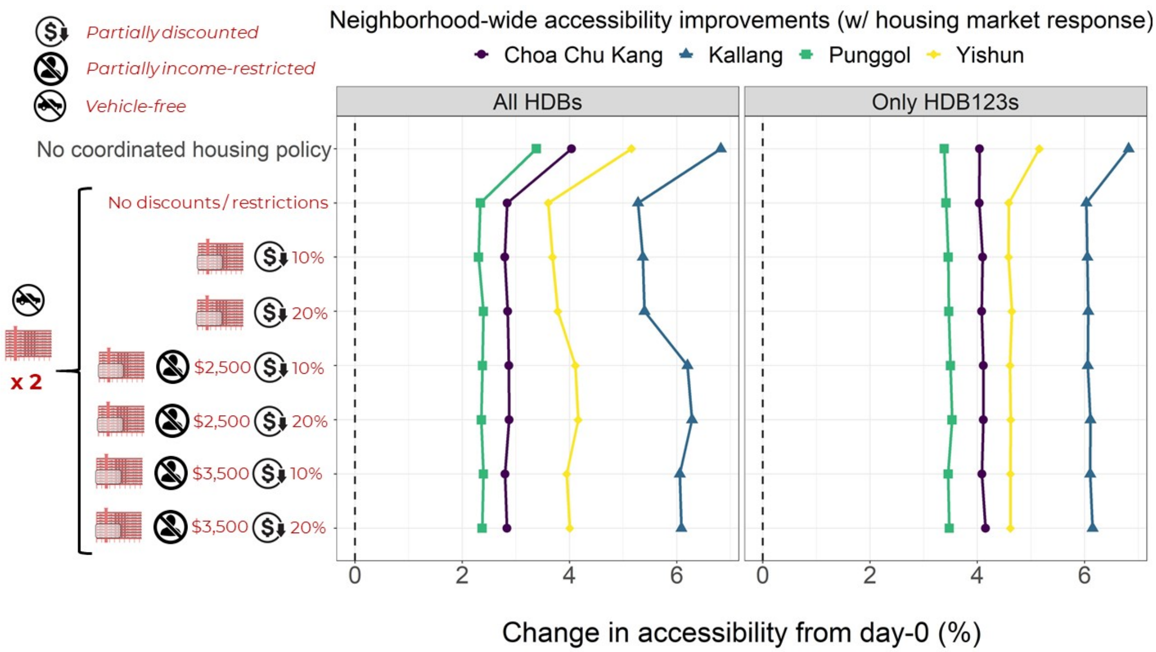
Figure 5-16: Income effect of coordinated vehicle-restricted housing supply in selected Singaporean neighborhoods

upzoning (see Figure 5-17a). This decrease is larger than what I observed for upzoning without parking constraints. However, the trends are largely the same, where affordability constraints can be effective in reducing the extent of this accessibility decrease in some neighborhoods. Regardless of this decrease, accessibility with vehicle-restricted upzoning remains much larger than initial day-0 levels. Contrary to the previous policy (i.e., upzoning without parking constraints), I find that introducing vehicle restrictions on new housing supply reduces welfare, which is in agreement with the car-lite policy explorations I presented earlier. A decrease in consumer surplus is observed for all scenarios across the four neighborhoods (see Figure 5-17b). Although upzoning by itself had increased consumer surplus relative to the scenario without any coordinated housing policy, parking constraints push welfare in the opposite direction. While affordability constraints work to a certain extent in mitigating this decrease in welfare, they are much more effective when only smaller public housing units are offered as vehicle-restricted new housing supply. Thus, tailoring private vehicle restrictions to particular types of new housing developments is going to be key if we want to increase the neighborhood vehicle-free share without compromising on residents' welfare.

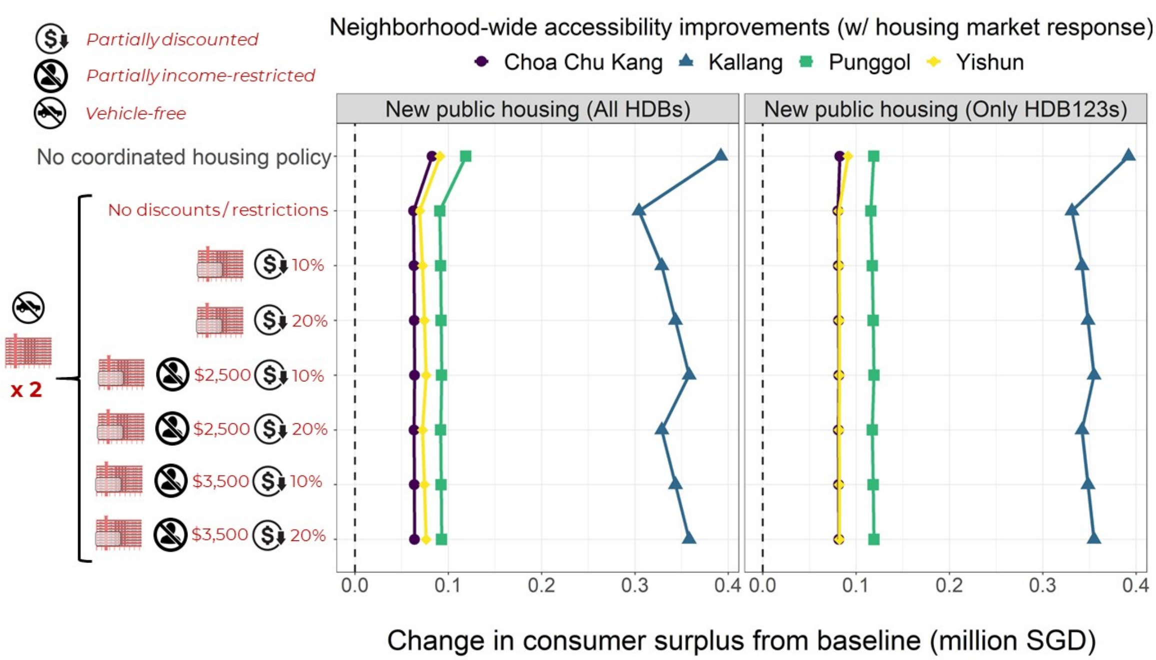
5.5 Summary

This chapter explored how neighborhoods might change in response to car-lite policies that include private vehicle restrictions and/or non-auto accessibility improvements. I designed four scenarios of potential car-lite policies that can be piloted at the neighborhood-level, in addition to a baseline scenario that I used as a reference. Neighborhood changes in response to these four policies, as measured through five evaluation measures, are summarized in Table 5.5. I found that a neighborhood-wide private vehicle ban does help in creating a fully vehicle-free neighborhood, but at the cost of significantly reducing accessibility and welfare. I also found evidence of accessibility-induced gentrification across several Singaporean neighborhoods, which, in turn, dampened the potential vehicle-free share increase.

Recognizing that accessibility improvements alone are always at the risk of inducing gentrification which may in turn dampen the increase in vehicle-free shares, I tested two types of housing policies — upzoning and parking restrictions. These policies, in conjunction with affordability constraints, can address accessibility-induced gentrification when coordinated with accessibility improvements. I summarize how neighborhoods change in response to these policies in Table 5.6. I found that coordinated housing policies show promise in being able to address gentrification concerns while enhancing the benefits of accessibility improvements. They become much more effective when they are combined with affordability



(a) Change in neighborhood-wide activity-based accessibility



(b) Change in neighborhood-wide consumer surplus

Figure 5-17: Accessibility and consumer surplus effects of coordinated vehicle-restricted housing supply in selected Singaporean neighborhoods

constraints that help distribute accessibility and welfare benefits more equitably.

In the next chapter, I analyze the extent to which my findings are sensitive to certain parameters, followed by whether they are robust to changes in a few key assumptions. I also

Table 5.5: Summary of accessibility-induced neighborhood changes

	Vacancy	**Area mean income**	**Vehicle-free share**	**Accessibility**	**Consumer surplus**
Baseline			***Reference***		
Private vehicle ban	∼	∼	100%	--	--
Accessibility improvements (*w/o housing market response*)	-	∼	++	++	∼
Accessibility improvements (*w/ housing market response*)	--	+	+	++	++
Private vehicle ban & Accessibility improvements	--	+	100%	+	- / +

Table 5.6: Summary of coordinated housing policy-induced neighborhood changes

	Vacancy	**Area mean income**	**Vehicle-free share**	**Accessibility**	**Consumer surplus**
No coordinated housing supply	***Reference — Accessibility improvements (w/ housing market response)***				
New housing supply					
w/o affordability constraints	++	++	- / +	-	+
w/ affordability constraints	+	- / +	+	-	++
Vehicle-restricted housing supply					
w/o affordability constraints	+	++	++	-	--
w/ affordability constraints	+ / ++	- / +	++	-	- / ∼

explore whether and how my findings can be generalized to contexts beyond Singapore by using the example of a virtual city.

Chapter 6

Generalizability & Transferability

This chapter discusses the generalizability of my findings by testing their sensitivity and robustness to key parameters of interest and core modeling assumptions. First, I examine the extent to which my scenario evaluation measures are affected by stochastic variation in the simulation. Then, I explore how assuming different magnitudes of accessibility improvement would affect neighborhood outcomes. In the previous chapter, I had assumed that households respond to accessibility improvements in a uniform manner. Here, I introduce non-uniformity in the responses by household income and examine the subsequent change in neighborhood outcomes. Moving on to robustness checks, I test whether choosing a different housing-mobility choice framework (simultaneous instead of sequential — see Section 4.4.3), introducing the cost of private vehicle holdings into the choice framework, or using a different accessibility measure (commute time instead of ABA) might change my observations. Finally, I assess the transferability of my findings related to how neighborhoods change in response to car-lite policies by testing the same policy scenarios but in a different, more auto-dependent setting.

6.1 Sensitivity analysis

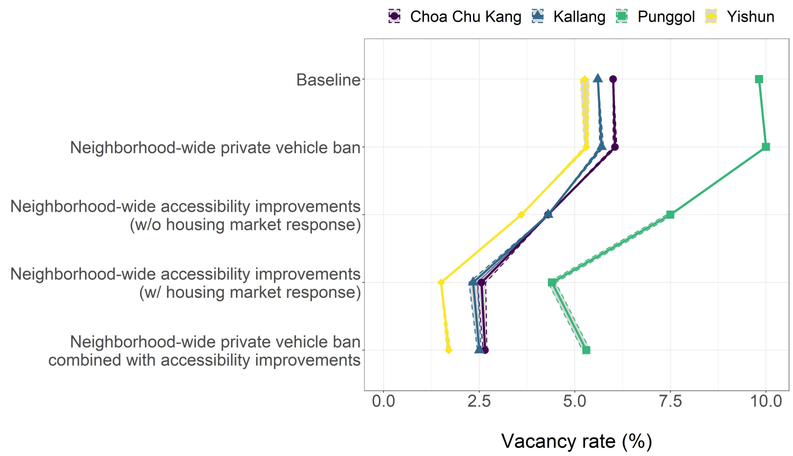
As in any simulation study, it is important to explore how the results I have presented thus far are sensitive to certain parameters of interest. Therefore, in this section, I first examine the extent of stochastic variation in my simulation results, which might affect my comparison of neighborhood outcomes. Then, I change the magnitude of accessibility improvements and measure changes in neighborhood outcomes relative to different extents of enhanced non-auto accessibility. Finally, instead of assuming uniform improvements across socioeconomic groups, I vary the extent to which different income groups receive or perceive these improvements and track how this changes neighborhoods. This can help us in understanding which groups to target when implementing these policies.

6.1.1 Stochastic variation across repeat simulations

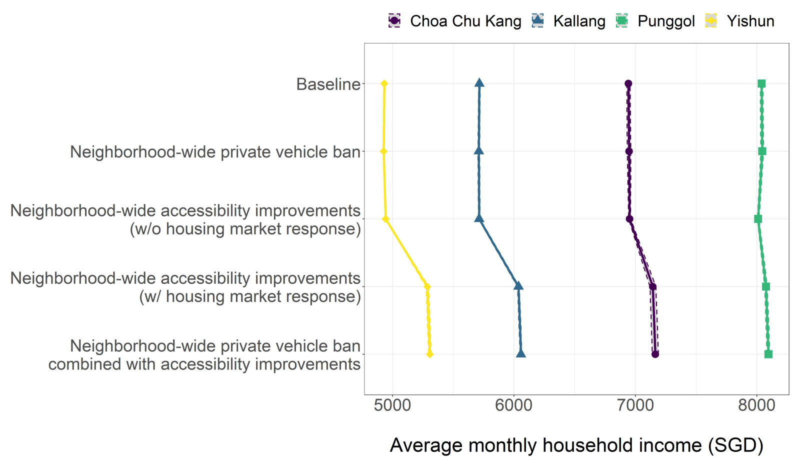
How does the stochastic variation across repeat simulations compare against the scenario-based changes in neighborhood outcomes? To address this question, I repeated each simulation five times with the same parameter settings. As I selected four neighborhoods for detailed analysis and created four car-lite policy scenarios (in addition to the baseline), I needed to run ($4 \ * \ 5 \ =$) 20 simulations with different parameter settings. For this sub-section, I repeated each of these 20 simulations five times without altering the parameters across the five iterations. This allowed me to examine standard deviations across the repeat simulations and report neighborhood outcomes as means with confidence bands, instead of 'just' point estimates. I show these confidence bands in Figure 6-1, where I find that the simulations are quite stable with regard to these neighborhood outcomes. While there is indeed variation in which specific households are awakened and their corresponding housing-mobility choices, aggregate neighborhood-level outcomes remain stable. The thinness of the confidence bands, implying low stochastic variation across repeat simulations, suggest that we can be 'confident' (statistically speaking) in the differences we observe across scenarios. When confidence bands overlap, we cannot make claims about distinct effect sizes, or differences across interventions or scenarios. However, that is not the case at the neighborhood-level, as illustrated in Figure 6-1.

6.1.2 Magnitude of accessibility improvements

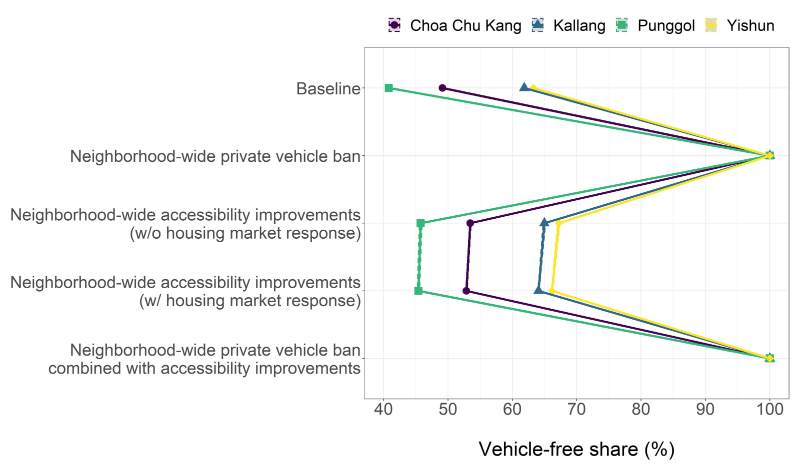
While operationalizing non-auto accessibility improvements in neighborhoods thus far, I assumed a significant magnitude of increase in accessibility such that being vehicle-free is just as 'good' as having access to a car (on average). In other words, I improved non-auto accessibility by the mean difference between 'one car' accessibility and 'zero vehicle' accessibility (which I represent as $\Delta \ ABA_{car}$). Augmenting non-auto accessibility by a full $\Delta \ ABA_{car}$ can indeed come across as bold, which is why I explored variations of $\Delta \ ABA_{car}$ ranging from ($0.5 * \Delta \ ABA_{car}$) to ($1.5 * \Delta \ ABA_{car}$). When the magnitude of accessibility improve-



(a) Variation in vacancy rate



(b) Variation in area mean income



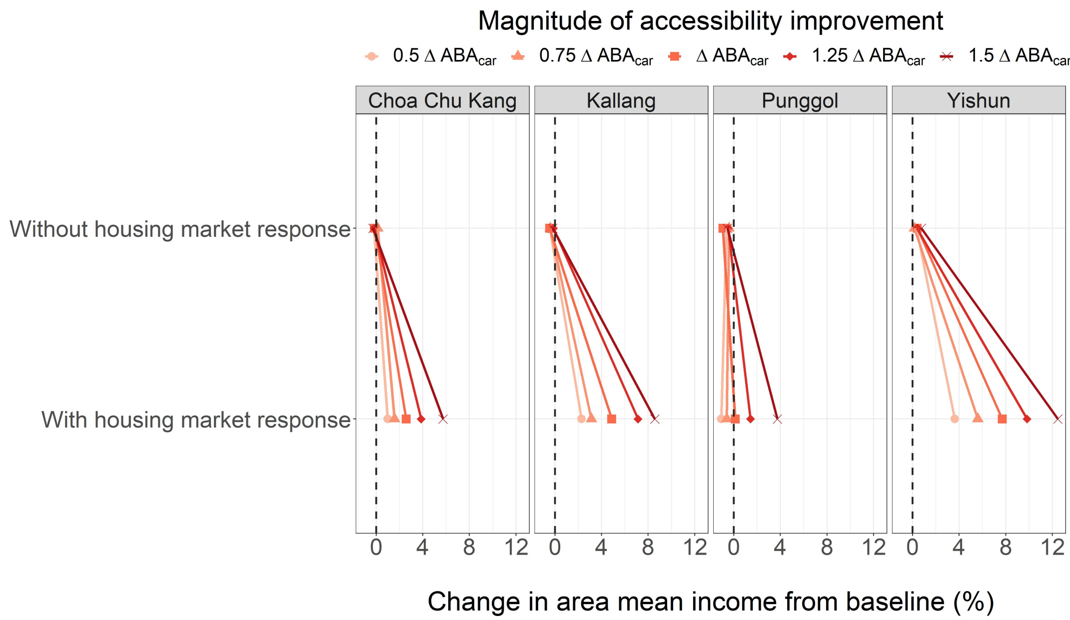
(c) Variation in vehicle-free share

Figure 6-1: Stochastic variation in neighborhood outcomes in selected Singaporean neighborhoods ment is less than $\Delta\ ABA_{car}$ (such as $(0.5 * \Delta\ ABA_{car})$ and $(0.75 * \Delta\ ABA_{car})$), it implies that non-auto accessibility has been improved but still remains lower than accessibility with a car (on average). On the other hand, improving accessibility by more than $\Delta\ ABA_{car}$ (such as $(1.25 * \Delta\ ABA_{car})$ and $(1.5 * \Delta\ ABA_{car})$) signifies a perhaps utopian scenario where non-auto modes provide better average accessibility than a private car.

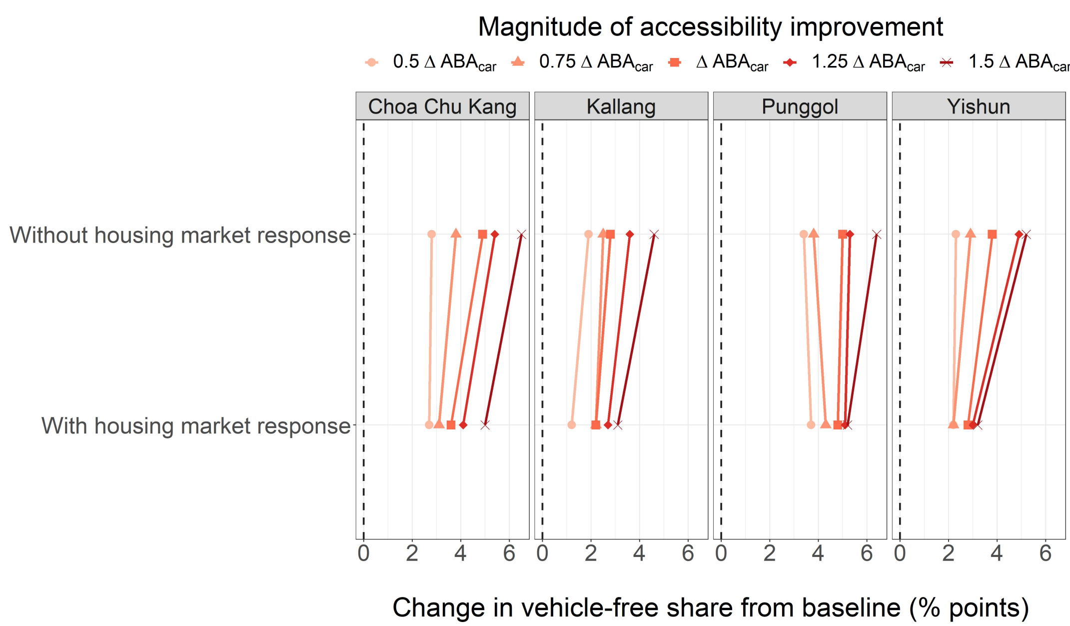
Figure 6-2 illustrates how changes in the magnitude of accessibility improvement affect changes in neighborhood outcomes such as area mean income and vehicle-free share. I explore only the two accessibility improvement scenarios (i.e., without and with housing market response), and use bolder shades to represent larger magnitudes of accessibility improvement. I find that we run the risk of magnifying the gentrification side-effect (as evidenced by greater increases in area mean income) when we improve non-auto accessibility to a larger extent compared to that with a car. This translates to a stronger dampening effect of the vehicle-free share, where the initial increases in vehicle-free share (when housing market response is absent) are reduced to a greater extent when the accessibility improvement is larger. Through this analysis, I underscore the risk of inducing unintended side-effects with non-auto accessibility improvements that may end up affecting lower-income communities to a greater extent. Providing even better accessibility by increasing the magnitude of improvement does not seem to nudge car-lite policy outcomes in the desired direction. Rather, coordinating housing policies with accessibility improvements can be much more effective in equitably distributing the benefits of such improvements.

6.1.3 Sociodemographic variation in accessibility improvements

Throughout Chapter 5, I assumed that accessibility improvements are distributed uniformly across socioeconomic groups. In other words, every household experiences the same amount of accessibility improvement. But what if accessibility improvements are distributed non-uniformly, where some groups experience more improvement than others? This could be a programmatic decision by policy-makers to target accessibility improvements towards certain groups. Another reason could be variation in behavioral response, where perceived accessibility differs across groups even though the actually implemented improvements are uniform. While further exploration into the causes of such non-uniform distribution is beyond the scope of this dissertation, I explore the consequences of such distributions in this sub-section.



(a) Change in area mean income



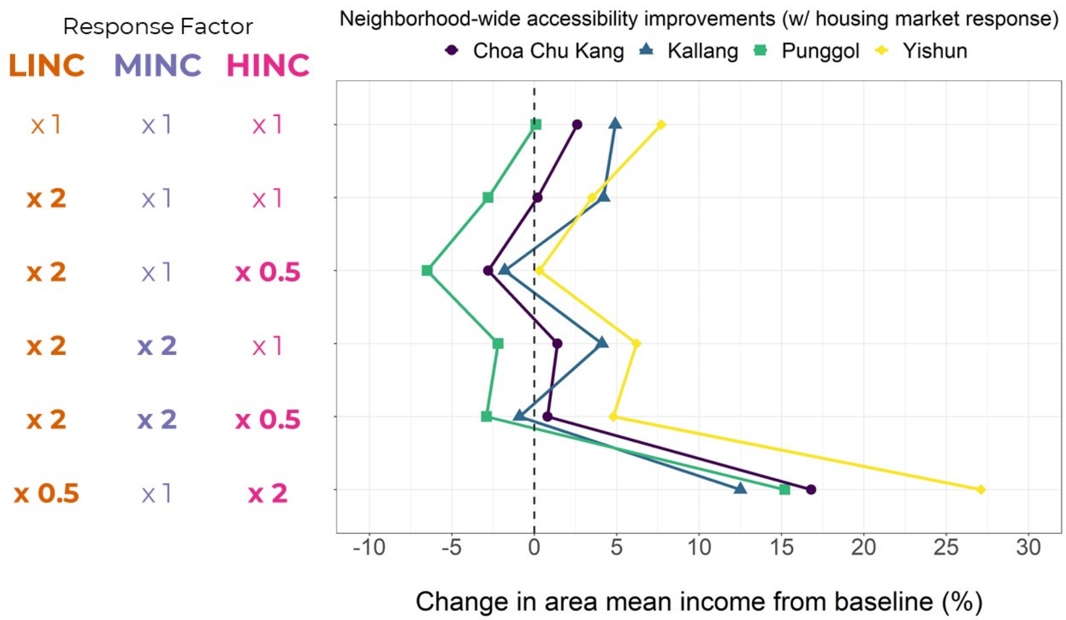
(b) Change in vehicle-free share

Figure 6-2: Sensitivity of neighborhood outcomes to magnitude of accessibility improvements in selected Singaporean neighborhoods

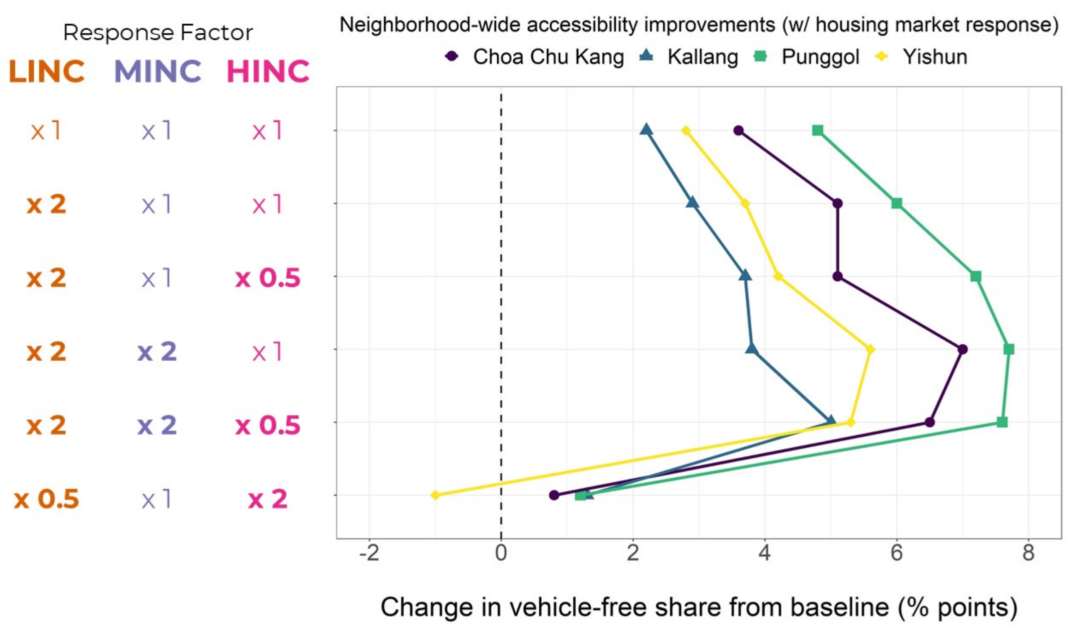
I created three income groups based on the distribution of household income across the synthetic population — (a) Low-Income (LINC) with monthly household incomes below SGD 2,500 (i.e., less than 25th percentile), (b) Middle-Income (MINC) with incomes between SGD 2,500 and 10,000 (i.e., 25th to 75th percentile), and (c) High-Income (HINC) with incomes greater than SGD 10,000 (i.e., above 75th percentile). I then introduced a '*response factor*' that can be defined separately for these three income groups to create a non-uniform distribution of accessibility improvements. For example, if the response factor for low-income households is equal to 2 but it is 1 for the other two income groups (i.e., LINC x 2, MINC x 1, HINC x 1), then low-income households experience twice the magnitude of accessibility improvement as other households. To simulate a uniform distribution of accessibility improvements (as I've been doing thus far), I can simply set the response factor to 1 for all three income groups.

In addition to the uniform distribution case (where the response factor is 1 for all three income groups), I explored various combinations of response factors. These simulations were conducted for the scenario where both buyers and sellers react to accessibility improvements, in order to understand the effect of non-uniform accessibility improvement across income groups on neighborhood change. I present the results of this exploration in Figure 6-3. Improving the accessibility of lower-income households comparatively more is found to enhance the intended consequences of the car-lite policy. In such situations, area mean income decreases (to below baseline levels at times), signifying that the gentrification side-effect can be significantly tempered by making the study area (with improved accessibility) relatively more attractive for lower-income households. This, in turn, increases the vehicle-free share, achieving the objective of the car-lite policy. Decreasing the relative accessibility improvement for higher-income households accentuates these trends.

When we improve accessibility to a greater extent for middle-income households as well as lower-income households, area mean income increases slightly but still remains less than the uniform distribution value (and within 5% of the baseline value). The vehicle-free share increases even further despite the slight increase in area mean income and goes up to 5-8% points above the baseline value. Finally, if higher-income households experience better accessibility at the expense of lower-income households, the consequences can be concerning. Area mean income shoots up to 12-27% higher than the baseline value, while the vehicle-free share drops to lower than that with uniform distribution (and can even be worse than the baseline in some neighborhoods). This analysis highlights the importance of considering non-uniform distribution of accessibility improvements, not just to guard against the magnification of unintended negative consequences, but also as a policy instrument to accentuate desired neighborhood outcomes.



(a) Change in area mean income



(b) Change in vehicle-free share

Figure 6-3: Sensitivity of neighborhood outcomes to sociodemographic variation in accessibility improvements in selected Singaporean neighborhoods

6.2 Robustness checks

I conducted three analyses to explore whether my findings about how neighborhoods change in response to accessibility improvements are robust to a few key modeling assumptions. First, I examined whether using the simultaneous housing-mobility choice framework (without including vehicle costs) will result in different outcomes compared to the sequential framework. I then introduced vehicle costs into the simultaneous choice framework and compared that to a no-cost scenario exploration with the same framework. Finally, I investigated whether choosing an accessibility measure different from the household-specific activity-based accessibility (such as public transit commute times) will affect my findings.

6.2.1 Does the type of choice framework matter?

I had introduced the simultaneous housing-mobility choice framework as a methodological extension to the existing sequential framework in SimMobility Long-Term in Section 4.4.3. In the sequential choice framework, households first consider residential relocation and then reconsider private vehicle holdings after they move into their new unit. Instead of framing private vehicle availability choice as conditional on just the new residential location, the simultaneous choice framework allows households to jointly consider potential units for residential relocation along with appropriate private vehicle holdings that are in line with their preferences should they choose to live in those potential units. The simultaneous framework also allows us to account for the cost of vehicle holdings and adjust the WTP for units accordingly. For example, if a household were to choose a location only if they also had a car, then the cost of the housing unit should be viewed as the purchase price plus the cost of the vehicle holding option. Hence, the housing choice that maximizes expected consumer surplus has the largest value for $WTP(h, v) - Price(h, v)$ among all choices of h (housing units) and v (vehicle holdings).

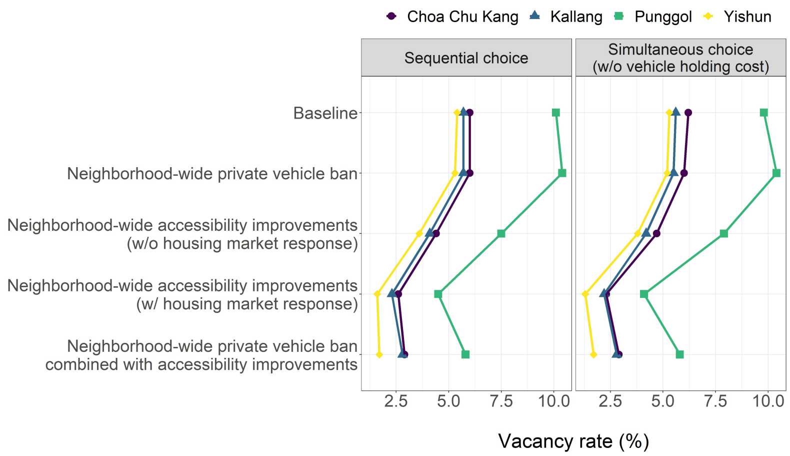
Since there are two elements to consider in the simultaneous framework — the decision-making framework itself and the cost of vehicle holdings, I examine them separately. In this sub-section, I compare the sequential framework against the simultaneous framework where WTP calculation is made for each possible vehicle holding option, but the cost of the vehicle option is not subtracted from WTP when computing expected consumer surplus. In the following sub-section, I explore the effect of including vehicle holding costs in the bidding process by subtracting them from WTP. Figure 6-4 reports neighborhood outcomes for both the sequential and simultaneous frameworks (where the latter does not include vehicle holding cost). Given the surplus-maximizing manner in which units are chosen for placing bids and the conditional manner in which vehicle holdings are determined for the unit with the maximum consumer surplus, I do not expect the findings to differ. This hypothesis is confirmed as I find almost no differences between the results of the two choice frameworks. Not only are the trends of neighborhood change very similar, the particular outcome values exhibit only marginal differences. Therefore, I can conclude that my findings are robust to the selection of housing-mobility choice framework (when vehicle choices are part of the WTP evaluation, but the cost of the vehicle holdings are not explicitly considered).

6.2.2 Does the cost of vehicle holdings matter?

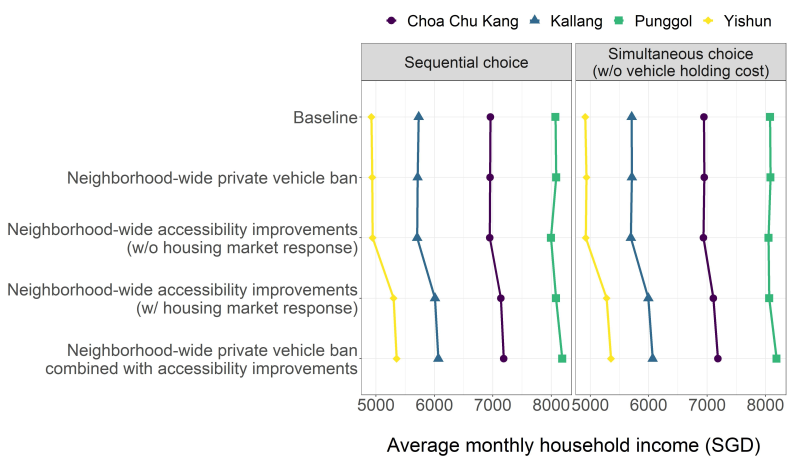
To understand the effect of including the cost of vehicle holdings, I used the simultaneous choice framework to compare two cases — one without the cost of vehicle holdings against one with vehicle costs. Figure 6-5 presents the results of this analysis. I do not find any evidence to suggest that the patterns of neighborhood vacancy rate and area mean income are dependent on whether vehicle costs are explicitly included in expected consumer surplus calculations. However, vehicle-free shares are expected to differ, and I confirm this by illustrating that there seems to be a translation of the vehicle-free shares (along the x-axis) by 4-6% points although the trends remain the same.

Data limitations prevented us from including vehicle holding costs in the private vehicle availability model. Therefore, the initial synthetic population assignments of households to housing units used the vehicle availability model without vehicle costs to probabilistically select vehicle holding options that, overall, averaged 51.8% across Singapore. However, when awakened households considered vehicle costs while evaluating relocation options, they tended to move to places that are relatively more attractive without a car. Hence, the overall vehicle-free share increased by 4% points (see Table 4.8), thus illustrating that vehicle holding costs do matter in influencing vehicle-free shares. If appropriate data were available, a vehicle availability model including costs would allow the original assignment to match the observed vehicle-free share of 51.8% in Singapore in a way that would remain unchanged during the burn-in.

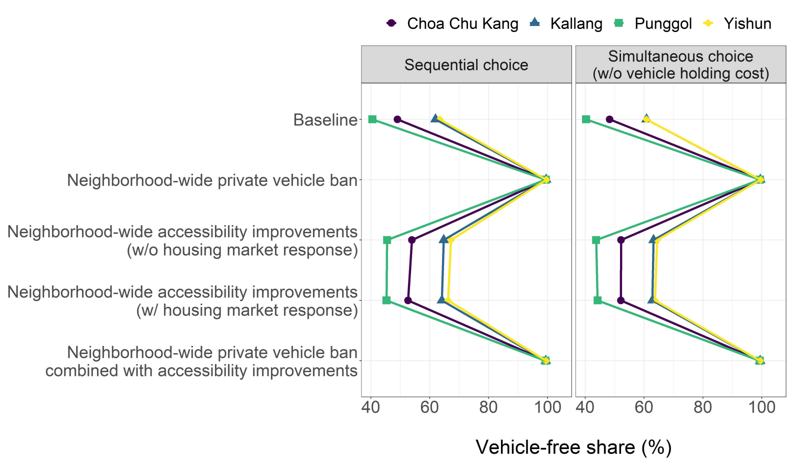
Nevertheless, my analysis suggests that including vehicle costs in the bidding process does not significantly influence neighborhood composition as characteristics of movers are not expected to change. However, the consideration of vehicle holding costs in the computation of WTP during housing relocation (but not in the vehicle availability model) does reduce consumer surplus for housing-mobility options that include private vehicles as the WTP is discounted by vehicle costs. This, in turn, influences many potential movers to prefer



(a) Change in vacancy rate

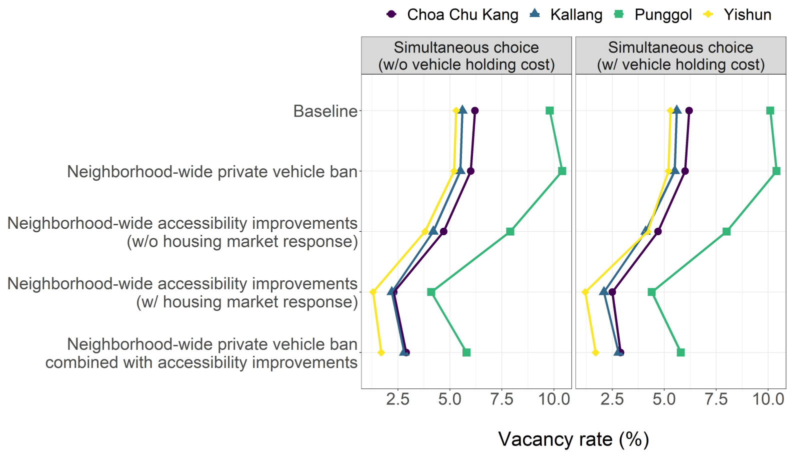


(b) Change in area mean income

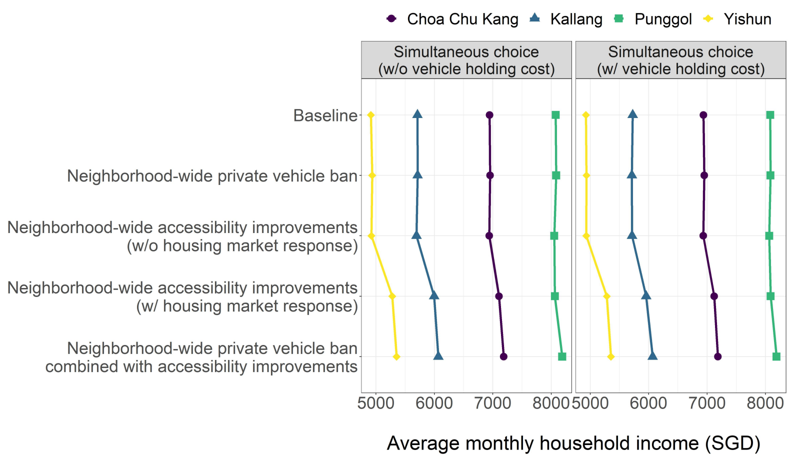


(c) Change in vehicle-free share

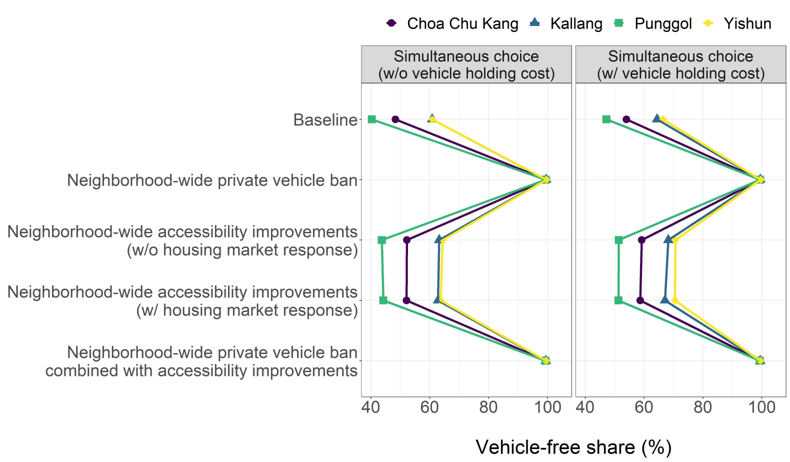
Figure 6-4: Neighborhood outcomes for different housing-mobility choice frameworks in selected Singaporean neighborhoods



(a) Change in vacancy rate



(b) Change in area mean income



(c) Change in vehicle-free share

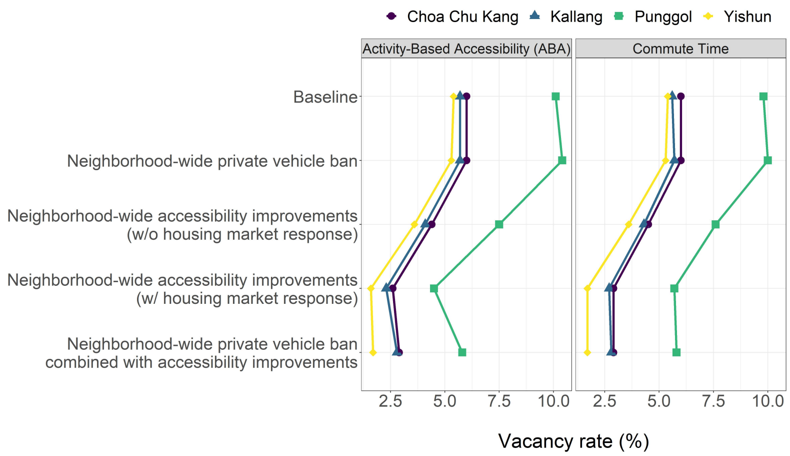
Figure 6-5: Neighborhood outcomes with and without the cost of vehicle holdings in selected Singaporean neighborhoods locations that do not necessitate the ownership of private vehicles (i.e., housing-mobility options that are vehicle-free). It is worth noting here that data limitations prevented us from including vehicle costs in the estimation of the private vehicle availability model, so being overly confident about the specific predicted values of neighborhood outcomes with vehicle costs may not be wise. Nevertheless, it is comforting to see the trends of neighborhood changes due to accessibility improvements (with housing market response) remain the same, both without and with vehicle holding costs.

6.2.3 Does the accessibility measure matter?

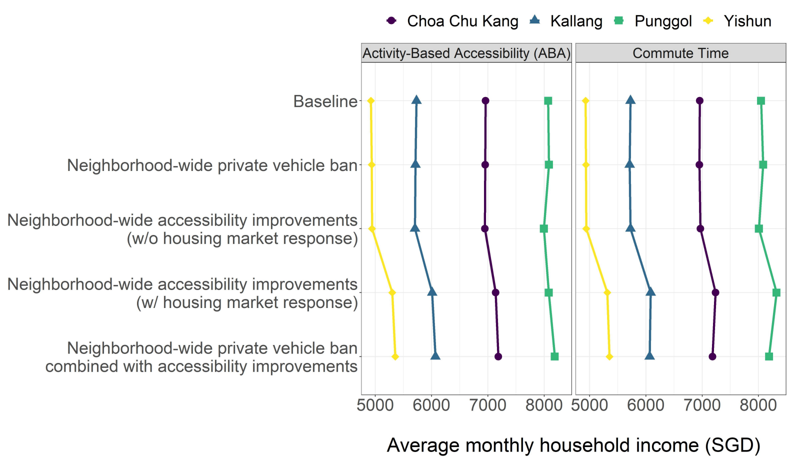
My final robustness check is with regard to the use of a measure of accessibility in the LT sub-models. Does my choice of accessibility measure influence my findings regarding how neighborhoods change in response to accessibility improvements? To address this question, I estimated WTP and private vehicle availability models separately switching out the household-specific activity-based accessibility (ABA) measure with household-specific public transit commute times (see Tables A.5 and A.7). The hedonic price model remains the same because, being a market model, it does not include any household-specific accessibility measure. I then conducted the same set of scenario explorations using these models and compared the ABA simulation results against those using public transit commute times. From Figure 6-6, I do not observe any major differences between the two sets of simulation results and the trends appear to be similar. Therefore, I can conclude that my findings of neighborhood changes due to accessibility improvements (with housing market response) are robust to my choice of accessibility measure. Nevertheless, we would prefer to have ABA measures since they can more readily account for particular changes in daily activity patterns that might result from the introduction of new mobility services (beyond private automobiles).

6.3 Transferability

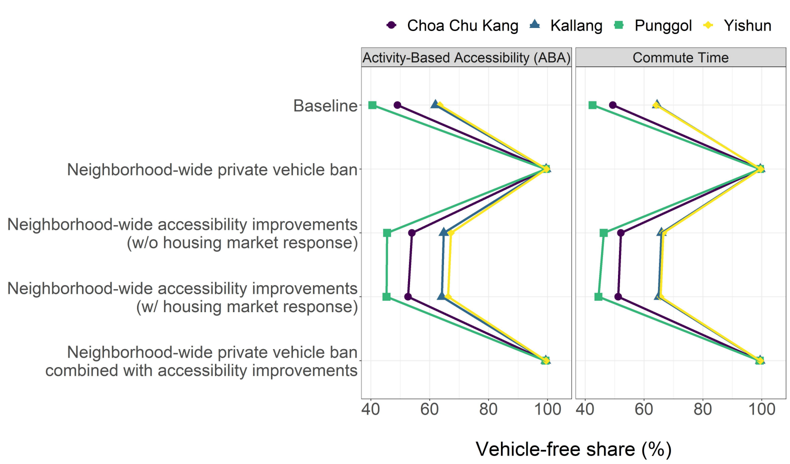
The Singaporean context is, in many ways, unique. Talking about housing and mobility choices, around 80% of Singaporean households live in public housing and more than half are vehicle-free (i.e., do not have access to any private vehicle). Readers may be wondering at this point about the extent to which my findings are influenced by the unique Singaporean



(a) Change in vacancy rate



(b) Change in area mean income



(c) Change in vehicle-free share

Figure 6-6: Neighborhood outcomes for different accessibility measures in selected Singaporean neighborhoods context. Would non-auto accessibility improvements made in a different and more auto-dependent context (such as the U.S.) result in similar outcomes? This question relates to the transferability of my findings, which has been an important critique of simulation studies in general and LUTI models in particular. Setting up a LUTI model for a different context can be time-consuming and expensive, so I tried out an exploration at a more limited scale. I (and several colleagues) constructed a 'virtual city' that has very different zoning, transport infrastructure, and built environment compared to Singapore, although behavioral preferences of residents are assumed to be similar. When thinking of a different context, both spatial configuration and residents' behavior come to mind. In this analysis, as I assume similar behavioral preferences, I am testing only the effect of a different spatial configuration (which can still lead to very different choices and outcomes). Using this sandbox as a testbed, I repeated the set of scenario explorations in different neighborhoods to examine the extent to which my findings are transferable to another context with a different spatial configuration.

6.3.1 Constructing a virtual city

I will provide a brief overview of the virtual city construction process in this sub-section. Readers interested in additional details of this process (as well as an assessment of the LT-MT integration) are invited to refer to Basu et al. (2021).

Our approach allows any hypothetical transport infrastructure to be combined with plausible land use constraints and then translated into a virtual city by distributing residents and jobs in a manner that reflects observed patterns in an actual city. Such a virtual city can be a useful sandbox for LUTI explorations since it enables the performance of any arbitrary transportation infrastructure to be simulated using population and employment distributions, and related behavioral models, that are sampled from real cities and spatially distributed in the virtual city so that socioeconomic patterns are similar along the density gradients of the real and virtual city.

We used various geospatial techniques to create disaggregate spatial geometry such as parcels and postcodes, with additional adjustments keeping future development and consistent spatial boundaries across layers in mind. In line with literature showing how population density follows transportation infrastructure density, we allocated households and firms that are randomly sampled from an actual city (Singapore) through a density-matching technique. Finally, students were matched to educational institutions and workers were matched with jobs to construct a calibrated synthetic population for the virtual city.

The zoning plan for the virtual city is shown in Figure 6-7. We chose to represent a monocentric city with commercial land use in the center, residential land use to the north and east, and industrial land use towards the south west. We also included separate zones for open spaces, educational institutions (such as schools and universities), and an airport.

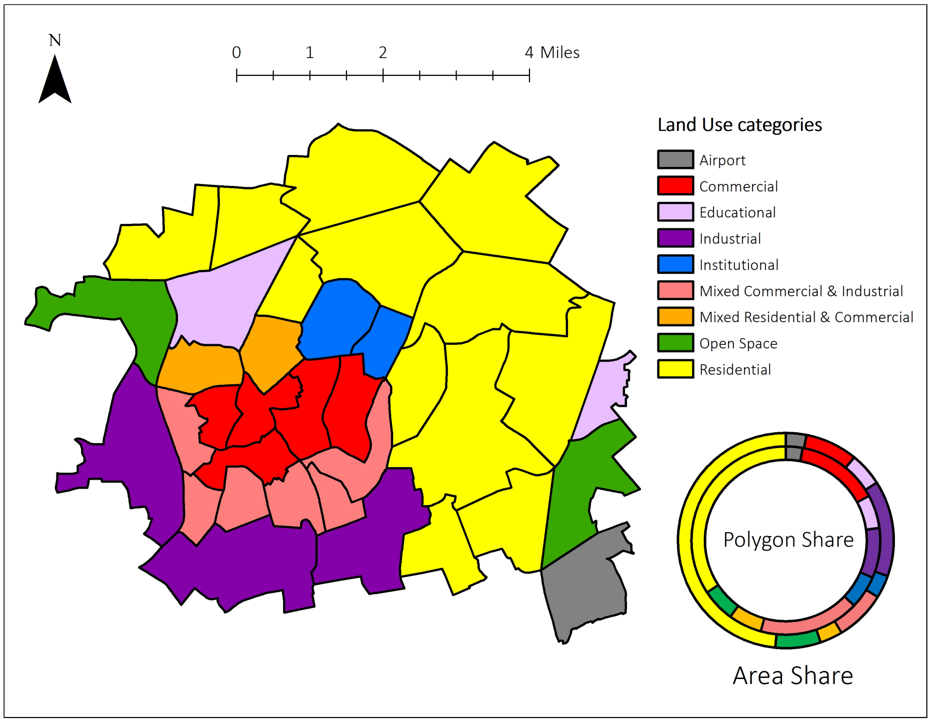
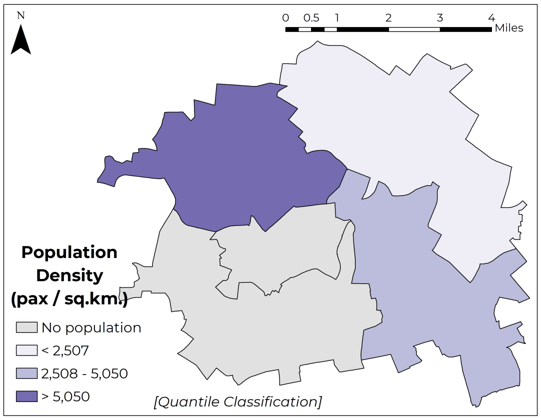
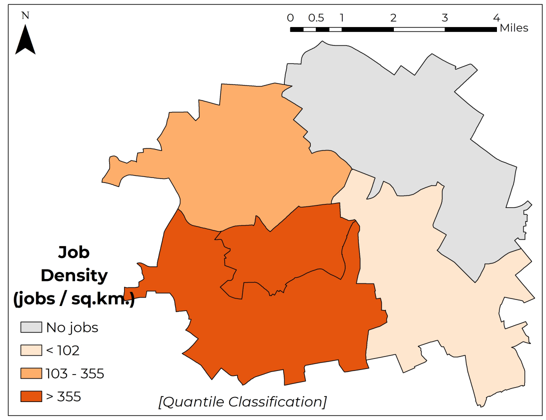


Figure 6-7: Zoning in the Virtual City

We wanted to represent a less extensive public transport network in the virtual city (compared to Singapore), so we chose to have only two MRT lines with eight stations (Figure 6-8d) and 86 bus stops, counting those on opposite sides of the road as distinct (Figure 6-8c). Our choices of the transport infrastructure and zoning plan are completely arbitrary, but plausible. Although the virtual city construction pipeline uses these data as inputs, the framework outlined in Basu et al. (2021) is independent of the nature of these inputs. We wanted to create a virtual city that is around 1/10th the scale of Singapore, so we randomly sampled roughly 10% of Singaporean households, housing units, jobs and establishments based on a density-based gradient. In contrast to 1.14 million households and 1.22 million housing units in Singapore, the virtual city has close to 90,000 households and 100,000 housing units. Based on the monocentric segregated land use zoning plan, only three of the five planning areas in the virtual city are populated and one planning area is purely residential. The population and job densities of planning areas in the virtual city are shown in Figures 6-8a and 6-8b.

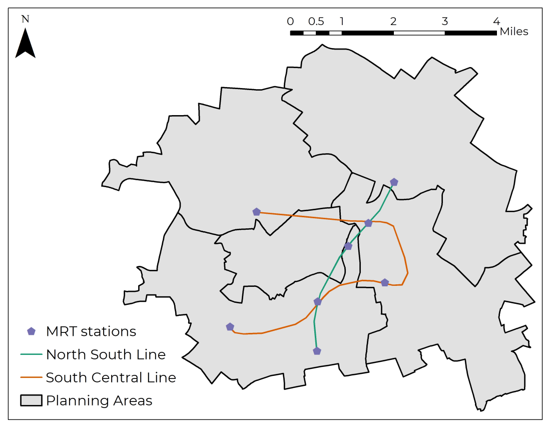


(a) Population Density



(b) Job Density

(c) Bus stops



(d) Mass Rapid Transit (MRT) stations

Figure 6-8: Spatial distributions of people, jobs, and transit infrastructure in the Virtual City

6.3.2 Simulated effects in a virtual city

I conducted scenario explorations in the virtual city in a similar manner by first choosing a few neighborhoods for detailed analysis. Since only three of the five planning areas in the virtual city are populated, I selected all three — *PAREA_35_VC*, *PAREA_47_VC*, and *PAREA_55_VC* (see Figure 6-9). The characteristics of these planning areas are presented in Table 6.1 along with those of the entire virtual city. We can see that the virtual city is significantly more auto-dependent than Singapore with a vehicle-free share of only 13.2%

compared to Singapore's 51.8%. *PAREA_35_VC* is comparatively lower-income and more vehicle-free, while *PAREA_55_VC* is higher-income and less vehicle-free compared to the city-wide average.

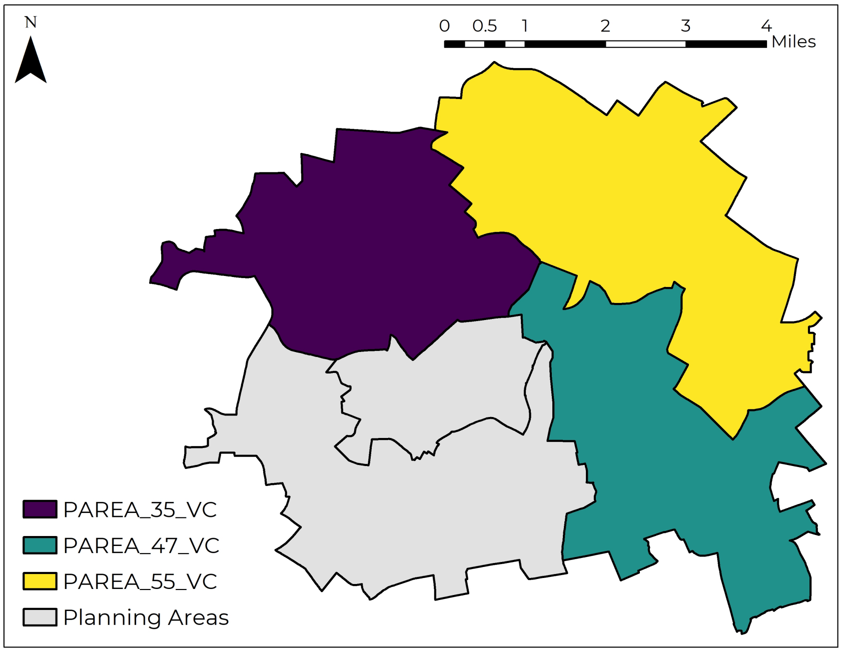


Figure 6-9: Selecting three (populated) planning areas for detailed analysis

Table 6.1: Characteristics of populated planning areas in the Virtual City

	Virtual City	**PAREA_35_VC**	**PAREA_47_VC**	**PAREA_55_VC**
Units	*97,590*	40,650	34,024	22,916
Vacancy rate (%)	*10.1%*	9.5%	6.5%	16.5%
Mean household income (SGD)	*$7,065*	$6,739	$7,103	$7,627
Vehicle-free share (%)	*13.2%*	17.1%	13.2%	5.8%

I operationalized non-auto accessibility improvements in these three neighborhoods in the same manner as earlier. First, I increased the 'vehicle-free' ABA for every household in the study area by the mean difference between the 'one-car' and 'zero-vehicle' ABA values. Second, I decreased public transit travel times by the mean difference between transit and car travel times, which is 15 minutes instead of 30 minutes owing to the smaller scale of the virtual city. I also operationalized the private vehicle ban in the same manner as earlier by changing the accessibility of every household in the study area to their 'vehicle-free' ABA and increasing public transit travel times by 25%. I simulated the same set of five scenarios (i.e., the baseline and four car-lite policies) for each of the three selected neighborhoods with some minor adjustments to the simulation parameters to reflect the smaller scale of the virtual city (e.g., awakening only 40 households every day instead of 400).

Figure 6-10 presents how accessibility changes affect the neighborhood-wide vacancy rate. The changes in vacancy rate with the introduction of accessibility improvements are similar to my observations for Singaporean neighborhoods. The vacancy rate is not affected when accessibility improvements are introduced without housing market response. When both buyers and sellers respond to these improvements, more in-movers are attracted to the study area, which leads to a subsequent decrease in the vacancy rate. I observe an increase in the vacancy rate for one of the planning areas ($PAREA\_55\_VC$). Similar to Punggol in Singapore, this neighborhood is also comparatively more auto-dependent (with a vehicle-free share of only 5.8%, compared with the Virtual City average of 13.2%). This reinforces my conclusion that private vehicle restrictions in more auto-dependent contexts can reduce the attractiveness of those locations and induce some out-migration.

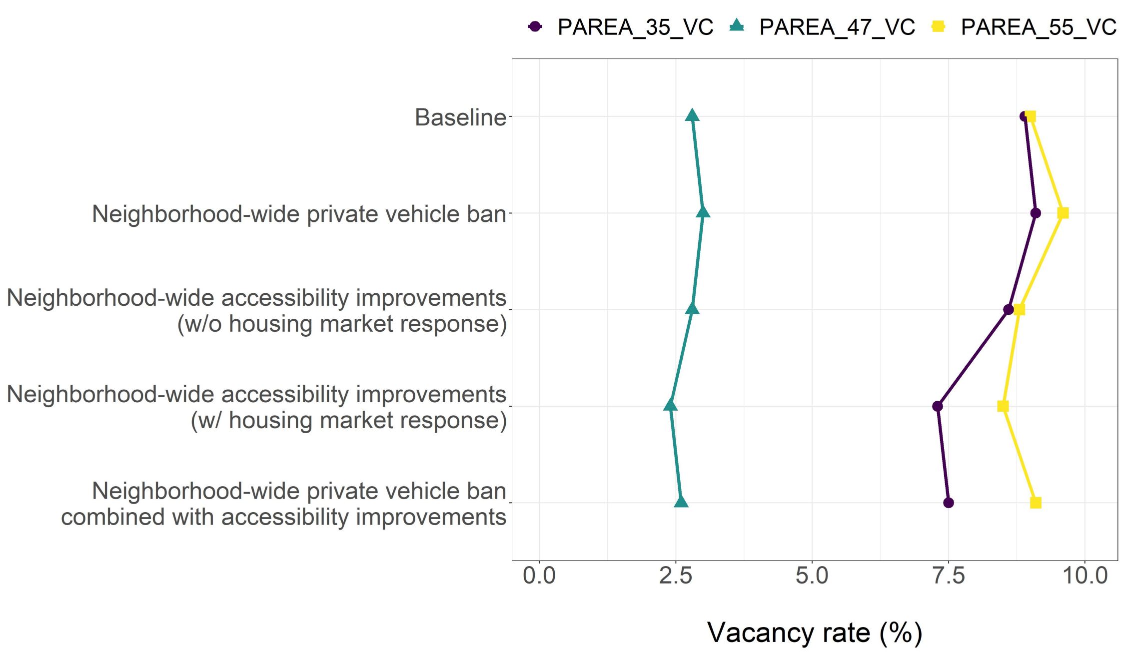
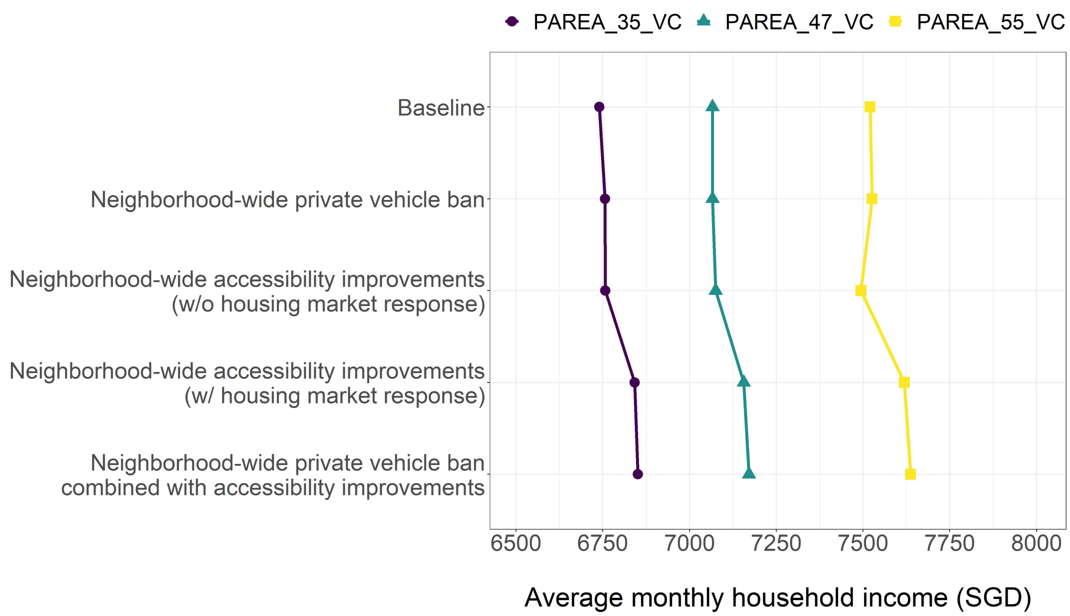
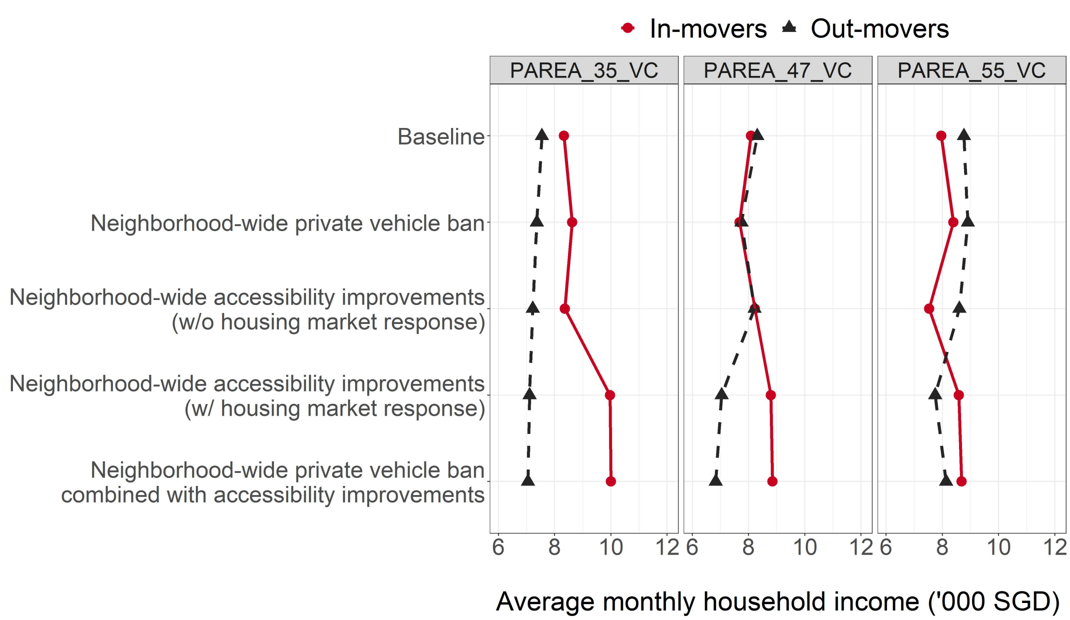


Figure 6-10: Vacancy effect of car-lite policies in the Virtual City

I then examine the income effect of car-lite policies in these three planning areas. Changes in the area mean income as well as a comparison of incomes of in-movers and out-movers are reported in Figure 6-11. The housing market effects captured through both buyer and seller response to improved accessibility drive up the area mean income. When comparing in-movers and out-movers, I find evidence to suggest that the study area attracts higher-income in-movers who displace lower-income out-movers due to the housing market response. Accessibility-induced gentrification is observed for two of the three planning areas. While the third planning area (which is lower-income and more vehicle-free) was gentrifying even in the baseline, the extent of gentrification is accentuated by housing market effects.



(a) Change in average neighborhood income



(b) Change in average income of movers

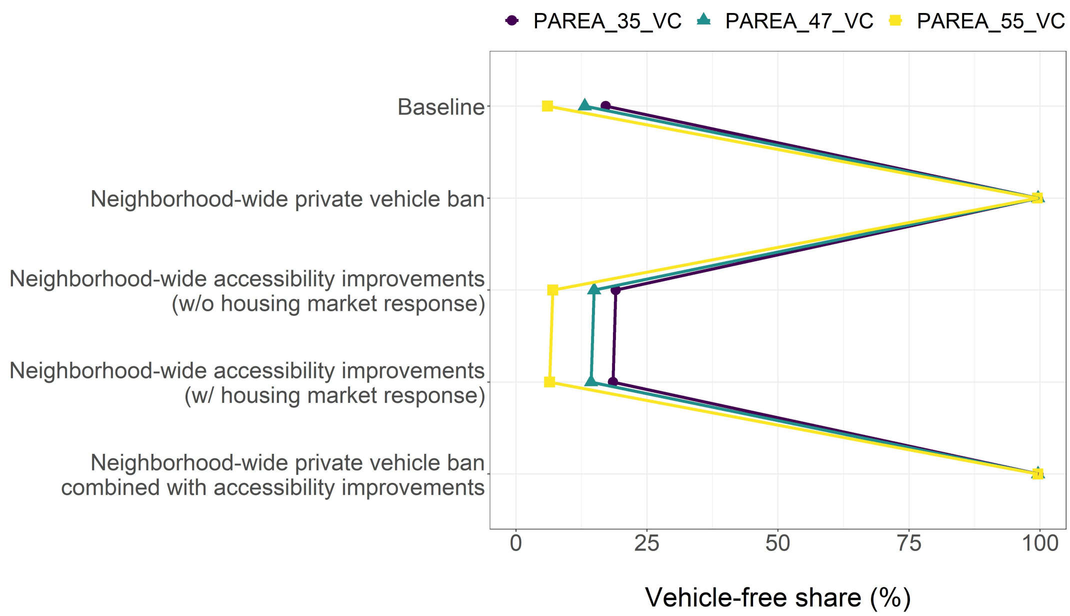
Figure 6-11: Income effect of car-lite policies in the Virtual City

Next, I explore how the vehicle-free share changes as a result of these neighborhood-wide accessibility changes. Figure 6-12 presents both aggregate vehicle-free shares and comparisons between in-movers and non-movers. The neighborhood-wide vehicle-free share increases when non-auto accessibility is improved without housing market response. When housing market effects kick in, higher-income in-movers who are comparatively less vehicle-free than the non-mover residents dampen the neighborhood vehicle-free share. There is one planning area (which is the highest-income and the least vehicle-free) where the dampening effect is strong enough to wipe out the initial vehicle-free increase entirely.

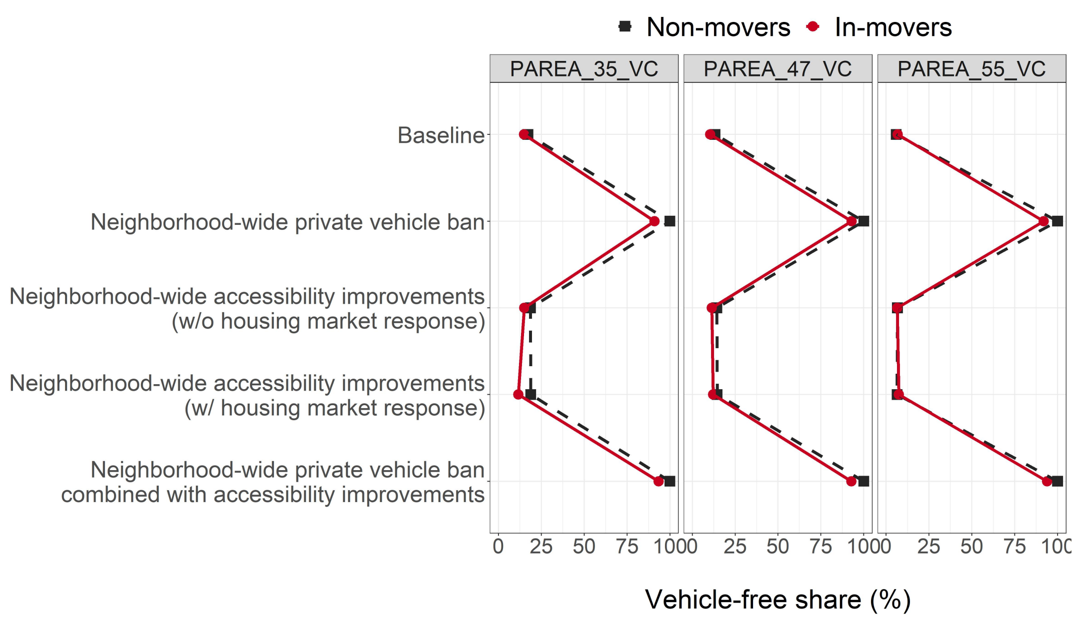
Finally, I report changes in accessibility and consumer surplus in Figure 6-13. Introducing a neighborhood-wide vehicle ban is found to decrease accessibility by 6-9% and consumer surplus by SGD 200,000 - 250,000. These effects are much more pronounced in the virtual city than in Singapore, where the same restriction had reduced accessibility by 2-4% and surplus by SGD 80,000 - 100,000. These observations suggest that vehicle restriction policies without improvements in non-auto accessibility in more auto-dependent contexts can worsen accessibility and welfare to a greater extent. When non-auto accessibility improvements are introduced, neighborhood-wide accessibility in the virtual city increases by 1-1.5% compared to 2.5-6.5% in Singapore. When both buyer and seller responses are accounted for, consumer surplus values are around SGD 180,000 - 630,000 higher than the baseline (and what I observed for Singapore). However, this welfare gain is wiped out when accessibility improvements are accompanied by a vehicle ban, similar to Singapore. These observations suggest that non-auto accessibility improvements are valued more in more auto-dependent contexts and can attract greater premiums, thus necessitating a more mindful eye towards the equitable distribution of the accessibility and welfare benefits of car-lite policies.

6.4 Summary

In this chapter, I conducted sensitivity analysis and robustness checks to confirm that my findings hold up to changes in parameter settings and key modeling assumptions. I also illustrated the case of a more auto-dependent context than Singapore, where the spatial configuration is very different but residents' behavioral preferences are similar. I found that just changing the spatial configuration alone (without change in behavior) can lead to different changes in accessibility and welfare of residents. However, the primary observation



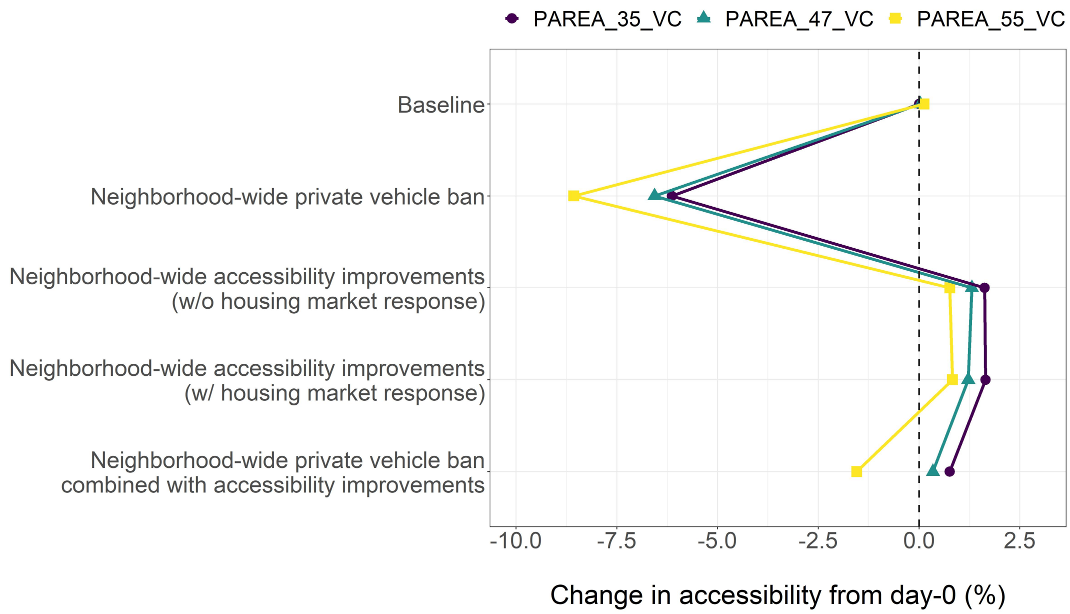
(a) Change in neighborhood-wide vehicle-free share



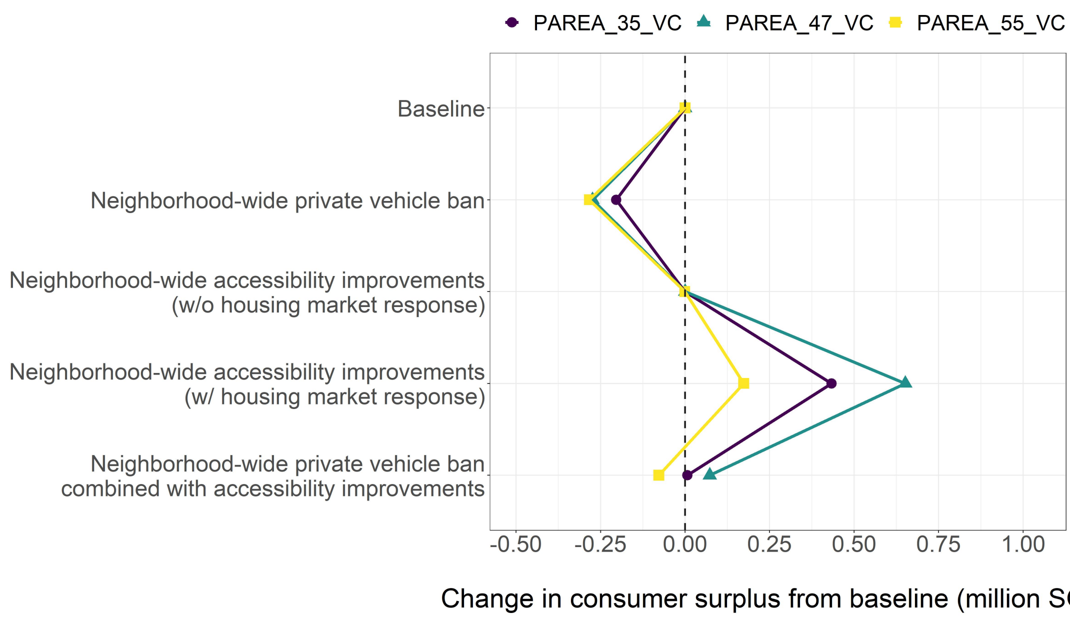
(b) Change in vehicle-free share of movers

Figure 6-12: Vehicle-free effect of car-lite policies in the Virtual City

of accessibility-induced gentrification still holds in the virtual city, albeit to a greater extent. I also found that car-lite policies aiming to ban private vehicles can be comparatively more detrimental in contexts that are heavily auto-dependent. In the next chapter, I will discuss how these findings can be translated into policy recommendations and outline a few areas that would benefit most from further research.



(a) Change in neighborhood-wide activity-based accessibility



(b) Change in neighborhood-wide consumer surplus

Figure 6-13: Accessibility and welfare effects of car-lite policies in the Virtual City

Chapter 7

Conclusion

The climate crisis has left us little choice but to be ambitious and urgent enough to reimagine the way of life we have taken for granted thus far. An example of this with far-reaching consequences beyond 'just' greenhouse gas emissions is our reliance on automobiles. As I explained at the outset, by 'reliance on automobiles' I mean the deployment of housing, jobs, and services in a manner that requires too large a fraction of trips to be made in single-occupancy motorized vehicles. Reducing auto-dependence can have significant public health and environmental benefits, while also freeing up land and funding that can be used for other purposes. As cities try out car-lite pilot programs that aim to reduce auto-dependence, it becomes necessary to understand how these programs might influence personal choices of residential location and private vehicle holdings. This is important because how these programs are rolled out can be crucial in determining how they are perceived and the possibility of 'success' that might accelerate their expansion to other neighborhoods beyond the pilot area. *How might car-lite policies change neighborhoods? Might housing policies be effective in mitigating gentrification side-effects while enhancing auto-dependence reductions?*

This dissertation addresses these policy-relevant questions using an agent-based land use-transportation interaction (LUTI) model (SimMobility). In addition to being a state-of-the art LUTI model that 'tightly' integrates the land use and mobility components using activity-based accessibility measures, SimMobility has a unique internal structure that enables simulation of daily transactions in the housing market. I proposed and implemented several key methodological extensions that enabled richer exploration of the housing market response to car-lite policies and various housing subsidies and regulations. Then, I designed and examined various policy scenarios related to private vehicle restrictions, non-auto accessibility improvements, and coordinated housing policies such as upzoning and restricted parking supply. I also explored the sensitivity, robustness, and transferability of my findings through various analyses. In this final chapter, I will first summarize my key findings from this research. I will then discuss the implications of my findings for guiding policy-making followed by the limitations in my analysis. Finally, I will outline a few promising avenues for future research efforts.

7.1 Summary of key findings

In their bid to reduce auto-dependence, policy-makers can design car-lite policies using a 'carrot' (i.e., an incentive, such as improving non-auto accessibility) or a 'stick' approach (i.e., a disincentive, such as restricting private vehicles). I tested the near-term response of residents to these policies, when implemented city-wide, using quasi-static analysis before running complex microsimulations. These analyses provide preliminary evidence of what we might expect to see in the very near-term, before enough people change their behavior resulting in a new equilibrium.

I found that banning vehicles would, not suprisingly, reduce accessibility and social welfare across the board. These detrimental effects will expectedly affect households with private vehicle holdings, especially those who are comparatively lower-income to a greater extent. To offset these negative consequences of a vehicle ban, policy-makers could opt to improve non-auto accessibility. While such improvements improve both accessibility and welfare across the population, vehicle-owning households may still not perceive their accessibility to be as good as it was when they were allowed to own vehicles, despite the accessibility improvements. I observed higher-income vehicle-owners to experience greater welfare gains in such situations. Thus, a vehicle restriction policy on its own is likely to negatively affect residents, even in relatively less auto-dependent contexts like Singapore. Non-auto accessibility improvements will be necessary to offset the loss of accessibility and welfare from banning private vehicles. Any such combination of restrictions and accessibility improvements are likely to be tested in a pilot study area before being implemented across a metro area. In such cases, residential moves within and beyond the study area might have a large impact and it will be especially important to examine the impacts in some detail.

Building on this finding, I examined the near-term effects of car-lite policies that include private vehicle restrictions and/or non-auto accessibility improvements on neighborhoods in Singapore using scenario analysis. I tracked neighborhood change using both place-based and people-based measures over the length of three calendar years. All of the 26 neighborhoods studied for this analysis exhibited varying degrees of accessibility-induced gentrification, which consequently dampened the potential vehicle-free increases that would have otherwise resulted from accessibility improvements had housing market effects been absent. On the other hand, a private vehicle ban within the study area significantly reduces residents' accessibility and welfare, even though it achieves the intended objective of creating a more vehicle-free neighborhood. Looking at neighborhood characteristics, I found that lower-income and more vehicle-free neighborhoods were associated with larger gentrification effects. Such unintended consequences can affect public support for car-lite policies that aim to improve non-auto accessibility. Moreover, piloting these policies in neighborhoods that are more susceptible to negative outcomes can bury these programs for good and delay sustainable mobility efforts by years.

Drawing from the literature on transit-induced gentrification, I then explored two housing policies — upzoning and restricted parking supply — as possible strategies to mitigate accessibility-induced gentrification. Upzoning alone was found to accelerate gentrification, especially in lower-income neighborhoods. Using affordability constraints in combination with upzoning helped to temper some of these concerning trends. Some combinations of income restrictions and discounts on asking prices were found to increase the vehicle-free share of the neighborhood, while also significantly improving the welfare of residents. Upzoning combined with parking restrictions on new housing supply was found to increase vehicle-free share appreciably, but at the cost of welfare. While affordability constraints helped limit the decrease in welfare, income restrictions were found to be more effective in mitigating gentrification compared to discounts on asking prices. My overall findings largely support the general findings that the literature had suggested, and they illustrate how carefully constructed and calibrated LUTI models can be used to estimate and compare the net effects for specific circumstances. Upzoning and parking restrictions have limited value on their own. They become much more effective policy instruments when combined with affordability constraints so that the accessibility and welfare benefits of car-lite policies can be equitably distributed across residents.

Next, I examined the extent to which my findings related to accessibility-induced gentrification hold up against changes in particular simulation parameters and a few key modeling assumptions. We are unlikely to be able to escape the gentrification trap by simply increasing non-auto accessibility to an even greater extent. My results show that the more we improve accessibility without coordinated housing policies, the greater the likelihood of inducing gentrification with obvious consequences for vehicle-free shares. We also need to accommodate variations in perception of accessibility improvements. When lower-income and middle-income households experience comparatively larger improvements in non-auto accessibility, the increase in vehicle-free share is larger. This could be used in a programmatic manner to target particular socioeconomic groups when implementing accessibility improvements. Not only can such targeting enhance intended program outcomes, but also improve the equitable distribution of program benefits.

Finally, acknowledging the uniqueness of Singapore in various aspects, I explored how my findings could translate to more auto-dependent contexts. A virtual city was constructed with very different built environment and land use configuration compared to Singapore, but with similar behavioral preferences. While more than half of Singaporean households were vehicle-free at the start, less than 15% of similar households with the same behavioral preferences would choose to be vehicle-free if they resided in the virtual city. When a vehicle restriction policy is implemented in this virtual city, the losses in accessibility and welfare of residents are more severe. The extent of accessibility-induced gentrification is higher than in Singapore, suggesting that non-auto accessibility improvements can be perceived to have greater value in more auto-dependent contexts. The resulting welfare values, even after accounting for the housing market response, further confirm this.

Thus, designing a ‘successful’ car-lite policy will require attention to not just whether it reduces the vehicle-free share, but also how it might change neighborhoods. As this dissertation shows, understanding that in detail is not trivial, and requires the use of a complex integrated urban modeling framework with adequate attention to how different components interact with one another.

7.2 Policy implications

Ex-ante analyses, such as those presented in this dissertation, are quite valuable in the context of land use and transportation planning. We can minimize unintended and negative consequences of phenomena such as transit-induced gentrification. Microsimulation models, in particular, can help planners and decision-makers better understand the tradeoffs between programmatic efficiency (e.g., the increase in vehicle-free share) and equity (e.g., welfare losses and displacement). My dissertation presents one such application of a microsimulation model for exploring how neighborhoods may change in the near-term when car-lite policies (and coordinated housing policies) are piloted within them. My findings can directly inform car-lite policy design and planning in Singapore, as well as provide lessons for places with more widespread car ownership.

Selecting an appropriate study area for piloting car-lite policies is likely to make or break the success of such programs in terms of being widely adopted beyond the pilot area. Therefore, ex-ante analysis of how different neighborhoods might respond to these policies is both necessary and valuable, especially when it comes to disruptive mobility technologies that are yet to be widely adopted or embraced. I found that lower-income and more vehicle-free neighborhoods are more susceptible to accessibility-induced gentrification. Similar findings in the literature related to public transit improvements or extensions suggest that perhaps any form of neighborhood improvement (such as better accessibility) that makes it more attractive will induce some extent of gentrification, as long as higher-income households are able to outbid others. This leads to a broader conundrum in urban planning efforts. Should we not improve lower-income neighborhoods for fear of inducing gentrification? Although addressing this question with supporting evidence is beyond the scope of this dissertation, what I do show here helps us understand the process of neighborhood change in significant detail, which can be helpful when designing car-lite policies (or, more generally, neighborhood improvements).

Coordinated housing policies showed promising results in mitigating some of these unintended but negative side-effects while enhancing the benefits provided by car-lite policies. Thus, if more susceptible (i.e., lower-income and more vehicle-free) neighborhoods are to be chosen as pilot areas, our best intentions and efforts to improve accessibility may require additional complementary policies. It is also worth understanding that there is no 'one-sizefits-all' housing policy. Particular policy instruments (such as upzoning, parking restrictions, and affordability constraints) will need to be tuned based on the characteristics of neighborhood residents. Targeting certain socioeconomic groups through these instruments can also be valuable. For example, when we provide new housing supply through upzoning, we might consider designing new housing units in a way that makes them differentially attractive to certain groups (e.g., those who are more likely to become and stay vehicle-free if adequate yet affordable housing is available).

At a very high level, my results suggest that there is no silver bullet to reduce auto-dependence. The Singaporean case suggests that appropriately pricing auto ownership and use can indeed increase the vehicle-free share, but without supplementary policies, making autos more expensive will likely punish lower-income households disproportionately. We will very likely need a menu of policy instruments at our disposal that we can pick and choose from. In line with the literature, I also find that improving non-auto (or transit) accessibility alone does little to convince households to transition to vehicle-free lifestyles. Without broader structural changes, we will continue to witness the 'inevitability of automobility' despite our best intentions to encourage non-auto modes (Kent, 2022). Zoning reforms, particularly housing regulations, and built environment design can be effective supplementary strategies to accelerate our vision of a sustainable mobility future and stimulate sustainable urban growth. There might be concerns surrounding how neighborhood-level changes can translate to city-wide effects. However, as both I and the literature observe, households who are displaced are not more likely to become vehicle-owners in their new residential locations. Therefore, expanding car-lite pilots beyond a single neighborhood is expected to provide considerably stronger positive spillover effects.

Using the 'virtual city' allowed me to test the same household preferences and behavior but in a different spatial configuration that encouraged (or forced) the same residents to become more auto-dependent. While this analysis is an admittedly limited exploration of non-Singapore settings, it did provide several valuable insights. In places like the US, much of the built environment, cultural norms, and labor market conditions are predicated on near-universal automobility (King et al., 2019). If we are to place restrictions on private vehicles through, for example, high purchase prices or outright bans, the consequences can be disastrous. Many lower-income households would effectively be shut out of the economy as they are dependent on their cars for daily commuting. Even in Singapore, the effects of banning cars are more detrimental for lower-income households. Thus, we cannot expect to solve our sustainable mobility issues by limiting car ownership of lower-income communities in a world where other policies cause us to be ever more dependent on cars (Wachs and Taylor, 1998). As J.H. Crawford remarks in his book 'Carfree cities', proposing to take the car away from the average American overnight, without making any other provisions, is likely to evoke an angry response (Crawford, 2000). Any restrictions should be accompanied with other benefits, e.g., having the restrictions apply only to new occupants of particular vehicle-restricted housing. Therefore, in such contexts, shifting the focus away from limiting car ownership to rather limiting car use may be more appropriate. However, unless auto use is priced appropriately by accounting for the externalities of automobile travel, auto ownership will continue to correlate strongly with auto use. Once people end up in auto-centric mobility lifestyles, a voluntary transition back is likely difficult to achieve.

Single-minded policies, such as accessibility improvements or vehicle restrictions, may remain ineffective in getting us to our desired outcomes. As my results indicated, even a substantial degree of accessibility improvement did not produce dramatic increases in vehicle-free share. Instead of providing 'carrots' (incentives to become vehicle-free, such as accessibility improvements) or 'sticks' (disincentives to own and use vehicles, such as high acquisition prices or vehicle restrictions), 'carrot-*and*-stick' approaches have shown promise in nudging people towards more vehicle-free lifestyles (Meyer, 1999; Piatkowski et al., 2019). Creating positive reasons to favor non-auto modes as well as increasing the 'price' of auto travel in combination, rather than solely either of these, may work in reducing auto ownership and use. For example, in London, charges for less fuel-efficient vehicles and trips into the city center have been implemented in tandem with redesigning road layouts in residential neighborhoods and offering schemes to incentivize cycling and public transit use. Even in Singapore, increasing the cost of private vehicle ownership may not remain as effective in the near future as household incomes have been rising significantly. The additional efforts undertaken to improve access to public transit through the design of better first- and last-mile connections and enhancing island-wide transit connectivity by extending MRT lines have likely been just as effective in maintaining low preference for auto ownership and especially auto use. Therefore, creating accessible and affordable alternatives to private vehicles is the need of the hour, particularly in more auto-dependent contexts where improvements in non-auto accessibility matter more.

7.3 Limitations

Despite my best efforts, several limitations in my analysis need to be acknowledged. Major accessibility changes such as private vehicle restrictions or non-auto accessibility improvements are likely to influence both long-term (e.g., residential location and private vehicle holdings) and medium-term (i.e., activity-travel) choices. These components are linked through individual-specific accessibility measures in our integrated LUTI framework (SimMobility). Individuals are expected to adjust their activity-travel patterns in response to non-auto accessibility improvements, which will change their activity-based accessibility (ABA). As a result of changes in ABAs, their longer-term choices will also be affected. This is what we call a 'full loop' simulation of SimMobility Long-Term (LT) and Medium-Term (MT). However, a full loop simulation may not be necessary if we are interested in examining only near-term changes as, in the near term, not enough people will have changed their activity-travel patterns to induce a new system equilibrium.

This does not imply that MT is not needed at all. We still use MT to determine the accessibility (ABA) in effect at the start of the simulation, so that near term, quasi-static preference and behavior changes can be realistically estimated. Therefore, instead of simulating the MT and obtaining 'actual' revised ABAs, I assumed a uniform adjustment across the study area. Households living or choosing to live in neighborhoods with non-auto accessibility improvements would receive the same accessibility without any private vehicle as with a car (on average). With this assumption, I went ahead to simulate long-term urban choices and tracked near-term neighborhood changes using only the LT component. This assumption is appropriate for examining differences in near-term neighborhood changes across various policy scenarios. That being said, using revised ABAs from MT would be ideal, especially as specific programs and systems are designed and developed to support emerging mobilities or fleets of autonomous vehicles. MT could then be used to simulate, for example, the performance of specific fleet sizes and deployment strategies to recompute household-specific ABAs periodically.

In my scenario analyses, I assumed the city (both Singapore and the virtual city) to be a closed system. This means that I did not allow for any changes in the total demand or supply over the two simulation years (equivalent to three calendar years) I considered. This assumption may not be reflective of real-world conditions, as new developments are often planned out ahead of time and can take several years to complete. Particularly in Singapore, the Build To Order (BTO) program is operationalized in a manner where units are bid upon and sold well before construction has even begun. Although assuming a closed system makes the identification of policy effects relatively easier, disregarding the advance sales of BTO units (which are not distributed spatially in a uniform manner) can affect the predicted effect sizes of neighborhood outcomes.

Moreover, the construction of new housing developments, especially apartments and condos, can be stimulated by accessibility improvements. Since I am interested in examining only near-term changes and I constrain my observation period to three calendar years, ignoring new private housing construction (which can take longer than three years) is acceptable. If we had to include this consideration, we would have used a development model that simulates the construction and sale of new housing developments on vacant parcels (that is available and calibrated). However, during the validation process, we noticed that most of these developments in the 'real world' were not on vacant parcels but on rezoned parcels. Unfortunately, we do not yet have a good way of modeling changes in zoning, which limits the use of our development model.

Validating my findings of accessibility-induced gentrification is challenging because we do not have data on non-auto accessibility improvements other than new MRT lines being introduced. While this could be a plausible candidate for validation, the closed system assumption adds complications. A few thousand HDB units (1,500 to 5,700) were scheduled for construction through the BTO program in three of the four planning areas I selected for detailed analysis. Ignoring the spillover effects of the advance sales of these units on other units in the neighborhood is likely to affect the comparison of simulated outcomes against ground truth observations. Moreover, the construction of treatment and control areas for validation using a difference-in-differences framework is not straightforward. The spatial distribution of BTO units may very well be spatially non-uniform, which could add a layer of complexity to identifying appropriate control areas.

Several data limitations also constrained our modeling efforts. Although I added vehicle holding costs through the simultaneous housing-mobility choice framework to the bidding process, data limitations prevented them from being included in the calibration of the private vehicle availability model. This is why the vehicle-free shares of the two burned-in synthetic populations (calibrated without and with vehicle costs) were different. It would be ideal to calibrate the choice model with the vehicle costs included, so that the predicted market shares would be reflective of the regulatory context of Singapore. Additionally, I had to estimate WTP by matching housing transaction data with travel survey data because we did not have any data available on 'actual' WTP. This constrained us to infer WTP from transaction prices of sold units, which may mirror biases related to which units are more likely to be sold. Finally, the logsum measure (ABA) MT generates has been found to be overly dependent on sociodemographics and not as responsive to spatial variation in activity-travel patterns as we would expect if we had better data on, e.g., the parking costs and employer-provided cars and parking that are (and are not) provided to various demographic groups. Thus, using the ABA in its current form, especially unscaled, as a measure of accessibility is likely to reinforce well-known differences across socioeconomic groups.

7.4 Future research

The contributions of this dissertation can be extended through further research efforts in the future. I outline a few key areas for improvement, focusing first only on the use of SimMobility and then expanding the scope to integrated urban modeling in general.

Improving the computation performance of SimMobility is critical for widespread use beyond the research community. As I discussed earlier, computing additional logsums in the simultaneous housing-mobility choice framework is computationally intensive since many such calculations are required for each housing alternative in the daily choice set of each household. Moreover, running a full day of activity-travel patterns using MT takes several hours even on a multi-threaded supercomputer with large memory. Thus, 'full-loop' LT-MT simulations can take weeks, especially if the new equilibrium requires several iterations until convergence. Although my colleagues and I have made important strides in improving the computation performance of LT, further attention is required on this critical issue. The virtual city was a way to work around this because we were able to test new models and code updates on a smaller scale, where the simulation ran considerably faster.

Further experimentation is necessary to improve the use of SimMobility to guide policy-making. Not only do we need access to better data and more realistic modeling frameworks, further analysis on the sensitivity to simulation parameters (especially those for which ground truth is challenging to observe) is recommended. The virtual city is a step towards strengthening claims of transferability by providing a testbed where similar behavioral preferences (as in Singapore) are merged with a different spatial configuration. The modular design of the virtual city framework allows us to create other virtual cities that resemble the behavior of residents elsewhere, which would allow us to compare different contexts more completely (i.e., with different spatial configurations and behavioral preferences) in the future. We also require more efforts towards creating synthetic populations and calibrating choice models in different 'real-world' contexts to enable us to compare simulation results across cities. Some of us have been engaged in an effort to create synthetic populations in an automated manner for any metropolitan area in the US, but the absence of a national zoning atlas and the fragmented nature in which geospatial data are collected and shared can be major impediments to such efforts for most places (unlike Singapore).

At the end of this dissertation, I remain convinced that LUTI models are particularly promising tools for examining the near-term evolution of urban and metropolitan development in response to changes in infrastructure, policy, and human behavior. However, most state-of-the-art LUTI models are not well-equipped to address the challenges of the day. For example, we still have not been able to satisfactorily model telecommuting within LUTI models, and none of the modern models have incorporated emerging mobilities to their full extent. The data collection and modeling efforts that have been funded over the last few decades have overly focused on automobiles, but researchers are now beginning to pay more attention to non-auto modes, especially active mobility. LUTI modelers have yet to respond to these shifts in focus, which could be part of a larger critique of the types of research that tend to be favorably viewed by funding agencies. What is needed over the next couple of decades is drastically different from what has been done thus far.

Next-generation LUTI modeling would do well to recognize and address interactions of land use and transportation with other dimensions of urban planning. For example, the link between the built environment and public health could be a key element in improving our understanding of what urban design changes we need to prioritize if we want to address longstanding health inequities. Emissions modeling could supplement this by providing estimates of the climate consequences of vehicle restriction policies or electrification of vehicle fleets, as measured through changes in activity-travel patterns and private vehicle holdings. The dynamic nature of long-term decision-making is also rarely considered. For example, life-events (such as coupling, the birth of a child, or a reduction in household size) often trigger longer-term decisions such as residential (re)location and private vehicle holdings (re)evaluation. We need to consider incorporating these dynamic decision structures into our modeling frameworks through transition models.

An additional way to engage in more realistic behavioral modeling would be to internalize contextual nuances, such as the cost of vehicle ownership, which is prohibitively high in places like Singapore but generally onerous for lower-income households globally. Accounting for attitudinal differences, such as 'car pride' or the social status some societies associate with car ownership, can also help. Finally, LUTI models also need to adapt to the changing mobility landscape such that a richer set of options besides the traditional comparison of car ownership and public transit can be examined in detail without overarching assumptions. As an example, car-sharing presents a dilemma when it comes to modeling car ownership and use within traditional frameworks.

In closing, I would like to iterate that we need to pay attention to both the mobility and housing market impacts of car-lite policies if we are to anticipate and prevent unintended side-effects such as accessibility-induced gentrification. LUTI models can be useful tools to conduct such ex-ante analyses, but they require modifications to address many pressing issues of the day in a credible yet timely manner. We need to showcase more such applications of scenario explorations related to complex policy interactions so that both policy-makers and planning practitioners become comfortable trusting these models as well as using them in their own work beyond academic research. If we live to see the end of this century, I hope we will have made significant strides towards reducing auto-dependence by then. Here's to more realistic policy-oriented modeling of sustainable urban futures before time runs out!

Appendix A

Supplementary data

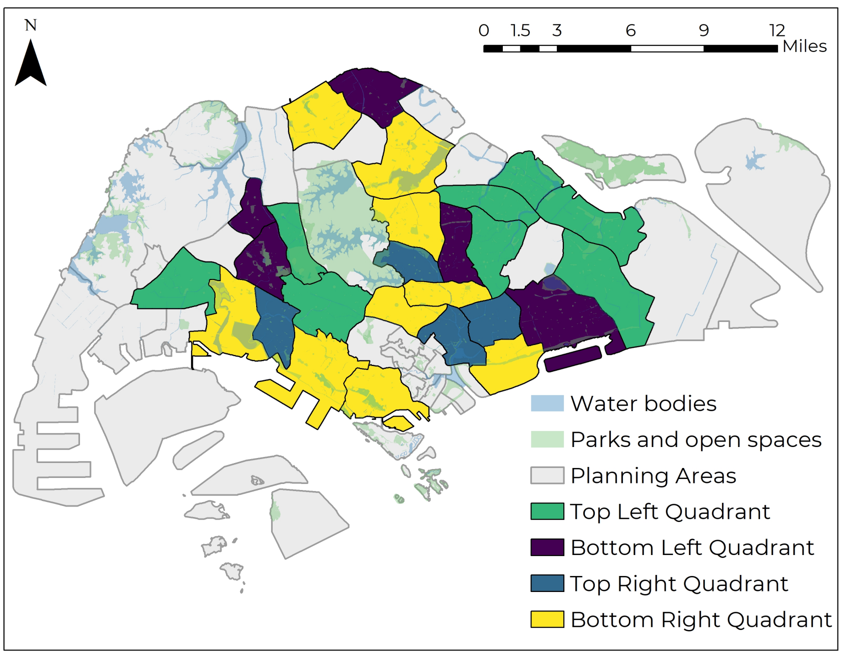


Figure A-1: Planning area typology based on housing market effects (as in Fig. 5-5b)

Table A.1: Data summary for household-level screening model ($n = 9,569$)

	Mean	***Std. Dev.***
Average distance to MRT station (weighted average of postcodes in zone, in kms)	0.90	0.21
Average distance to top-30 primary school (weighted average of postcodes in zone, in kms)	1.43	0.56
Average transit travel time to all jobs (weighted average of postcodes in zone, in mins)	56.65	6.45
Land Use Diversity (weighted average of postcodes in zone)	0.51	0.03
Share of total housing units in zone-unit type category (%)	4.74%	2.15%
% of residential area (weighted average of postcodes in zone)	43.90%	5.82%
% of commercial area (weighted average of postcodes in zone)	3.37%	2.49%
% of undeveloped area (weighted average of postcodes in zone)	16.93%	6.37%
Income difference of household and zone-unit type category average (natural log)	-1.04	2.45
Size difference of household and zone-unit type category average	0.18	1.41
% of Chinese households in zone * Household is Chinese	54.24%	35.12%
% of Indian households in zone * Household is Indian	1.83%	4.79%
% of Malay households in zone * Household is Malay	1.25%	3.99%
% of households with children in zone * Household has a child	10.74%	12.69%
% of households with teenagers in zone * Household has a teenager	6.60%	13.33%
% of households with seniors in zone * Household has a senior	14.39%	19.19%
% of HDB4 and HDB5 units in zone * Household size > 3	3.70%	5.21%
% of apartments and condos in zone * Household per-capita income > $3,500	0.87%	4.97%
% of landed properties in zone * Household per-capita income > $3,500	0.35%	3.13%
% of detached and semi-detached private units in zone * Household per-capita income > $3,500	0.09%	1.49%

Table A.2: Data summary for hedonic price model of public housing (HDB) units

	HDB12		**HDB3**		**HDB4**		**HDB5**		**Executive HDB**	
	Mean	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***
ln(Age of unit)			3.47	0.26	2.94	0.51	2.78	0.46	2.90	0.32
ln(Age^2)			6.89	0.55	5.76	1.10	5.43	0.97	5.69	0.68
ln(Storey)	1.90	0.50	1.92	0.54	1.99	0.59	2.09	0.61	1.94	0.56
ln(Storey^2)	3.49	1.15	3.52	1.24	3.69	1.34	3.90	1.38	3.57	1.29
In 'mature' HDB estate			0.61	0.49	0.38	0.49	0.32	0.47	0.33	0.47
In 'other-mature' HDB estate			0.02	0.13	0.01	0.08	0.01	0.10	0.01	0.05
MRT station within 400 meters	0.33	0.47	0.17	0.37	0.17	0.37	0.16	0.37		
MRT station between 400 and 800 meters	0.41	0.49	0.40	0.49	0.37	0.48	0.34	0.47		
% of residential area in 1km buffer	40.88%	11.14%	43.10%	10.43%	44.45%	10.68%	44.37%	11.16%	45.43%	10.78%
% of HDB units in planning area	22.11%	7.29%	19.06%	7.05%	18.29%	6.50%	18.46%	6.62%	16.91%	6.55%
Avg. transit travel time to all jobs (mins)	48.81	6.49	54.64	7.63	58.46	7.71	59.39	7.29	61.09	6.25
Observations	844		21,949		28,962		17,828		6,168	

Table A.3: Data summary for hedonic price model of private housing units

	Condo		**Condo**		**Condo**		**Apt.**		**Apt.**		**Apt.**		**Exec. Condo**		**Terrace**		**Detached &**	
	(< 60 sq.m.)		**(60 - 100 sq.m.)**		**(> 100 sq.m.)**		**(< 70 sq.m.)**		**(70 - 130 sq.m.)**		**(> 130 sq.m.)**						**Semi-Detached**	
	Mean	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***
New sale	0.88	0.33	0.68	0.47	0.39	0.49	0.79	0.41	0.39	0.49	0.21	0.41						
Freehold	0.17	0.37	0.15	0.36	0.30	0.46	0.68	0.47	0.58	0.49	0.64	0.48			0.46	0.50	0.68	0.47
Unknown age	0.91	0.28	0.72	0.45	0.41	0.49	0.82	0.38	0.40	0.49	0.27	0.45			0.38	0.48	0.31	0.46
ln(Age of unit)	0.10	0.42	0.56	1.04	1.24	1.25	0.19	0.55	1.22	1.21	1.67	1.36			1.49	1.35	1.71	1.44
$ln(\text{Age}^2)$	0.17	0.78	1.06	2.01	2.34	2.45	0.32	1.00	2.29	2.37	3.16	2.73			2.86	2.67	3.31	2.87
ln(Storey)	1.93	0.74	2.03	0.68	2.00	0.76	2.02	0.68	1.99	0.74	1.97	0.89	2.12	0.58				
$ln(\text{Storey}^2)$	3.56	1.61	3.76	1.51	3.69	1.70	3.75	1.52	3.69	1.60	3.67	1.87	3.98	1.32				
Large unit (area > 75^{th} %ile)													0.16	0.36	0.17	0.37	0.17	0.37
MRT station within 400 meters	0.26	0.44	0.26	0.44	0.18	0.38	0.28	0.45	0.29	0.46	0.22	0.42	0.02	0.13	0.04	0.20	0.06	0.23
MRT station between 400 and 800 meters	0.28	0.45	0.25	0.43	0.29	0.45	0.42	0.49	0.37	0.48	0.41	0.49	0.30	0.46	0.20	0.40	0.26	0.44
Land Use Diversity	0.49	0.11	0.49	0.09	0.48	0.09	0.50	0.10	0.49	0.10	0.49	0.10	0.51	0.07	0.45	0.10	0.43	0.09
Avg. transit travel time to all jobs (mins)	57.15	9.51	58.01	9.30	56.70	9.50	48.76	8.63	49.77	8.27	48.88	7.93	65.31	5.42	60.86	8.92	58.84	9.05
Observations	5,979		18,641		30,405		11,405		10,848		3,129		9,511		2,409		1,812	

Table A.4: Data summary for household-level willingness-to-pay (WTP) model with activity-based accessibility as accessibility measure

	HDB12		**HDB3**		**HDB4**		**HDB5**		**Apt. & Condo**		**Landed property**	
	Mean	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***
Activity-Based Accessibility * At least one worker	1.64	1.51	2.78	1.31	2.80	1.40	3.07	1.55	3.92	2.05	2.83	2.26
Activity-Based Accessibility * No workers	0.29	0.39	0.06	0.21	0.05	0.22	0.05	0.20	0.06	0.27	0.06	0.21
Avg. transit travel time to all jobs (mins)	48.18	6.64	54.54	7.64	58.51	7.71	59.93	7.04	54.61	9.48	58.00	8.43
ln(Area of unit)	6.17	0.13	6.59	0.09	6.94	0.09	7.20	0.11	6.93	0.47	7.94	0.52
ln(Age of unit)	3.58	0.38	3.47	0.26	2.93	0.52	2.81	0.43	1.01	1.23	1.64	1.49
ln(Age^2)	7.09	0.82	6.87	0.56	5.75	1.11	5.48	0.92	1.91	2.40	3.18	2.95
ln(Storey)	1.90	0.50	1.92	0.54	2.00	0.59	2.05	0.60	1.96	0.75	0.01	0.08
ln(Storey^2)	3.47	1.15	3.51	1.24	3.69	1.34	3.81	1.37	3.62	1.64	0.01	0.08
In 'mature' HDB estate	0.87	0.33	0.61	0.49	0.38	0.48	0.31	0.46				
In 'other-mature' HDB estate	0.01	0.08	0.01	0.11	0.01	0.08	0.01	0.09				
Freehold									0.42	0.49	0.65	0.48
ln(Household income)	4.91	3.40	7.64	2.15	7.89	2.17	8.18	2.15	8.69	2.31	8.66	2.31
Marginal effect of household size	0.66	0.43	1.00	0.42	1.14	0.38	1.21	0.39	1.06	0.43	1.31	0.34
Marginal effect of children	0.36	0.50	0.38	0.51	0.47	0.54	0.52	0.54	0.59	0.54	0.56	0.55
Marginal effect of seniors	0.63	0.59	0.34	0.51	0.36	0.52	0.35	0.51	0.15	0.38	0.53	0.57
% of adults who are workers	41.63%	37.47%	64.30%	29.99%	65.59%	29.47%	65.49%	30.06%	64.82%	30.29%	55.09%	27.92%
% of adults who are young professional workers	17.06%	30.03%	25.44%	30.99%	21.46%	29.85%	18.28%	27.97%	20.43%	31.46%	10.06%	17.61%
Observations	856		22,081		29,214		24,075		55,536		7,456	

Table A.5: Estimation results for household-level willingness-to-pay (WTP) model with commute time as accessibility measure

	HDB12		**HDB3**		**HDB4**		**HDB5**		**Apt. & Condo**		**Landed property**	
	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*
(Intercept)	10.283***	0.243	9.720***	0.060	11.846***	0.048	8.499***	0.062	10.410***	0.031	10.304***	0.126
Transit commute time to job (head) * At least one worker	-0.032***	0.008	-0.003**	0.001	-0.002**	0.001	0.003*	0.001	0.005**	0.002	0.070***	0.009
Transit commute time to all jobs * No workers	-0.003	0.008	-0.002	0.002	0.003	0.002	0.010***	0.002	0.009***	0.003	0.044***	0.011
Avg. transit travel time to all jobs	-0.228***	0.028	-0.558***	0.006	-0.662***	0.004	-0.666***	0.006	-0.736***	0.007	-0.522***	0.027
ln(Area of unit)	0.527***	0.021	0.816***	0.006	0.538***	0.006	0.956***	0.007	0.911***	0.002	0.812***	0.006
ln(Age of unit)	-0.762*	0.416	-0.582***	0.092	0.320***	0.043	1.634***	0.091	0.295***	0.012	-0.304***	0.046
ln(Age^2)	0.337*	0.194	0.218***	0.043	-0.210***	0.020	-0.830***	0.043	-0.182***	0.006	0.144***	0.023
ln(Storey)	0.134	0.231	0.772***	0.045	0.670***	0.031	1.001***	0.039	0.165***	0.017	-0.368***	0.042
ln(Storey^2)	-0.046	0.100	-0.318***	0.020	-0.270***	0.014	-0.413***	0.017	-0.045***	0.008		
In ‘mature’ HDB estate	0.077***	0.010	0.038***	0.001	0.097***	0.001	0.115***	0.002				
In ‘other-mature’ HDB estate	0.153***	0.033	0.281***	0.005	0.348***	0.006	0.450***	0.007				
Freehold									0.189***	0.002	0.186***	0.007
ln(Household income)	0.006**	0.003	0.002**	0.001	0.004***	0.001	0.004***	0.001	-0.009***	0.001	0.017***	0.004
Marginal effect of household size	0.036***	0.013	0.001	0.002	-0.007***	0.002	-0.004**	0.002	0.063***	0.003	-0.086***	0.014
Marginal effect of children	-0.005	0.010	-0.0005	0.001	-0.002**	0.001	-0.010***	0.001	-0.044***	0.002	-0.026***	0.008
Marginal effect of seniors	0.012*	0.006	0.005***	0.001	0.005***	0.001	-0.006***	0.001	-0.016***	0.003	0.010	0.007
% of adults who are workers	0.057***	0.018	0.013***	0.003	-0.007***	0.002	-0.014***	0.003	0.075***	0.005	-0.131***	0.017
% of adults who are young professional workers	0.013	0.014	-0.002	0.002	0.001	0.002	-0.009***	0.002	0.001	0.003	0.103***	0.020
Observations	855		21,721		28,152		23,218		54,283		7,406	
Technical efficiency (TE)	0.85		0.87		0.88		0.89		0.82		0.88	
Adjusted R^2	0.487		0.623		0.774		0.719		0.797		0.725	

Note: The model was estimated using ln(WTP) as the dependent variable. Coefficient estimates (β) and robust standard errors (*S.E.*) are reported with *** denoting $p < 0.001$, ** denoting $p < 0.01$, and * denoting $p < 0.1$.

Table A.6: Data summary for household-level vehicle availability model with activity-based accessibility as accessibility measure

	Vehicle-free		Motorcycle		Off-Peak car		Normal car		Normal car & Motorcycle		Multiple normal cars	
	Mean	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***
Activity-Based Accessibility (ABA)	3.02	1.27	3.67	0.94	3.81	0.98	4.14	1.41	4.33	0.91	4.79	1.38
Taxi ownership							0.01	0.10				
Chinese ethnicity					0.47	0.50	0.81	0.39			0.87	0.34
Indian ethnicity			0.14	0.35								
Malay ethnicity			0.35	0.48								
Household size			4.13	1.45			4.04	1.35	4.95	1.45	4.78	1.47
Marginal effect of per-capita income					0.18	0.12	0.22	0.15	0.18	0.08	0.28	0.13
Marginal effect of children					0.66	0.53	0.56	0.54			0.54	0.54
Marginal effect of teenagers											0.26	0.45
Marginal effect of seniors							0.35	0.51	0.47	0.54		
% of male adults			50.44%	16.96%			44.90%	17.09%	48.57%	15.05%		
% of adults who are workers							63.57%	28.14%			63.03%	25.14%
% of adults who are young professional workers							15.19%	25.21%	24.50%	25.12%		
% of adults who are retired									6.57%	12.68%		
% of adults who are blue-collar workers			20.68%	24.91%								
% of adults who are white-collar workers							40.64%	31.75%			47.07%	26.89%
Lives in HDB2 unit					0.01	0.11						
Lives in HDB3 unit					0.11	0.31	0.09	0.28	0.10	0.31	0.02	0.14
Lives in HDB4 unit							0.30	0.46			0.11	0.31
Lives in HDB5 unit							0.36	0.48				
Lives in private apartment or condo			0.01	0.05			0.18	0.38			0.32	0.47
Lives on landed property							0.04	0.19			0.24	0.43
Bus stop within 200 meters (home)			0.90	0.30	0.90	0.31	0.87	0.33	0.91	0.29	0.75	0.43
Bus stop between 200 and 400 meters (home)			0.10	0.30	0.10	0.31	0.13	0.33	0.09	0.29	0.22	0.41
MRT station within 400 meters (home)			0.14	0.35			0.19	0.39			0.15	0.35
MRT station between 400 and 800 meters (home)							0.35	0.48			0.30	0.46
Land Use Diversity							0.50	0.08				
Housing density							0.91	0.28	0.92	0.29	0.74	0.32
Observations	5,011		423		172		2,697		86		329	

Table A.7: Estimation results for household-level vehicle availability model with commute time as accessibility measure

	Vehicle-free		Motorcycle		Off-Peak car		Normal car		Normal car & Motorcycle		Multiple normal cars	
	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*
Alternative-Specific Constant (ASC)											-4.290***	0.758
Transit commute time (female head)					0.355*	0.177						
Transit commute time (male head)	-0.541***	0.068										
Transit - Car commute time difference (female head)									0.627*	0.377	0.581**	0.225
Transit - Car commute time difference (male head)							-0.444***	0.116			-0.472*	0.218
Taxi ownership							-1.060***	0.227				
Chinese ethnicity					-0.596***	0.165	1.090***	0.069			1.710***	0.185
Indian ethnicity			0.167	0.151								
Malay ethnicity			1.080***	0.123								
Household size			0.200***	0.038			0.336***	0.024	0.575***	0.068	0.934***	0.060
Marginal effect of per-capita income					1.650*	0.731	5.640***	0.425	2.760***	0.888	7.900***	0.625
Marginal effect of children					0.608***	0.151	0.165**	0.060			-0.478***	0.143
Marginal effect of teenagers											-0.392**	0.146
Marginal effect of seniors							-0.107*	0.057	0.507*	0.254		
% of male adults			1.210***	0.254			0.014	0.134	0.572	0.534		
% of adults who are workers							-0.619***	0.125			-0.623*	0.341
% of adults who are young professional workers							-0.563***	0.112	0.419	0.378		
% of adults who are retired									-1.610*	0.886		
% of adults who are blue-collar workers			0.648***	0.189								
% of adults who are white-collar workers							0.254*	0.111			0.504*	0.292
Lives in HDB2 unit					-1.410*	0.724						
Lives in HDB3 unit					-1.010***	0.251	-0.306*	0.135	-0.675*	0.355	-1.910***	0.393
Lives in HDB4 unit							0.359***	0.124			-1.150***	0.198
Lives in HDB5 unit							0.909***	0.127				
Lives in private apartment or condo			-1.220**	0.456			1.040***	0.157			0.927***	0.207
Lives on landed property							1.880***	0.253			2.730***	0.314
Bus stop within 200 meters (home)			-4.620***	0.213	-4.270***	0.235	-3.090***	0.285	-6.630***	0.509	-4.440***	0.637
Bus stop within 200 meters (female head's job)			0.221*	0.112								
Bus stop between 200 and 400 meters (home)			-4.480***	0.260	-4.180***	0.325	-2.990***	0.289	-6.620***	0.625	-3.990***	0.647
Bus stop between 200 and 400 meters (male head's job)											0.475***	0.164
MRT station within 400 meters (home)			-0.353**	0.144			-0.120*	0.075			-0.327*	0.193
MRT station within 400 meters (female head's job)					0.488**	0.189						
MRT station within 400 meters (male head's job)					0.339*	0.179	-0.162**	0.064				
MRT station between 400 and 800 meters (home)							-0.126*	0.059			-0.207	0.150
MRT station between 400 and 800 meters (female head's job)					0.460**	0.189						
Land Use Diversity							-0.891**	0.323				
Housing density							-0.385***	0.116	-1.170***	0.402	-0.503*	0.264

Note: The model was estimated on 9,222 observations and achieved an adjusted McFadden's rho-squared value of 0.518. Coefficient estimates (β) and robust standard errors (*S.E.*) are reported with *** denoting $p < 0.001$, ** denoting $p < 0.01$, and * denoting $p < 0.1$.

Table A.8: Estimated offset values for household willingness-to-pay (WTP)

Unit type	**WTP offset**	
	w/o vehicle costs	***w/ vehicle costs***
HDB12	0.333	0.364
HDB3	0.136	0.139
HDB4	0.088	0.093
HDB5	-0.065	-0.058
Executive HDB	0.049	0.062
Apartment (<70 sq.m.)	0.193	0.311
Apartment (70 - 130 sq.m.)	0.295	0.408
Apartment (>130 sq.m.)	0.148	0.184
Condo (<60 sq.m.)	0.353	0.386
Condo (60 - 100 sq.m.)	0.259	0.357
Condo (>100 sq.m.)	0.358	0.410
Executive Condo	-0.198	-0.150
Terrace	0.451	0.488
Detached & Semi-Detached	0.563	0.583

Table A.9: Characteristics of Singaporean neighborhoods based on housing market effects (as in Fig. 5-5b)

	Singapore	**Top left**	**Bottom left**	**Top right**	**Bottom right**
Increase in area mean income	-	Small	Small	Large	Large
Decrease in vehicle-free share	-	Small	Large	Small	Large
Units	*1,219,394*	45,617	49,161	36,126	44,255
Vacancy rate (%)	*5.8%*	5.5%	5.5%	5.4%	6.0%
Mean household income (SGD)	*$6,886*	$7,558	$7,534	$6,786	$5,839
Vehicle-free share (%)	*51.8%*	46.7%	46.8%	54.0%	59.8%

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