STRATEGIES FOR INCENTIVIZING HIGH-OCCUPANCY, ZERO-EMISSION, NEW MOBILITY OPTIONS

Final Report

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Table of Contents

List of Tables

List of Figures

1 Introduction

The growth of high-occupancy shared mobility, zero-emission vehicles, and active transportation modes in California, as well as the role they can potentially play in reducing transportation emissions, increases the priority of studying their potential impacts. In particular, the availability of various shared mobility modes (i.e., the shared use of a device, ride, or vehicle on an as-needed basis) may help encourage shifts toward higher occupancy, lower emission modes. This research project aims to identify barriers to the adoption of alternatives like shared mobility as well as to examine strategies to incentivize its usage. The implementation of these strategies might impact segments of the population in different ways. This report explores the potential impact of these strategies on transportation-related metrics while also considering their differential impacts on diverse socio-demographic groups. This report consists of seven sections including:

1. **Methodology:** A review of the different qualitative and quantitative methods employed in the research;
2. **Literature Review:** Summary of relevant literature on the topic areas including various shared modes (e.g., user demographic characteristics, impacts on other modes), equity considerations for vulnerable populations, transportation demand management (TDM) strategies, shared mobility differences across land uses, and COVID-19-related changes (e.g., teleworking, housing);
3. **Expert Interviews:** Key findings from the expert interviews that covered different subjects including COVID-19 impacts, pooled rides, ridesharing, public transit, pricing, active transportation, electrification, and social equity;
4. **Focus Groups:** Description of the focus group findings including the demographic makeup of the participants and information on travel behavior, pandemic impacts, land use and housing, public transit, micromobility, pooling and park-and-ride facilities, and pricing strategies;
5. **Activity Analysis:** Review of the activity data and analysis used to understand modal use patterns;
6. **Survey:** Summary of the survey tool used and relevant findings;
7. **Policy Scenario Analysis:** Description of various policy scenarios that could be implemented and modeled potential impacts; and
8. **Conclusion:** A summary of all the key findings to date.

2 Methodology

The following subsections describe the methodology employed for the literature review, expert interviews, focus groups, surveys, and mobility data specification (MDS) collection and analysis.

2.1 Literature Review

From May 2021 to June 2022 the research team collected literature for this report. The literature selected for this review was identified through searches of journal articles, scholarly databases, and gray literature (to capture recent findings from a quickly evolving transportation landscape) using keywords, such as “bikesharing user demographics” and “carsharing environmental impacts” as well as variations of the words (e.g., “bikesharing,” “bike-sharing,” “bike sharing” and “Transportation Network Companies,” “TNCs,” “ridehailing,” “Lyft,” and “Uber”). The resulting research was then reviewed and documents that had substantiated, relevant findings were selected for inclusion in the literature review. These findings helped inform the research tools used in the study including the expert interview and focus group protocols, activity analysis, and survey.

To provide further background information on the shared mobility space, additional information collected from literature reviews is included in Appendix A Shared Mobility Users and Impacts and Appendix B Trends and Policies Impacting Travel Behavior. In many subsections throughout the report, findings from multiple studies were aggregated and key takeaways summarized in tables to provide an overview of current trends. However, it is possible that relevant studies and documents were inadvertently missed in the literature included in the report and its appendices. This is especially true given the rapid changes that have occurred in the transportation industry throughout the course of the global pandemic. Additionally, it is important to note that not all findings and strategies may be applicable across every built environment type and community. Local characteristics and needs likely need to be considered.

2.2 Expert Interviews

The research team compiled a list of organizations to interview including the California Air Resources Board’s (CARBs) Clean Mobility Options (CMO) Voucher Pilot Program[1] recipients, community-based organizations (CBOs), shared mobility operators, private companies, public transit agencies, travel demand modelers, and other transportation stakeholders. Twenty-five organizations were contacted, and 14 responded, yielding a response rate of 56%. Interviews were conducted between July and October 2021. The organizations, and their organization type, are summarized in Table 1.

The interviews typically lasted an hour and covered the topic areas described in the expert interview protocol, which can be found in Appendix C – Expert Interview Protocol. Some experts only spoke about specific sub-topic areas due to subject matter expertise. The expert interview findings informed the subject areas discussed in the focus group.

[1] The Clean Mobility Options Voucher Pilot Program is a voucher-based funding program for transportation services (e.g., carpooling, bikesharing) that reduce greenhouse gas emissions, strengthen the economy, and improve public health and the environment in historically underserved communities.

Table 1. Expert Interview Organizations

	Clean Mobility Options Grantees	CBOs	Private Companies	Public Transit Agencies	Travel Demand Modelers	Other
Cambridge Systematics					X	
East Bay Housing Organizations		X				
Fresno Metro Black Chamber of Commerce*	X	X				
Housing Authority of the City of Los Angeles**	X	X				
Lyft			X			
Oakland Department of Transportation				X		
Ride Amigos			X			
RSG					X	
Shared-Use Mobility Center						X
Shasta Regional Transportation Agency				X		
Steer Group					X	
TransForm						X
Uber			X			
Via			X			
Totals	**2**	**3**	**4**	**2**	**3**	**2**

*The Fresno Metro Black Chamber of Commerce received a Mobility Project Voucher for their project "Expansion Of E-Bike Services In Fresno."

**The Housing Authority of the City of Los Angeles received a Mobility Project Voucher for their project "Charging Forward: HACLA's EV Lending Library For Economic Equity."

2.3 Focus Groups

In November 2020 two focus groups were held – one with nine participants from Southern California (Los Angeles region) and one with 10 participants from Northern California (San Francisco Bay Area). The groups helped the researchers understand people's travel patterns, housing choices, and how COVID-19 has impacted them. Participants were recruited through online forums (e.g., Craigslist) with ads that included information about the focus group (e.g., subject, time, location, contact information). Participation was incentivized by a $75 gift card distributed after the completion of the focus group. Participants were selected based on their travel behavior decisions and ability to reflect the area's demographics.

The focus groups took place virtually via Zoom due to COVID-19 social distancing measures. Prior to the focus groups, participants completed a five-minute Qualtrics screening survey that collected demographic characteristics (e.g., age, education level, family size), travel behavior information (e.g., modes used in a typical week and trip types), and COVID-19 related changes (e.g., shift to teleworking, differences in mode choices). The survey information helped guide the focus group conversations. The focus groups helped refine the survey (e.g., question wording, response option) that was later used in the research.

2.4 Activity Analysis

The literature review also informed the subjects reviewed in the activity analysis. An analysis of activity data was conducted to gain a better understanding of micromobility, telework, high occupancy vehicle and high occupancy toll lane pricing, and park and ride options as strategies to improve transportation-based emissions. Two data sources were used for this analysis: General Bikeshare Feed Specification (GBFS) and the American Community Survey (ACS). The GBFS data are open-source data that operators can use to display system information. GBFS data include both docked and dockless systems. The trip data include trips that start and terminate within the metropolitan regions of San Francisco (N=734,124), Sacramento (N=192,949), Los Angeles (N=234,918), and San Jose (N=42,011). The timeframe of the trips span January 6th, 2020, to February 28th, 2020. These data points were then evaluated based on different trip characteristics. The ACS data includes census tract-based data that encompass 42 demographic groups. The information was then used to evaluate the following metrics: 1) trips per person, 2) vehicle dwell time, and 3) households per vehicle.

2.5 Survey

The survey was a general population survey of five major metropolitan regions: 1) San Francisco Bay Area, 2) Los Angeles, 3) Sacramento, 4) San Diego, and 5) the Central Valley. The survey resulted in a sample of 2,354 responses. The demographic makeup of the respondents was compared to the demographic distributions of the population, as defined by the US Census's American Community Survey. The demographic attributes compared included income, age, education, race/ethnicity, and gender. Additionally, the responses were analyzed along the four areas of interest: 1) micromobility, 2) telework, 3) high occupancy vehicle and high occupancy toll lane pricing, and 4) park and ride facilities. These analyses were conducted by selecting key survey questions and analyzing their responses. The key questions explored include 1) What perceived user barriers exist with respect to using micromobility? 2) What are (and could be) the overall impacts of teleworking on VMT? In this report, insights on the VMT impacts of teleworking that occurred during the pandemic are explored through an analysis of the sample. Finally, this report evaluated 3) what responses users have to HOV/HOT lane pricing and Park and Ride and pooling? Responses to the survey methodology was informed by the initial literature review efforts were applied to present insights on these and related questions within the survey results section of the report.

2.6 Policy Modeling

Three separate microsimulation modeling systems were integrated to create a robust research platform. The platform combines UrbanSim, which models evolution of urban development and the location patterns of households and jobs; ActivitySim, which models daily activity schedules and travel demand; and BEAM, which models traffic flow. This modeling framework is also among the first to integrate land-use and transportation modeling in a systematic, sequential, and time-consistent way. Most modeling frameworks forecast land use models to 30 or 50 years, and then a travel model is simulated only for the last forecast year. However, this framework does not update traffic conditions that might influence land use modeling and vice-versa. Our integrated model system is designed to run sequentially for each iteration year(s). Therefore, this modeling framework aims to capture a more realistic and complex interdependency between land use and transportation systems.

This research focuses on a sensitivity analysis and a policy scenario analysis to quantify the potential of land use and transportation policies to improve transportation-based emissions and equity outcomes. The set of policies in this report was chosen in coordination with the CARB team and the capabilities of the model framework. The sensitivity analysis can aid relevant stakeholders and decision-makers in exploring the outcomes of different policy decisions as well as the impact of varying degrees of change in variables outside their control. The policy scenario combines variations of the modeling framework input variables.

The modeling framework uses agent-based simulations using a synthetic population. The synthetic population is constructed from census data and contains detailed information about the characteristics of the agent, such as age, race, income, and household structure. This information is particularly valuable in this study since it supports detailed measurement of the elasticity, sensitivity, and impact of the proposed policies on different population segments, especially marginalized populations.

3 Literature Review

3.1 Safety

Micromobility has been identified by multiple studies to have a diverse set of barriers preventing non-users from using these services. One common concern shared by both users and non-users is the issue of safety (Sanders et al., 2020; Rayaprolou and Venigalla, 2020; Winters et al., 2011; McNeil et al., 2017; and Bartkowiak et al., 2021). Safety concerns include unsafe riding environments, traffic safety, and motor vehicle interactions (Sanders et al., 2020). McNeil et al. (2017) reported that 48% of residents in underserved communities in Philadelphia, Chicago, and Brooklyn were particularly concerned about traffic safety and 22% of lower-income people of color reported they were also concerned about personal safety due to potential harassment or crime as a result of riding bikes in their communities. These residents cited similar concerns over lack of safe areas to leave bikes in public areas or lack of safe places to store the bike at home (McNeil et al., 2017). While McNeil et al. (2017) reported these statistics from their sample of underserved communities of low-income and Black, Indigenous, and People of Color (BIPOC) populations, Rayaprolu and Venigalla (2020) found that among a professional population of faculty members at Arizona State University, women were more likely to express concern over safety.

3.2 Disinterest/Non-Viability

Rayaprolu and Venigalla's (2020) survey results from their study on e-scooters and bikeshare programs revealed that disinterest in and nonviability of micromobility services are major barriers. Each micromobility mode was found to cater to different trip lengths and purposes, rendering certain modes non-viable (of limited utility) and inconvenient, depending on user needs (Rayaprolu and Venigalla, 2020). Uncertainty of availability was cited as another contributing factor to disinterest in these modes (Rayaprolu and Venigalla, 2020). Bartkowiak et al. (2021) similarly found that among their sample of 352 Polish users, the other primary barrier was the issue of availability. This issue of availability points to a matter of unreliability and inequitable access to, and distribution of, these services.

3.3 Spatial Barrier

The matter of reliability and inequitable access and distribution of these services is further explored by studying the spatial distribution of these services. In Shaheen et al.'s (2017) framework for transportation equity, spatial inequity occurs when a user's ability to access opportunities in a timely and affordable manner is impeded. The authors noted that tendencies to concentrate transportation services in the urban core could place populations in the lower-density areas at a disadvantage (Shaheen et al., 2017). Another study by Ursaki and Aultman-Hall (2015) investigated the equity of bikeshare access in several U.S. cities using spatial analysis. They found that bike sharing systems may be targeting a specific demographic through bikeshare station placement but noted that these allocations may have been done for the main purpose of ensuring maximum number of users (i.e., most densely populated areas). However, this spatial strategy in station placement consequentially limited access for other disadvantaged groups (Ursaki and Aultman-Hall, 2015). Meng and Brown (2021) likewise looked at spatial distribution of bikeshare systems to investigate geographic inequities of these services. In this study, the authors considered both docked and dockless systems. Docked systems refers to bikeshare systems in which bikes can be rented or borrowed from an automated station and returned to any other station within the system. Dockless systems do not require docking stations and typically have a lock that is integrated into the system for renting/borrowing. Meng and Brown (2021) found that the distribution of docked systems, especially in low-density areas, were unequal and other micromobility services (e.g., dockless scooter sharing) were also limited in these areas. However, they did find that in areas where docked services were less prevalent, such as communities of color, dockless systems reduced such disparities in the docked systems (Meng and Brown, 2021). Mooney et al. (2019) focused on the equity of spatial access for dockless bikeshare system and found that the scale of the dockless systems in Seattle, Washington ensured that there was baseline access throughout the city. The dockless bikes eliminated the constraint of bike pickup and drop-off, allowing for broader spatial access. However, Meng and Brown (2021) found there were other areas of spatial inequity, in the form of 'rebalancing' efforts by bikeshare operators. 'Rebalancing' is a process in which bikeshare operating companies move bikes that have been idle to meet demand in other locations where they are more likely to be ridden. This process could impact spatial equity, depending on where the idle and rebalanced locations are, and Meng and Brown's (2021) study revealed that rebalancing destinations strongly correlated with demand in that area. Meng and Brown (2021) also suggested that dockless bikeshare could offer promising contributions to addressing inequitable spatial access.

3.4 Spatial Access and Sociodemographic

In studies that examine spatial access, many also suggest that sociodemographic are a contributing factor. Shaheen et al. (2017) pointed out that in addition to lower-density areas being at a disadvantage due to concentration of services in the urban core, lower-income households have also been pushed to peripheral "public transit deserts" due to increasing housing costs. Some of these rural areas also experience further disadvantage from limited mobile service and high-speed data (e.g., 4G/5G internet access), impeding access to micromobility services that may be dependent on Internet and mobile devices. Ursaki and Aultman-Hall (2015) used ArcGIS to define the location of bikeshare stations and t-test compared socioeconomic characteristics of populations with and without proximate access to these stations. Their statistical tests showed disparities across race, income, and education level, suggesting inequity in bikeshare access. Mooney et al. (2019) also compared access between neighborhoods along resident sociodemographic and economic characteristics and found there were also modest inequities in spatial access in dockless bikeshare across income and education levels. However, unlike Ursaki and Aultman-Hall's (2015) results, Mooney et al. (2019) did not find disparities in access by racial or ethnic composition, nor disproportionate risks of gentrification-related housing displacement. Meng and Brown (2021) collected and analyzed neighborhood characteristics of service geographies for docked and dockless systems and noticed unequal distribution of docked systems and limited micromobility services in low-median household incomes. Smith et al. (2015) examined the geographic allocations of bike-share infrastructure in the United States in relation to the demographics of surrounding communities serviced by the bike share systems. To examine the differential access that lower-income communities experience, an economic hardship index was created using six component variables, including unemployment, dependency (population under 18), education, proportion of housing costs relative to income, percent of occupied housing units with more than one person per room, and the percent of the population over 18 with no health insurance. Using spatial regression models, Smith et al. (2015) created a model from the six predictor variables and an analysis of this model showed that economic hardship and race and/or ethnicity were significant predictors for variations in the infrastructure. More than 75% of the stations were found in communities with lower or lowest economic hardships, revealing that the stations were skewed towards locations where the populations may be higher income. Martinez et al. (2021) performed a similar study on the effect of income on micromobility use, using comparative causal analysis across four United States cities – Chicago, Los

Angeles, New York City, and Washington, DC – and found that low-income contributes to lower number of e-scooter trips, with low-income accounting for 2.1-23.3% less e-scooter trips compared to their higher income counterparts.

3.5 Temporal Barrier

Shaheen et al.'s (2017) Spatial Temporal Economic Physiological Social (STEPS) framework for transportation equity includes the category of temporal barriers. Shaheen et al. (2017) defined this to occur when one's ability to make time-sensitive trips in a reliable and cost-effective manner is impeded. The authors noted that docked bikeshare users might experience this when they encounter empty stations with no bikes at the start of their trip or full stations with no space to dock at the end of their trip. This may force them to divert to other stations, adding unplanned travel time. Rayaprolu and Venigalla (2020) and Bartkowiak et al. (2021) suggested similar barriers from uncertainty of availability, making these services unreliable and unappealing for time-sensitive trips. Such time-sensitive trips would include connecting to transit, which may impact the overall mobility that is achievable through micromobility.

3.6 Economic Barrier

Shaheen et al. (2017) defines economic barrier as part of their STEPS framework and states that this occurs if basic travel costs prevent spending on other basic goods. Rayaprolu and Venigalla (2020) also identified pricing of micromobility services as one of the major barriers in their sample of Polish users. High upfront costs of membership, credit hold, and liability due to bike damage or deposit for theft insurance are strong deterrents preventing lower-income users from using these services (Shaheen et al., 2017 and McNeil et al., 2017). McNeil et al. (2017) found that lower-income people and people of color were more likely to use bikeshare if there were changes to address cost and liability concerns such as discounted membership or use options, and access to free or low-cost equipment. Other relevant economic barriers come in the form of limited payment methods for these services (Shaheen et al., 2017). Users who are unbanked or do not have credit or debit cards, are unable to use these services altogether (Shaheen et al., 2017). McNeil et al. (2017) suggested that changes to payment methods (e.g., cash payment) could also allow underserved communities to use these services and Shaheen et al. (2017) points out that this economic barrier could be slightly mitigated by reloadable prepaid cards. Users can load funds onto these reloadable prepaid cards via cash or direct deposit and use at unaffiliated merchants. Universal payment systems, which allow users to pay for all modes of transportation using a single payment method, can be part of the solution. Such systems are currently in-use with various metropolitan regions within California. For example, the TAP Card in Los Angeles allows for users to pay for Metro Bike Share along with the broader set of public transit systems operating in the region (LA Metro, 2023). At the same time, the Bay Area's Clipper card works on most public transportation systems within the region and can unlock bikes, but cannot yet pay for rides within Bay Wheels, the region's docked bikesharing system (Burckin, 2022). The California Integrated Travel Project (Cal-ITP) is working to expand the efforts made at the metropolitan level and streamline payment options across modes throughout the state (Cal-ITP, n.d.). This statewide streamlined, integrated transportation payment system would also include features, such automatically applied eligibility (e.g., if an individual's income or age qualifies them for other social services, they are automatically enrolled for similar payment discounts like senior discounts). This points to the fact that micromobility and universal payments are presently at different levels of integration depending on the region.

3.7 Physiological Barrier

One barrier identified by Shaheen et al. (2017) that is not explored or addressed by other studies is physiological barrier. It is defined to occur for users who have physical or cognitive difficultly navigating the transportation options (Shaheen et al., 2017). As a result, micromobility options may not be very physiologically accessible for those with disabilities.

3.8 Social Barrier

The final barrier included in the STEPS framework is social barrier in which the comfort of using these services is inhibited (Shaheen et al., 2017). Low-income communities agree that this is usually due to services being designed without their needs in mind (Shaheen et al., 2017). This barrier intersects with the other barriers previously discussed, as seen in the inequitable spatial distribution of micromobility services across different income and education levels and racial and ethnic composition. Similarly, McNeil et al. (2017) found that people of color and lower-income residents experienced more barriers compared to higher-income white residents, such as concerns over personal safety (discussed earlier in this section regarding safety concern as a barrier) from using these services in their communities. Another study by McNeil (2017) found these underserved communities were also less likely to have exposure to bikeshare through their existing network and lacked better-quality bike infrastructure.

3.9 Telework

In addition to barriers, such as safety concerns and limited spatial access, telework is also impacting travel behavior. Many studies have investigated telework before the COVID-19 outbreak. Most of them have reached a consensus that telework plays a crucial role in the reduction of trips, vehicle miles traveled (VMT), and emissions. Prior to the pandemic, interest in telework and its impacts on VMT peaked in the late 1990s and early 2005s. Choo et al. (2005) employed a multivariate time series analysis using VMT as a function of a set of explanatory variables (e.g., economic activities) and found that telework could reduce 0.79% VMT nationwide. However this reduction could change based on the variables included and studied. In the late 90s, Mokhtarian (1998) concluded from a multiplicative model that 1% of household VMT could be eliminated if 6.1% of the overall workforce telework and 1.5% of the workforce telework every day. In terms of commute trips, Henderson and Mokhtarian (1996) found that home-based commute VMT reduced by 90% among the 72 employees who were recruited to telework from home rather than commute to an office or telework from another site. In contrast, employees that commuted to a telework center rather than their main worksites (i.e., center-based telecommuting) saw 62% reduction in commute VMT.

Projects/programs focused on telework as a trip reduction instrument also started to appear a few decades ago. These included the Teleworking Pilot Project in California and the Trip Reduction Program (CTR) in Washington State. Both projects were proven effective in reducing total VMT (i.e., commute and non-commute combined). The California project found that a teleworking day resulted in a 77% decrease in VMT (Hillsman et al., 2001). Similarly, teleworking under the CTR in Washington led to an overall 1.33% VMT reduction in a 3-hour morning peak (Koenig et al., 1996). In more recent years, an increasing number of telework policies started to burgeon across the nation. The goal of many of these programs was to stimulate the local economy and to bring diversity to lower-density areas. One of the more prominent examples is the Tulsa Remote program, which has attracted over 2,000 people to move over to Tulsa, Oklahoma. Tulsa Remote started in 2018 and offers a $10,000 cash incentive as well as connections to resources that help with finding housing and co-working spaces (Tulsa Remote, n.d.).

Eligibility requirements include a full-time remote or self-employment outside of Oklahoma. Likewise, in other places like Baltimore, the Shoals, and Southwest Michigan, eligible applicants can receive an incentive of $5,000 to $20,000 toward their move or purchase on their new home (Lui, 2021). There are some variations in the types of the relocation incentives (e.g., upfront, installment, post-paid), and the payment amount is sometimes dependent on income, employment, and household composition (Liu, 2021). In contrast, several remote relocation programs in California are primarily paying workers to move away. Some of these were even in place prior to the pandemic. In 2019, a San Jose-based startup company started to offer a $10,000 temporary incentive to applicants who were able to conduct their jobs remotely and decided to move out of the Bay Area (Kim, 2019). They also promised to provide remote communication trainings and to build satellite offices. A similar program in 2017 was offered by another Silicon Valley tech company also with a $10,000 incentive (Robinson, 2017). Companies implemented these programs in the hope that the relocations could help them recruit skilled workers who desired to live out of state.

Research has also explored the possibility that telework may stimulate induced travel demand other than commute purposes. The longer commute distance of teleworkers is another competing factor. These effects have a potential to increase the number of trips so that they equal the number of trips reduced from removing commutes. This can sometimes even increase VMT. As Mokhtarian (1998) pointed out, future VMT reduction may be small since workers tend to live farther away from work, and because of the potential grow in other, non-commute trips. Using a self-administered survey (n=218 employees in California) conducted in 1998, Collantes and Mokhtarian (2003) found that the portion of commute VMT by teleworkers were lower than the portion of teleworkers, meaning that teleworking can effectively manage trip demand. However, they also observed that the ratio of these two portions exhibited an increasing trend over time, which indicates that the reduction in commute VMT caused by teleworking is becoming less prominent over time. Employing a Tobit model on the 2001 and 2009 National Household Travel Survey, Zhu and Mason (2014) reached a conclusion that is opposite to the expectations of policy makers. They investigated the marginal effect of teleworking on VMT and found an additional 40 miles per telecommuter per day. These additional VMT were contributed by both work and non-work trips of teleworkers.

Studies have also made efforts to understand the sociodemographic characteristics of teleworkers. In Finland, Helminen and Ristimäki (2007) identified teleworkers through a nationwide labor force survey (n=19,000). They concluded that teleworkers were primarily aged 25 to 40, highly educated, and upper level (e.g., administrative, managerial) employees. Additionally, men were found more inclined to telework based on a probit regression model (i.e., a type of regression model where the dependent variable is binary) (Shabanpour et al., 2018). Similarly, Vilhelmson and Thulin (2016) applied binary logistic regression on the Swedish National Survey data and found the factors that positively affect the likelihood of telework were being male, having family and young children, permanently employed in advanced services (e.g., informational, financial, scientific), earning higher incomes, university educated, and living in larger urban regions. In Korea, Eom et al. (2016) analyzed a national survey to investigate the intention and adoption of teleworking. According to the survey (n=17,214), younger workers in lower positions and workers in quasi-governmental organizations expressed greater intention and were also teleworking more frequently.

While telework can potentially be effective in many aspects (e.g., trip reduction), there are several tradeoffs that employers and policy makers may need to consider. In an early exploration, Tsiligirides

(1993) suggested that telework could imply both benefits and barriers to employers, employees, and the society respectively. Employers may be able to save cost on workspace and hire skilled and productive labor through telework; employees can have better control of their own time and spend less on housing and commute; telework can also help reduce congestion, energy consumption, and environmental damages. On the other hand, telework may lead to managerial problems, isolation, less collaborations, technical difficulties (e.g., Internet equipment), etc. (Tsiligirides, 1993).They recommended that telework as a key rural development element should be integrated with improvements of infrastructure and other services (e.g., business, health care) (Tsiligirides, 1993). Similarly, Pratt (2002) seconded the productivity and cost benefits and observed from a nationwide online survey that many people would telework every day if their broadband equipment was paid for or provided by their companies. In Netherlands, another survey-based (n=1102) analysis suggested that over half of the teleworkers did not receive compensation for their computers/hardware (Vermaas and Bongers, 2007). Other studies argued that working productivity may not grow as expected due to concerns about keeping a work-life balance and other responsibilities such as childcare (Prager et al., 2022).

Ever since the onset of the COVID-19 pandemic, the world has witnessed many changes in individual trip-making behaviors. One of the changes is a broader experiment and application of telework, which has gained unprecedented public attention during this time. Observations from a survey (n=7,613) conducted between July and October 2020 in the U.S., Salon et al. (2021) found that the percentage of respondents who expect to telework at least a few times per week after the pandemic is twice the percentage before COVID, and there is a 20% decrease in those who expect to always commute by personal vehicle after the pandemic. In California, Lu et al. (2022) conducted surveys (n=1985) and interviews (n=28) with both employees and managers to understand the patterns and trend of teleworking before, during, and after COVID. According to their analysis, travel demand significantly dropped in response to a shift toward telework. Most respondents reduced their drive-alone commute trip frequency from five to zero days per week, along with a considerable decline of commute distance and time. Overall, more than half of them observed an improvement in road congestion. These findings generally align with conclusions of other studies that were conducted earlier before the outbreak. Besides, they found that telework increased from 25% to 35% during the early pandemic, causing some respondents to move out of state without planning to move back. In addition, greater trip reductions were observed in lower-income areas, whereas rural counties contributed a greater proportion of commute trips. The authors further observed that these new patterns reached a certain level of stability and could possibly continue in the next three years. Moreover, another study investigated the pre- and during-pandemic telework adoptions in the south bay region of Los Angeles (Prager et al., 2022). Similarly, they found a desirable persistence of telework practices in the long run, and thus suggested using training programs and promotional campaigns to further incentivize telework in the post-pandemic era.

To summarize, most studies claimed that telework could be beneficial in many aspects such as trip reduction, cost saving, job-creating, and opportunities to increase productivity, while many of them also acknowledged the caveats, including isolation and the potential to work overtime due to a mix of work and personal life. The ability and desire to telework usually depends on factors like sociodemographic characteristics and the type of jobs. In addition, the pandemic was found to be an enabler of the further adoption of telework, which is likely to remain stable in the near future.

4 Expert Interviews

Expert interviews were conducted to further the findings of the literature review and focus groups. The experts represent various organizations in the public, private, and non-profit sectors. This section summarizes the expert interview findings and is divided into the following seven subsections:

1. **COVID-19 Impacts:** Overview of the COVID-19 pandemic transportation impacts including teleworking options, household changes (e.g., relocating to lower-density areas), and ridership trends (e.g., less peak travel);
2. **Pooled Rides:** Description of existing ridesharing trends and discussions of ways to increase vehicle occupancy, such as through park-and-ride facilities and pricing strategies;
3. **Public Transit:** Summary of strategies to encourage public transit use and recovery (e.g., increasing information availability);
4. **Pricing:** Description of pricing strategies to shift people to higher-occupancy modes;
5. **Active Transportation:** Identification of the opportunities and challenges to active transportation adoption;
6. **Electrification:** Overview of the barriers and strategies to electric vehicle (EV) adoption; and
7. **Social Equity:** Identification of potentially vulnerable populations and strategies to increase transportation equity.

4.1 COVID-19 Impacts

The interviews revealed that the global pandemic is impacting operations for most of the experts' organizations. Many of the experts said their organizations shifted to teleworking and their operations and services changed to support COVID-19 protocols (e.g., increasing social distancing, providing personal protective equipment [PPE]). Experts also identified changes in household trends due to increased teleworking capabilities, these changes may remain in the future. The following subsections detail these COVID-19 impacts.

4.1.1 Telework and Operations

Overall, the COVID-19 pandemic is altering shared mobility operations and highlighting the demand for shared mobility services to meet community members' changing needs. For example, one mobility service provider shifted from offering microtransit rides to grocery delivery services. In the remaining cases of passenger services, mobility providers are focusing on increasing flexibility and safety. However, some mobility providers are facing challenges meeting increasing trip demand and maintaining vehicle hygiene and safety. Additionally, health and safety messaging now has to rely on science but be phrased in a way that does not alienate individuals.

All of the CMO recipients are also experiencing challenges conducting stakeholder engagement. The CMO recipients faced particularly difficult outreach challenges during early shelter-in-place orders. The CMO recipients had to pivot from their initial plans of in person community meetings and demonstrations to virtual meetings. The virtual meetings resulted in a slight disconnect from CMO constituents. One CMO recipient believes that limited in person outreach led to reduced service adoption and ridership rates. However, experts stated these changes positively impacted guidelines by requiring greater equity measurements and awareness.

4.1.1.1 Funding

In addition to necessitating operational changes, the pandemic is highlighting the need for flexible funding. Some experts faced difficulties accessing and using funding sources that are tied to stringent regulations and requirements, especially for critical but unanticipated demands (e.g., PPE). For example, one public agency described a funding challenge they faced where there appeared to be ample funding, but a lot of it was inaccessible due to inflexible requirements and state level limitations. If the funding had been accessible, it could have helped improve the overall transportation network, kept people employed, and delivered high quality transportation services. Additionally, rural agencies struggled to gain access to necessary equipment (e.g., cleaning supplies) that larger agencies were more easily able to procure. Stakeholders' limited resource access resulted in additional impacts to operational budgets.

4.1.2 Household Changes

The pandemic is also leading to household changes, such as residents relocating to lower density areas outside of the urban core. Many household changes are occurring along demographic lines, namely income. The transportation modeling experts described higher-income professionals in dense, urban areas moving to more suburban and/or scenic destinations. However, one stakeholder stated that vulnerable populations, particularly low-income households, are not likely to move due to limited financial resources. The only household change lower-income individuals are likely to make is increasing housing occupancy to improve affordability. However, changing housing demand is complicated by shortages, such as in labor and supplies. Shortages can not only delay the housing construction process, but also increase housing prices making them less affordable for lower-income individuals.

Long-term housing changes for all demographic groups are likely to correspond to impacts to commercial leases (e.g., large scale employers giving up their commercial leases). However, the housing impacts that correspond to commercial lease changes will likely be delayed due to the longer time frame of commercial leases. Despite the trends identified, about half of the experts believe that, especially compared to transportation trends, housing changes have not been pronounced enough to see drastic, conclusive differences.

4.1.3 Ridership Trends

Transportation ridership trends are also accompanying housing changes. The general consensus on transportation trends include: low ridership, increase in goods delivery, less peaking travel (i.e., more consistent throughout the day), and faster weekend ridership recovery. Experts are also witnessing an increase in public transit use during off-peak hours, likely by individuals who do not own a vehicle and are essential workers. Several experts identified other ridership trends including:

- **Built Environment-Based Differences:** Suburbanites may witness an increase in multimodal travel and walking while urban dwellers are more likely to purchase a vehicle to avoid high-capacity transportation modes. Additionally, travel patterns are localizing at the neighborhood level (e.g., less long-distance trip commutes) and resulting in smaller transportation footprints (e.g., people walking and biking to nearby locations).
- **Commuting Changes:** How frequently people travel into work is changing (e.g., most professional service companies are more willing to consider teleworking and/or flexible work schedules). Indicators exist demonstrating that this will be a longer-term trend (e.g., labor shortages granting potential employees greater bargaining power when requesting workplace designs and expectations).

- **Income-Based Differences:** The pandemic is highlighting the mobility dichotomy between lower- and higher-income households. Lower-income households may have less ability to afford other options (e.g., personally owned vehicles) and hold jobs that allow them to telework, which may result in them relying on potentially lower-quality and/or higher-risk transportation options. One private transportation stakeholder observed that in lower-income tracts, public transit ridership has remained the same.
- **Mode Shifts:** According to one organization's COVID-19 Panel Survey, vehicle-focused modes are expected to prevail (e.g., driving a personal vehicle, participating in carsharing) while public transit ridership will likely continue to be depressed. Lower public transit ridership is also expected as there may be less congestion in the areas that transit serves best (e.g., dense, urban downtowns) because employees of these areas can telework. The experts agree that public transit agencies and other transportation operators will have to adjust their service models to meet these new needs.

While all of the experts noted the drastic decrease in public transit ridership, many of them view this as an opportunity to repurpose transportation services to better meet individuals' needs. For example, resources devoted to peak period public transportation operations (e.g., vehicles, drivers) can be redistributed to off-peak hours (e.g., vehicles that are smaller but arrive more frequently throughout the day). This change can offer more transportation options to essential workers and transit dependent populations. The experts think these service changes may be necessary as people's willingness to share rides, particularly with strangers, is greatly decreased. Experts also believe that enhanced cleaning protocols are likely to be the expectation going forward.

4.2 Pooled Rides

As COVID-19 containment increases and travel patterns continue to change, pooled rides can help improve mobility, decrease congestion, and reduce environmental impacts. However, barriers exist to shifting people to multimodal trips and higher-occupancy modes. The experts offered insights to these barriers and potential strategies to address them. The following subsections discuss barriers and strategies to increase ridesharing and public transit ridership, including potential pricing tools.

4.2.1 Ridesharing

Travelers' lingering concerns about COVID-19 transmission and infection will likely impact their willingness to share rides in the future. Most of the experts believe that COVID-19 concerns will go away, although the timeline for this is unclear. Experts from every sector stated that COVID-19 concerns can be addressed through actions including clearly communicating (e.g., telling riders what agencies are doing to keep them safe, offering information on vaccine effectiveness) and reducing vehicle capacity (e.g., five to 10 passengers).

However, one expert stated that even prior to the COVID-19 pandemic, drivers did not always like pooled rides because of routing challenges and unsatisfied passengers. Riders like the cost savings pooled rides offer, but not the long wait times. A non-profit representative described additional barriers that exist to shifting people to higher-occupancy modes including: existing access to traditional transportation modes (e.g., personal vehicles), knowledge gaps regarding vehicle sanitation in light of COVID-19, and difficulty engaging people in shifts toward higher-occupancy modes without incentives.

Strategies, such as park-and-ride facilities, may be opportunities that can be used to encourage pooled rides.

4.2.2 Park-and-Ride

Park-and-ride facilities are locations used to connect drivers and passengers to facilitate pooled rides. The experts were asked about their opinions on park-and-ride facilities (e.g., if they could be leveraged to support shared rides). The experts had mixed responses, with the majority of the experts stating that park-and-ride facilities, particularly a network of them, may work well in some environments but not all.

All of the travel demand modelers stated that park-and-ride facilities work well in locations with congested corridors, where pooled rides can offer significant time savings. Locations with high density on both ends (i.e., origin and destination) can be ideal for park-and-ride facilities. However, inbound (i.e., morning commutes) trips will likely have higher ridership than outbound trips as people may end work at different times and have different plans. One public transit representative advocated for park-and-ride facilities stating that they do not require a lot of infrastructure and are relatively easy to implement. Experts from all sectors stated that park-and-ride facilities can be beneficial and support higher occupancy trips, with certain considerations in place including:

- **Incentives:** Park-and-ride facilities need to be incentivized (e.g., carpool lane access, mileage-based car insurance discounts, parking cash outs at work).
- **Infrastructure:** Design considerations and additions (e.g., seating, designated loading zones, EV charging) can support park-and-ride facility use. Infrastructure elements will likely precede people using park-and-ride facilities.
- **Network:** Park-and-ride facilities may work best if they are designed as an accessible network.
- **Seamless Connections:** Especially if park-and-ride facilities are designed as mobility hubs, seamless connections to other modes will be a key consideration for their use.
- **Wait Times:** Long and/or uncertain wait times will need to be addressed (e.g., through trip routing, offering on demand services) as people have relatively limited thresholds for how long they are willing to wait.

4.2.3 Pooling Strategies

In addition to park-and-ride locations, the experts discussed strategies to increase vehicle occupancy. Generally, the experts think that pooled rides are successful in locations where public transit is less efficient (i.e., suburban and rural regions), within flexible transportation systems (e.g., short headways between vehicle arrival times), communities without pedestrian infrastructure, and areas with relatively temperate weather.

Experts anticipate the need to leverage social networks to encourage shared rides in the future. Riders will likely feel more comfortable if they have commonalities with other riders (e.g., live in the same building, work for the same organization). Ride matching apps can help group riders with commonalities together. Ride matching apps can also be designed to increase pooling convenience (e.g., optimize pick-up routes for drivers). Pooling, whether facilitated through ride matching apps or other mobility options (e.g., transportation network companies or TNCs like Lyft and Uber), can be improved by setting expectations for drivers and riders and designing services as “first in, first out” (i.e., the first rider picked up is the first rider dropped off). Despite these improvements, pooling will need to reach a critical mass of interested people to be efficient. Experts described additional ways to reach this critical mass including:

- **Education and Outreach:** Providing information on available pooling options can help raise awareness and increase vehicle occupancy.
- **Employer Incentives:** Employers, especially larger ones, can support pooling through various means, such as: enrolling in vanpooling services, offering more off-street pooling parking spaces, and lowering the cost for pooled ride parking.
- **Infrastructure Investments:** Infrastructure changes that offer time, rather than cost, savings can encourage pooling. For example, a network of high-occupancy vehicle (HOV) lanes that expands throughout the San Francisco Bay Area (e.g., Vallejo) and covers all of the bridges (e.g., Bay Bridge, Dumbarton Bridge) can save commuters' time.

4.2.4 Public Transit

Supporting public transit can also help increase vehicle occupancy. The experts suggested strategies for supporting public transit including:

- **Integrating Trip Planning and Fare Payment:** Stakeholders integrating different mobility options (e.g., pooled rides, public transit) into a single app and/or platform can encourage multimodal trips using public transit. Additionally, platforms can be designed to offer discounts for public transit trips (e.g., free scooter sharing rides that connect to public transit, weekly bundles and discounts). However, the experts noted that coordinating different stakeholders to integrate various modes may be challenging.
- **Leveraging Shared Micromobility:** Since shared micromobility (e.g., bikesharing and scooter sharing) is well suited for short, point-to-point trips it can be used to fill first-and last-mile public transit gaps. Public and private partnerships can support multimodal trips using shared micromobility and public transit.
- **Providing Information:** Riders' COVID-19 transmission concerns may be amplified by riders feeling like they have less control while taking public transportation rides (e.g., versus a private vehicle). Public transit agencies can address these concerns by offering information (e.g., vehicle occupancy, time of last vehicle sanitation).
- **Spatially Changing Services:** Many mobility providers are exploring spatially changing their services to serve their markets as efficiently as possible (e.g., offer first- and last-mile connections in lower-density areas, provide high-capacity services in higher-density areas with lots of congestion). These service changes can offer more flexible public transit options for individuals who do not live along a transit corridor. As stakeholders rethink transportation networks, they also need to include intercity and rural routes to create a comprehensive network.

4.2.5 Pricing

The experts were also asked about different pricing strategies that can be used to shift people to higher-occupancy modes. The experts described characteristics of effective pricing changes including:

- **Cross Cutting:** Ideally, fees applied to one mode would act as a discount for the preferred mode (e.g., fees leveraged on single occupancy rides would act as a discount for higher occupancy vehicles).

- **Dollar Savings:** Pricing changes should be presented as a dollar amount rather than a percentage because it is usually a more effective communication strategy.
- **Parking-Based:** Typically in transportation models parking prices are the most influential variable in travel behavior changes.
- **Revenue Neutral:** Ideally, future pricing strategies should be revenue neutral or offer returns that benefit communities (e.g., provide infrastructure funding).
- **Size:** Pricing signals need to be large enough for people to change their behavior (e.g., $30 per day parking fees).
- **Time Savings:** Pricing changes also need to be coupled with time savings, otherwise people are less likely to change their behaviors.

Transportation stakeholders are currently exploring various pricing strategies to increase vehicle occupancy and public transit use. The pricing strategies include free public transit fares, comparative service rates (e.g., trip cost for carsharing versus public transit), and employer-based incentives. Some public agencies are looking at free transit fares for all, in part to ensure that individuals who need public transit the most are not financially burdened by it. However, free fares are a strategy that requires further research.

4.3 Active Transportation

Similar to pooled rides, active transportation options can help reduce negative transportation impacts (e.g., pollution, congestion) while offering additional health benefits to travelers (e.g., increased physical activity). However, approximately half the experts interviewed stated that a key barrier to active transportation adoption is safety concerns. Travelers' concerns include both existing challenges (e.g., a lack of a network of protected bike lanes) and perceived ones (e.g., not knowing how to operate a device). Additionally, communities may be unwilling to adopt and support some active transportation options (e.g., scooter sharing) due to the perception that they are a nuisance (e.g., unsafe riders, improperly parked devices) and not useful (e.g., lack of storage space for bags and other goods).

4.3.1 Active Transportation Adoption Strategies

Despite the challenges facing active transportation adoption, opportunities exist to encourage its use. For example, a private sector expert noted that electric bikes (e-bikes) present a unique opportunity to encourage active transportation. E-bikes can decrease trip times with less effort than traditional bikes and still have lower energy requirements than a vehicle. Active transportation, especially shared micromobility, adoption can be supported through additional strategies including:

- **Accessories:** Offering necessary accessories (e.g., bike locks, helmets) for device rentals, especially longer term options;
- **Coordination:** Continuing to work with land use authorities and other agencies to reclaim streets (e.g., through Complete Streets[2] efforts) for active modes;
- **Education:** Providing information on how to safely operate different modes (e.g., dockless bikesharing) as well as maintain personally owned devices;

[2] Complete Streets is a transportation policy and design approach focused on increasing the accessibility and usability of built environments for everyone. Further information can be found here.

- **Infrastructure:** Implementing supportive infrastructure (e.g., protected bike lanes, secure device storage) to address traveler concerns;
- **Insurance and Liability:** Providing insurance for riders and clarifying liability, such as in the case of accidents;
- **Integrated Fare Payment:** Integrating fare payment with other modes (e.g., public transit);
- **Local Context:** Considering local land uses and contexts when deciding which active transportation modes to offer;
- **Multimodal Trip Incentives:** Offering incentives for taking multimodal trips (e.g., free scooter sharing trips if they connect to public transit);
- **Permitting Processes:** Streamlining permitting processes to increase their efficiency and decrease their costs; and
- **Service Area Evaluation:** Reviewing service areas to identify potential areas of concerns for both drivers and riders (e.g., high volume streets).

4.4 Electrification

In addition to increasing vehicle occupancy and supporting active modes, shifting travelers to EVs can help reduce transportation-based emissions. Experts from all sectors also agreed that infrastructure availability is a key precursor to EV adoption. However, the experts identified infrastructure-based challenges facing EV adoption including:

- **Accessibility:** EV infrastructure needs to be accessible to people with a range of capabilities, especially in lower-income and historically underserved areas.
- **Charging Station Locations:** Charging stations need to be available to the public (e.g., not inside private apartment complexes).
- **Cost:** High upfront costs (e.g., for infrastructure, vehicles) may prevent widespread EV adoption, although strategically designed incentives may help mitigate this challenge.
- **Funding:** EV infrastructure may require funding that is difficult to acquire. Available funding sources may, intentionally or unintentionally, exclude EVs.
- **Grid Capacity:** Some neighborhoods (e.g., older ones) may lack the energy grid capacity to support EV charging. In instances like this, alternatives like solar charging may be necessary to implement. Similarly, as EV adoption increases, mobility providers and utility companies will need to work together to ensure that vehicles can be charged without overburdening the energy grid.
- **Incentives:** Neighborhoods that currently lack EV infrastructure (e.g., rural locations) may require incentives to encourage development.
- **Maintenance:** EV infrastructure (e.g., charging stations, signage) need to be kept up to a good state of repair.
- **Security:** Vehicles should be placed in safe and secure locations (e.g., covered parking) to protect them against vandalism and theft. Ideally, vehicles and chargers should be located in fenced-in areas with good lighting, but this may not be available in all communities.
- **Signage:** Clear signage is needed to differentiate between EV parking, charging, and parking spaces equipped with chargers.
- **Vehicle Capacity:** The battery capacity of existing vehicles may not be large enough to meet certain needs (e.g., longer range shuttle services).

- **Vehicle Type:** Higher capacity vehicles (e.g., buses) may not be available for mobility operators to purchase, partially due to prohibitive prices.
- **Voltage:** Chargers need to be equipped with the proper voltage and converters to charge vehicles efficiently and safely.

In addition to infrastructure, the experts identified the challenge of the social acceptance of EVs. In disadvantaged communities a mentality persists regarding EVs that they "aren't for me." This belief is rooted in the idea that EVs are only accessible and available to higher-income individuals who can afford the vehicles and understand the system (e.g., which chargers their vehicles can use, how long vehicle charging takes). The stigma stems from a lack of exposure to electric modes and experiences with racism while driving and charging EVs (e.g., pressure to leave charging stations, accusations that vehicles are stolen). The fact that many EV chargers are located in higher income, predominantly Caucasian neighborhoods may further this challenge.

4.4.1 EV Adoption Strategies

The majority of the experts cited the importance of education and financial incentives for EV adoption. Educational campaigns can target all community members – from high schoolers learning how to drive to immigrants. Outreach and education can help address knowledge gaps (e.g., vehicle maintenance) and concerns (e.g., range anxiety). Community members can act as ambassadors and help teach others about EV programs and resources. "Ambassador" programs can help increase EV understanding and familiarity through one-on-one relationships. Community members can be encouraged to act as ambassadors through benefits (e.g., reduced EV carsharing fees). One public sector expert also noted that it is important to include funding in EV program budgets to cover minor vehicle damages (e.g., damaged mirror, scratched door), due to inexperienced drivers operating the vehicles. Additionally, tax credits and benefits, which may vary by state and can be supported at the federal level, can be leveraged to support EV programs (e.g., carsharing, transportation network companies that use EVs). Regulatory and financial incentives can also support electrifying higher capacity vehicles (e.g., 40-foot public transit buses) for both public and private mobility providers.

4.5 Social Equity

As shared mobility options are developed and deployed in different communities, they present equity opportunities and challenges for different vulnerable populations including:

- **Immigrants:** Individuals who have recently moved to the U.S., who may or may not have legal citizenship status;
- **Low-Income Households:** Households whose incomes are 80% or less than the median income of the area;
- **People with Disabilities:** Individuals with auditory, cognitive, mobility, physical, and/or visual disabilities;
- **Racial Minorities:** People who are African-American/Black, Alaska Native, American Indian, Asian, Hispanic/LatinX, and/or Pacific Islander; and
- **Rural Populations:** Residents of areas with between 2,500 and 50,000 people outside of urban clusters.

The unique challenges these demographic groups may face include:

- **Immigrants:** Multiple experts stated that future shared mobility programs will need to include other languages and minorities. The languages included may need to vary based on the demographics of the area. For example, in certain areas of California Hmong may be the prevalent language, while in others it may be Spanish or Punjabi. Additionally, immigrant populations may face challenges obtaining necessary identification, like drivers' licenses (e.g., lack of vehicles to practice driving, prohibitive costs).
- **Low-Income Households:** The experts described the challenges low-income households may face regarding vehicle ownership and commute times. Many low-income individuals have vehicles, but they are typically older, unreliable, and have maintenance issues and/or are expensive to repair. Low-income individuals who do not own a vehicle are typically transit dependent but may have commute times 45 minutes or longer each way. Lower-income communities may have less mobility options than denser, higher-income areas that may be more profitable for shared mobility operators. Additionally, low-income households may be unable to afford privately provided mobility options.
- **People with Disabilities:** The experts agreed that all aspects of a transportation service, from the platform it operates on to the devices and vehicles it uses, need to be designed accessibly so people with a range of capabilities can use it. Transportation accessibility challenges may be furthered by financial accessibility difficulties as people with disabilities face the greatest challenge accessing and affording housing options.
- **Racial Minorities:** A travel demand modeler stated that historic inequities in transportation planning (e.g., highways bisecting communities, redlining practices) have resulted in discrepancies today regarding where transportation benefits and costs are. Transportation cost and benefit discrepancies tend to be along racial lines, rather than income ones. Additionally, racial minorities may face challenges, such as racial profiling.
- **Rural Populations:** Rural communities may face unique challenges, such as difficulties with public health messaging and government mistrust. Rural populations may also feel unsafe traveling to more densely populated areas where COVID-19 transmission rates may be higher.

A private mobility operator noted that an underserved demographic group, across most transportation services, is essential workers. Essential workers are the population group most likely to need transportation services, but their needs have not been clearly identified or addressed. Especially as budgets and services shift as COVID-19 is contained, public transit agencies need to focus on ensuring the riders who need public transit the most are served.

4.5.1 Social Equity Strategies

Various strategies exist to increase mobility for vulnerable populations. A public sector expert stated that providing reliable, consistent, and affordable transportation is key to support a positive cycle of economic development. Table 2 summarizes different strategies across different project and planning components (e.g., project planning and development, implemented pricing options) that can be used to support transportation equity for various vulnerable populations.

The experts agree that the COVID-19 pandemic presents the opportunity to rethink and redesign public transit options in new, innovative, and more equitable ways. Key questions to identify ways to rethink public transit includes:

- Who has access to different modes?
- Who is currently driving?
- Who wants to change modes?
- Who is price sensitive and how is that changing their travel decisions?
- How can we support different populations?

As public transit and shared mobility options evolve, a private mobility operator stated that any positive travel behavior change, no matter how seemingly minor (e.g., carpooling one day a week instead of driving alone all five days), needs to be rewarded. Constantly rewarding these small shifts can lead to greater overall changes.

Table 2. Social Equity Strategies

		Demographic Group				
Strategy	**Description**	Immigrants	Low-Income Households	People with Disabilities	Racial Minorities	Rural Populations
Alternatives	Provide various ways to pay (e.g., cash, debit cards) and book services (e.g., smartphone app, phone number)	X	X	X		X
Demonstrations	Conduct demonstrations to expose communities to new modes and familiarize them with how to use them	X	X	X	X	X
Discounts	Offer income-based discounts to qualified individuals		X			
Education	Clarify differences in modes and service models (e.g., carsharing versus carpooling), especially in communities who have not previously seen these modes and may view them as exclusive	X	X	X	X	X
Fleet Distribution	Distribute fleets, even portions of fleets, into historically underserved communities		X		X	X
Follow Up	Start with initial, short outreach efforts that meet people where they are at (e.g., two-minute door-to-door surveys), with the option for participants to follow up and continue to participate	X	X	X	X	X
Frameworks	Leverage environmental justice and/or equity frameworks to help guide changes	X	X	X	X	X
Incentives	Target incentives to the objective demographic groups (e.g., minority communities)	X	X	X	X	X
Long-Term Evaluations	Conduct long-term reviews of transportation services and modes to identify potential gaps and consequences	X	X	X	X	X
Normalization	Create policies and procedures to actively work against stereotypes and stigmas of public transit use	X		X	X	X
Off-Peak Travel	Offer transportation options during non-peak travel hours for transit dependent populations	X	X	X	X	X
Outreach	Integrate transportation outreach with different community efforts (e.g., PPE distribution, community meetings) to reach the broadest population possible	X	X	X	X	X
Service Design	Design services to allow trips to be terminated anywhere (i.e., point-to-point) to increase flexibility and mobility	X	X	X	X	X
Trusted Messengers	Develop relationships with community members to do outreach person to person	X	X	X	X	X

4.6 Expert Interview Key Takeaways

- **COVID-19 Measures:** According to the experts, COVID-19 is impacting operations for most mobility providers including increasing social distancing (e.g., limiting public bus capacities), altering and suspending existing services (e.g., shifting from microtransit services to goods delivery), and changing outreach methods (e.g., webinars and Zoom meetings instead of community demonstrations). Additionally, the pandemic is demonstrating the need for available funding with limited restrictions.
- **Household Changes:** Experts are witnessing individuals, typically who are higher-income, move to locations further from their places of work and into more suburban built environments. Housing trends are anticipated to continue to change as commercial leases and land uses are altered.
- **Transportation Trends:** Generally, the experts identified low overall ridership across modes, increased goods delivery, and less peaking travel. Teleworking capabilities are also impacting travel patterns and these changes are expected to remain as many employers offer teleworking options and hybrid work models. As a result, public transit agencies and other mobility providers will likely need to rethink and redesign their services to increase flexibility and serve shorter distance trips at the neighborhood level. In the long term, experts anticipate needing to continue to provide transportation options for transit dependent populations, while encouraging other populations to shift from personal vehicle use to higher occupancy, active, and electric modes.
- **Shared Rides:** The experts anticipate that lingering COVID-19 transmission concerns will negatively impact people's willingness to share rides, especially with strangers in larger capacity vehicles. COVID-19 concerns can compound previously existing ridesharing concerns, such as routing challenges and longer trip times. However, experts offered strategies to increase pooling including strategically selecting service areas, clearly setting expectations for riders and drivers, improving infrastructure, conducting education and outreach, and offering incentives.
- **Park-and-Ride Facilities:** The general consensus is that park-and-ride facilities may work well in some locations (e.g., higher-density areas with strong commute patterns), but not others. However, stakeholders can leverage various strategies (e.g., incentives, infrastructure changes, network enhancements, seamless connections) to support park-and-ride facilities. The experts also offered insights on ways to increase ridesharing through price incentives. The experts agreed that pricing changes need to be large enough to impact travel behavior and, ideally, be designed as cross cutting changes that are clearly communicated.
- **Active Transportation Adoption:** The experts noted that active transportation adoption may be challenged by safety concerns. To support active transportation, the experts recommended strategies including: offering necessary accessories, providing education on the different modes, implementing supportive infrastructure, clarifying insurance options and liability, integrating fare payment, offering multimodal trip incentives, streamlining permitting processes, and strategically selecting service areas.
- **Electric Vehicle Adoption:** The experts also identified challenges facing EV adoption. The challenges are primarily concerned with infrastructure (e.g., charging station location, power availability). Despite these challenges, experts provided ways electric modes can be encouraged including educational campaigns that target a broad demographic of community members and offering financial incentives for EV use and development.

- **Social Equity Concerns:** The generally agreed upon communities of concern and challenges facing them include:
    - **Essential Workers:** This demographic group is frequently excluded from transportation research so their needs may be unknown and unmet.
    - **Immigrants:** People who have recently moved to the U.S., and who may not have legal citizenship status, may not be fluent in English and/or have necessary identification (e.g., drivers' licenses).
    - **Low-Income Households:** Households with lower incomes may face financial accessibility challenges and are more likely to be transit dependent with limited mobility options available to them.
    - **People with Disabilities:** Mobility options, from their operating platforms to their devices and vehicles, may not be designed accessibly enough for people with a range of capabilities to use them.
    - **Racial Minorities:** Communities of racial minorities may face challenges, such as historically unjust transportation planning practices and discrimination when using shared mobility options.
    - **Rural Populations:** Lower-density and less developed regions may face challenges obtaining necessary resources (e.g., funding, PPE) and have additional COVID-19 related concerns.
- **Social Equity Strategies:** The experts provided strategies that can help address these challenges including increasing transportation accessibility (e.g., financially, physically), working with community members to educate them on shared mobility options and hear their concerns and questions, and strategically investing in and implementing different mobility options. The majority of the experts agreed that COVID-19 poses a unique opportunity to redesign mobility options to best serve communities.
- **Future Research:** Going forward, further clarity is needed regarding the impacts of COVID-19 on various industries including transportation, teleworking, and housing. Additionally, as residential densities and mode share shifts, mobility providers will need to understand how to accommodate these changes and alter their services accordingly. Further research is also needed to understand how to efficiently integrate different modes into trip planning and fare payment services, as well as implement necessary EV infrastructure.

5 Focus Groups

This focus group review is separated into eight sections that provide information on key focus group themes including:

1. **Demographics:** This section summarizes participant demographic information including household income, educational attainment, age, race/ethnicity, gender, marital status, and number of children.
2. **Travel Behavior:** This section provides information on travel behavior including commonly used modes both active (e.g., walking, shared micromobility) and vehicle-based (e.g., personal vehicle, transportation network company [TNC]).
3. **COVID-19 Impacts:** This section discusses how COVID-19 changed participants' travel patterns.
4. **Land Use, Housing, Telework, and COVID-19:** This section provides an overview of variables that have impacted participants' travel decisions including surrounding land uses, housing locations, telework options, and COVID-19 concerns.
5. **Public Transit:** This section describes public transit use including how participants access transit, parking around stops and stations, and service opportunities and challenges.
6. **Micromobility:** This section discusses micromobility, both personally owned and shared, such as how devices are used and what would encourage greater use.
7. **Pooling and Park-and-Ride:** This section provides details on participants' understanding and use of pooling services and park-and-ride facilities.
8. **Pricing:** This section summarizes participant feedback on different pricing strategies including cordon, congestion, and high-occupancy vehicle (HOV) lanes.

The first three sections (Demographics, Travel Behavior, and COVID-19 impacts) are based on data from the pre-screener survey. This information likely informed the focus groups' responses to the topics later discussed in the focus groups. The following sections (Land Use, Housing, Telework, and COVID-19; Public Transit; Micromobility; Pooling and Park-and-Ride; and Pricing) summarize and are based on focus group findings. The section concludes with a list of key takeaways from both the pre-screener survey and focus group. Throughout the focus group discussion summary, the Northern and Southern California groups are often compared to each other. This comparison shows how different variables may influence each other, such as how land uses may alter travel behavior. However, the similarities and differences identified cannot be extrapolated to characterize large regions of the state.

5.1 Demographics

Focus group participants were selected, in part, based on their ability to reflect the locations' population demographics. This information was collected through the pre-screener survey. In both locations, focus group participants were relatively equally divided between female and male and diverse in terms of age, with participants ranging from age 18 to 69. The groups were also fairly well educated and participants in each group had at least some college education and a few participants had a master's degree.

However, there were slight differences in the demographic makeup of each group. Less Northern California participants were married than their Southern California counterparts. The Northern California group also had less participants with at least one child. Additionally, the Northern California participants had less racial diversity with participants predominantly identifying as Asian/Pacific Islander or Caucasian. Southern California participants identified as Asian/Pacific Islander, African American, Caucasian, and Hispanic/Latin. Northern California participants tended to have higher incomes, with most participants reporting that their household income ranged from $35,000 to $199,000 annually. The Southern California group had more participants that made less than $34,999 annually but did have some participants that made $75,000 to $200,000 or more. Further information on the demographic information of each focus group can be found in Table 3.

Table 3. Focus Group Demographic Information

		Focus Group Participants			U.S. Census Bureau*	
		N. California (n=10)	**S. California** (n=9)	**Both** (N=19)	**N. California** (n=4.73 million)	**S. California** (n=13.21 million)
Gender	Female	50%	44%	47%	51%	51%
	Male	50%	56%	53%	49%	49%
	Other	0%	0%	0%	n/a	n/a
	Decline to answer	0%	0%	0%	n/a	n/a
Current Marital Status	Single	80%	44%	63%	36%	40%
	Married	10%	44%	26%	49%	45%
	Separated	0%	11%	5%	2%	2%
	Divorced	10%	0%	5%	9%	9%
	Widowed	0%	0%	0%	5%	5%
	Decline to answer	0%	0%	0%	n/a	n/a
Age	18 to 29	30%	22%	26%	15%	18%
	30 to 39	20%	11%	16%	16%	15%
	40 to 49	20%	33%	26%	14%	13%
	50 to 59	10%	22%	16%	13%	13%
	60 to 69	10%	11%	11%	11%	11%
	70 years or older	10%	0%	5%	11%	10%
	Decline to answer	0%	0%	0%	n/a	n/a
	Average age	43	42	43	n/a	n/a
Children	Have child(ren)	0%	66%	32%	27%	24%
	One child	0%	22%	11%	n/a	n/a
	Two children	0%	44%	21%	n/a	n/a
	No children	100%	22%	63%	n/a	n/a
	Prefer not to say	0%	0%	0%	n/a	n/a
Highest Level of Educational Attainment	Less than high school	0%	0%	0%	6%	11%
	Some high school	0%	0%	0%	5%	8%
	Graduated high school or equivalent (GED)	0%	0%	0%	18%	20%
	Associate degree	10%	22%	16%	7%	7%
	Some college	10%	33%	21%	18%	19%
	Bachelor's degree	50%	33%	42%	26%	23%

		Focus Group Participants			U.S. Census Bureau*	
		N. California (n=10)	S. California (n=9)	Both (N=19)	N. California (n=4.73 million)	S. California (n=13.21 million)
	Some graduate school	0%	0%	0%	n/a	n/a
	Master's degree	30%	11%	21%	13%	8%
	Ph.D. or higher	0%	0%	0%	6%	4%
	Decline to answer	0%	0%	0%	n/a	n/a
Race/Ethnicity	Asian/Pacific Islander	40%	22%	32%	28%	16%
	Black/African-American	10%	11%	11%	7%	6%
	Caucasian	40%	22%	32%	39%	29%
	Hispanic/Latin	0%	44%	21%	22%	45%
	Two or more races	10%	0%	5%	4%	3%
	Other	0%	0%	0%	0%	0%
	Decline to answer	0%	0%	0%	n/a	n/a
Household Income	Less than $15,000	10%	11%	5%	7%	9%
	$15,000 to $24,999	0%	11%	5%	5%	7%
	$25,000 to $34,999	0%	11%	5%	5%	7%
	$35,000 to $49,999	10%	0%	5%	8%	10%
	$50,000 to $74,999	10%	0%	5%	13%	16%
	$75,000 to $99,999	40%	22%	32%	11%	12%
	$100,000 to $149,999	20%	33%	26%	17%	17%
	$150,000 to $199,999	20%	0%	11%	12%	9%
	$200,000 and above	0%	11%	5%	23%	13%
	Decline to answer	0%	0%	0%	n/a	n/a

**Source: American Community Survey, 2019a; American Community Survey, 2019b*

5.2 Household Characteristics

In addition to demographic information, the pre-screener survey asked participants about household characteristics, such as vehicle and micromobility device ownership. These questions revealed relatively similar trends. Every participant household had at least one license. However, Northern California participants had less vehicles per household than their Southern California counterparts. Bicycle ownership was higher than scooter ownership across the groups. This trend was particularly true in Northern California, where over half of the participants had at least one bicycle per household, but no participants owned a scooter. The household differences between the focus groups likely contribute to their varied responses to the subject areas probed (e.g., public transit and micromobility use). Further information on the household characteristics can be found in Table 4.

Table 4. Focus Group Household Characteristics

		Number						
Characteristic	**Location**	Zero	One	Two	Three	Four	Five	Average
Licenses per Household	Northern California	0%	50%	30%	10%	0%	10%	1.4
	Southern California	0%	44%	44%	11%	0%	0%	1.7
Vehicles per Household	Northern California	30%	30%	10%	20%	10%	0%	1.2
	Southern California	0%	55%	22%	22%	0%	0%	1.3
Bicycles per Household	Northern California	30%	30%	30%	10%	0%	0%	0
	Southern California	11%	66%	0%	22%	0%	0%	0.3
Electric Scooters per Household	Northern California	100%	0%	0%	0%	0%	0%	1.5
	Southern California	77%	11%	11%	0%	0%	0%	1.7

5.3 Travel Behavior

The pre-screener survey also asked participants about their use of various active and vehicle-based transportation modes. In terms of active transportation, Northern California participants walked and used a personally owned bicycle, a personally owned scooter, bikesharing, and scooter sharing less than Southern California participants. These travel behavior differences may be attributed to differences in built environment type and service availability, which will be discussed in subsequent subsections. More detailed information on active transportation mode use can be found in Table 5.

Table 5. Active Transportation Travel Behavior Information

		Use Frequency					
Mode	**Location**	Never	Rarely	Sometimes	Regularly	Often	Daily
Walking	Northern California	10%	0%	10%	30%	20%	30%
	Southern California	0%	11%	22%	22%	0%	44%
	Average	5%	6%	16%	26%	10%	37%
Personally Owned Bicycle	Northern California	50%	30%	20%	0%	0%	0%
	Southern California	11%	11%	33%	22%	22%	0%
	Average	31%	21%	27%	11%	11%	0%
Personally Owned Scooter	Northern California	100%	0%	0%	0%	0%	0%
	Southern California	77%	0%	11%	11%	0%	0%
	Average	89%	0%	6%	6%	0%	0%
Bikesharing	Northern California	70%	30%	0%	0%	0%	0%
	Southern California	22%	11%	44%	11%	0%	0%
	Average	46%	21%	22%	6%	0%	0%
Scooter Sharing	Northern California	80%	20%	0%	0%	0%	0%
	Southern California	44%	0%	33%	22%	0%	0%
	Average	62%	10%	17%	11%	0%	0%

Northern California participants were more frequent public transit users whereas Southern California participants tended to use personal vehicles and TNCs more frequently. Neither focus group had high rates of carsharing, microtransit, or ridesharing use. More detailed travel behavior information for vehicle-based transportation modes can be found in Table 6.

Table 6. Vehicle-Based Travel Behavior Information

		Use Frequency					
		Never	Rarely	Sometimes	Regularly	Often	Daily
Personal Vehicle Use	Northern California	40%	10%	0%	20%	10%	20%
	Southern California	11%	0%	0%	11%	33%	33%
	Average	26%	5%	0%	16%	22%	27%
Carsharing Use	Northern California	60%	10%	10%	10%	10%	0%
	Southern California	66%	0%	11%	11%	0%	0%
	Average	63%	5%	11%	11%	5%	0%
Microtransit	Northern California	80%	10%	10%	0%	0%	0%
	Southern California	66%	11%	11%	0%	0%	0%
	Average	73%	11%	11%	0%	0%	0%
Public Transit	Northern California	0%	0%	20%	20%	30%	30%
	Southern California	0%	11%	44%	11%	0%	33%
	Average	0%	6%	32%	16%	15%	32%
Ridesharing	Northern California	60%	30%	0%	0%	10%	0%
	Southern California	77%	11%	0%	11%	0%	0%
	Average	69%	21%	0%	6%	5%	0%
TNC	Northern California	30%	10%	40%	0%	10%	10%
	Southern California	11%	0%	77%	11%	0%	0%
	Average	21%	5%	29%	6%	5%	5%

5.4 COVID-19 Impacts

The onset of the COVID-19 pandemic in March 2020 is greatly impacting various aspects of society. To try and capture some of these changes, the pre-screener survey also asked participants about their employment pre- and post-COVID-19. Employment remained about the same for Northern California participants, while Southern California participants faced employment reductions and job losses. Employment information is summarized in Table 7.

Table 7. Focus Group Employment Information

	Northern California		Southern California	
	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID
Single job, fully employed	40%	40%	77%	22%
Single job, partially employed	10%	20%	11%	33%
Multiple jobs, fully employed	20%	10%	11%	0%
Multiple jobs, partially employed	10%	0%	0%	0%
Unemployed, searching	10%	20%	0%	22%
Unemployed, not searching	10%	20%	0%	0%

5.5 Land Use, Housing, Telework, and COVID-19

Similar to the pre-screener survey, during the focus group participants were asked questions about the impact of COVID-19 regarding transportation choices, housing decisions, and telework options. Both focus groups stated that COVID-19 has caused them to replace their use of public transit and TNCs with an increased use of personal vehicles and active transportation modes (e.g., walking, shared micromobility). COVID-19 also caused participants to consider moving their residential locations. Moving was predominantly motivated by amenity availability (e.g., having a backyard, proximity to a beach) and housing affordability.

At the time of the focus groups, two of the Northern California participants had moved and three were considering moving. These decisions were based on COVID-19 related changes (e.g., shift to teleworking). Eight of the 10 participants were teleworking and would like to continue even after the containment of COVID-19. After one participant moved from the Bay Area to the less dense town of Madera, they purchased a vehicle. Other Northern California participants changed their travel patterns by overall traveling less, in part due to shelter-in-place orders, and trip chaining errands to limit potential COVID-19 exposure.

Unlike the Northern California group, the Southern California focus group participants were generally satisfied with their housing location and its proximity to amenities (e.g., public transit stops, retail opportunities, grocery stores). Also inverse to the Northern California participants, only two of the nine Southern California participants were teleworking, and they wanted to return to work in person in some capacity (e.g., at a satellite office) after the containment of COVID-19. The low number of participants teleworking was partially due to the fact that two participants could not work remotely due to their professions (e.g., barber). Similar to Northern California participants, Southern California participants stated COVID-19 altered their travel behavior, but their change was reflected in travel decreases and goods delivery increases.

5.6 Public Transit

In addition to COVID-19 related changes, focus group participants were also asked about public transit access, parking, and improvements. Participants in both focus groups accessed public transit by: driving and parking personal vehicles, getting dropped off, public transit connections (e.g., bus to rail), shared micromobility, and walking. Driving to and parking at public transit stations was a viable option for most participants as they viewed the parking fees (about $3 to $12 per hour) reasonable, especially when compared to the cost of parking garages in denser downtown areas. However, participants did mention that parking at public transit stations used to be free and they preferred that price point. Despite the relative appeal of parking at public transit stations, no one from either focus group was waitlisted for a public transit parking permit.

The willingness to pay for parking differed between the two groups. Northern California participants were willing to pay for parking at public transit if a space was guaranteed. Participants classified the stress and time consumption of searching for a parking spot at public transit stations as a disincentive for parking there. Due to these difficulties, many Northern California focus group participants have typically chosen to forgo searching for parking at public transit stations and instead park on nearby streets. Participants who required an accessible parking spot had an especially difficult time finding available parking spaces. Unlike their Northern California counterparts, participants in the Southern California focus groups preferred to park at public transit stations due to concerns of tickets, vandalism, and theft if they parked elsewhere.

Participants from both focus groups offered recommendations to improve public transit services including increased cleanliness, maintenance, and service levels (e.g., frequency, reduced travel and wait times, fewer connections). Public transit was appealing to Northern California participants due to its relatively low environmental impacts. However, the risk of contracting COVID-19 decreased their willingness to take public transit. Southern California cited similar concerns regarding COVID-19 exposure on public transit in addition to other considerations, such as inconvenience (e.g., limited bus routes drastically increasing travel times), safety (e.g., assault on public transit vehicles), and comfort (e.g., lack of air conditioning during the summer months).

5.7 Micromobility

Focus group participants were asked about other transportation modes including micromobility. Focus group participants from both locations stated that they used micromobility for shorter trips (e.g., recreational trips, to nearby grocery stores). However, the presence of hills and inconvenient weather conditions (e.g., rain, heat) impacted their willingness to use shared micromobility. Additionally, participants had concerns regarding public health (e.g., contracting COVID-19), safety (e.g., collisions with vehicles), reliability (e.g., locating a device when needed), and affordability/price variability (e.g., different pricing schemes from each operator).

Overall, Northern California focus group participants had very limited experience with micromobility. For example, only two households owned bicycles. Participants who did have shared micromobility experience typically used bikesharing for shorter trips (e.g., connect to public transit, explore a new place). One commonly mentioned barrier to use was the ease of using the devices (e.g., understanding how to start, ride, and pay for them). However, participants were interested in trying shared bicycles with an electric assist. One participant stated that they would use shared micromobility to try devices before purchasing one for themselves.

Unlike the Northern California participants, multiple Southern California participants owned micromobility devices, both bicycles and scooters. For shared micromobility users, scooter sharing was more popular than bikesharing, and typically used for recreational trips and to avoid paying for parking (e.g., parking further away from the final destination and scootering the last-mile). Southern California participants stated that micromobility use could be encouraged through infrastructure improvements (e.g., protected bike lanes). Despite the interest in shared micromobility, some participants stated that they would prefer to walk the distances that they would typically use micromobility (e.g., one to two miles).

5.8 Pooling and Park-and-Ride

Participants were generally familiar with the concept of park-and-ride facilities. Despite conceptual understanding, participants had limited to no experience with park-and-ride facilities and many did not know how to use them. Common points of confusion included where these facilities were located and how to identify where drivers were headed. Prior to the pandemic participants were hesitant to ride with strangers from park-and-ride locations, and these concerns were exacerbated with worries regarding COVID-19. However, participants stated that they would be more willing to use park-and-ride facilities if they had the option to ride with someone they knew, riders and drivers were vetted through a screening system, and cleaning measures with proof of completion were implemented.

Northern California participants had heard more anecdotes of negative experiences with ridesharing than positive experiences (e.g., riders not paying their share of the ride). Participants from this group preferred pooling and park-and-ride for commuting to work over other modes, such as public transit. One participant had experience with Scoop, a digital ridematching platform, and felt more comfortable ridesharing through that app since the profiles provided user information.

Southern California participants had experience using park-and-ride and pooling when they were facilitated by community organizations (e.g., churches, universities). Participants preferred to use park-and-ride and pooling as a means to connect to public transit. However, one participant stated that they would rather stay and have their needs met otherwise (e.g., goods delivery) than travel in a shared ride. To increase knowledge of park-and-ride and pooling, focus group participants recommended placing advertisements on billboards and public transit apps and websites.

5.9 Pricing

Conversations about pricing mechanisms brought up equity concerns in both focus groups. Participants were concerned about the idea of “double taxation” (e.g., travelers paying both a congestion fee and a toll) and affordability, especially for disadvantaged communities. Cordon pricing was particularly poorly received, especially if travelers were still required to pay for parking within cordon areas. In addition to these concerns, participants emphasized the importance of transparency with potential pricing mechanisms (e.g., clarity with how the money was spent).

The Northern California group felt that existing bridge tolls were effectively the same as a cordon fee. Since bridge tolls already vary based on the time of the day, participants were somewhat open to congestion pricing. The participants were willing to change their travel times in response to congestion pricing but were concerned about their ability to change plans (e.g., attending an appointment that could not be moved).

In Southern California, the participants had used express lanes before, predominantly because of the appeal of convenience and travel time reductions. Participants stated that the cost of the lane was worth the reduced time in traffic. However, one participant expressed concerns regarding the safety of express lanes (e.g., vehicles quickly merging into the lane). Regarding cordon fees, participants preferred to live and work outside of the cordoned area to avoid paying the fee. In terms of congestion pricing, participants stated that they had less flexibility with changing their travel and work schedules, which would make it difficult to avoid congestion fees. Due to the volume of congestion in the Los Angeles area, participants believed that congestion pricing would be an ineffective policy.

5.10 Focus Group Key Takeaways

- **Demographics:** Both focus groups were relatively diverse in terms of gender, age, income, education, and race. However, the Southern California focus group was more diverse in terms of family structure (e.g., marital status, children).
- **COVID-19 Related Changes:** Participants in both groups changed travel patterns due to COVID-19 to decrease travel overall and increase personal vehicle use and/or walking.
    - *Telework:* More participants in the Northern California focus group were teleworking than in Southern California. Additionally, more participants in the Northern California group were interested in continuing to telework, at least in a hybrid model.
    - *Household Changes:* More participants from the Northern California group had or were considering moving due to COVID-19. Individuals who had moved or were considering

moving were looking for amenities, such as increased affordability and/or access to green space.

- **Parking:** Participants in Northern California were more concerned with competition for finding a parking spot at public transit stations, while Southern California participants were predominantly concerned with vehicle risks (e.g., tickets, vandalism, etc.), if they did not park at transit stations.
- **Public Transit:** Public transit was not perceived well due to public health, safety, convenience, and comfort concerns.
- **Micromobility:** More participants in the Southern California group owned devices or had experience using micromobility.
    - *Micromobility Concerns:* Common concerns regarding micromobility devices included affordability, public health, operational understanding, and safety. However, improvements, such as electric assist on bicycles and protected lanes, would encourage micromobility use.
- **Pooling and Park-and-Ride:** Southern California participants had more experience with pooling services and park-and-ride facilities.
    - *Pooling and Park-and-Ride Concerns:* Most concerns with pooling were associated with public health/safety (i.e., COVID) and riding with strangers (particularly without any screening or connection to other riders (e.g., a common employer).
- **Pricing:** Northern California participants were more familiar with and open to congestion pricing. Southern California participants did not believe in the feasibility of congestion pricing for the area and were concerned about the removal of an existing highway lane for repurposing as a congestion priced lane.
    - *Pricing Concerns:* Pricing strategies were typically accompanied by social equity concerns.

6 Activity Analysis

This section presents the results of activity data analysis that evaluates barriers to the access and use of micromobility. The analysis evaluates a unique set of micromobility trip activity data to explore how the spatial distribution of the vehicles relates to the demographic distribution of residents in the region. One of the research questions relates to evaluating barriers of access to micromobility. Namely, are there systematic spatial inequities to the distribution of micromobility systems that disfavor low income and vulnerable populations? The research develops and evaluates several measures to explore this question. In the sections below, the data and methodology describe the data applied and the metrics calculated to evaluate spatial inequities. This is followed by the results section presenting the metrics and their interpretation in the context of the key research question noted above.

6.1 Data and Methodology

This study incorporates two data sources to evaluate the degree to which shared micromobility is physically accessible (i.e., individuals can physically access the shared bikes/scooters with ease). One is the shared micromobility activity data, and the other is the demographic information within the geographic areas of interest.

The General Bikeshare Feed Specification (GBFS) is an open data standard that shared micromobility operators can use to display system information in an organized way (North American Bikeshare & Scootershare Association [NABSA], 2020). Shared micromobility systems may publish activity attributes that describe the state of the system both in real-time and historically using data fields and formats derived from the GBFS structure. The format of GBFS has undergone several revisions. The version applied with this data (Version 1) organized real-time shared micromobility trip information in the form of trip start and end times, trip start and end locations, as well as IDs of bikes or scooters as unique identifiers. The GBFS reports activity through both docked and dockless systems. In the meantime, trip data of some docked systems are also readily available directly from the operators. To reach a better accuracy, we use GBFS only when operator-provided data are not available. For the purpose of this study, we evaluate trips that both start and terminate within the metropolitan regions of San Francisco (N=734,124), Sacramento (N=192,949), Los Angeles (N=234,918), and San Jose (N=42,011). The timeframe of the trips span January 6th, 2020 to February 28th, 2020. These trips included all trips observed to occur across operators that reported GBFS feeds within the regions evaluated. This would be any activity that of the systems within the region since the feeds report on the entire system status continuously. Table *8* presents a series of summary statistics of the data analyzed in this section.

Table 8. Summary Statistics of GBFS Information

City		San Francisco		Sacramento	Los Angeles		San Jose
System Type		Docked	Dockless	Dockless	Docked	Dockless	Docked
Total Trips		555420	178704	192949	42613	192305	42011
% Times being Moved		9.46%	13.21%	9.68%	9.39%	16.35%	6.67%
Trips/person vs Dwell/person		0.93	0.91	0.87	0.87	0.95	0.95
# Tracts	Low-Income Tracts	7		24	146		0
	Middle-Income Tracts	137		116	964		180
	High-Income Tract	51		0	54		60
	Total Tracts	195		140	1164		240

In addition, the demographic information of those regions in combination with the trip data can help identify the accessibility barriers experienced by certain groups of population in terms of the use of shared micromobility services. The American Community Survey (ACS) is a sample-based survey conducted on a yearly basis on the demographic and living status of individuals and households in the U.S., enabling the analysis of demographic distributions under different levels of resolution such as by census blocks or tracts (US Census Bureau, n.d.). In this exercise, we incorporate the 2019 ACS data release regarding age, gender, income, race and ethnicity, and education, by census tract within each of the four regions of California.

6.1.1 Description of the Methodology

The methodology evaluates the usage pattern and accessibility of shared micromobility services across various areas within the cities. The goal is to develop and evaluate the spatial distributions of metrics describing trip activity and vehicle accessibility. This process entails the analysis of three main components: demographics, trip activity, and the accessibility of shared micromobility devices/vehicles (bikes or scooters). The latter two components are dynamic features. These components are further embodied in a set of quantitative measurements and metrics.

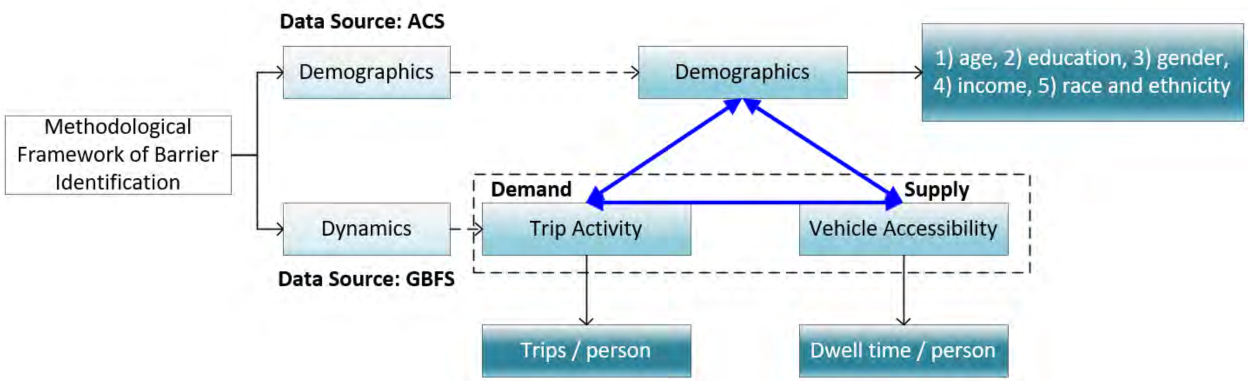
For demographics, we incorporate the census tract-based ACS data that include the percentage of population within 42 demographic groups (eighteen groups of age, four groups of education, two groups of gender, ten groups of income, and eight groups of race and ethnicity).

Collectively, this information is used to compute and analyze three metrics. These metrics include 1) “trips per person”, 2) “vehicle dwell time per person”, and 3) “households per vehicle”. Each of these metrics is computed within each census tract. The behavior of these metrics within each census tract, as classified by certain population attributes (e.g., income) allows us to evaluate differences in accessibility for different types of populations.

The first metric is one of demand, a larger number of trips per person indicates a larger number of activities, which also translates to a greater demand for shared micromobility services. The accessibility of shared micromobility devices is assessed by two other metrics. The first metric computes the total dwell time of bikes and scooters on a per-person basis. This metric indicates for how long the bikes and scooters are available to an individual in the census tract. This measurement of time available is a measurement of supply per person. Another metric, the number of households per vehicle, is also used to measure accessibility. This metric is informative when assessed across a dynamic set of thresholds and will be discussed in greater detail in the results section.

These three metrics are by themselves informative, but their relationship with the surrounding environment is also very insightful. For example, the correlation between trip activity and the percentage of population within each demographic category shows how shared micromobility is utilized among people of different backgrounds. Likewise, the correlation between vehicle accessibility and the demographics tells how well the population is served by shared micromobility. Finally, the correlation between trip activity and vehicle accessibility indicates the degree to which the demand for shared micromobility services is met by its actual supply. Figure 1 presents a framework that summarizes the methodological approach. We carefully follow the steps below to compute the pertinent metrics in Figure 1.

Figure 1. Methodological Framework of Barrier Identification



6.1.2 Identification of System Movements

System movements, or rebalancing trips, are often performed with rebalancing trucks owned by operators. These rebalancing activities can help maintain the number of bikes and scooters at a healthy level, in case that the natural trips completed by customers may lead to an oversupply at one place and an undersupply at another. These movements are not recorded in the dataset, but it is necessary to identify them for the purpose of computing the vehicle dwell time as well as the spatial distribution of bikes and scooters. After sorting the trips by bike IDs and trip start times, we flag a movement if the destination tract of one trip is different from the origin tract of the next trip completed with the same bike or scooter. These movements are then reconstructed into the same structure as the trip data (which include device IDs, start and end times, and locations), where the start location corresponds to the destination of the former trip, and the end location corresponds to the origin of the latter trip.

6.1.3 Calculation of Dwell Time

Dwell time is defined as the duration during which bikes and scooters stay in a census tract. It is calculated as the difference between the departure time of the latter trip and the arrival time of the former trip completed with the same vehicle, summed across all bikes and scooters that once visited that census tract. This is again done by sorting the trips, first by vehicle IDs and then by trip start times. For each census tract, we compute the total dwell time by adding up those time differences only if the destination of the former trip and the origin of the latter trip by the same vehicle fall into that tract. The metric is a useful alternative measure for bike availability relative to trip activity. The reason dwell time is useful is because it quantifies the *time* that vehicles are available. For example, if trip activity results in high vehicle turnover, where vehicles are constantly being used for trips, then the high trip activity with low dwell times could signal an underserved demand for micromobility vehicles. The evaluation of the time that a vehicle is within a given area serves as an additional metric to determine if there are relative differences in dwell time that are correlated with census tracts that exhibit demographic associations that are different from those of trip activity.

6.1.4 Calculation of the Count of Bikes and Scooters by Census Tract

We follow a two-step procedure to estimate the initial spatial distribution of bikes and scooters as of the start of the data collection period (January 6th, 2020):

1. For each bike or scooter, identify the census tract from which it was first ridden;
2. For each tract, we add up the number of vehicle IDs that appear within the census tract, which in turn is the initial count of devices in that census tract.

This methodology assumes all shared bikes and scooters that were physically present in the census tract were ridden at least once. This estimate of the initial spatial distribution can serve as the base case, from which the count of bikes and scooters can change at any time when there is either a customer trip or a system movement. That is, the count in a census tract increases by one if a trip terminates in this tract, or if a bike or scooter is relocated to this tract due to a system movement. Correspondingly, the count decreases under the opposite circumstance (i.e., when a trip is started in this census tract). We monitor the changes over time by rearranging the trips and system movements in chronological order.

6.1.5 Thresholds Imposed on Households per Bike or Scooter

The counts derived in the previous step can be used to compute the number of households per bike or scooter. Intuitively, the greater the number of households per vehicle, the harder it becomes for a single household to access a bike or scooter, and thus the worse the accessibility of shared micromobility services.

Since the number of households per vehicle is a dynamic metric that fluctuates over time, and that the metric is sensitive to varying fleet sizes across different geographic contexts, it might not be practical to apply a fixed universal standard that simply judges the accessibility of shared micromobility systems as good or bad. One strategy we implemented was to apply a flexible threshold that ranges from the lowest to the highest number of households per bike or scooter over time, at an increment of one household per vehicle, and compute the percentage of time when the metric (number of households per bike/scooter) is under each threshold. If the metric of households per vehicle is under a given threshold for a greater proportion of time, that implies that the households or individuals in that census tract are more likely to have a chance to access those vehicles. The function is monotonically increasing in a sense that this percentage of time can only go up with the increase of thresholds. The analysis of these three metrics (“trips per person”, “vehicle dwell time per person”, and “households per vehicle”) are presented in the section that follows.

6.2 Demographic and Modal Impacts

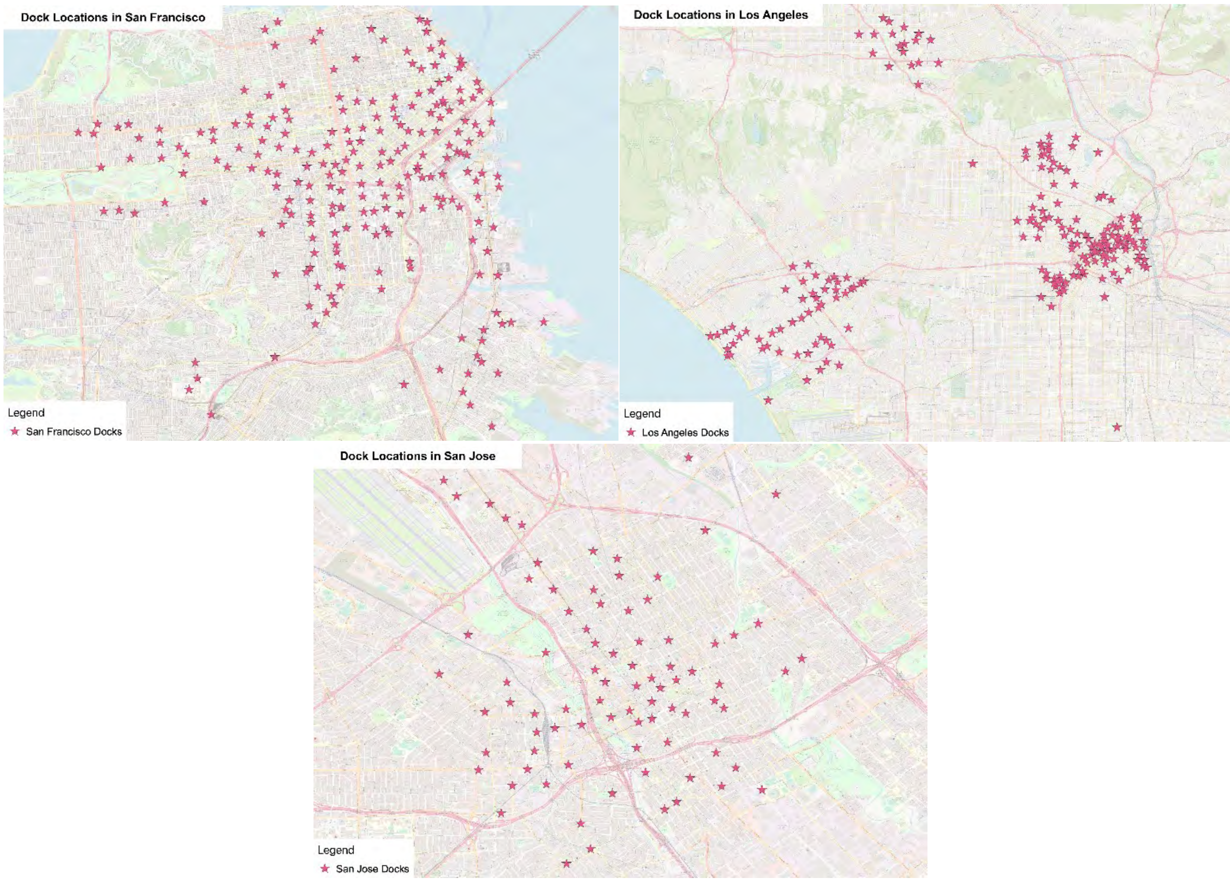
This section first introduces several high-level results to set the stage and will then dive into the metric computation and analyses. These results will help us understand there are accessibility barriers of shared micromobility on different groups of population, as well as the level of severity of these barriers.

Across the four regions of California, we present the fleet size and the total system movements as noted in the methodology (Table 9). The dockless bikes and scooters in Los Angeles and the docked bikes in San Francisco are among the systems with the greatest fleet sizes (9,601 and 5,683 respectively). Other systems have only one to two thousand vehicles that are actively in use. Meanwhile, the shared micromobility vehicles in San Francisco and Sacramento are most efficiently used (about 80 trips per vehicle over two months). In Los Angeles and San Jose, however, the bikes and scooters completed about 20 trips per vehicle. Figure 2 shows a map of the docked bikesharing stations during the period of the dataset within the cities that had docked bikesharing.

Table 9. Basic Information of the Shared Micromobility Activity Data

	Dockless Systems (Bikes and Scooters)		**Docked Systems** (Bikes)	
	Number of Bikes or Scooters	Number of Trips per Vehicle	Number of Bikes or Scooters	Number of Trips per Vehicle
San Francisco	2,211	81	5,683	98
Sacramento	2,621	74	--	--
Los Angeles	9,601	20	1,820	23
San Jose	--	--	1,637	26

Figure 2. Map of Bikesharing Docks During the Period of the Dataset within San Francisco, Los Angeles, and San Jose



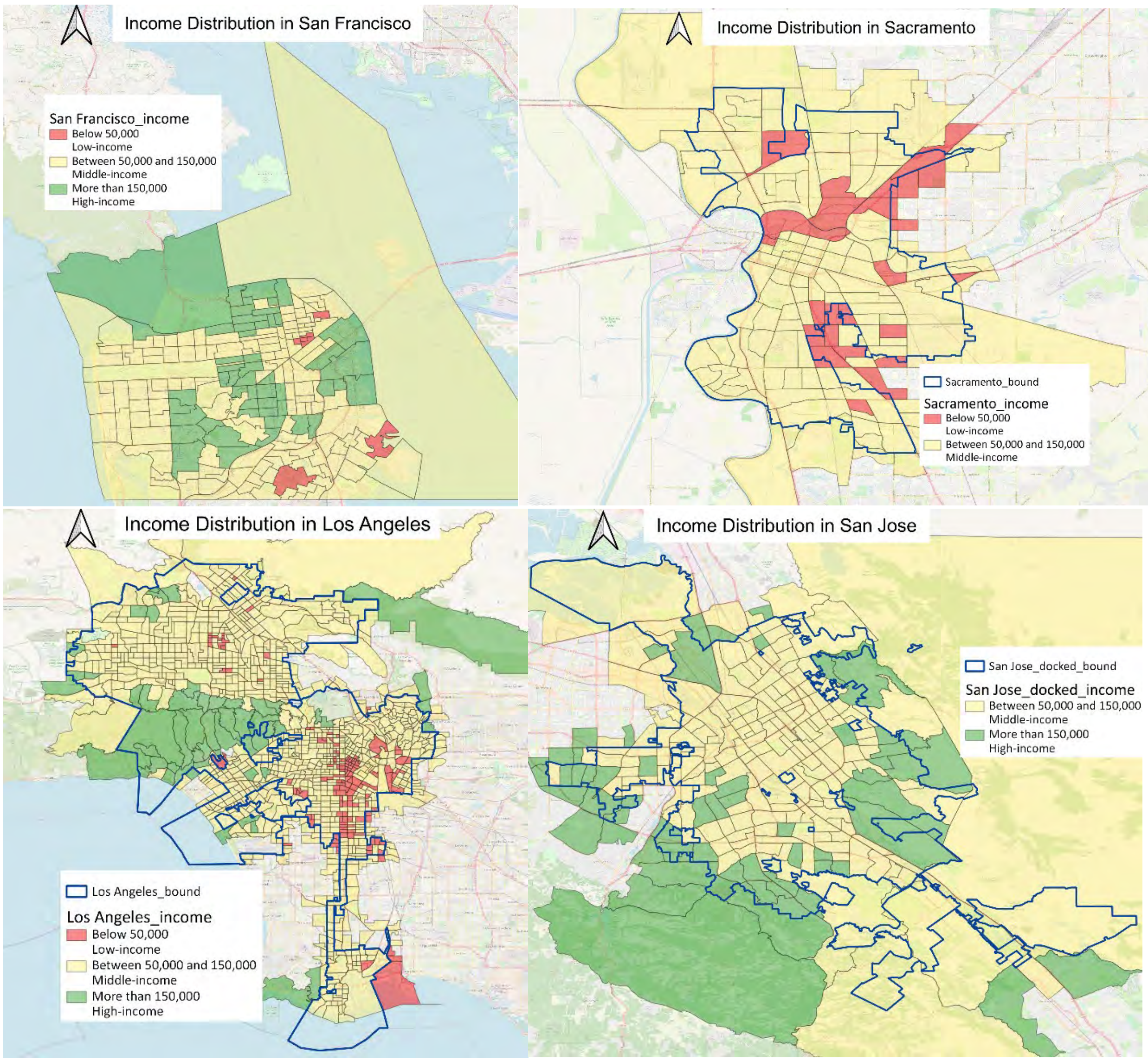
6.2.1 Demographics

The distribution of demographic groups is measured by within-region percentages. This distribution varies across the four cities. San Francisco has the greatest percentage of population between ages of 25 and 35 (about 24%). It is also one of the most educated cities with almost half of the population (49%) holding a bachelor's degree, followed by San Jose (34%) (US Census, 2020). More than a quarter of the households in San Francisco and San Jose typically earn more than $200K per year, while in Sacramento and Los Angeles, the annual income of most households is between $35K and $150K. In terms of race and ethnicity, White and Asian population take up the majority in San Francisco and San Jose (above 60%). In Los Angeles, individuals identified as Hispanic or Latino account for the largest proportion (47%) of the city's population. In each region, the gender groups appear to be almost evenly distributed.

Three income classes are defined to categorize the census tracts based on their levels of wealth. According to Pew Research Center, families that are in the middle-income tier have annual incomes between two-thirds to double the national median (Horowitz et al., 2020). That translates to $50,697-$152,092 for a family of three (DePietro, 2021). Similarly, this study divides the census tracts into low-, middle-, and high-income with boundaries of $50K and $150K.

Figure 3 exhibits the income distribution derived with this rule. By this definition, there were no high-income tracts in Sacramento, and no low-income tracts in San Jose. In all four cities, the middle-income tracts seem to be the most ubiquitous and higher-income tracts are mostly located in the outer periphery, which is particularly the case in Los Angeles and San Jose.

Figure 3. Income Distribution in the Four Cities



6.2.2 Count of Bikes and Scooters

Following the methodology, the total number of bikes and scooters is computed by counting the vehicles by census tract of their first appearance, updated along with trip and system movements. The average bike/scooter count per low-, middle-, and high-income census tract is presented in Table 10. Due to the diverse scales of shared micromobility systems in different cities, it is more reasonable to perform a within-system (i.e., the same bikesharing or a scooter sharing operator), versus inter-system, comparison on these counts. In shared micromobility systems in San Francisco, the total number of bikes/scooters increases with the average income, and there are always more bikes and scooters in high-income tracts relative to low-income tracts over time. In contrast, in Los Angeles and San Jose, high-income tracts have the smallest number of vehicles distributed. In Sacramento, however, there is almost no distinction in the counts among census tracts of different income levels. These counts are not calibrated with demographic information such as the size of population, and thus cannot serve as standalone arguments regarding barriers to accessing shared micromobility.

Table 10. Average Count of Bikes and Scooters

Average Vehicle Count per Census Tract		Low-Income Tracts	Middle-Income Tracts	High-Income Tracts
San Francisco	Dockless	3.15	6.86	11.27
	Docked	15.49	17.64	34.02
Sacramento	Dockless	12.09	10.54	--
Los Angeles	Dockless	5.72	6.78	3.45
	Docked	1.79	1.19	0.42
San Jose	Docked	--	7.61	0.48

6.2.3 Correlations of Demographics and Trip Activity

For all systems included in this analysis, correlation coefficients are computed between the percentage of population in a certain demographic group and the total number of trips per person conducted within an individual in a census tract. The formula describing the correlation coefficient calculation r is shown below:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where,

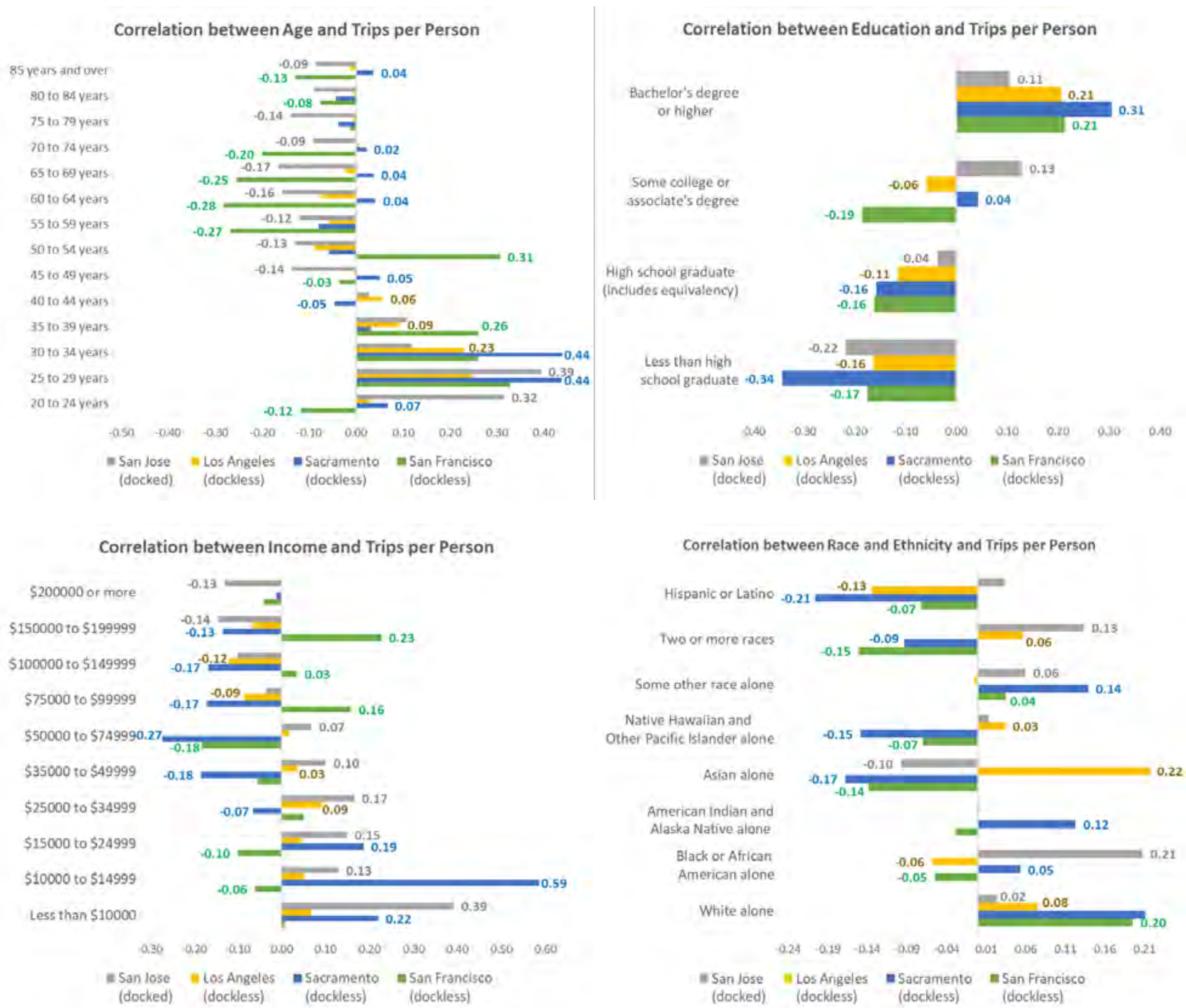
x_i = The percentage of population within a given demographic group in census tract i (e.g., x_i = 10%, if 10% of the population are in this group)

y_i = The number of trips per person in census tract i

n = The total number of census tracts within a given city

The correlation coefficient is a unitless measurement of association that is restricted to values that are between -1 and 1. It describes the degree to which the movement of two variables move together linearly. A positive correlation means that two variables move in the same direction, while a negative correlation means that they move in opposite directions. A correlation measure of 1, means that two series move together in a manner that is perfectly linear, while a measure of -1 implies that two series move in opposite directions in a manner that is perfectly linear. Correlation coefficients do not imply causality, but are a measurement of association and nearness to a perfectly linear relationship. The closer the correlation coefficient is to 1 or -1, the closer is the association of two variables to positive or inverse linear relationship. The correlation coefficient can be interpreted as a measure of relative association a given demographic attribute and the level of activity within census tracts. Due to some similar patterns observed between docked and dockless systems, results of no more than one system per city are presented in Figure 4.

Figure 4. Correlations of Demographics with Trips per Person



In most cities, the trip activity is positively correlated with the percentage of population between ages of 20 and 39, and negatively correlated with older and younger age groups. To verify this conclusion, we tested the degree to which these correlation coefficients are different from each other. This was performed via a z-test (i.e., a statistical test that determines whether two parameters are significantly different from each other) using the Fisher transformation, which is a commonly used method to transform Pearson correlation coefficients into z-scores (Fisher, 1915). We tested the pairwise differences of the coefficients across all age groups and obtained results as displayed in Figure 5. It is observed that for the dockless trips in San Francisco, the coefficients of age groups between 25 and 39 are all significantly different from all older ages (i.e., 40 to 49, and above 55 years) at the 0.01 level at least. This finding is simultaneously supported by Figure 4, where those aged between 25 and 39 are found more likely to use shared micromobility services while others are not as likely to.

Sacramento exhibits a slightly different pattern, where the correlation with older population is not clearly positive nor negative. We conducted a similar test on this statement (Figure 6). The results indicate that the correlations are generally not significantly different from each other among older population (i.e., above 35) groups. Note that the results below correct for multiple hypothesis testing of 91 hypotheses in each region using the Bengamini-Hochberg method. This correction approach sorts the p-values and lowers the alpha values to linearly rise to the 5% level among the tests. The correction slightly adjusts the relative levels of statistical significance for some comparisons relative to tests as evaluated without the correction, but does not change the broader findings.

Figure 5. Significance Levels of Differences between Correlation Coefficients of Age (San Francisco, Dockless System)

Significance Levels of Differences between Correlation Coefficients of Age (San Francisco, Dockless)

(Multiple Hypotheses Controlled)

	20 to 24 years	25 to 29 years	30 to 34 years	35 to 39 years	40 to 44 years	45 to 49 years	50 to 54 years	55 to 59 years	60 to 64 years	65 to 69 years	70 to 74 years	75 to 79 years	80 to 84 years	85 years and over
20 to 24 years		***	***	***			***							
25 to 29 years					**	***		***	***	***	***	**	***	***
30 to 34 years					*	**		***	***	***	***	*	**	***
35 to 39 years					*	**		***	***	***	***	*	**	***
40 to 44 years							**	*	*	*				
45 to 49 years							**	*	*					
50 to 54 years								***	***	***	***	**	***	***
55 to 59 years												*		
60 to 64 years												*		
65 to 69 years												*		
70 to 74 years														
75 to 79 years														
80 to 84 years														
85 years and over														

* p ≤0.05, ** p ≤0.01, *** p ≤0.001

Figure 6. Significance Levels of Differences between Correlation Coefficients of Age (Sacramento, Dockless System)

Significance Levels of Differences between Correlation Coefficients of Age (Sacramento, Dockless)

(Multiple Hypotheses Controlled)

	20 to 24 years	25 to 29 years	30 to 34 years	35 to 39 years	40 to 44 years	45 to 49 years	50 to 54 years	55 to 59 years	60 to 64 years	65 to 69 years	70 to 74 years	75 to 79 years	80 to 84 years	85 years and over
20 to 24 years		**	**											
25 to 29 years				**	***	**	***	***	**	**	**	***	***	**
30 to 34 years				**	***	**	***	***	**	**	**	***	***	**
35 to 39 years														
40 to 44 years														
45 to 49 years														
50 to 54 years														
55 to 59 years														
60 to 64 years														
65 to 69 years														
70 to 74 years														
75 to 79 years														
80 to 84 years														
85 years and over														

* p ≤0.05, ** p ≤0.01, *** p ≤0.001

Shared micromobility activity is generally positively correlated with areas that have higher education levels. As for income, there is a common pattern in Sacramento, Los Angeles, and San Jose, that the trip activity is positively correlated with lower-, and negatively correlated with higher-income groups. The critical income at which the correlation shifts from negative to positive is different across cities. In Sacramento, only the population with annual incomes below $25K are more likely to use shared micromobility, whereas in Los Angeles and San Jose, this shift does not happen until their incomes reach $75K. Notably, the correlations of docked trips in Los Angeles (not shown in Figure 4) are weak (i.e., most absolute correlation coefficients are below 0.1). This suggests that the distribution of trip activity is relatively uncorrelated with the income of the residents within the service region. In San Francisco, the story is almost completely the opposite, where positive correlations largely exist in census tracts with annual household incomes between $75K and $200K, which might indicate that people beginning trips in higher-, rather than lower-, income census tracts are more likely to use shared micromobility in that city.

Results on race and ethnicity do not look alike across systems (i.e., shared micromobility systems by operator, region, and vehicle type) either, except for the fact that the percentage of White population is always positively correlated with trip activity. This pattern appears to be most apparent in San Francisco and Sacramento (0.20). In San Francisco, almost all race and ethnicity groups encounter negative correlations except the White population. In contrast, the strongest positive correlation in Los Angeles is observed among the Asian population, whereas this group is found to be less likely to be riding a shared bike or scooter in other cities. In addition, Hispanic or Latino populations are found to be the least likely to use shared micromobility. Lastly, it is worth mentioning that in San Jose, trip activity is positively correlated with most population groups, especially with the Black and African American population (0.21).

Finally, the correlation of trips per person with gender groups (not presented in Figure 4) exhibits a common pattern across cities and systems (i.e., docked or dockless). That is, the intensity of shared micromobility trip activity is positively correlated with the percentage of males, which indicates that males are more likely to use these services. This correlation is the strongest in Sacramento where the correlation coefficient is the greatest (0.35).

6.2.4 Correlations of Demographics and Vehicle Accessibility

Another correlation analysis is conducted between the demographics and the accessibility of shared micromobility devices/vehicles, where the accessibility is quantified as the total dwell time of bikes and scooters per person. This correlation indicates the extent to which the vehicles are accessible to an individual in each population group.

Our results suggest this set of correlations ends up being very similar to that of the trip activity, and these correlations are thus not included in this report. That is, if the percentage of a population is positively correlated with the total dwell time per person, it is very likely to be positively correlated with the total trips per person as well. Therefore, the conclusions drawn from the previous section can potentially be applicable to both trip activity and vehicle accessibility. In San Francisco, for example, shared micromobility services are both more frequently used among, and more accessible to, the population of White males between 20 to 55 years old, with a bachelor’s degree, and having annual incomes above $75K. These extended conclusions, however, rely on the hypothesis that trip activity and vehicle accessibility are highly correlated.

6.3 Demographic and Modal Discussion

This analysis presents a collection of methods and metrics for the purpose of evaluating barriers to shared micromobility access employing trip activity and sociodemographic data across a variety of land-use contexts within California.

The main goal of barrier identification was to understand the relationship of three major components: demographics, trip activity, and vehicle accessibility. To be specific, trip activity is associated with the number of trips per person. On the other hand, vehicle accessibility is evaluated through the total vehicle dwell time per person. With these metrics, the accessibility barriers of shared micromobility services are identified via pairwise comparisons (i.e., comparisons between different categories within demographic attributes) and correlations among the define metrics.

There are several limitations and caveats in this study. First, the definition of the demand for shared micromobility services may require further refinement. Trip activity can serve as a rough indicator, but it can underestimate the demand when demand is saturated and limited by supply (when vehicles are not available). Therefore, the high correlation between trip activity and vehicle accessibility may not indicate that there is a demand-supply equilibrium, rather it indicates that activity and vehicle dwell time are not spatially mismatched.

The derivation of the bike and scooter count can also be biased because this estimation assumes that every bike/scooter was ridden at least once. This may be an underestimate since the untouched vehicles remain unseen in the dataset, but this bias may be subtle since a two-month period is long enough for most vehicles to become active in the system.

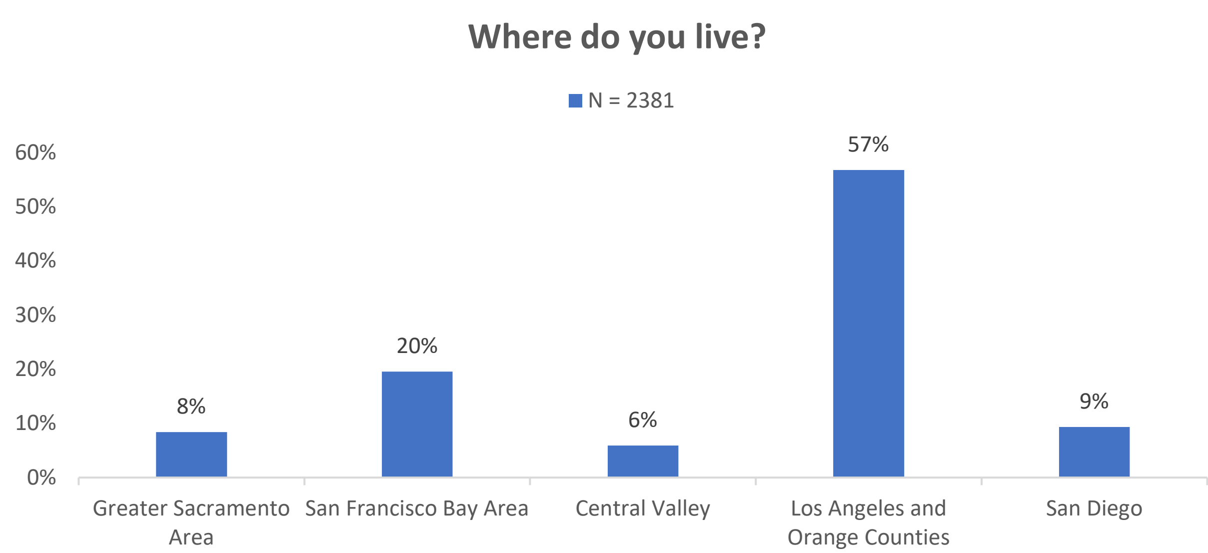
In addition, it is arguable that defining low-, middle-, and high-income census tracts with fixed bounds may not be applicable to all cities. This classification also leads to the fact that some cities do not have low- or high-income tracts available for evaluation. However, it is likely that a more rigorous income categorization that is tailored for each city will suggest similar findings. Moreover, flexible bounds will add more complexity to inter-city comparisons. Another possible improvement is to increase the number of income categories given that the middle-income range is relatively wide. This can add more resolution to the existing findings.

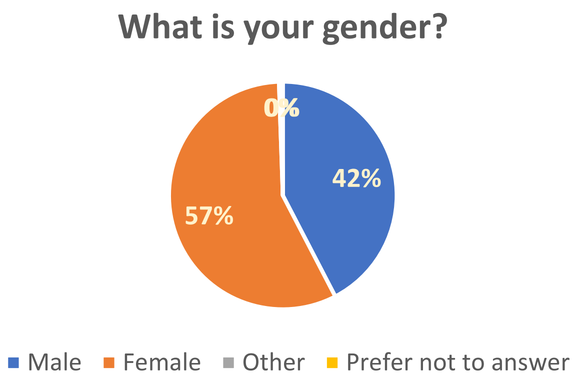
In conclusion, this analysis evaluates the accessibility of shared micromobility services among various groups of population across California. It illustrates several methods for shared micromobility equity analysis and introduces and explores several metrics that convert activity data into measurements of access. The analysis presented explores barriers to micromobility by evaluating spatial distributions of system activity. The goal of this analysis was to explore whether there exist inequities of spatial access to micromobility systems that may be associated with specific demographics. In particular, the results evaluate whether there are relative differences in spatial distributions of vehicles that would limit the ability of vulnerable populations to access the vehicles relative to non-vulnerable populations. The correlation between activity and census-based demographics suggests that micromobility was most accessible in regions that had young and middle-aged adults and more educated populations. In addition, correlations were generally positive with regions that had higher shares of males and whites. Associations with income exhibited mixed accessibility patterns across cities and systems. In most cities, lower income areas had greater access to shared bikes and scooters. The main contrary case was San Francisco, where vehicle accessibility was found to increase with income. The results of this analysis found that in one of the cities explored, San Francisco, there is a high level of micromobility access available to wealthier populations. The metrics devised showed that spatial access to micromobility vehicles was correlated with higher incomes and other attributes associated with more affluent populations. In the other cities explored, micromobility vehicles were found to be located in areas associated with more vulnerable populations, where lower income demographics were generally more closely positioned to micromobility vehicles. Overall, the results suggest that spatial inequities that are tilted against vulnerable populations is likely a city-specific issue, rather than being systematic to the mode. The previously identified focus group findings complement these activity analysis findings by adding insight as to why activity rates may differ by region. In addition to device access, micromobility use is likely impacted by factors including: affordability, operational understanding, safety concerns, and lack of supportive infrastructure (e.g., protected bike lanes). Taken together, these findings can explain variations in micromobility use.

7 Survey Analysis

The spatial analysis above constitutes an effort to identify metrics and understand the spatial implications of equity in access to the micromobility operating within cities, based on the location of vehicles. The research effort also deployed a survey of the general population within major regions of California in 2021 between the months of April and December. These regions included the metropolitan regions of San Francisco Bay Area, Los Angeles, Sacramento, and San Diego, as well as the Central Valley. Respondents were asked which region they lived in. Those reporting that they did not live in California were screened out. Respondents could pick "Other" and specify a locale with California. Other responses were reviewed and reclassified to the most appropriate region based on the nearness of the locale stated to a region and/or home and work locations reported at the end of the survey. The survey resulted in a sample of 2,381 respondents. The analysis of the survey explored the topics within four areas of interest, noted earlier as micromobility, telework, HOV and HOT lane pricing, and park and ride. The sections that follow detail insights that have been drawn to date from the survey data. These include summaries of responses to key questions that were asked on specific topics. The results begin with a presentation of the sample demographics and regional breakdown of the survey respondents. This analysis explores the departure of the demographics from the true distributions of the general population. The results will help inform the parameterization of additional policy analysis in the context of over or under-represented demographics that could systematically influence conclusions. In this and subsequent sections, we present results that summarize survey responses to key questions related to behavioral response and VMT impacts within the policy areas of interest.

Figure 7. Survey Respondent Region, Gender, and Age





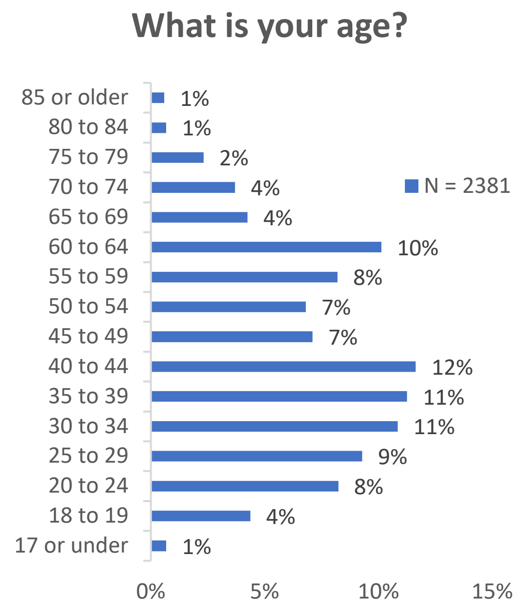
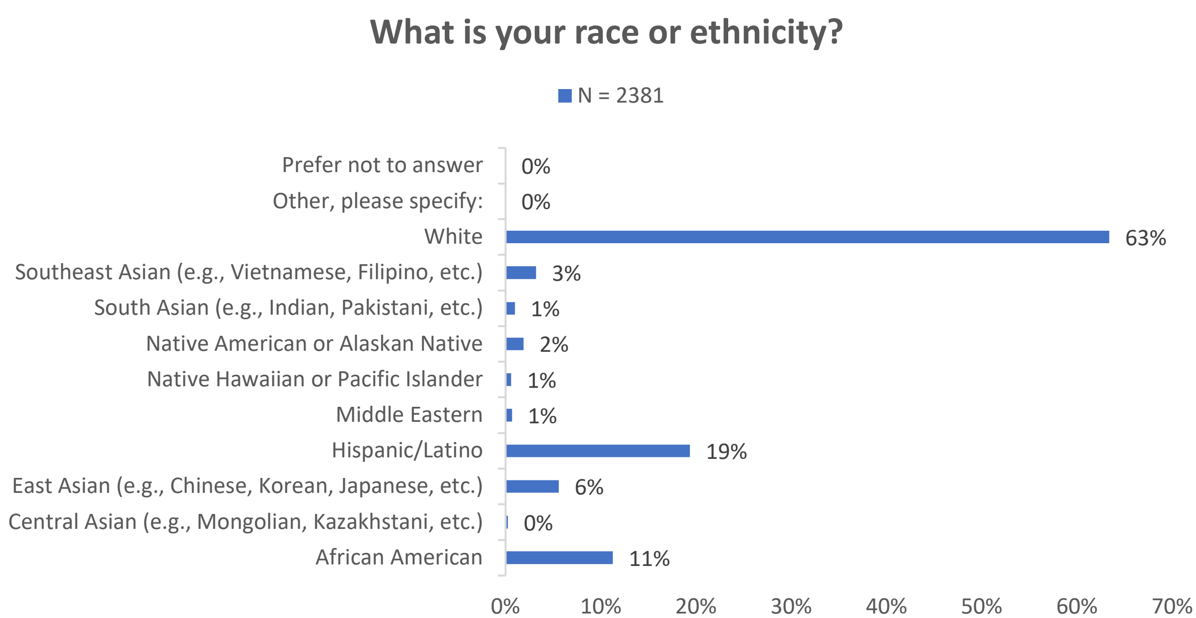
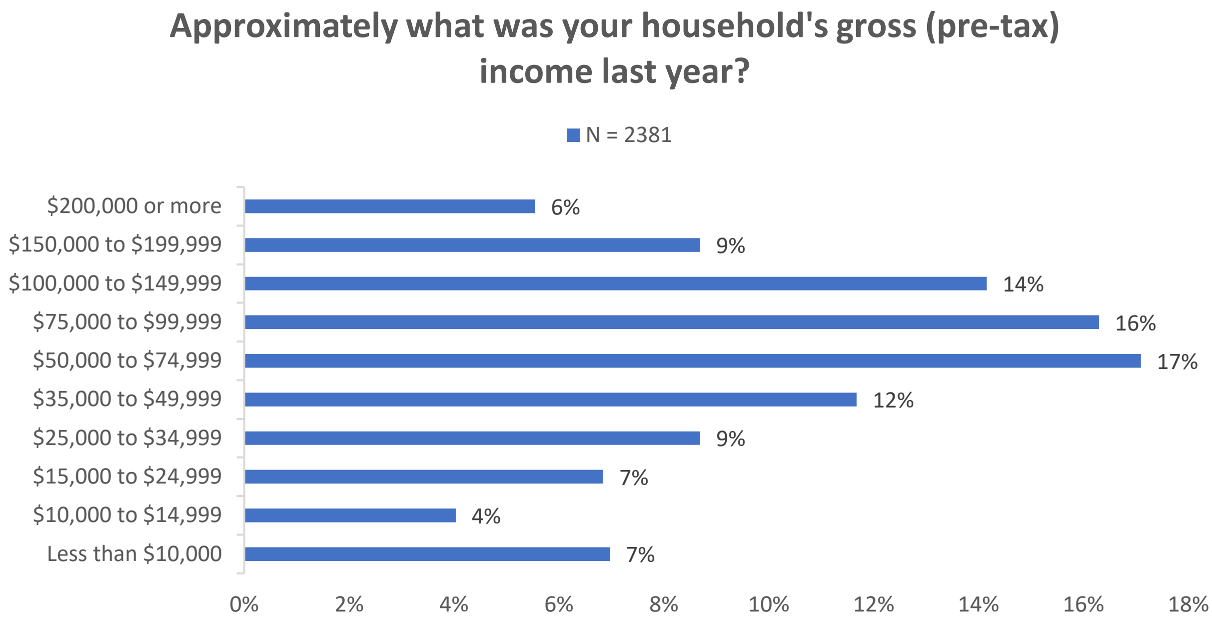


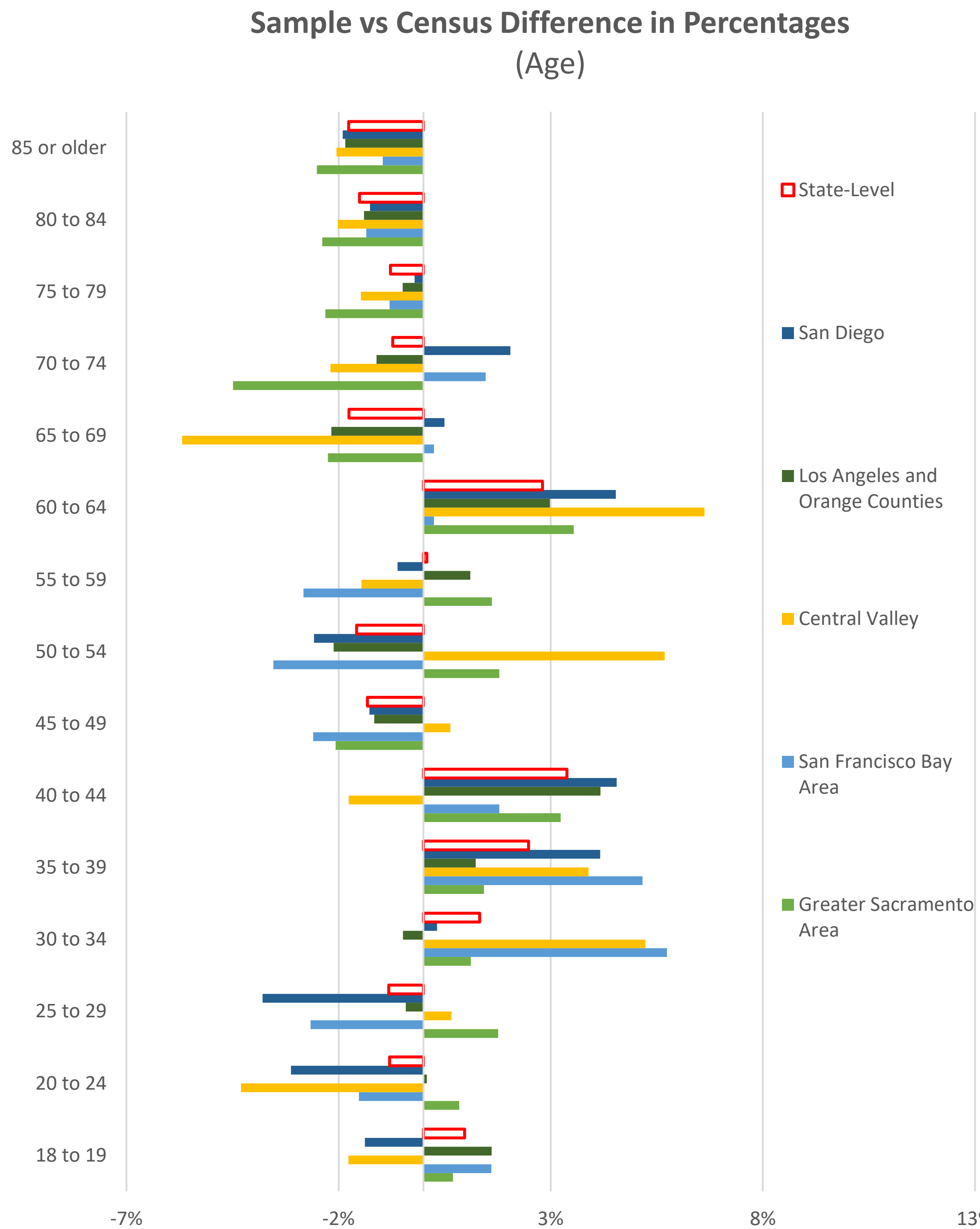
Figure 8. Survey Respondent Race/Ethnicity and Income





The demographics distributions suggest that respondents were more likely to be female (57%). About a third (34%) were between the ages of 30 to 45. The dominant race/ethnicity among respondents was White at 63%, while household incomes were predominantly middle income between $50,000 to $150,000 per year. The differences in these demographics from the state populations within these regions varied depending on the demographic attributes. The differences in demographics by age was more mixed and shown in Figure 9. These difference by category are relatively small in magnitude by vary across region, with the Central Valley exhibiting the largest differences.

Figure 9. Differences in Survey Sample vs. Population by Age



Regarding differences in race, the survey also exhibited mixed results, but was consistent across regions. As shown in Figure 10, the survey sample under-represented Hispanics and Latinos, while overrepresented Whites and Blacks, where Whites were more heavily over-represented. Finally, the relative representation of income and education showed that respondents had educations that were relatively high as compared to the population, while the survey slightly over-represented households of lower incomes within most regions. These comparisons are shown in Figure 11 and Figure 12.

Figure 10. Differences in Survey Sample vs. Population by Race/Ethnicity

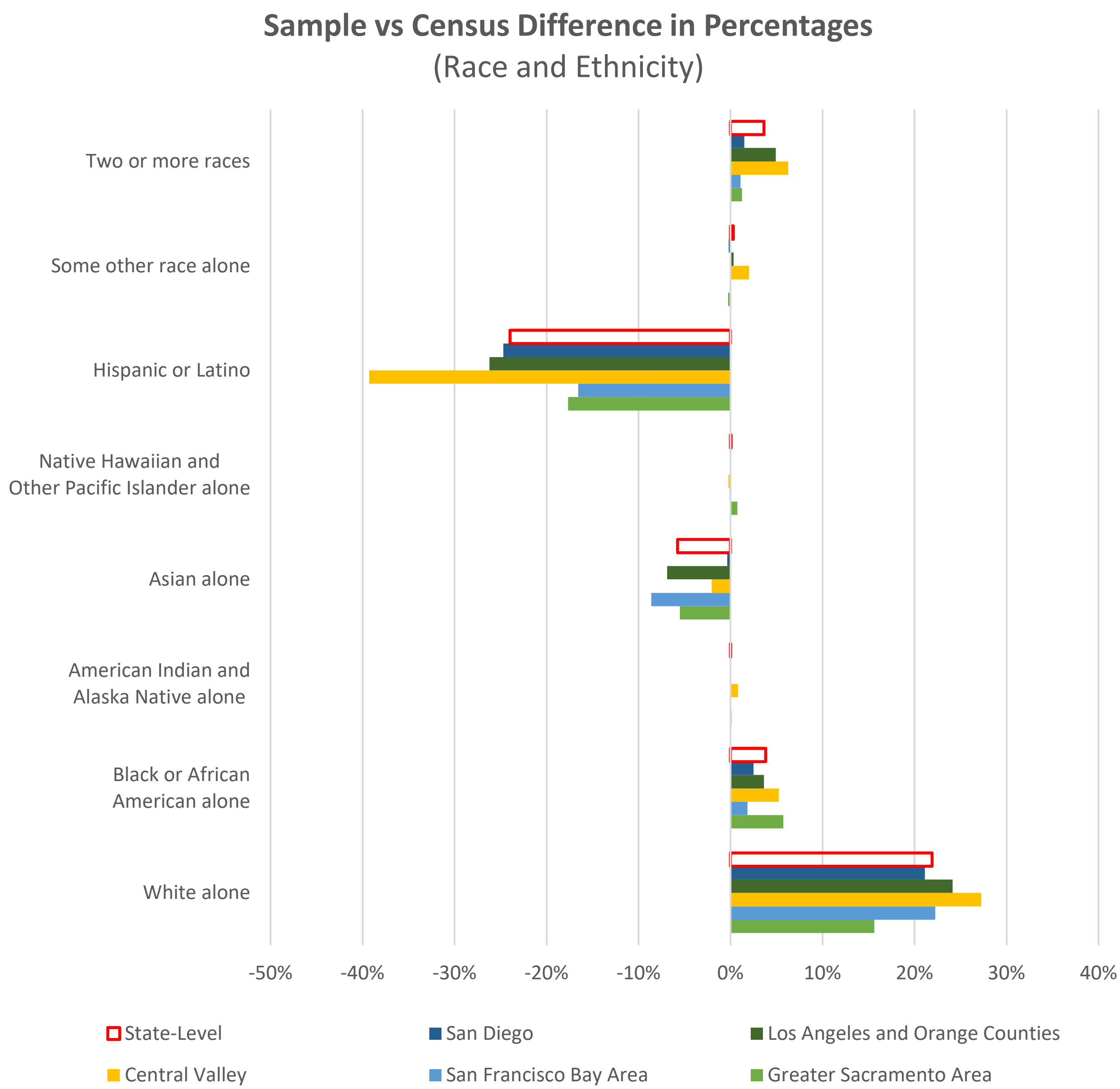


Figure 11. Differences in Survey Sample vs. Population by Education

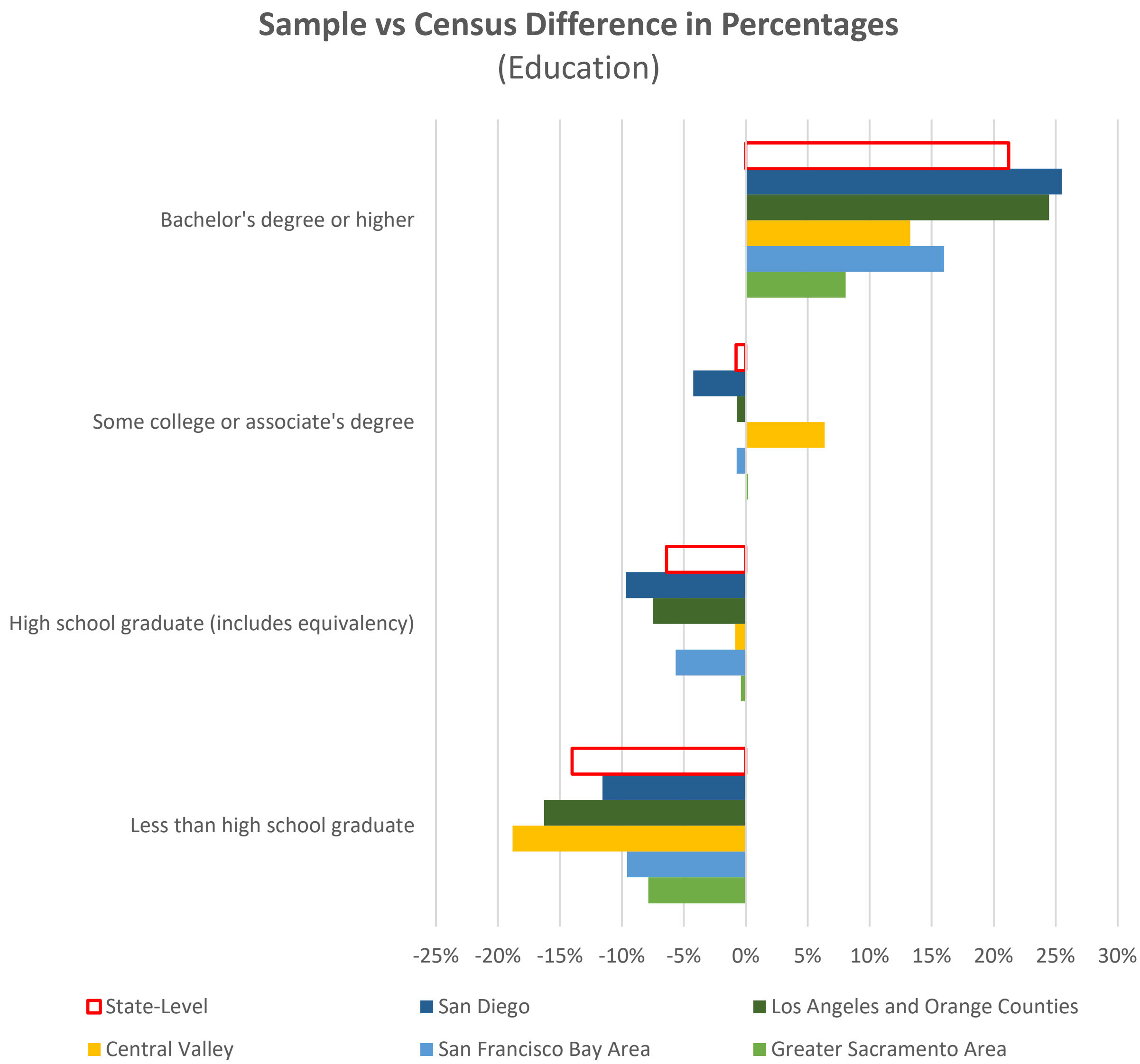
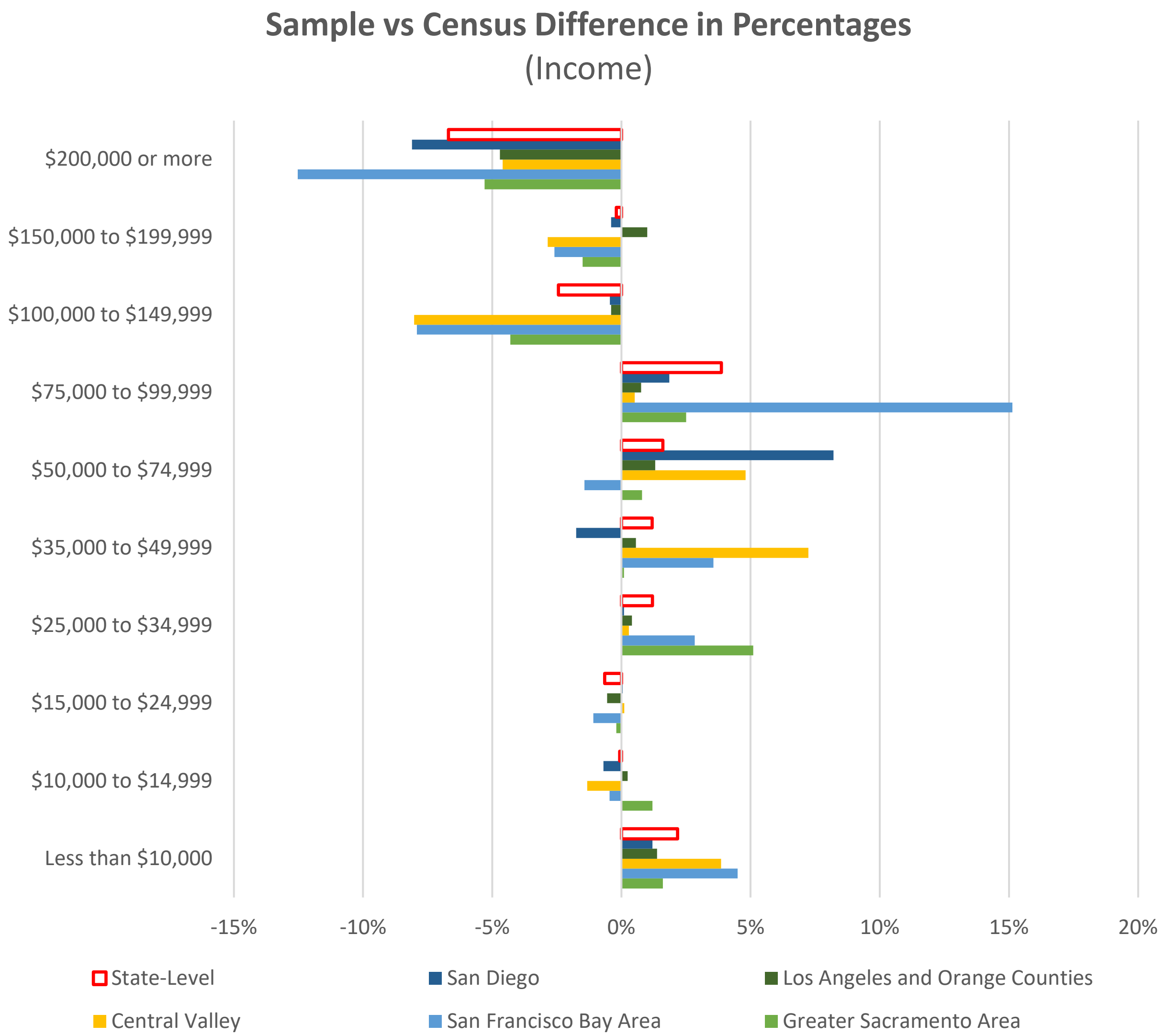
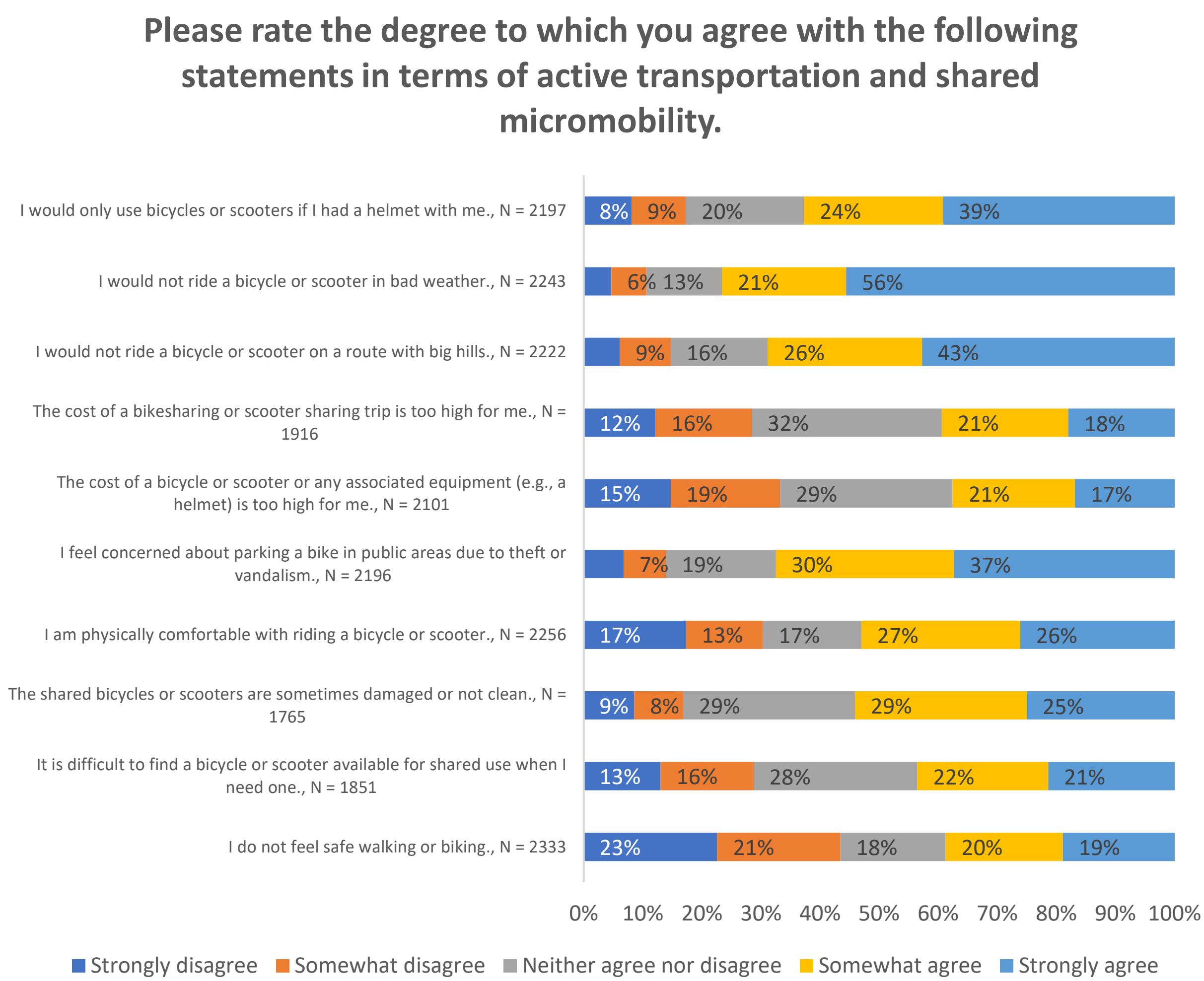


Figure 12. Differences in Survey Sample vs. Population by Income



To explore barriers in micromobility within the survey, a series of questions was asked of respondents to evaluate their ownership and relative level of comfort with micromobility. The responses to these questions were on a likert scale and responses of all respondents are shown below in Figure 13. The responses show that the availability of a helmet is a strong factor influencing micromobility use, as well as the presence of bad weather and hills. For helmet use, 65% reported that they would only use micromobility if a helmet were available, while 77% reported that they would not ride in bad weather, and 69% would not use micromobility on a route with big hills. The cost of micromobility was also an influential factor for both shared trips and personal micromobility vehicles for about 40% of respondents. Additional factors influencing use include physical comfort with riding a vehicle and the cleanliness of those vehicles, where about 50% of respondents reported that they were comfortable riding a bicycle or scooter and that the vehicles were sometimes damaged or not clean. Finally, the ability to find a scooter and the safety of riding that vehicle was considered relevant by about 40% of respondents, who somewhat agreed or strongly agreed that it was difficult to find shared vehicles and that they do not feel safe walking or bicycling. It is important to note that technical solutions addressing barriers identified in the survey, such as providing helmets, may not result in a substantive increase in ridership. During the mid-2010s, helmet kiosks were deployed in Seattle, Boston, and Melbourne bikesharing systems. In Seattle and Melbourne, their deployment was motivated by a law that required helmets to be worn by all bicyclists. These three docked bikesharing systems have since shut down (Melborne Bike Share, 2020; Seattle 2017; Boston, 2018). In February 2022, Seattle's all-ages helmet law was repealed and the bikesharing systems operating in Seattle today do not dispense helmets. Boston still operates a docked bikesharing system, but under a new name (BlueBikes). The helmet kiosks servicing the previous system (Hubway) were not retained by the new system. The present results may seemingly contrast with the analysis previously presented regarding the distribution of vehicles. That analysis evaluated the distribution of micromobility vehicles on a relative basis across census tracts and used several measures to ascertain the equity of distribution. It found that in cities outside of San Francisco, that micromobility activity was not correlated with high income areas. User perception however is a separate measure of the perception of accessibility that is relative to an individuals' experience. Both types of measures provide context in separate ways to inform on the overall accessibility of micromobility vehicles to user populations. These measures can come to different conclusions depending on who is providing the response and the nature of different barriers to access that they may experience.

Figure 13. Attitudinal Factors Influencing Micromobility



7.1.1 Key Survey Findings on Teleworking

The online survey explored how respondents teleworked and the associations of teleworking under different circumstances with reported changes in annual household vehicle miles traveled (VMT). The survey asked respondents to estimate the annual miles that they drove before the pandemic and at the time of the survey. The results of the analysis draw from those estimates and assume that the estimates provided by households are reflective of the actual annual driving estimated to have occurred before the pandemic and at the time of the survey.

Table 11 presents the number of respondents by the ability and status of telework. Among the 2,381 respondents who completed this survey, about two thirds were employed. Approximately half of these workers are teleworking. The other half of them are either not able to telework or not teleworking while having the ability to telework. For the purpose of a more detailed comparison, the teleworking group (n=738) further breaks down into those who did not move due to telework (n=503) and those who did (n=235). As a result of survey skip logic, the number of respondents who are teleworking, those who can but are not teleworking, and those who cannot telework does not add up to the total number of workers.

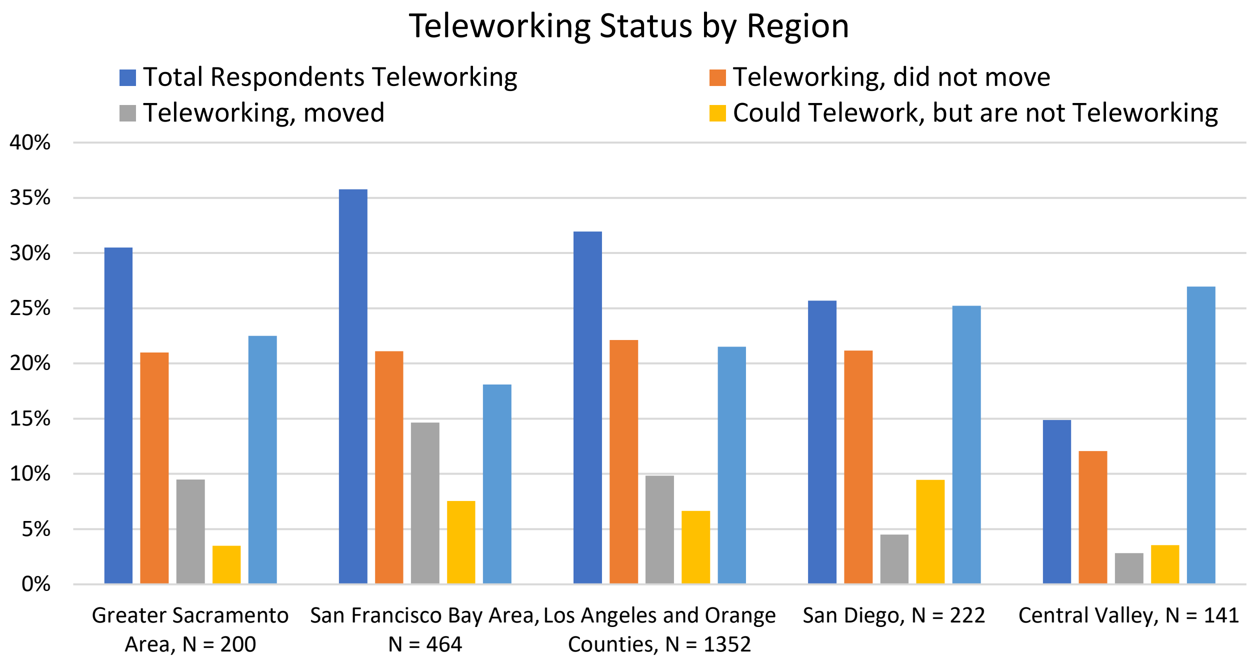
Table 11. Respondents by Teleworking Status

Type of Respondents	Respondents within the Entire Survey Sample	
	Pre-Pandemic	At the Time of the Survey
Total Respondents Teleworking	327	738
Teleworking, did not move	--*	503
Teleworking, moved	--*	235
Could Telework, but are not Teleworking	262	158
Cannot Telework	823	515
Those that are Employed and reported teleworking status	1,411	1,412
Total Respondents	2,381	

* The survey did not distinguish between those who moved or not moved due to telework in the pre-pandemic timeframe.

An exploration of the attributes of respondents within these teleworking profiles can reveal additional insights as to where they reside and their general demographic profile. Figure 12 shows a distribution of teleworking profiles by region of residence at the time of the survey. Note that during the pandemic, the percentage of survey respondents reporting teleworking was relatively high. Also, all percentages reported are as a total of all respondents within the given region. Because there were respondents who were not employed as well as those who did not report their teleworking status, the percentages do not add up to 100% within any regions. They are useful however for cross-regional comparisons. The results show that the regions with the greatest percentage of teleworkers included those within the San Francisco Bay Area, followed by Los Angeles and Sacramento. Teleworking was reported to be far lower within the Central Valley. The Central Valley also reported the highest percentage of respondents who were not able to telework. Because the pandemic was characterized by the unique circumstances of indefinite teleworking, a number of people moved in response to the long-term teleworking arrangement. On a relative basis, this phenomenon was found to be the highest in San Francisco followed by the Los Angeles and Sacramento regions. The dynamic of moving was found to be the lowest in the Central Valley and San Diego regions. Overall, the distribution of teleworking categories by attributes shows, not surprisingly, that teleworking was strongly influenced by the region of residence. In areas of higher housing costs, a greater relative share of respondents reported re-locating in response to the extended teleworking arrangements brought on by the pandemic.

Figure 14. Teleworking Status by Region of Residence



Further analysis explores the descriptive statistics of how teleworking varied across key demographic attributes. Key demographic attributes of interest included income, education, race/ethnicity and gender. An exploration of the distribution of teleworking by income shows a few interesting dynamics. Figure 15 shows this income distribution in two ways. The top graph shows the income distribution within each category of teleworking status. Each distribution of this top graph is “within category”, in that the percentages they add to 100%. The distributions show that teleworkers are generally skewed towards higher incomes, but still has representation at middle income level. Teleworking begins to become more prevalent starting at incomes of $50,000 per year. Among those who cannot telework, the income distribution is almost normal in shape. A comparison of those who teleworked and moved versus those who did not move reveals that those who moved had an income distribution that skewed relatively higher. This income comparison by teleworking status is further illustrated by the bottom plot of Figure 15. This graph shows the full distribution of the teleworking status by income. It shows that those moving in response to the teleworking arrangements of the pandemic were on average the highest income earners. While those who could not telework are more evenly spread out across incomes. To be clear, both graphs illustrate the same data, but different x-axes to allow different visual representations of same information.

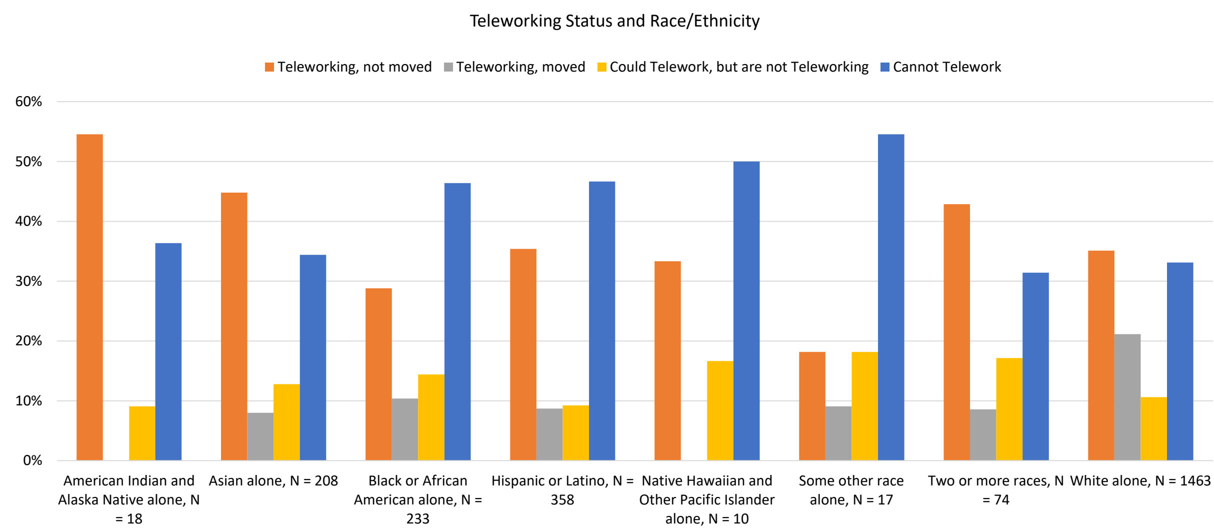
Figure 15. Teleworking Status by Income

Another attribute that deserves inspection with respect to telecommuting status and descriptive statistics is race/ethnicity.

Figure 16 shows the distribution of this attribute by teleworking in two ways. The top plot shows the percentage of each race/ethnicity category by teleworking status. The graph shows that all categories are dominated by the White alone demographic. However, this is because this demographic is dominant within the sample overall. The lower graph shows the difference between the overall sample representation and the representation of the race/ethnicity within each teleworking category. This latter set of distributions more clearly accentuates the representation of teleworking activity by race/ethnicity. The lower graph of Figure 16 shows that the White alone demographic broadly over-represents those that could telework and move and telework overall. While the Asian, Black, and Hispanic/Latino demographic under-represented those with similar flexibility. The Black and

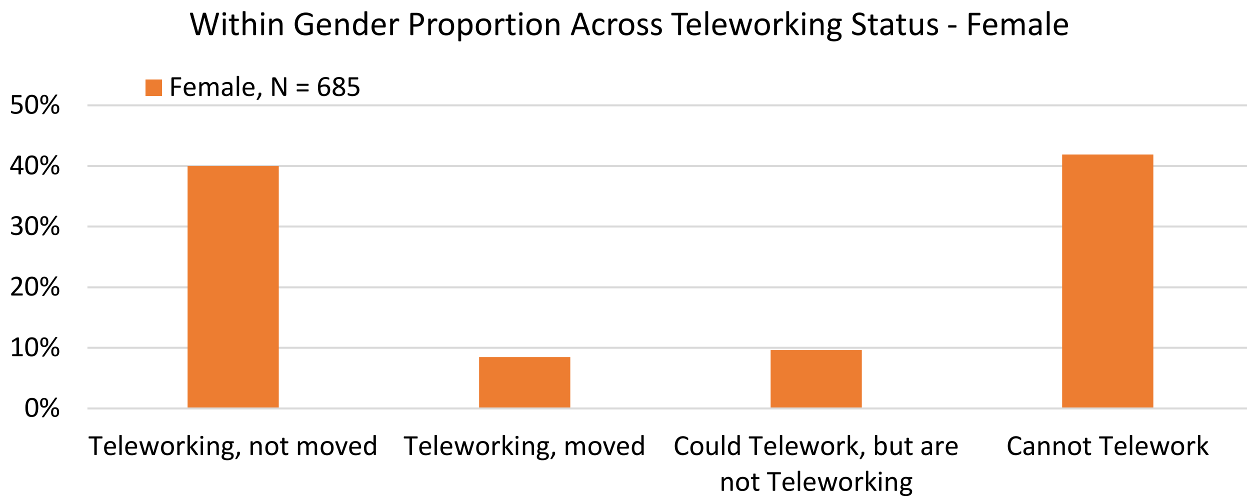
Hispanic/Latino demographics were also over-represented among those who reported being unable to telework at all.

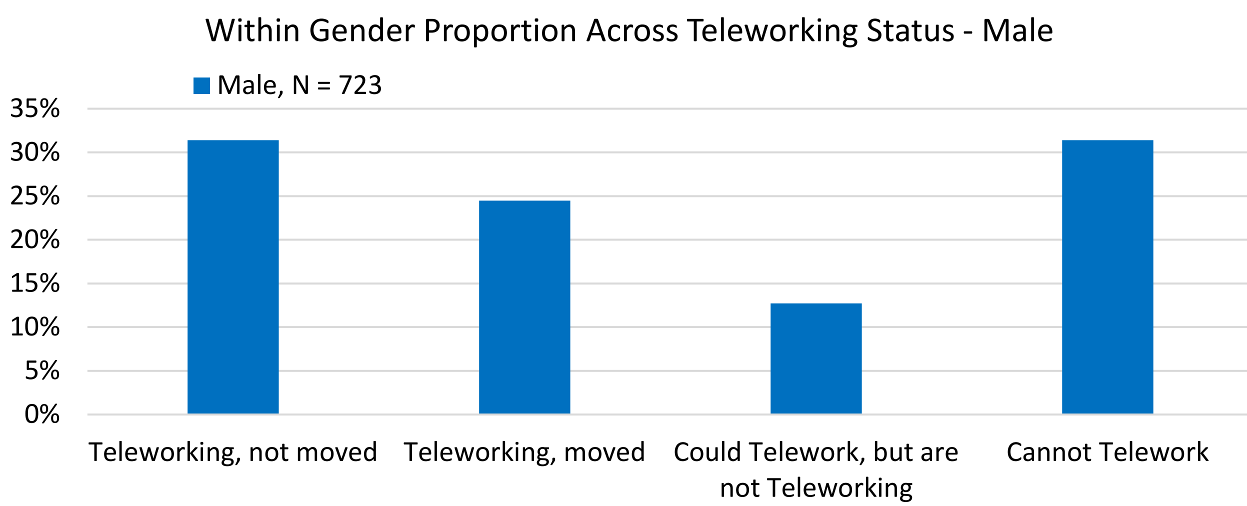
Figure 16. Teleworking Status by Race/Ethnicity



Finally, the descriptive statistics of gender by teleworking show the relative gender balance of teleworking status. Figure 17 shows five teleworking status categories along with the gender distributions. The proportions are computed within gender across teleworking categories. The top figure shows the distribution for females while the bottom distribution shows that for males. The within-gender distributions shows that 42% of females reported that they cannot telework. A nearly equivalent 40% reported that they are teleworking but did not move. A remaining 8% reported that they teleworked and moved, while 10% reported that they could telework but are not. The within-gender distribution similarly shows equivalency at between those who teleworked without moving (31%) and those who cannot telework (31%). About a quarter of men reporting teleworking and moving, while the remaining 13% reported that could telework but are not.

Figure 17. Within Gender Proportions Across Teleworking Categories





Overall, the descriptive statistics teleworking categories defined through survey responses show that there are several regional and demographic dissimilarities as related to teleworking. Teleworking, among those that moved and did not move was found frequently reported by respondents in the urban regions in the order of 1) San Francisco (57%), 2) Los Angeles (54%), 3) Sacramento (52%), San Diego (47%), and then distantly followed by respondents in the Central Valley (27%). Within-gender proportions showed that about equal proportions females teleworked without moving and could not telework. A similar dynamic was shown for males albeit at lower proportions (31%). A main difference between these distributions is that a higher proportion (24%) of males had teleworked and moved relative to females (8%). With regards to race ethnicity, the White (56%) and Asian (53%) demographic reported the most flexible arrangements, namely teleworking and teleworking and moving. Whereas within race proportions showed that fewer African American (39%) and Hispanic/Latino (44%) respondents were teleworking with or without moving. The next section introduces an analysis that is focused on VMT change associated with telework activities through an analysis of household VMT.

7.1.1.1 Household Miles Driven by Teleworking Status

Respondents were asked about the miles that were driven within the household before the pandemic and currently (effectively during the pandemic). The question was phrased slightly differently depending on the living circumstances of the respondent. Respondents who lived with other people with whom they shared income were asked VMT questions in the context of being a household. Respondents who lived alone or who only shared costs with any co-inhabitants (e.g., living with roommates) were asked questions in the context of being a household of one. Taken together, measurements of driving this section are reported as household driving. Table 12 summarizes the per-household annual miles driven, broken down by timeframe and teleworking status. On average, those who are currently teleworking reported their household driving about 5,700 miles on a yearly basis, while they used to drive almost 7,800 miles before the pandemic. Furthermore, those who never moved due to the telework policy reported their household driving about 5,200 miles on an annual basis, while those who did move travel 6,700 miles per year in an automobile. For context, data from the California add-on to the National Household Travel Survey (NHTS) suggested that average household VMT per adult was about 6082 miles per year (this is household divided by the number of household members 18 years of age or older) (TSDC, 2019). The survey asked respondents to report how many drivers were in the household, this was used to compute the average the miles per driver reported in the survey pre-pandemic was about 4,000 miles. Overall, the respondents who are currently employed experienced a cut in their total miles driven (22%), but the degree varies across groups. The total miles decreased by as much as 35% for those who telework without moving, but only around 10-20% for those who moved or are not teleworking.

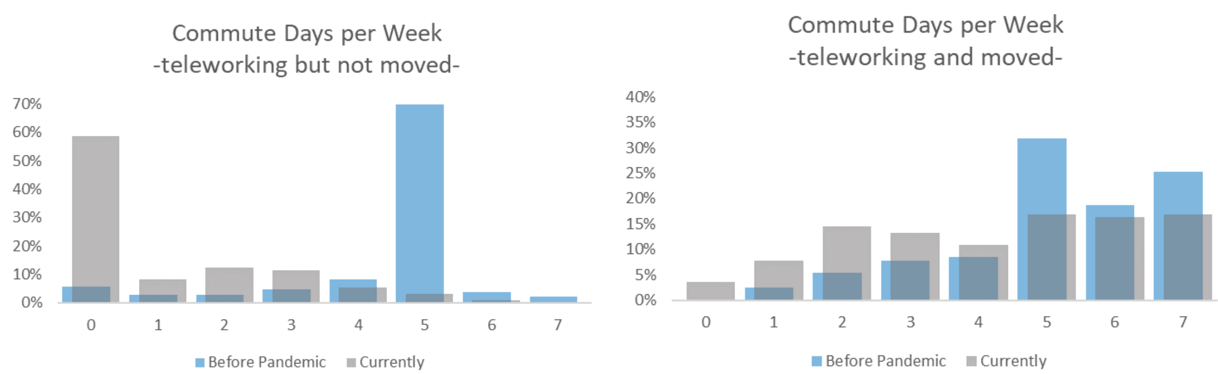
Table 12. Annual Miles Driven per Household

	Survey Sample		
	Current	Pre-Pandemic	Percentage Miles Reduction
Teleworking	5,660	7,771	27%
Teleworking, not moved	5,174	7,979	35%
Teleworking, moved	6,700	7,326	9%
Can but not teleworking	6,104	7,589	20%
Cannot telework	6,482	7,568	14%
Those that are Employed	5,979	7,633	22%
Average of All Respondents in the Survey	5,109	6,650	23%

The annual miles are much higher among those who typically drive to work. Among these respondents, there is a greater percentage of miles cut from before the pandemic. Particularly, those who did not move are driving 35% less.

Figure 18 shows a comparative distribution of the commuting days per week among those that moved and those that did not move due to teleworking. These two groups exhibit different travel patterns in the pre-pandemic timeframe. Most respondents in the first group reduced their commute days from five to zero days, meaning that they are completely working from home. For those who moved, they display a more flexible commute pattern. Most of them traveled five to seven days a week to work before the pandemic. During the pandemic, only 3% shifted entirely to remote, while the rest of them are still traveling at least one day to work. As shown in the descriptive statistics presented earlier, this may be because the sociodemographic characteristics and travel patterns are by themselves distinct between these two groups, which in is further manifested through different shifts in weekly days commuting. Not surprisingly, commute patterns before and during the pandemic are quite similar for those who can but are not teleworking and those who cannot telework.

Figure 18. Change in Commute Patterns of Those Who are Teleworking but Did Not Move (left) and Those Who are Teleworking and Moved (right)



The analysis of the survey responses as related to teleworking explored responses as defined by several different categories of teleworking behavior. Several key findings emerged from this analysis. The descriptive statistics showed that the respondents most likely to be able to take advantage of telecommuting have higher incomes, are more likely to be male, and generally more likely to be White, relative to the population. The analysis of changes in household vehicle miles within these categories suggested that among those that teleworked, those who did not move with the teleworking arrangements of the pandemic saw the biggest reduction in VMT. This average reduction was 2,805 household VMT per year, which at the sample size (n = 503, see Table 11), is statistically different from zero (p = 0.000). This reduction is statistically different from the reduction observed within the overall sample of 1,541 household VMT per year (n=2381, see Table 11). The difference between these two reductions, that of those who teleworked and did not move and the broader sample is statistically significant (p = 0.000). Similarly, the average reduction of 626 annual VMT by those households that teleworked and moved is statistically different from zero (n = 235, see Table 11). This reduction is statistically different from the reduction of those who teleworked and did not move (p = 0.000). Finally, the difference between those that teleworked and moved and the broader sample is statistically significant (p = 0.001). This final difference is such that the reduction in VMT of the broader sample is actually larger than those who teleworked and moved. The implication being that those who teleworked and moved appeared to make lifestyle changes that gave back VMT exceeding the changes that were associated with the pandemic along. This dynamic may be the result of workers moving out of high cost, transit rich environments to lower density auto-oriented environments where on balance they experience a net increase in VMT. Whereas those who teleworked and did not move experienced the largest overall changes in annual VMT, exceeding that reported by the overall sample.

The household VMT data contains the general reductions in driving of the pandemic within its estimates, and the individual effects of telework and moving cannot be fully disentangled. However the pattern of average change suggests that teleworking did reduce VMT among those given the flexibility to do so and also did not move their location of residence in response. These are other supporting findings yields insights on the nature of VMT shift that may result through different categories of teleworking. Notably, households that moved and teleworked in response to pandemic related shutdowns seemed to negate any reductions in VMT as a result of their new land-use environment. Whereas, households that switched to teleworking but stayed put where they lived were found to reduce their annual household VMT relative to the broader survey sample by a degree that was statistically significant.

7.1.2 HOV and HOT

High-Occupancy Vehicle (HOV) and High-Occupancy Toll (HOT) lanes are traffic management strategies intended to increase the number of people and vehicles that can move through a congested corridor. This requires increased travel demand and travel congestion to be addressed, which can be done through two incentives: travel time savings and travel time reliability. HOV lanes restrict use to vehicles that meet a minimum occupancy requirement or other vehicle eligibility during its operation hours. If the HOV lane is not operated 24 hours per day, then the operation hours would typically fall during peak commute hours. Outside of operation hours, there is no restriction on vehicle occupancy and all vehicles can use the lane.

By giving priority treatment to buses, pooling vehicles, and HOVs, HOV lanes have been found to encourage ridesharing and use of transportation. Cohen et al., 2020 conducted a data-driven assessment and found that HOV lanes can increase carpool intent and adoption, which can further enhance the effectiveness of HOV lanes. This can simultaneously remove congestion from general purpose lanes. The US Department of Transportation Federal Highway Administration states that this results in direct beneficiaries – HOV lane users – and indirect beneficiaries – passengers in the general purpose lanes with reduced congestion.

HOT lanes are another way to increase throughput in these lanes. High-occupancy vehicles can continue to use these lanes at no cost, but vehicles that do not meet the occupancy or eligibility requirements can now use these lanes for a toll. Depending on the toll, the performance of these high occupancy lanes could be improved or degraded. Thus, the fees are typically variable according to the time of day or level of congestion. The Federal Highway Administration state that these paying vehicles would be able to take advantage of trip reliability, as the lanes would ideally be monitored for compliance to maintain speeds, allowing for uninterrupted pace. This could also make express bus service more attractive, especially during peak periods (Poole, Reason Foundation, 2020). According to Konishi and Mun (2010), HOT lanes are generally favorable due to three reasons: turning underutilized HOV lanes into HOT can make better use of these lanes, HOT lanes can generate additional revenue for new road and lane projects, it is a political feasible policy. Unfortunately, some are critical of the HOT lanes, calling these lanes “Lexus Lanes” due to beliefs that only higher-income drivers can use these lanes whereas lower-income drivers will be stuck in congested general-purpose lanes (U.S. DOT, FHWA 2016). Some state Department of Transportations (DOTs) with HOT lanes have conducted studies using data collected from their electronic toll systems and found that the distribution of vehicles in the HOT lanes and general purpose lanes were similar (Poole and Reason Foundation, 2020).

Despite the anticipated benefits of HOV and HOT lanes, studies have shown that they are not as effective as expected or have other consequences. High occupancy lanes are still underutilized to some degree and have limited effectiveness in easing congestion (Konishi and Mun, 2010). Common responses to poor HOV or HOT performance are conducted through changes in policy regarding pricing, occupancy requirement, and vehicle eligibility. Depending on whether the issue is underutilization or overcrowding, these policies could be changed to increase or loosen restrictions. Changing these restrictions would induce or reduce volume in high occupancy lanes.

Conversion of HOV to HOT lanes is another policy response that is expected to relax restrictions on HOV lanes, but HOV lanes and these conversions could have other negative effects (Konishi and Mun, 2010). While HOV lanes do encourage carpooling, they also introduce a distortion in congestion levels among the different types of lanes (i.e., general purpose and HOV) (Konishi and Mun, 2010). Conversion to HOT lanes address this as they allow single occupancy vehicles (SOVs) into these lanes, but this could also adversely discourage carpooling. Guensler et al., 2013 studied the conversion of an HOV2+ lane to HOT3+ on I-85 in Atlanta and found that average vehicle occupancy decreased along with vehicle throughput. However, this effect could also be seen and tied to general occupancy increase in high occupancy lanes. A review of HOV lane performance conducted by Chang et al., 2008 revealed that increased HOV occupancy policy decreases eligible carpool formation, which could lead to further congestion in general purpose lanes. Eligible carpools in this context are carpools that qualify for the carpool lane. For example, a 2-person carpool is a carpool, but not a carpool that is eligible to travel in an HOV-3 lane. Alternatively, another approach to addressing underutilization of HOV lanes would be to decrease occupancy requirements. Similar to what is expected in HOV to HOT conversion, there will be a volume shift from general purpose lanes to HOV lanes as a result of relaxed restrictions (Chang et al., 2008).

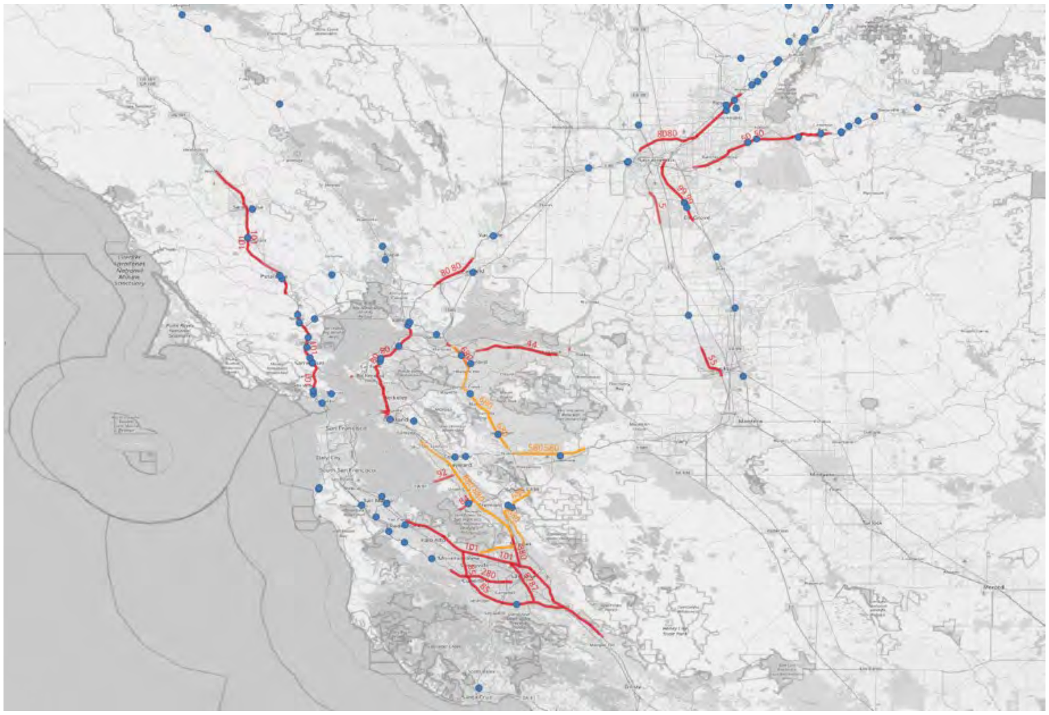
Pricing policies are popular strategies used to increase utilization, as it relaxes the restrictions on high occupancy lanes. According to Poole and Reason Foundation (2020), this may not be well-accepted as most would see this toll as an overall loss. Chang et al., 2008 believes that pricing strategies may be a more promising approach to lane management compared to occupancy policies, but it is more difficult to implement and will require more investments and complimentary action by federal, state, and regional government. Among complimentary actions that were mentioned included policies such as changes to hours of HOV lane operation or occupancy changes. They also found that areas more familiar and accepting of tolled facilities are more likely to buy into new pricing concepts.

The efficiency of HOV and HOT lanes are investigated in this section as we analyze survey responses regarding availability, desire, and need for HOV and HOT lanes. Cost of HOV and HOT lanes are also analyzed to see if they pose as a substantial barrier to driving and use of HOT lanes.

7.1.2.1 HOV and HOT Results

HOV and HOT lanes are distributed within the major urban areas of the state along specific corridors. To put the distribution of these lanes in context, Figure 19 shows a map of their distribution within northern and southern California as derived from GIS data published by Caltrans (Caltrans, 2022). The red lines are HOV lanes, whereas the orange lines and HOV/HOT lanes. The blue dots are Park and Ride lots (which are more widely distributed in other areas of the state).

Figure 19. Distribution of HOV and HOT Lanes within California



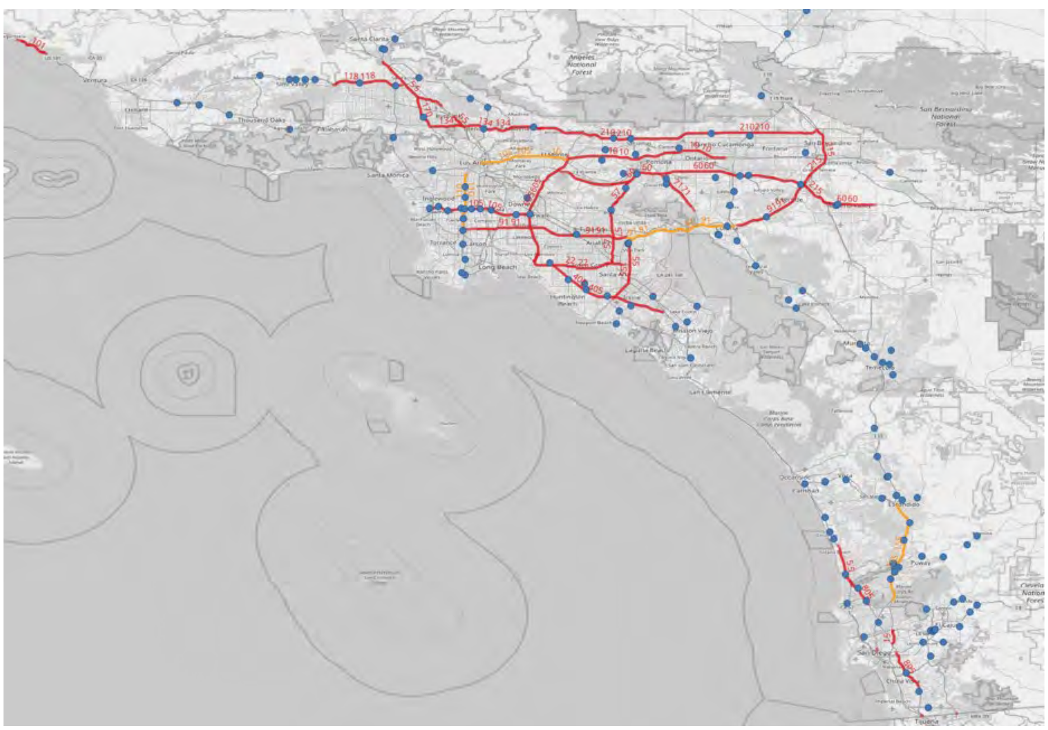


Figure 20 presents a summary of responses to questions exploring the awareness of and use of HOV and HOT lanes. The top two graphs show respondent awareness and use of the lanes. The bottom two questions in investigate behavior and mode choice depending on availability of HOV and HOT lanes. The questions asked respondents who did not report having HOV or HOT lanes within their region how their travel behavior might change if such lanes existed close to them. Among the respondents within this subset, 41% did not know if they would use them and 27% would not use any of the lanes. Only 10% of this subset would have considered using either of the lanes and 22% would consider using both.

Another subset of respondents who lived in areas with HOV or HOT lanes and used those lanes for commuting were asked a different question. They were asked how they would change their commute if the HOV lane was not available or if the HOT lane was too expensive. This question is important for understanding which changes in behavior would occur in response to changes in accessibility of the lanes. Among this subset, the most common response (62%) was that commuters would just drive in regular lanes rather than HOV and HOT lanes. Only 5% of this subset would purchase an eligible carpool-sticker to continue using HOV lanes, while 9% would continue to carpool, and 12% would shift to public transit. Finally, 10% would seek to telework, while a final 1% would seek to change jobs.

Figure 20. HOV/HOT Availability and Mode Choice Behavior Questions

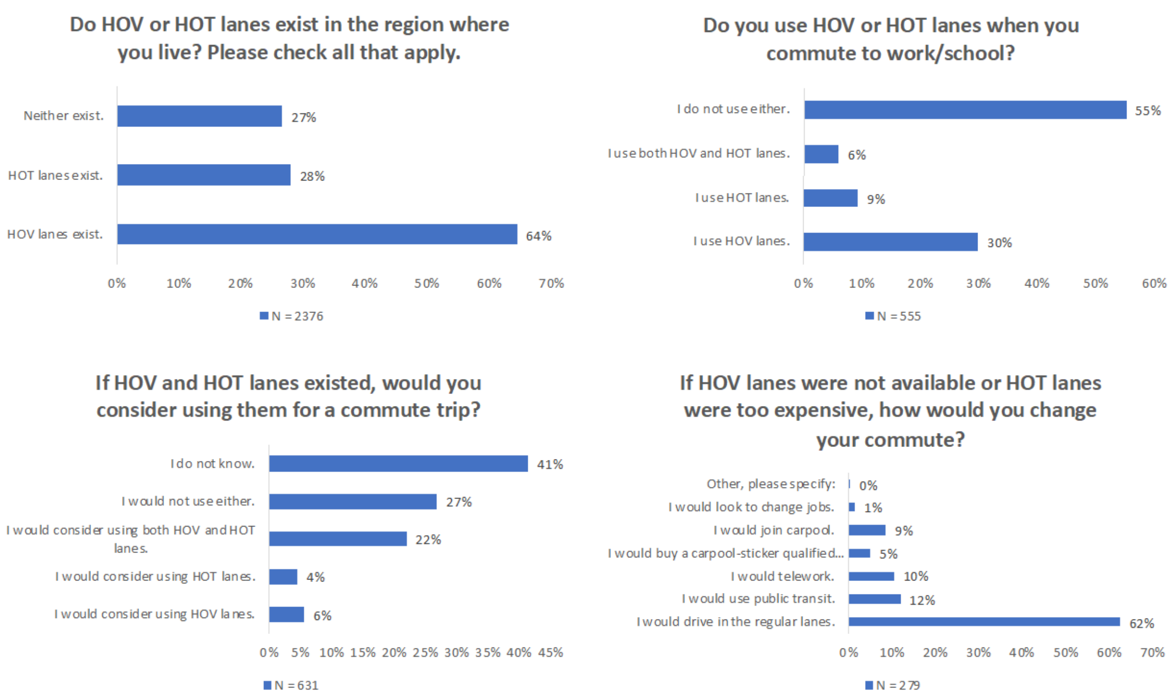


Figure 20 includes the responses to basic questions regarding availability of HOV and HOT lanes and desire to use these lanes. Nearly 30% of respondents state there are neither HOV or HOT lanes that exist in their region. While 28% responded that there exists HOT lanes near them, HOV lanes were stated to exist by 64% of the respondents. However, a follow up question reveals that more than half of the respondents do not use either of the lanes and only 6% use both HOV and HOT lanes. As demonstrated in the first question, twice as many people were aware of HOV lanes in their area compared to HOT lanes. This same trend is reflected in the reported usage, with 36% reporting HOV lane usage, which is approximately twice times the percentage of respondents using HOT lanes (15%).

Respondents were asked to report their monthly commute costs before, during, and expected after the pandemic. The distribution of these costs is shown in Figure 21. Note that the question was phrased to prompt the respondent to consider all costs for any mode. Some costs may be perceived as highly variable, while others are the result of long-term activity (such as vehicle maintenance). The respondent was prompted to include what they considered to be their incurred monthly commute costs. Notably, the distribution in Figure 21 does not shift much across the time frames, but the sample size does. The average monthly commute cost reported before pandemic was reported to be $239 per month, while the average reported during the pandemic was reported to be $236 per month. The average monthly commute cost expected after the pandemic was reported to be $259. Only respondents who reported commuting to work within the last two years were asked this question and, if respondents reported that they did not commute to work at the time of the survey, then they were not asked about their commute costs within their current time frame. This is why the sample moves across the time frames, with a notably lower sample size of responses for the current time frame.

Figure 21. Distribution of Monthly Commute Costs

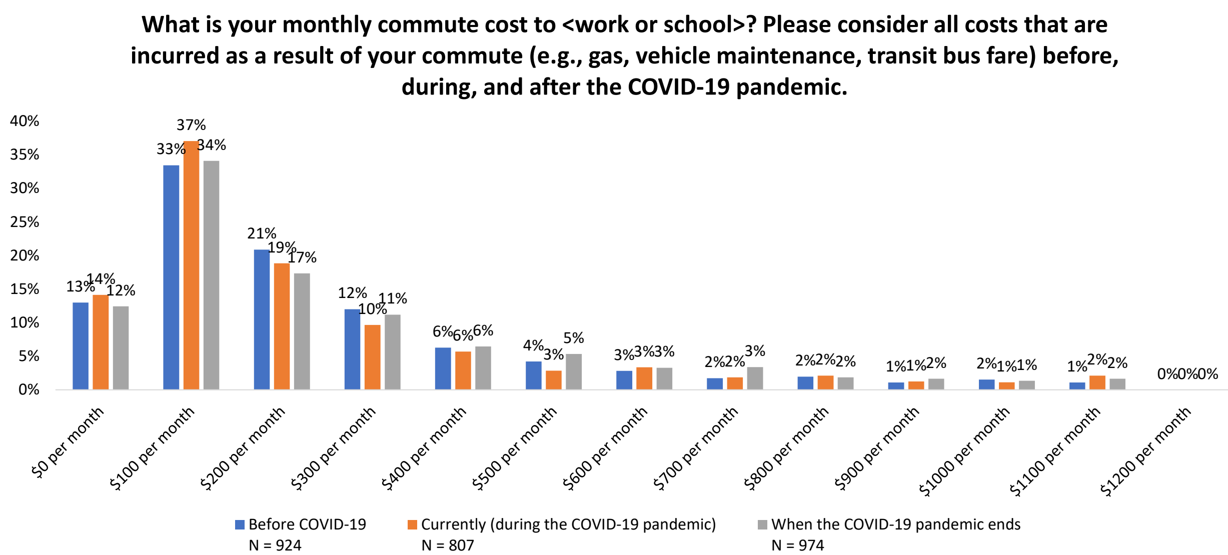


Figure 22 displays the breakpoint cost at which respondents would not consider driving. 10% think any amount is too expensive. 54% would consider $200 per month or less to be their breakpoint cost. Another 15% would consider $300 per month to be too expensive, leaving nearly 70% respondents to consider mode shift at or below this threshold cost. On the other hand, less than 15% consider $600 per month and above to be too expensive.

For context, according to the National Transportation Statistics reported by the Bureau of Transportation Statistics, the average total monthly cost was approximately $894 in 2022 (assuming 15,000 miles per year, note this assumption of annual miles is high by most measures). This includes fixed ownership costs, such as insurance and tax, and other variable costs such as oil cost and maintenance. These results are based on data released by the American Automobile Association (AAA), which also releases their own in-depth report and statistics (BTS, 2022).

Figure 22. Breakpoint Cost for Driving

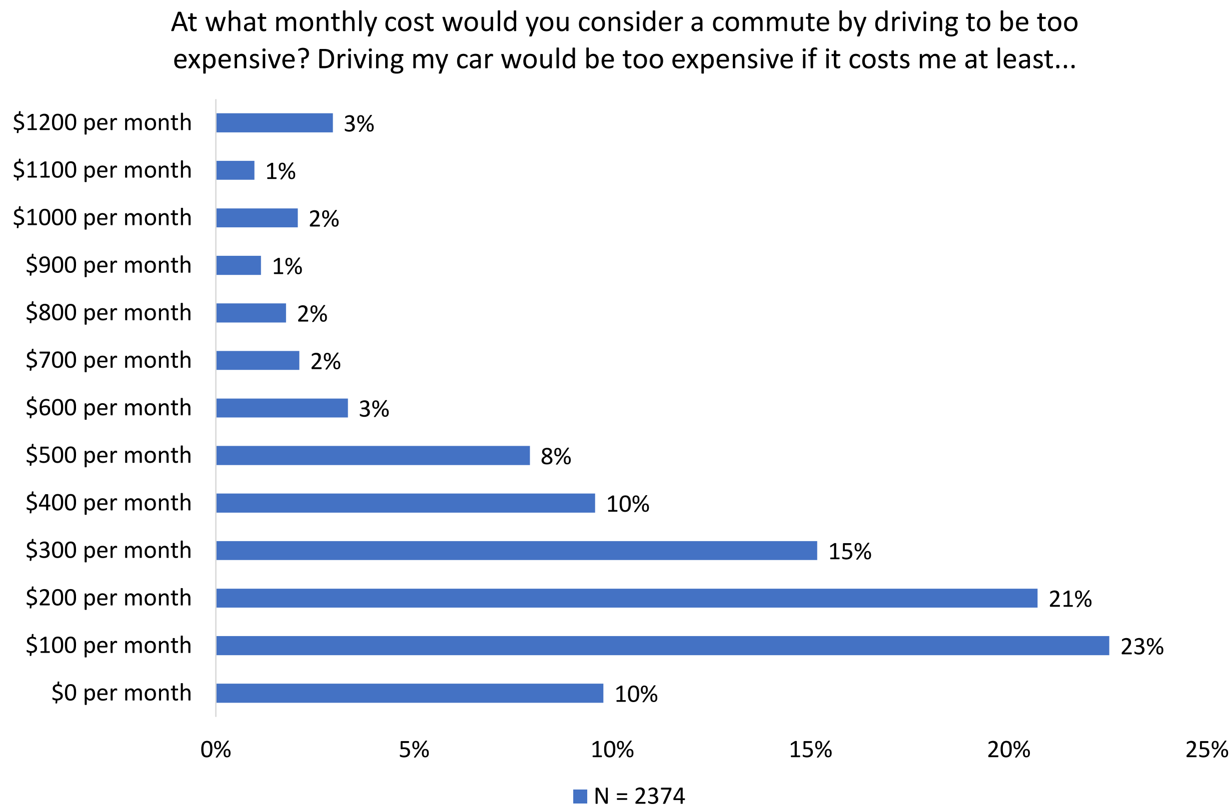


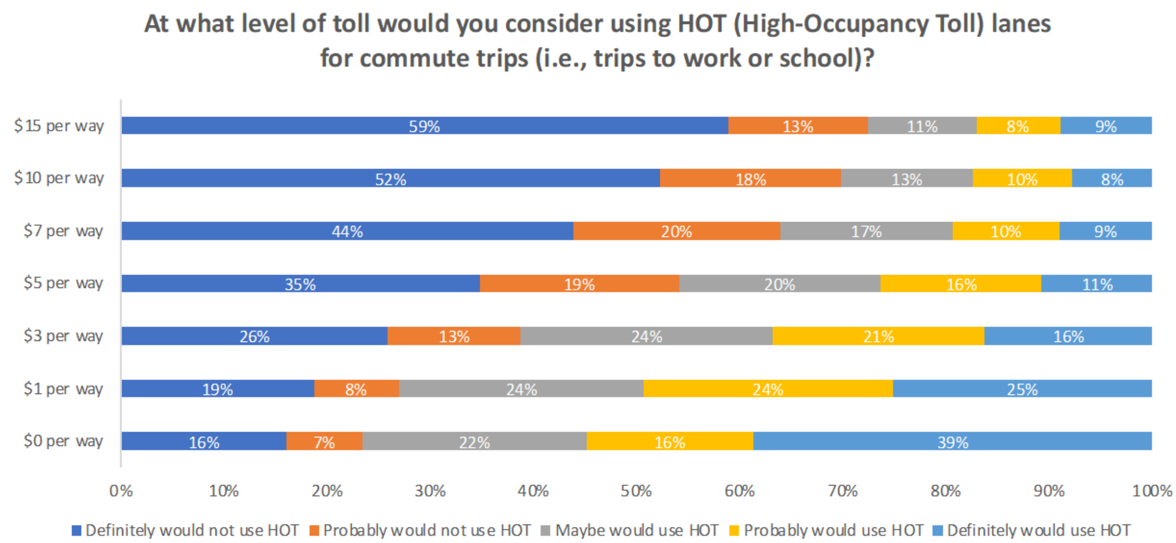
Figure 23 presents the percentage of respondents that would or would not consider using HOT lanes at different price points. At $0 per way and $1 per way, 55% and 49% of respondents, respectively, chose probably or definitely would use HOT. However, at $5 per way, 54% responded that they probably or definitely would not use HOT and only 27% stated they probably or definitely would use HOT. Between those prices at $3 per way, each end of the spectrum (i.e. probably or definitely would use and would not use) was selected by approximately 40% of the respondents, each.

The $0 per way was provided as a response option in order to calibrate the responses for analysis. There was no clear indication in the responses why someone may still opt-out of using HOT lanes despite it being free. However, there are some possible reasons for this. One main reason could be that they simply did not need to use HOT on their commutes, for reasons such as other preferred modes of transportation, lack of personal vehicle, preferring to drive on local roads over highways, or that their commute simply does not require HOT use.

The U.S. Department of Transportation Federal Highway Administration reported 8 interstate system toll roads in California that have HOT lanes. All of the roads except for the I-680 SMART Carpool Lanes collect toll that account for both ways. All roads have dynamic pricing in which the rate depends on current traffic conditions. The average passenger vehicle fee across all California tolls roads with HOT lane is $5.41, with the average minimum being $0.50 and the average maximum being $13.80 (calculated from averaging the min and max values over all the roads). Virginia is the next state with the most toll roads with HOT lanes. Virginia has 4 toll roads with HOT, and their average passenger vehicle fee is $8.19. Other states with 1-3 toll roads containing HOT lanes include Florida, Georgia, Minnesota, and Washington. Their average passenger vehicle fee ranges from $4.13 to $6.38.

Based on the average values above, the average toll fee per way would be approximately $2.71. At $3 per way, approximately 39% believed it was too expensive to use, while 37% stated they would consider using it at this price.

Figure 23. Breakpoint cost for HOT lanes



7.1.3 HOV and HOT Findings

HOV and HOT lanes are available at varying degrees in different regions. However, survey results indicate that HOV lanes are twice as common compared to HOT lanes. This outcome could point to possibilities: a general lack of HOT lanes, and a lack of awareness of HOT lanes. However, survey responses also indicate that a little over half of the respondents do not use either of the lanes. Only 6% use both types of lanes. Despite 64% stating that HOV lanes are available near them, only 30% respondents would use the HOV lanes. This discrepancy could be an indicator that other factors play a role such as pricing or route incompatibility, that discourage or contribute to the decision not to use HOV lanes. Similarly, HOT lanes are only used by 9% of the respondents and could have other contributing factors to this low percentage of usage.

Respondents were surveyed on mode choice in regard to using HOV and HOT lanes for commutes. Given the circumstance that HOV and HOT lanes were available within their region, an overwhelming 41% stated that they do not know whether they would use these lanes. This could suggest that these respondents are not equipped with sufficient information about HOV and HOT lanes to make a decision on HOV and HOT usage, or that their response varies depending on conditions such as if they are riding with another person. Surprisingly, another 27% would use neither of the lanes while 22% would use both. This could further support the hypothesis other factors outside of availability influence the decision to not use these lanes. Alternatively, this could also pose a larger question of whether these lanes are generally necessary for a commute. When respondents were provided with the alternative situation where HOV and HOT lanes are unavailable and expensive, 62% would resort to using regular lanes, which could suggest that driving is a commonly preferred mode of commute regardless of HOV and HOT lanes. Only 12% of HOV/HOT users reported that they would change to public transit and another 5% would seek to acquire carpool stickers to use HOV lanes. This suggests that few consider HOV lanes beneficial enough to consider purchasing carpool lanes to continue using HOV lanes

The tolerance for the perceived total cost of commuting by driving is a strong factor that could naturally influence the decision to use HOT lanes. As shown in Figure 21.

Figure 21. Distribution of Monthly Commute Costs

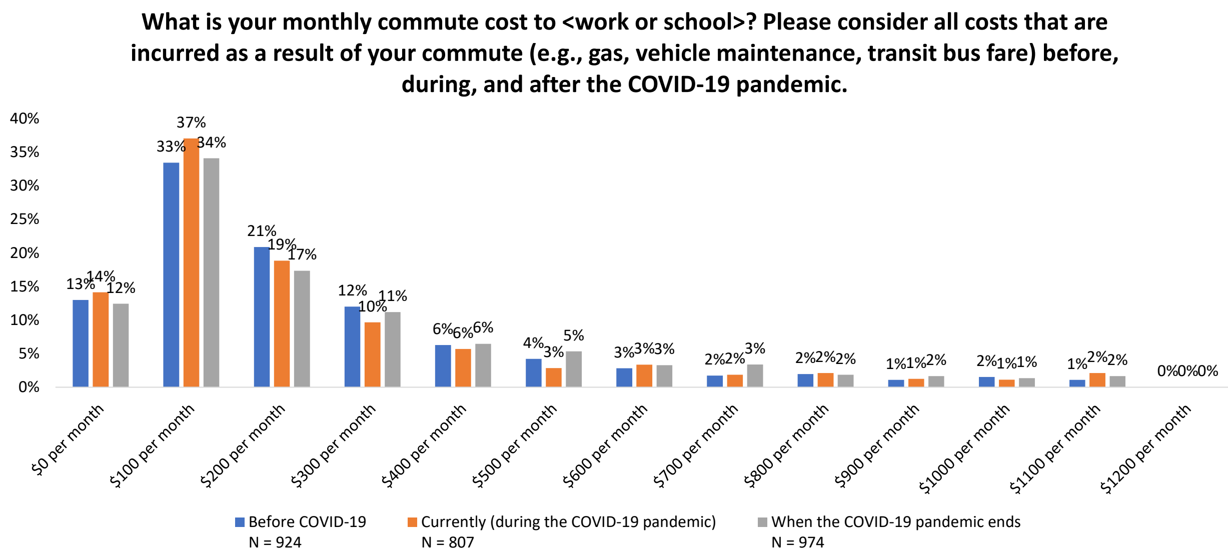


Figure 22 displays the breakpoint cost at which respondents would not consider driving. 10% think any amount is too expensive. 54% would consider $200 per month or less to be their breakpoint cost. Another 15% would consider $300 per month to be too expensive, leaving nearly 70% respondents to consider mode shift at or below this threshold cost. On the other hand, less than 15% consider $600 per month and above to be too expensive.

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In Figure 22, 10% think any cost involved in driving is too expensive for commute. A total of 54% believe that $200 per month or less is too expensive, while $300 per month brings the total percentage up to approximately 70% that believe pricing to be a strong influence on the decision to commute by driving. Therefore, a monthly cost within this $200-$300 range is a potential threshold cost that makes driving cost burdensome for most commuters. This value could be used in calculation and determination of subsidization costs for driving. Respondents were also surveyed on what costs they would consider for HOT lanes. Survey results indicate that $3 per way is a potential threshold cost as approximately 40% responded positively at this cost, and another approximate 40% also responded negatively at this cost.

$0 and $1 per way received positive responses by 49-55%, suggesting that keeping prices around this point may lower the pricing barrier for about half of the respondents.

A large share of respondents stated that they would not use either lanes could suggest that these lanes are not needed to service the commutes of a fair share of the population. The underlying reason may be that HOV/HOT lanes serve a limited share of the general population and that only a subset of that population can make reasonably use of such lanes. Pricing could also be a potential barrier to use HOV and HOT lanes as approximately 50% believe that driving costs of $200 per month are too high and $5 per way for HOT lanes would not be considered. However, it should be noted that these survey results were collected before gas prices had risen to approximately $6-7 USD per gallon. These inflation prices could substantially affect the threshold and breakpoint costs.

7.2 Park and Ride

Park and ride lots is a resource that provides a convenient location to transfer from single passenger vehicle to other ridesharing, pooling or public transit systems. These locations are essentially parking lots where vehicles can be parked for a certain period of time as they complete the rest of their trip through pooling or public transit. Thus, the primary benefit of constructing a park and ride facility is encouraging ridesharing and public transit. The increased passenger occupancy would ideally remove vehicles from the transportation network and increase person throughput (Caltrans, 2010). This in turn would reduce traffic congestion and improve the overall mobility and performance of the transportation system (Public Works Los Angeles County and Parkhurst, G., 2000). Simultaneously, park and ride users benefit through reduced costs and time travel savings from the shift to multiple occupancy vehicles and transit. Improved accessibility is another expected byproduct of park and ride lots as it serves as a connection point to a variety of modal options (Caltrans, 2010). This is especially true for travelers from suburban and rural areas trying to reach urban destinations. Facilities situated at the urban fringe allow these travelers to park their cars and switch to other modal options that can take them to the city center. Situating Park and ride lots at the urban fringe would not only improve urban accessibility for these users, but also allow them to benefit from travel time savings as the number of vehicles entering the city is reduced (Zijlstra, T. et al., 2015). Overall, park and ride facilities can serve as means of sustainably meeting transportation demand and needs through encouraging multiple occupancy and transit use.

However, there is no solid consensus that park and ride facilities leave a net positive effect on the transportation system. Katoshevski-Cavari R. et al. (2018) found park and ride facilities could induce a shift to multi-modal travel as commuters may first drive to the facilities before transferring to public transportation. This could lead to increased car dependence and additional trip generation (Parkhurst, G., 2000). Assuming that the generalized cost of travel was reduced due to park and ride, Parkhurst, G. (2000) noted that two studies reported a maximum of approximately 11-20% of samples stating they would not have made their trips without the park and ride lots (WSA, 1998 and Parkhurst, 1996). Attractiveness to park and ride schemes could turn these lots into a source of traffic growth as transit users would switch to accessing these sites by car. However, Katoshevski-Cavari R. et al. (2018) has noted that these additional car trips are undertaken in uncongested areas. Parkhurst, G. (2000) noted that of the eight park and ride schemes he had investigated, traffic was avoided in seven out of eight cases, whereas traffic was redistributed to outside the urban areas due to drivers making detours to the park and ride. He concluded that park and ride's effect on traffic is better described as traffic redistribution rather than traffic reduction.

Other studies on the effectiveness and success of park and ride facilities have produced more positive results. In Katoshevski-Cavari, R.'s (2018) study in which the park and ride scheme is merged with a fast lane, and a shuttle running on the fast lane, it was found that the main group of potential users were daily commuters in the 26-50 year-old age group. This service was especially popular during the morning rush hours and shifted more than 50% of their current riders from commuting by car to public transportation. A study in Netherlands showed that approximately 40% of their 738 respondents would not ride transit without a park and ride facility (Mingrado, 2013), indicating that park and ride can be effective in attracting users to public transit. Several studies identified that the factors that contribute to the success and effectiveness of park and ride facilities include time travel savings, quality and quantity of offered public transportation at the facility, available shuttle services, price, and size of the facility. Many studies agree that time travel savings is one of the prime motivators that make the park and ride schemes effective (Van der Waerden et al., 2011; Sherwin, 1998; Zijlstra et al., 2015). Previous studies by Bowler et al. (1986) and Foote (2000) showed that offering shuttle services at these facilities significantly increase their attractiveness. Katoshevski-Cavari, R. et al. (2018) reaffirms this with their study as 30% of the users stated they were willing to pay for the service (at the time of the study, it was free) given that the service was comfortable and frequent. In Zhao et al.'s (2019) study, they investigated the effect of ORCA LIFT program, a reduced fare program for low-income riders (income at or below $35,000 per year). They found that the ORCA LIFT program and bus-rail integration to be the most efficient policy tool, as it jointly created a positive effect on ridership and positive externality on park and ride utilization.

California currently has park and ride facilities in all 12 districts as defined by Caltrans. Park and ride facilities are specifically for commuter parking and not for other long-term parking purposes. Parking restrictions vary according to the different locations, but most locations do not allow parking for more than 24 hours. Most are free of charge and permits are usually not necessary. Parking spaces offered at each lot can be at a minimum of less than 10 spaces, while other larger lots could accommodate up to more than 500 spaces (Caltrans, 2021). Most locations will have 1 or more regional transit options.

In this section, we investigate park and ride and whether it affects carpooling, vanpooling and ridesharing. We will look at the public sentiment regarding these services and try to identify potential barriers. Due to common use of park and ride lots for commutes, we looked at key associating factors such as commute distance, commute cost, and commute frequency. It should be noted that this survey was conducted during the pandemic, which is reflected in some of the survey questions and responses.

7.2.1 Park and Ride Results

Park and Ride infrastructure is distributed around major transportation corridors and mostly urbanized regions within the state. A distribution of Park and Ride lots is shown in Figure 24, also derived from Caltrans GIS data (Caltrans, 2022). As noted in Figure 19, manty of the Park and Ride lots are located along highway and transit corridors. However, the scope of all such lots extends beyond the core urbanized regions of the state, including into locations that do not have HOV/HOT lanes or any form rail public transit.

Figure 24. Park and Ride Lots within California

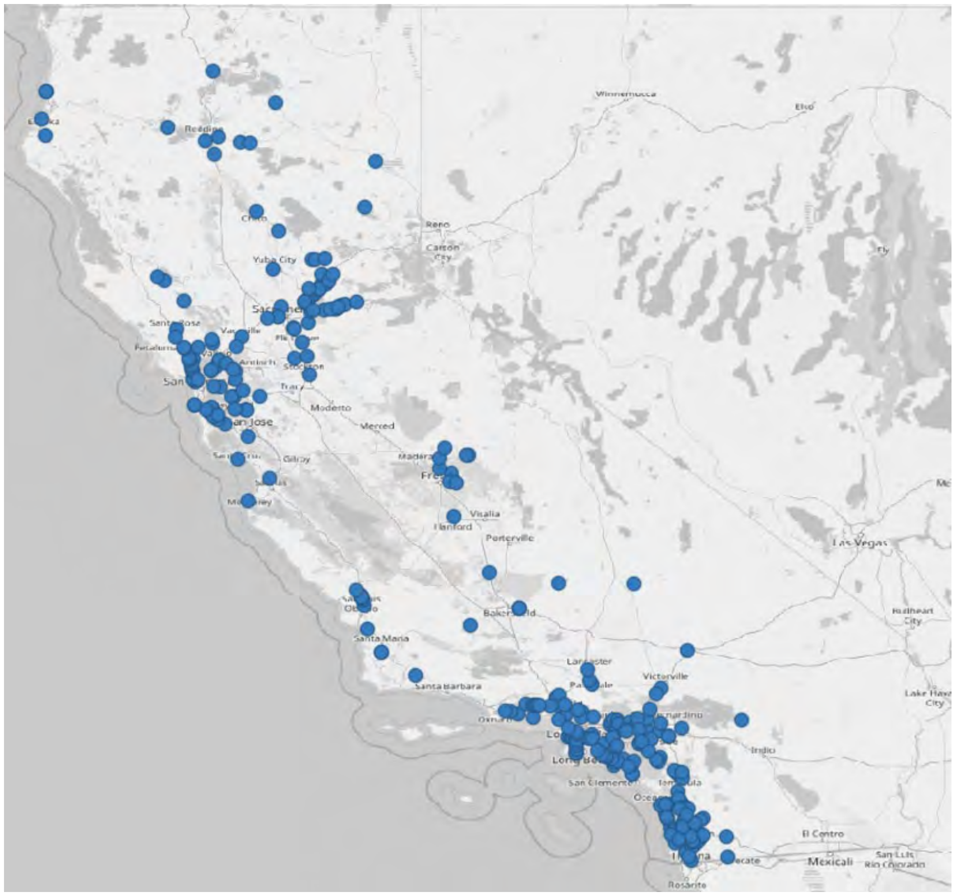


Figure 25 investigates the respondent's opinions on pooled ride services. When analyzing these results, we grouped the answer choices into 3 general categories: positive/agreeable reaction (strongly/somewhat agree), neutral reaction (neither agree nor disagree), and negative/disagreeable reaction (strongly/somewhat disagree). Approximately 60% agree with the statements that they are uncomfortable sharing rides with strangers and that they do not feel safe doing so. Only 24% would prefer to share rides rather than ride alone, while 54% preferred the opposite. There is a roughly equal percentage of agreement (35%) and disagreement (34%) on the statement that the reduced costs of shared rides are worth its drawbacks.

Respondents who indicated that they have used Transportation Network Companies (TNCs) such as Uber or Lyft were further asked if any of their TNC rides were shared. Based on the results, most preferred to ride these TNC services alone. Nearly 50% of respondents stated that none of their current rides with TNCs used shared services. Only 15% stated that 1-10% of their rides used shared services. As the percentage of rides using shared services increased, the percentage of respondents decreased. Across 11% to 75% of rides range, there are 10%-15% of respondents who fall in this category.

Figure 25. Opinions on Pooled Ride Services

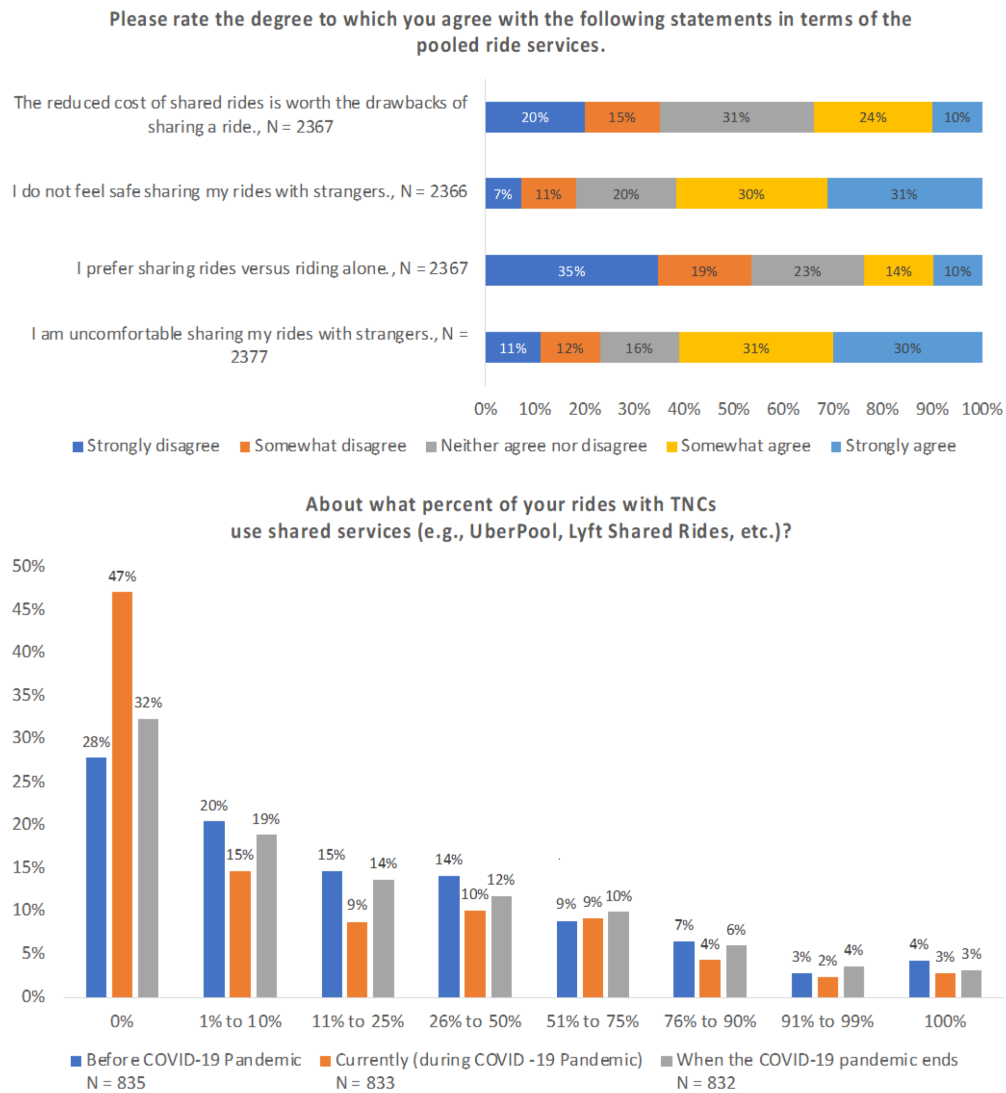


Figure 26 looks at respondent's general willingness to carpool or vanpool for work/school commute. Descriptions of each mode were provided. Carpool was defined as 2-5 commuters sharing a commute in their personal vehicles. Vanpool was defined as a commute shared among 6 to 13 people, in a leased van. Both modes were suggested to commonly meet at park and ride lots.

If the respondents had to choose between carpool and vanpool, 82% would prefer carpooling over vanpooling. This may suggest that policies focused on pooling may find more success with promoting carpooling versus vanpooling. Respondents who previously indicated that they were employed full-time or part-time or students were inquired whether they would consider pooling for their commute. 53% of these commuting respondents would still prefer other options over carpool/vanpool. Of the 53%, the most preferred method would be to drive themselves. Of the remaining 46% who indicated positive interest in carpooling or vanpooling, only 13% would definitely use them if the cost was low enough and if it worked with their schedules. The results suggest that about half of respondents within the sample that had a job or school to go to would be receptive to the concept of carpooling/vanpooling and would consider the mode if the costs of it were competitive with commuting by driving alone.

Figure 26. Opinions on Carpool/Vanpool

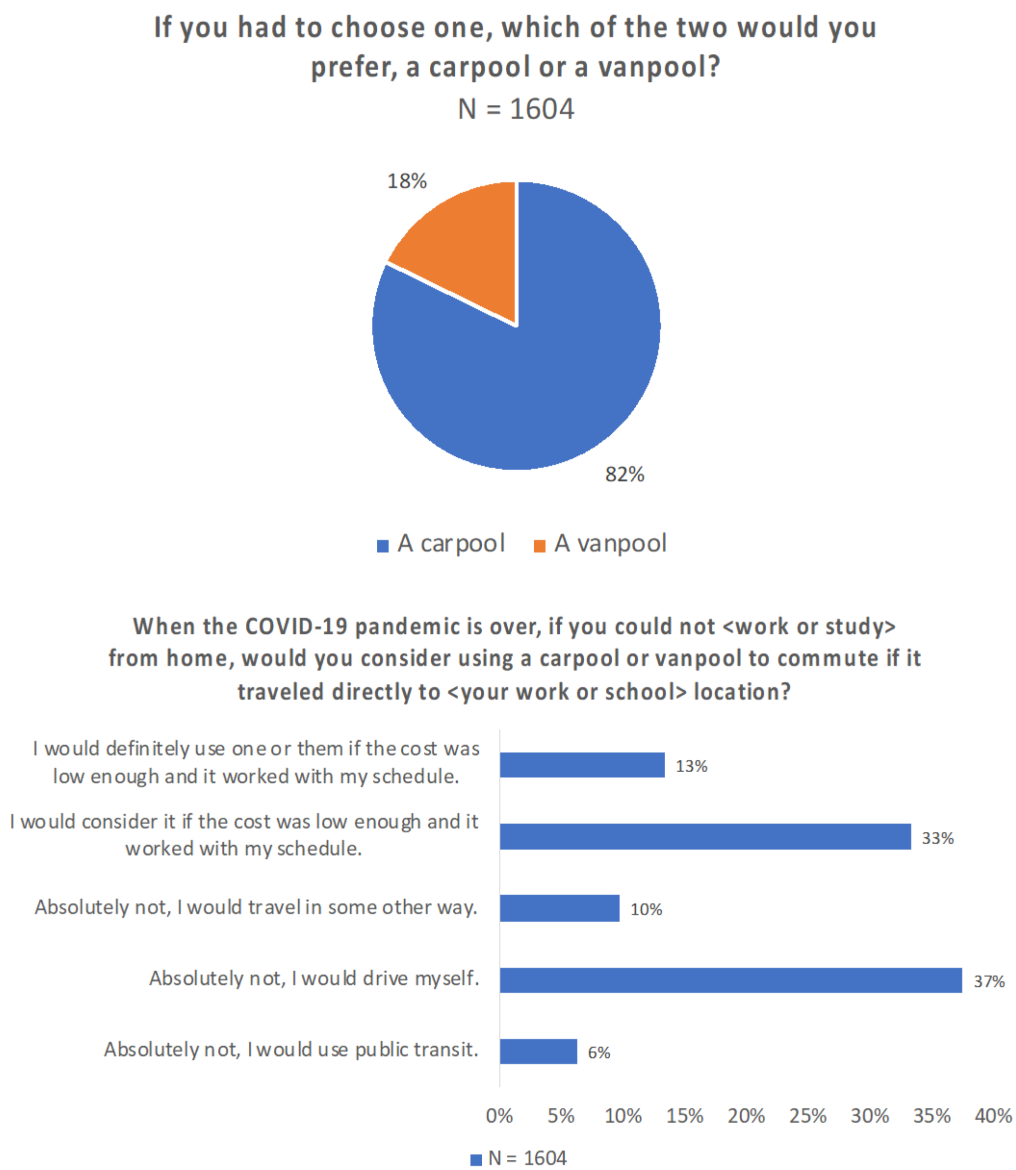
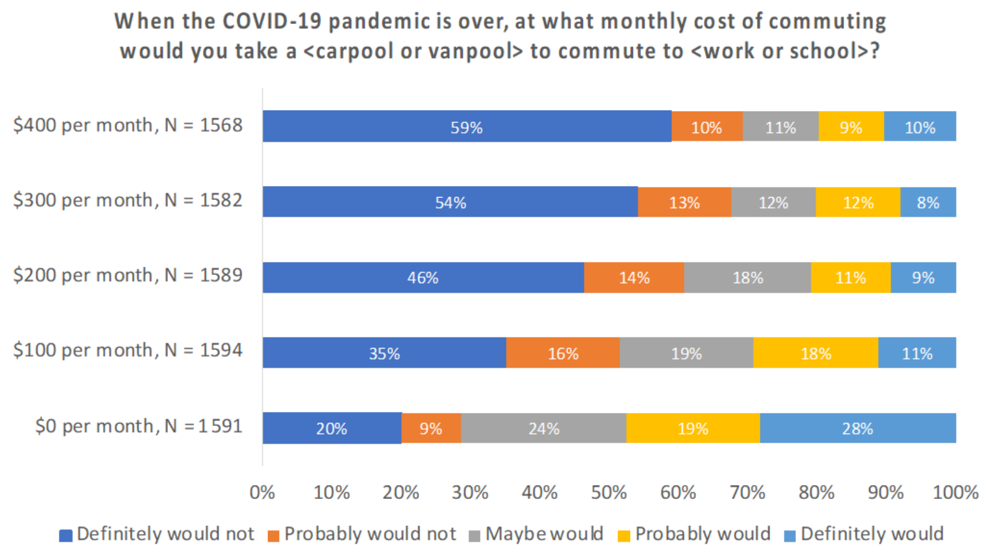


Figure 27 investigates factors that may affect consideration of carpooling or vanpooling after the COVID-19 pandemic. In the first chart, respondents are more inclined to carpool/vanpool at lower monthly costs. At $0 per month, 47% stated they probably or definitely would use these forms of commute. However, at $100 per month, this percentage dropped to 30%. Starting at $200 per month, this percentage consistently stays around 20%. Conversely, 30% still probably or definitely would not use carpool/vanpool at $0 per month. This percentage increased to 51% at the next price range of $100 per month. From $200 to $400 per month, this percentage increased from 60% to 70% that probably or definitely would not carpool or vanpool.

The second chart looks at a question that provides respondents with different circumstances to consider in the decision to carpool/vanpool after COVID-19. Note that at the time of the survey, the restrictions and ongoing impacts of COVID-19 were still very active, and the purpose of this question was to allow respondents to opine as to how they felt certain travel behaviors might return following the end of the pandemic. Naturally, the exact timing of the end-of-the-pandemic was unknown to respondents and such an event probably does not have a precise date. The purpose of these types of questions was to assess what their post-pandemic normal circumstances might look like with respect to travel behavior. The three circumstances include: riding with someone you know, accommodating individual preferences by vetting passengers and drivers, and clean, sanitized vehicles. In all three circumstances, there were similar distributions across the different degrees of opinions. Around 40-45% stated they probably or definitely would consider taking a carpool/vanpool. 30% stated they maybe would consider carpooling/vanpooling and 25-30% probably or definitely would not consider it.

Figure 27. Consideration of Carpool/Vanpool under Different Circumstances and Pricing



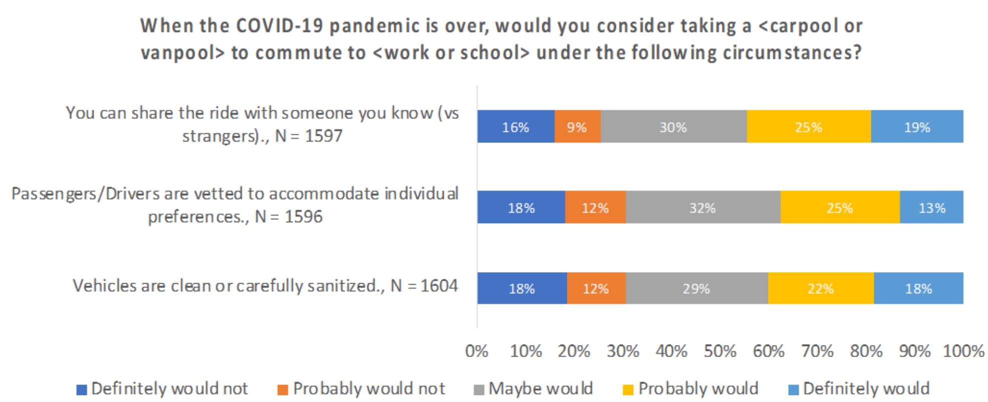
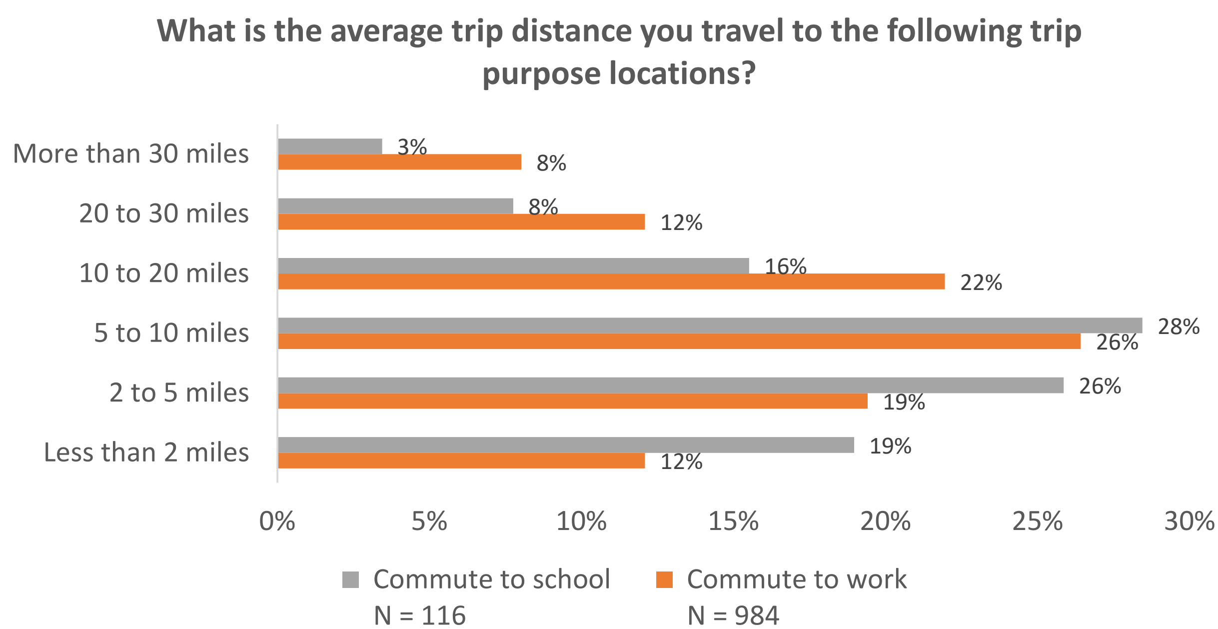


Figure 28 shows the reported average distances of the work/school commute that may affect the need or desire to carpool/vanpool. 26% and 28% of commute to work and school, respectively, require an average trip distance of 5 to 10 miles. 67% of commute to work ranged from 2 to 20 miles. 73% of school commute range from less than 2 miles up to 10 miles. Only 11% and 20% of commutes to school and work, respectively, were 20 miles or more.

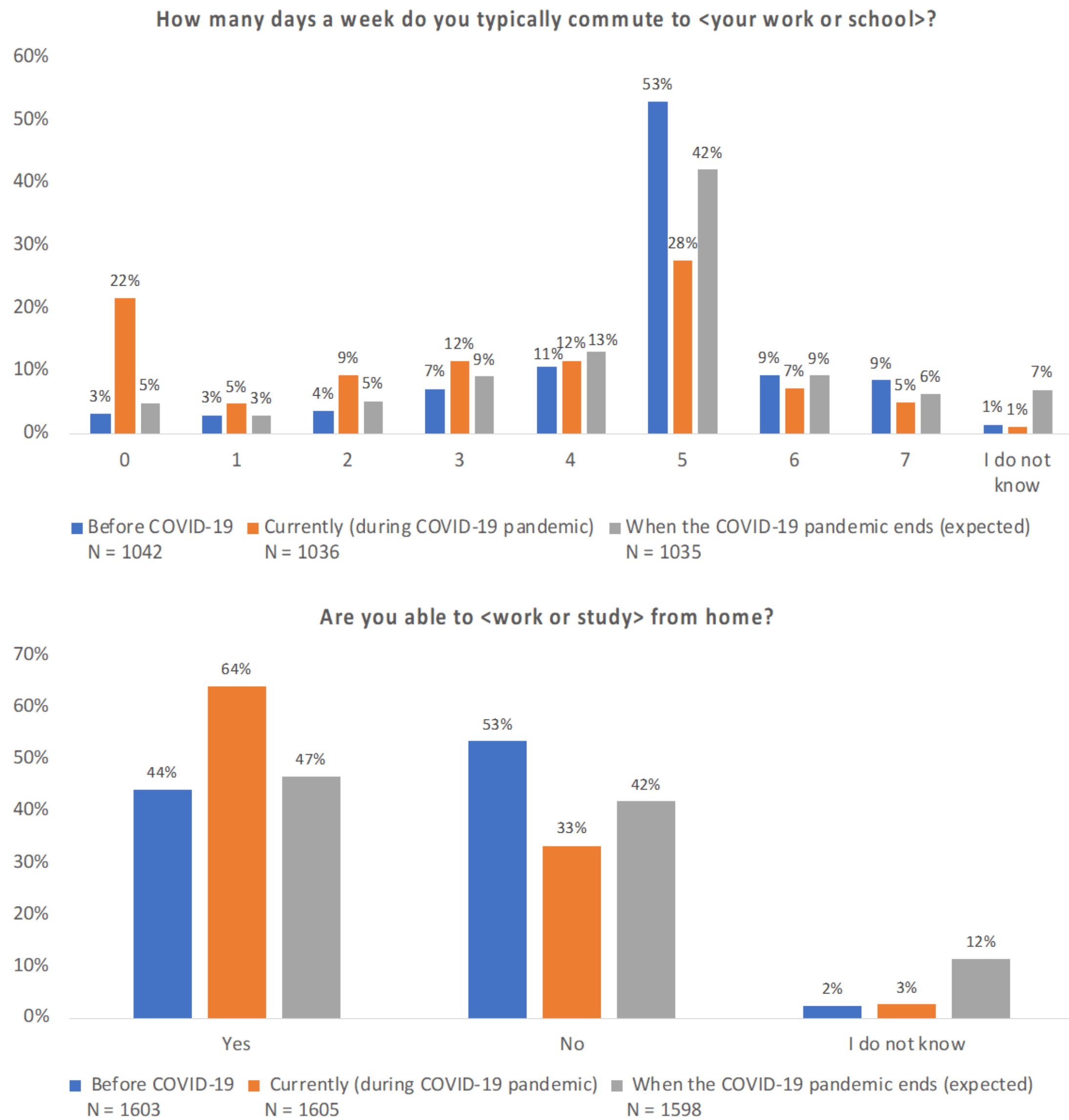
Figure 28. Average Distances of Commute



Commute was typically required 5 days of the week, as seen in Figure 29, where 53% of respondents reported commuting 5 times a week before COVID-19. However, this dropped to 28% during COVID-19 and is expected to rise back to 42% after the pandemic ends. Another 22% responded that they did not need to commute at all during the pandemic, but this is also expected to drop to 5% when the pandemic ends.

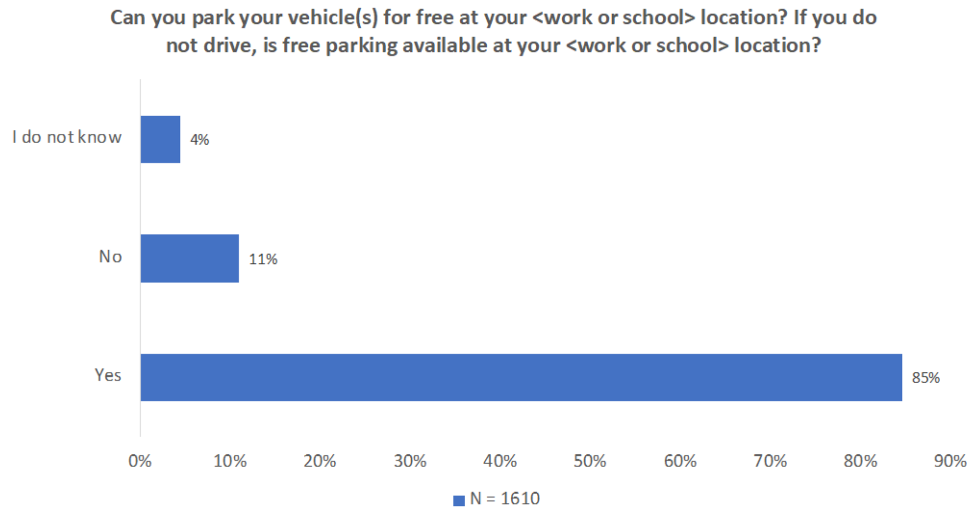
Respondents were also inquired about their ability to work/study from home. During the pandemic, 64% are able to work/study from home, but this is expected to fall back to 47% after the pandemic. The percentages after the pandemic are similar to percentages prior to the pandemic, possibly suggesting that conditions are expected to return to normal, with the exception of a slight increase in the ability to work/study from home after the pandemic. Notably, 12% are unsure about their situation after the pandemic.

Figure 29. Commute frequency and Ability to Work/Study from Home



To investigate whether work/school locations support commute by personal car ownership/user, we inquired respondents about accessibility to free parking at these locations. Figure 30 shows an overwhelming 85% stating that such accommodation is available at their work/school locations. Just over 10% stated that this is not available at their locations.

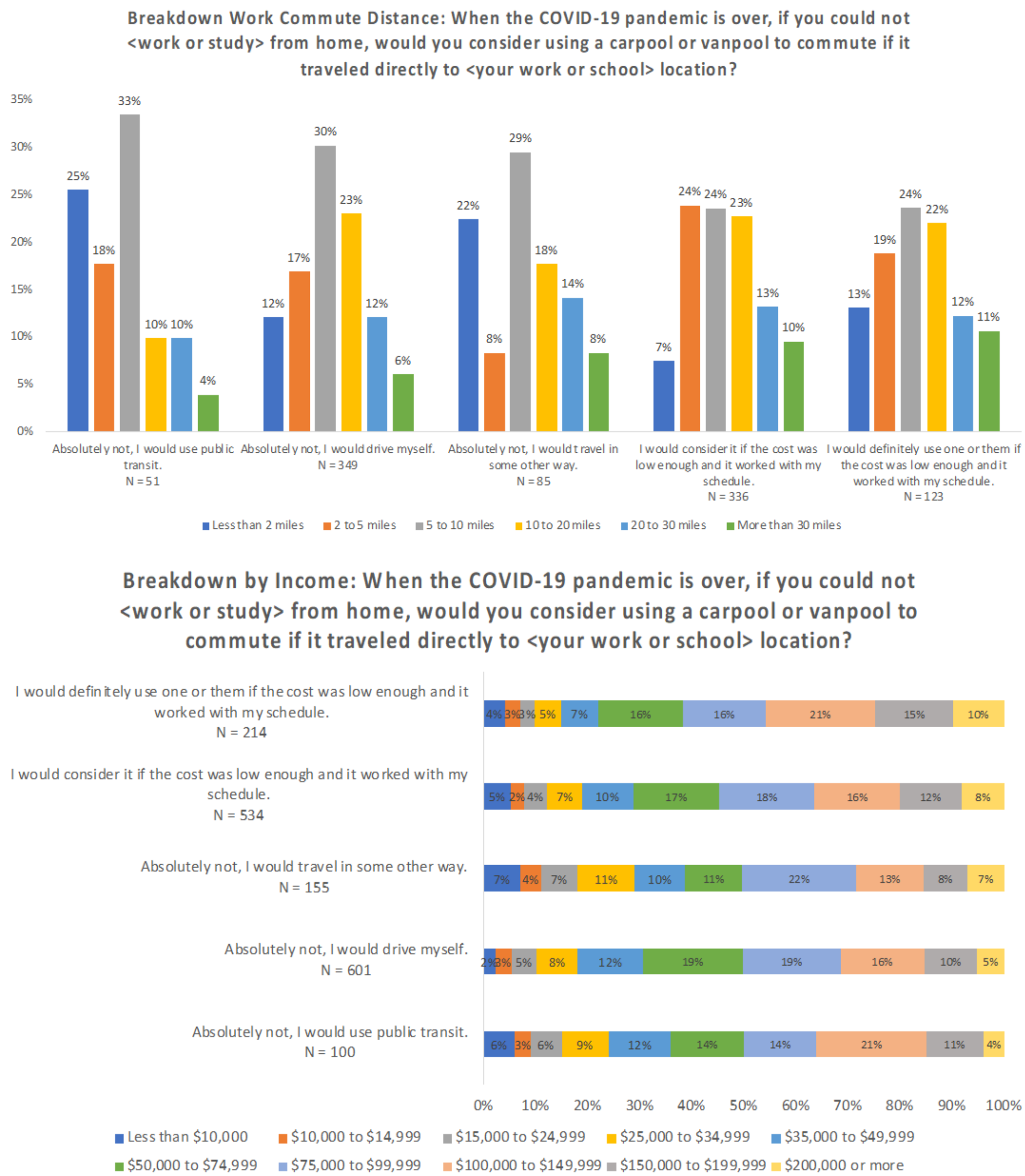
Figure 30. Free Parking Availability at Work/School Locations



Breakout analysis on the question asking about interest in commuting by carpool or vanpool was performed and the results are shown in Figure 31 below. The first chart is an analysis of the distribution of work commute distance among each answer selection. Although the preference to drive oneself received the most selections (N = 349), the other two options that positively considered carpooling or vanpooling were the next two popular selections (N = 336 and N = 123). The breakout analysis shows that around 65% to 71% of respondents who selected these options had a work commute distance from 2 to 20 miles. These three categories of commute distance also had a relatively equal distribution within these answer selections. Of the three other answer options, those that had shorter travel distances would prefer public transit, and those that a commute distance closer to the average 5 to 10 miles were more likely to drive themselves to work. Those that traveled shorter distances for work commute as well as those that traveled 5 to 20 miles would prefer to find another mode of travel.

The second chart is an analysis of the income distribution among each answer selection. Approximately 50% of the respondents in each answer selection comprised of income levels from $50,000 to $149,999. In both positive answer selections, there was an approximately equal distribution in the remaining respondents, with income below $50,000 and income above $149,999. In all of the negative answer selections, 15% of the respondents had income above $149,999 and 30-40% of the remaining respondents had income below $50,000. Of these three answer selections, a greater percentage of respondents who preferred to travel in some other way or by public transit, had income below $50,000.

Figure 31. Breakout Analysis of Opinions on Carpool/Vanpool

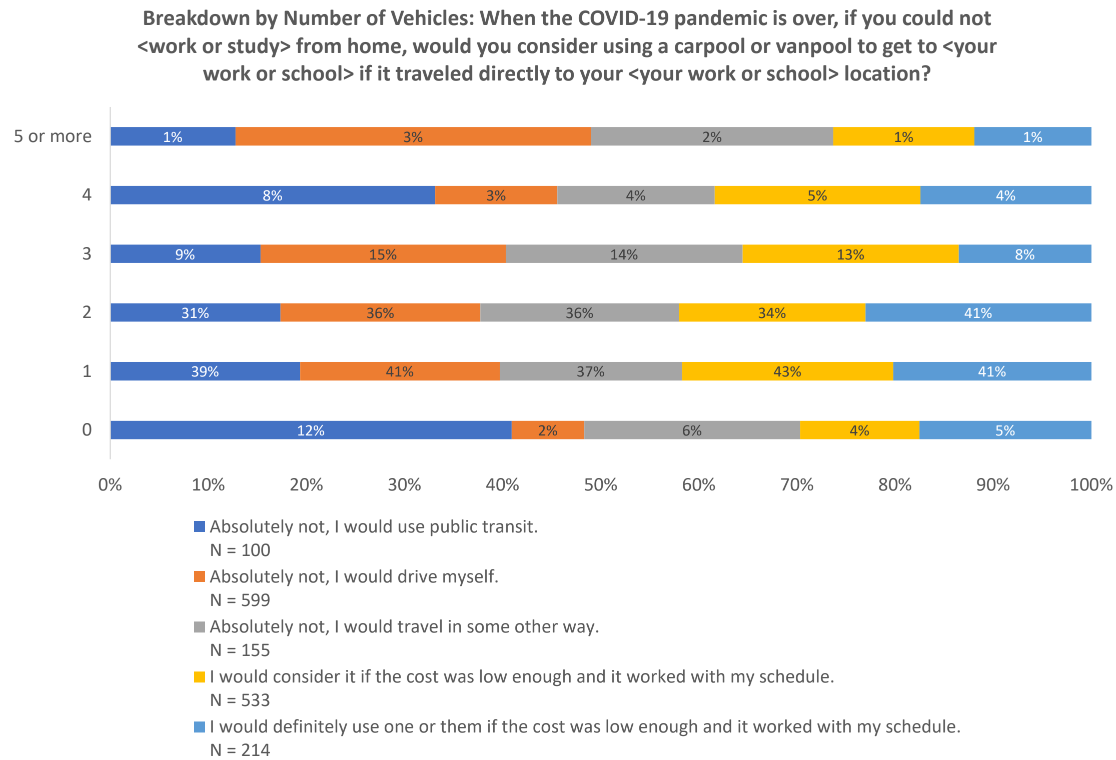


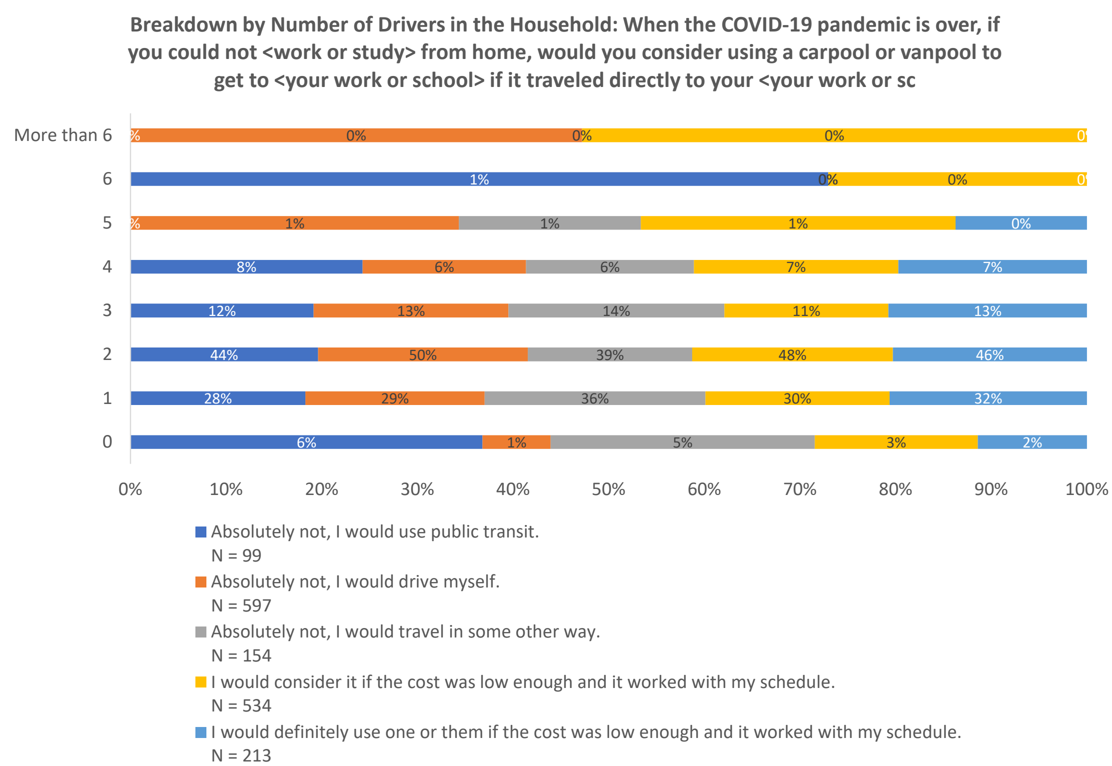
Breakdown by the number of vehicles and drivers in a household was performed in Figure 32 to see if there is any correlation with opinions on carpool/vanpool. For every answer selection, 70-80% of each answer option was selected by respondents with 1 or 2 vehicles. Similarly, the breakdown by the number of drivers had 70-80% of respondents with 1-2 drivers in their household for each answer option.

Although the proportion of respondents with 0 vehicles are much less compared to the proportion of those with 1-2 vehicles, there were approximately 31 people in the 0 vehicles category who responded positively to this question. In the three other answer options, approximately 33 of the respondents were also in the 0 vehicles category. Notably, there were around 24 people in this category who would prefer driving themselves or using public transit, whereas there were 21 people who stated they could consider carpool/vanpool given that it was convenient and cost-friendly. 13-20% of the respondents for each answer option had 3 or more vehicles in their household. While approximately 125 people in this category responded that they would drive themselves, another 129 respondents from this category stated they would consider the carpooling/vanpooling.

Breakdown by number of drivers in the household also saw approximately 20% of each answer option selected by those with 3 or more drivers in the household and had similar distribution of counts as seen in the breakdown by number of vehicles. Of the respondents that did not have any drivers in their household, 20 of them responded positively to carpooling/vanpooling, whereas the other 17 responded negatively.

Figure 32. Breakdown by Number of Vehicles and Drivers in the Household





7.2.2 Park and Ride Findings

Park and ride lots support shared rides. However, survey responses generally indicate that most do not prefer to share rides. Most cite that they are uncomfortable with sharing rides, particularly with strangers. Another top concern of pooled ride services is feeling unsafe pooling with strangers. Each of these concerns were indicated by approximately 60% of respondents. Only 35% agreed that reduced costs were worth the drawbacks of sharing a ride, suggesting that cost is not a top priority compared to other factors and/or cost may not be a considerable barrier in riding individually. These concerns are also reflected in behavior as most respondents indicated that they rarely or do not use shared services when riding with TNCs. The COVID-19 pandemic seems to have introduced an additional factor of health risk, leading to projections of greater percentages that would not use shared services, even after the end of the pandemic. Even with considerations such as the option to ride with familiar passengers, careful sanitization, and vetting of drivers and passengers to accommodate individual preferences, only 40-45% responded positively.

Carpooling/vanpooling and use of park and rides are typically used for commute to work or school. Thus, respondents asked whether they would consider carpooling/vanpooling for their commute if it took them directly to their destination. 46% responded positively under the condition that cost was low enough and it worked with their schedules. Although responses to other questions suggested that cost may not be the topmost concern in sharing rides, targeting costs and bringing them down could still bring in more potential users. These potential users are most likely to come from household income levels within $50,000 to $149,999, and also potentially from household income levels below $50,000. These households are also likely to have 1 to 2 vehicles and drivers.

The influence of cost was also investigated by inquiring about what monthly cost would encourage respondents to commute by carpool/vanpool. At $0 per month, less than half of respondents would consider carpool/vanpool, and at $100 per month, this percentage drops to 30%. Responses also show that 30-40% already have existing monthly commute costs at $100 per month. Thus, cost may not be a strong incentive for a majority of the population even at $0 per month, but there is a substantial amount of potential users for whom cost may remain a top barrier to these options.

We looked at whether there was a need for carpooling/vanpooling by investigating commute frequency, parking availability, and commute distance. On average, commute distance typically falls within 2 to 20 miles for work and 2 to 10 miles for school. Of the respondents who responded positively to considering carpooling/vanpooling, approximately 70% of respondents have work commute distance within the average range of 2 to 20 miles. These respondents typically commute 5 times a week, but it has dropped throughout the pandemic and transitioned to working from home and is generally expected to rise back to the same frequency when the pandemic ends. These results further suggests that most of the potential users will comprise of working adults that commute every day of the work week for an average commute distance within 2 to 20 miles. However, most workplace locations have free parking available, supporting personal car ownership and usage.

Most seem to be deterred from sharing rides due to the convenience of driving oneself and concerns over safety and feeling uncomfortable sharing rides with strangers as over 60% of respondents reported that they do not feel safe sharing a ride with strangers. About 46% of respondents reported that they would ride a carpool or vanpool if the cost is low enough. Just under 30% of respondents reported that they would take a carpool or vanpool to work or school if the monthly cost was $100, while just under

50% stated that they would use one if the ride was $0 per month. These responses, while stated preference, suggest that users would consider shifting their behavior if the costs of using carpools and vanpools began to drop considerably below the alternatives.

7.3 Discussion

The analysis presented in this report explored the impacts of telework on overall VMT. The results of the analysis presented estimates the changes in overall VMT (within the sample population) that resulted from telework. These changes were presented in the context of pre-pandemic and during-pandemic behavior. The survey, given in 2021, was administered during a time of increasing recovery and opening from the lockdowns of 2020. But it was a still a time when many large-scale teleworking arrangements were in place. The analysis of the survey sample shows that the impacts of teleworking on household VMT are present, particularly among households that did not move due to teleworking. However, the presence of the pandemic is likely to have influenced the magnitude of impacts found within the analysis. Perhaps surprisingly, those that moved in response to remote work environments experienced a considerably smaller decline in VMT than those that did not move, but were allowed to telework. The analysis also presented a summary of survey responses in key areas of interest. The sample of demographic attributes and departures from the distributions of the population are shown. Additional survey results on micromobilty shown preferences and perceptions of respondents to the use and accessibility of micromobility, including user-based barriers (e.g., helmets, hills, etc.) that may also inhibit use even when vehicles are nearby. Survey results are further presented on the topics of HOV and HOT as well as Park and Ride use. Building on literature reviews of previous research in each, these survey results show responses describing awareness of HOV and HOT lanes and the propensity to use them under specific circumstances. A number of findings emerge from the summary of these results, among them, that 62% of respondents would drive in the regular lanes to commute if HOV lanes were not available or if HOT lanes were too expensive. Alternatives selected by respondents including using public transit (12%), teleworking (10%), joining a carpool (9%), and other alternatives. Such results may be helpful in informing how commute patterns may shift in response to policies that influence pricing. In the section that follows, modeling of a series of policy actions and scenarios are presented using activity-based models that parameterize scenarios with the subject areas similar and related to those addressed in the survey analysis.

8. Modeling

The rapid growth of high-occupancy, shared mobility, zero-emission vehicles, and active transportation modes in California has brought attention to their potential benefits in reducing transportation emissions. However, the full extent of their impact on travel demand and wellbeing remains uncertain. Thus, the primary objective of the modeling component of this research is to quantify their impact on travel behavior and wellbeing across different population segments for the year 2050.

To accomplish these objectives, we have integrated three separate microsimulation modeling systems into a robust research platform. The platform combines UrbanSim, which models evolution of urban development and the location patterns of households and jobs; ActivitySim, which models daily activity schedules and travel demand; and BEAM, which models traffic flow. This modeling framework is also among the first to integrate land-use and transportation modeling in a systematic, sequential, and time-consistent way. Most modeling frameworks forecast land use models to 30 or 50 years, and then, a travel model is simulated only for the last forecast year. However, this framework does not update traffic conditions that might influence land use modeling and vice-versa. Our integrated model system, on the other hand, is designed to run sequentially for each iteration year. Therefore, this modeling framework aims at capturing a more realistic and complex interdependency between land use and transportation system.

In this section, we present the results of a simulation of a policy scenario for the nine-county San Francisco Bay Area Region that extends to the year 2050, using the modeling framework previously described. The set of policies included in the scenario were chosen in coordination with the CARB team and were based on a sensitivity analysis, considering the capabilities of the model framework. The policy scenario includes a range of policy variables aimed at increasing the use of high-occupancy, shared mobility, zero-emission vehicles, and active transportation modes. Moreover, the scenario also considers possible technological and behavioral developments, such as the penetration of Autonomous Vehicles (AVs) and telecommuting.

To assess the impact of the policy scenario, we defined key performance indicators that incorporate multiple transportation-related metrics, as well as a welfare analysis. Along with the impact evaluation of the policy scenario on travel behavior and well-being, the distribution and equity of the impacts across different population segments are also evaluated. In this research we consider population segments based on income, race and ethnicity, and geographical distribution. Lastly, we conclude the modeling section with a discussion of the results, and the potential implications of the implementation of the policies.

8.1 Modeling Framework

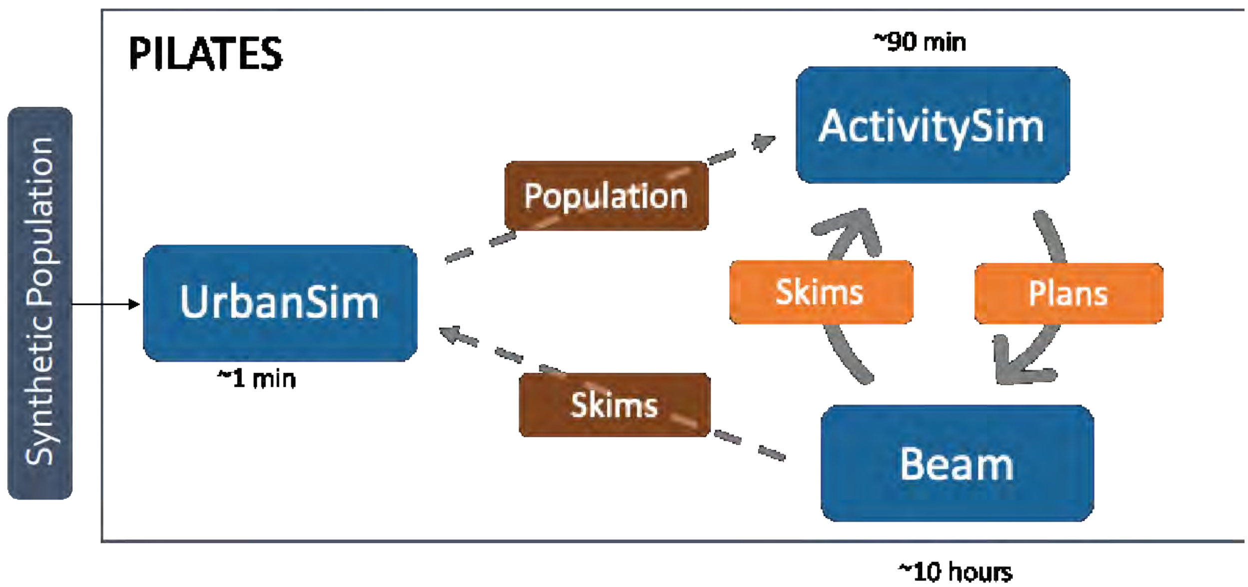
Three model systems (UrbanSim, ActivitySim, and BEAM) have been integrated for use in this project and applied in the nine-county San Francisco Bay Area (see Figure 34):

- **UrbanSim:** Land-use simulator, which models the choices made by households, businesses, and real estate developers, taking into account how these choices are influenced by different policies and investments and examine how these factors interact with transportation systems;
- **ActivitySim:** Travel demand modeling tool, which models auto ownership, workplace choice, school choice, scheduling of arrival and departure for mandatory and non-mandatory activities, as well as their mode choice; and

- **BEAM:** A tool that performs the network assignment and uses discrete choice models in agent-based simulations to predict how travelers might choose between modes and routes and hence will output behavior change indicators given different assumptions.

Although the three model systems are independent, we operate them in a combined manner using the PILATES run management framework, as depicted in Figure 33. This framework is specifically designed to facilitate the integration of various containerized microsimulation applications that fully model the co-evolution of land use and transportation systems.

Figure 33. Modeling Framework



The modeling framework in this study employs three primary inputs/outputs that flow throughout the simulator: the synthetic population, the travel plans, and the skims (defined below). The synthetic population is a comprehensive representation of the population residing in the study area, including their demographic and economic characteristics. The UrbanSim models modify the synthetic population to update household decisions, such as their residential location, based on different residential availability, cost, and transportation accessibility metrics.

The travel plans represent individual trips made by the synthetic population and are the primary output of the ActivitySim model. They contain information about the purpose, origin, destination, time of day, and mode of transportation. These plans are a crucial input for the BEAM model, which updates travel times and costs for all modes of transportation, generating what is known as *skims*. The skims reflect the travel times and costs for each mode of transportation and are used as inputs for both the UrbanSim and ActivitySim models for the following simulation year.

The present research project utilizes 2020 as the baseline year and conducts simulations until 2050 in five-year intervals. Given the approximate 10-hour runtime of BEAM, integration with ActivitySim takes place every five simulation years. While UrbanSim preserves a one-year simulation increment, skims are updated only every five simulation years.

To model individual choices, the model system uses discrete choice analysis and Random Utility Models (RUM). In discrete choice analysis, decision-makers choose from a finite set of alternatives that maximize their utility. The utility function for each alternative includes variables such as the characteristics of the decision maker, and attributes of the alternatives. The output of the discrete choice model is a probability distribution for each alternative in the choice set. To predict the actual choice, the modeling framework uses a Monte Carlo simulation technique to randomly sample a choice for the given probability distribution. When possible, we maintain the same random seed, a starting point where a computer generates a random number, for all simulation to make results as comparable as possible. A more detailed explanation of the theory and decision-making process can be found in Section 8.2.1

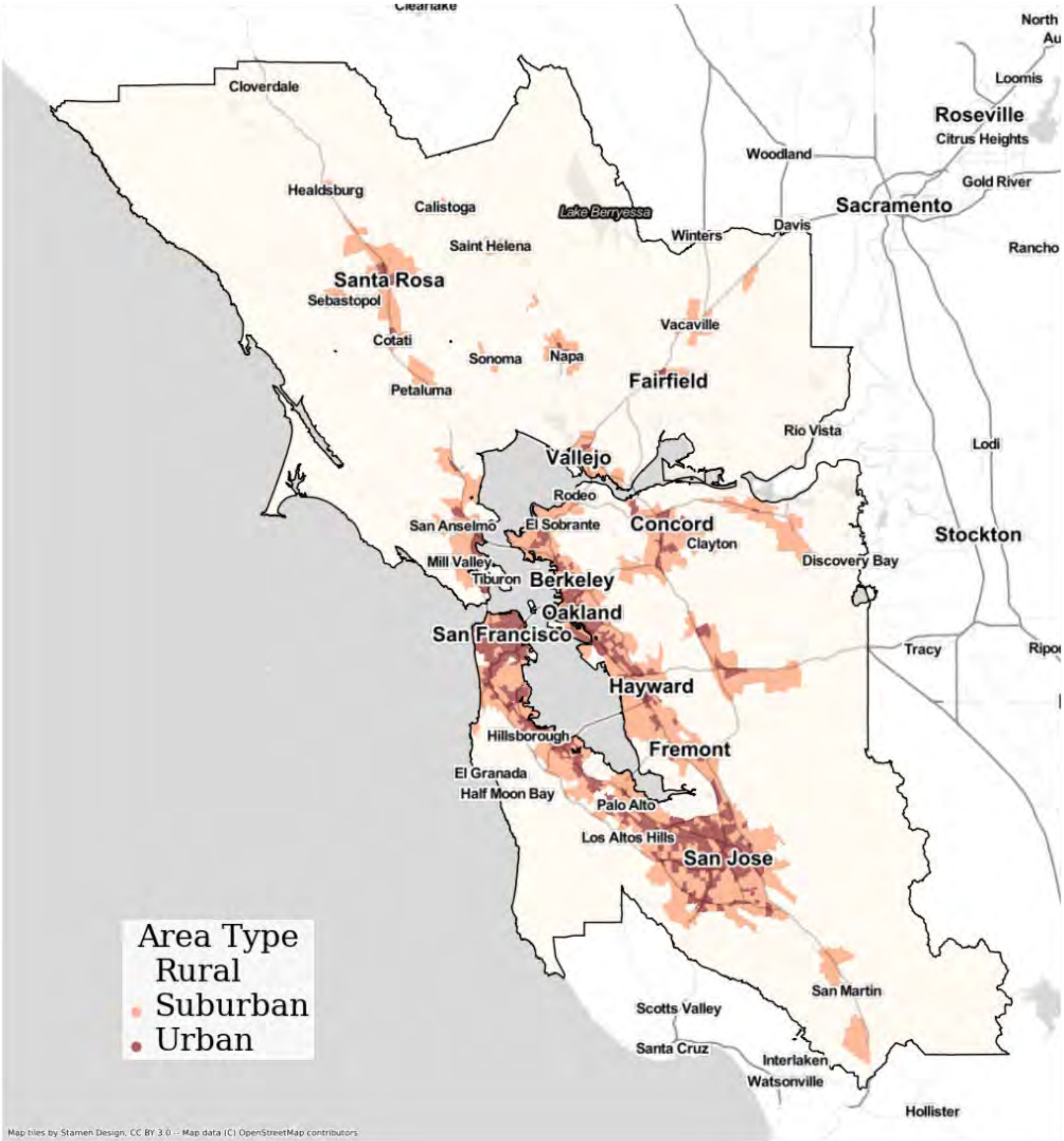
The following sections provide more detailed information on the inputs and each model system. Given different levels of documentation and multiple sources for each model, we have included relevant links to references that can serve as supplementary resources for further documentation.

8.1.1 Model Inputs and Assumptions

This section presents inputs for the models, including the synthetic population, land use, and transit operations for the nine-county region of the San Francisco Bay Area. The nine counties included in the region are: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma. A map depicting the area of analysis, along with the area type for the 2020 baseline year, is presented in Figure 34. Additionally, references for further documentation are also provided.

- **Blocks:** The block is the unit of analysis in the UrbanSim Models. The model uses the 2010 census block geometries identified with the 15-digit Federal Information Processing Standard (FIPS) number. For the Nine-county San Francisco Bay, the total number of census blocks is 108,469.
- **Synthetic Population:** The synthetic population is built using a synthesizer Synthpop (Ye et al., 2009) using block-group level demographic marginals distributions (e.g., income, household children, head of household age, number of vehicles) from the 2009-2013 5-year American Community Survey (ACS), Public User Microdata Survey (PUMS) and the Public Use Microdata Areas (PUMAS). The synthesizer uses the marginal distributions to create joint distributions using an iterative proportional updating algorithm. Given that the base data is only a subsample of the population, the synthesizer uses the joint distributions to create a full representation of households and persons, such that it matches the total household population in the census data. For the 2020 baseline year, the households and persons summary statistics in the nine-county San Francisco Bay Area are presented in
- In this study, the population growth is projected based on a control total obtained from the census data, as presented in Table 15. Addition of new households and agents involves sampling households from the existing population until the control total is attained. While this approach facilitates the modeling of population growth, it presupposes a certain level of homogeneity in the demographic composition over time.

Figure 34. Nine-County San Francisco Bay Area Type by TAZ (baseline year 2020)



The area type category is obtained based on the population and employment density consistent with the MTC definition: (population + 2.5 employment)/Area (in acres). Rural: 0-6, Suburban: 6-30, Urban: 30+.

In this study, the population growth is projected based on a control total obtained from the census data, as presented in Table 15. Addition of new households and agents involves sampling households from the existing population until the control total is attained. While this approach facilitates the modeling of population growth, it presupposes a certain level of homogeneity in the demographic composition over time.

Table 13. 2020 Baseline Household Summary Statistics

Demographic Attribute	Category	Count	Pct.
Income[3]	Low ($0 - 80k)	1,475,456	51.7%
	Middle ($80k - $150k)	761,433	26.7%
	High Income ($150k+)	615,832	21.6%
Car Ownership	None	217,310	7.6%
	One	827,110	29.0%
	Two	1,195,753	41.9%
	Three	428,542	15.0%
	Four or more	184,006	6.5%
Household Workers	None	636,027	22.3%
	One	1,153,136	40.4%
	Two or more	1,063,558	37.3%
Household Size	One	761,385	26.7%
	Two	893,810	31.3%
	Three	461,482	16.2%
	Four or more	736,044	25.8%
Total Households		**2,852,721**	**100.0%**

Table 14. 2020 Baseline Population Summary Statistics

Demographic Attribute	Category	Count	Pct.
Race	White	4,254,794	57.1%
	Asian	1,773,365	23.8%
	Black	1,000,122	5.6%
	Other	420,110	13.4%
Hispanic	Yes	1,654,872	22.2%
	No	5,793,519	77.8%
Sex	Female	3,789,038	50.9%
	Male	3,659,353	49.1%
Age	0-20	1,905,444	25.6%
	20-30	914,122	12.3%
	30-40	1,006,261	13.5%
	40-50	1,116,800	15.0%
	50-60	1,137,774	15.3%
	60+	1,367,990	18.4%
Total Population		**7,448,391**	**100.0%**

[3] Income categories are based on the 2019 median income of the San Francisco – Oakland – Berkeley Metropolitan Area of $106,025 (ACS, 2019). Low income is roughly 80% less of the median income, middle income is 80% to 150% of median income, and high income is 150% greater than median income.

- **Employment Data:** The employment data is based on the Census Longitudinal Employer-Household Dynamics (LEHD) data, which contains job estimates at the census block level. The employment data is stored in the jobs table and contains information about the sector (using NAICS sector ID) and the location where the job is located.

For future simulation years, the population and employment growth are controlled by target values derived from census projections, as shown in Table 15. To add new agents due to population growth, we re-sample households from the available pool to maintain the population demographic distribution.

Table 15. Control Totals - Number of Households and Jobs in the San Francisco Bay Area 2020 – 2050

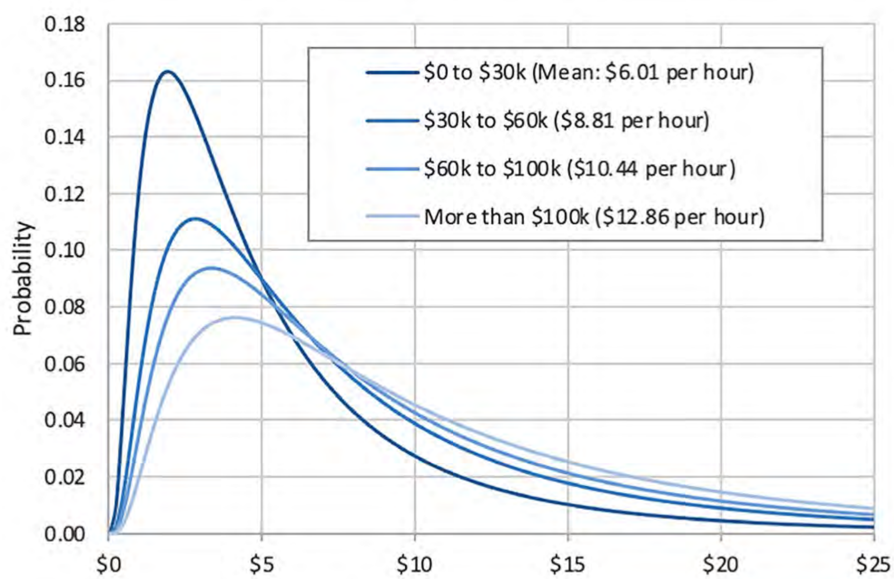
Year	Control Totals *Number of Households*	Control Total *Number of Jobs*
2020	2,852,721	5,261,920
2025	2,927,113	5,364,976
2030	3,014,649	5,468,408
2035	3,096,392	5,575,060
2040	3,173,057	5,685,031
2045	3,238,257	5,798,430
2050	3,287,392	5,915,370

- **Residential Units:** The residential units are extrapolated from a joint distribution estimated with the 2009-2013 5-year ACS, using a marginal distribution of units per structure built and tenure at the census tract level. The total number of residential units matches the residential units in the census.

  For more information on the synthetic population, employment, and residential units, refer to the following:
  https://cloud.urbansim.com/docs/general/documentation/urbansim%20block%20model%20data.html#block-households-table
- **Enrollment:** Enrollment data contains information on k-12 and higher education enrollment using the Education Data Explorer API. The information includes data on public and private schools for the year 2015. Further information can be found at: https://educationdata.urban.org/data-explorer
- **Transit Operations:** The standard General Transit Feed Specification (GTFS) format contains information such as routes, stops, and trip information of public transit systems. The following is a compiled list of the 28 transit agencies in the San Francisco Bay Area that publish their GTFS on their websites and therefore are included in the simulation: Tri Delta Transit, AC Transit, Capitol Corridor, American Canyon Transit, BART, Caltrain, County Connection, ACE Altamont Corridor Express, San Mateo County Transit, Dumbarton Express, Emery Go-Round, Golden Gate Transit, Alcatraz Hornblower Ferry, Marin Transit, Petaluma Transit, Rio Vista Delta Breeze, San Francisco Bay Ferry, San Francisco Municipal Transportation Agency (SFMTA), Stanford Marguerite Shuttle, Sonoma County Transit, Santa Rosa CityBus, SamTrans, Union City Transit, Vacaville City Coach, Vine, VTA, WestCat, and Livermore Amador Valley Transit Authority.
- **Road Network:** The network used is publicly available from the open street map API. For the San Francisco Bay Area, the network encompasses the nine-counties region.

- **Transit Analysis zones:** A Transit Analysis Zone (TAZ) are predefined zones within the area of analysis, such that the travel demand for each zone is relatively similar. The Metropolitan Transportation Commission has defined 1454 TAZs for the San Francisco Bay.
- **Model specifications:** The model specifications employed in this study are consistent with those utilized in the original implementation of each model system for the nine-county San Francisco Bay Area region. It is important to note that the models utilized in ActivitySim and BEAM do not possess an inherent time component, thus the model specifications remain constant over time. Policies pertaining to time are better captured in UrbanSim.
- **Value of Time:** The value of time (VOT) refers to the monetary value an individual is willing to pay to save time. For example, a value of time (VOT) of $5 per hour indicates that an individual is willing to expend $5 to save an hour of commuting time. In the ActivitySim model, the VOT is randomly selected from one of four log-normal distributions, with the specific distribution chosen based on the household income as show in Figure 35.

Figure 35. Value of Time Distributions



Source: Plan Bay Area 2050 - Forecasting Modeling Report October 2021

8.1.2 UrbanSim

UrbanSim is an urban simulation system developed over the past several years to better inform deliberation on public choices with long-term, significant effects[4]. A key motivation for developing such a model system is that the urban environment is complex enough that it is not feasible to anticipate the effects of alternative courses of action without some form of analysis that could reflect the cause-and-effect interactions that could have both intended and possible unintended consequences.

UrbanSim was designed to reflect the interdependencies in dynamic urban systems, focusing on the real estate market and the transportation system, initially, and on the effects of individual interventions and combinations of them on patterns of development, travel demand, and household and firm location.

[4] This section draws in part on reference (Waddell et al., 2008)

The implementation used for this project is the UrbanSim block model for the San Francisco Bay Area (see Figure 33). UrbanSim predicts the evolution of jobs, households, and real estate and their characteristics over time, using annual steps to predict the movement and location choices of businesses and households, the development activities of developers, and the impacts of government policies and infrastructure choices at the census block level. The land use model is interfaced with a metropolitan travel model system to deal with the interactions of land use and transportation. Access to opportunities, such as employment or shopping, is measured by the travel time or cost of accessing these opportunities via all available modes of travel. UrbanSim model specification is summarized in Table 16.

We adopted the UrbanSim block model, designed to predict the dynamics of jobs, households, and real estate characteristics in the San Francisco Bay Area at the block level. The model employs annual time steps to simulate the movement and location decisions of businesses and households, the development activities of developers, and the effects of government policies and infrastructure decisions. Additionally, the model interfaces with a transportation system to account for the interplay between land use and transportation. Access to different opportunities, such as employment or shopping, is evaluated based on travel time or cost across all available modes of transportation. A summary of the main UrbanSim model is provided in Table 16.

Table 16. Specification of the UrbanSim Block Model

Model	Agent	Dependent Variable	Functional Form
Household Location Choice	Household (new or moving)	Residential blocks with vacant residential units	Multinomial logit
Employment Location Choice	Establishment (new or moving)	Non-residential block with vacant space	Multinomial logit
Building Location Choice	Building	Block	Multinomial logit
Real Estate Price	Block	Price	Multivariable Linear Regression

The household location choice model predicts the residential location of new households (e.g., those resulting from population increase) or existing households that decide to relocate. Given that the relocation data is collected after household relocation and the information on the attributes of the previous residence is lacking, it is challenging to identify the factors that influenced households' decisions to move. Consequently, we employed a rate-based relocation model estimated with the 5-year ACS survey as a viable alternative. When UrbanSim predicts that a household will relocate, their current residential unit is marked as vacant, and the location choice model is used to simulate their new location from the set of alternatives, which consists of all blocks with enough vacant residential units. The model focuses exclusively on the residential market within the nine-county region, although moves in or out of the region are accounted for with the population control totals. For instance, in the event that the resulting population for a given year exceeds the anticipated population, a random sample of the current population is designated as having moved outside the region. Following a similar logic, the employment location choice and building location choice are simulated in the model. Additionally, the real estate prices are updated annually using a multivariable linear regression.

Additional information and documentation for UrbanSim block models can be found in Waddell, (2008) and https://cloud.urbansim.com/docs/block-model/viewer-index.html

8.1.3 ActivitySim

ActivitySim is an open-source travel behavior modeling software developed by a consortium of Metropolitan Planning Organizations (MPOs), Departments of Transportation (DOTs), and other transportation planning agencies. This modeling tool is composed of discrete choice models, activity duration models, time-use models, entropy maximization models, etc., to predict a travel plan and its mode choice at the individual level for one typical day.

The San Francisco Bay Area ActivitySim model is based on the MTC Bay Area Metro Travel Model One[5], which uses the 1454 Transit Analysis Zones (TAZs) as the geographical aggregation. The decision-makers units are households and persons based on a synthetic population (the output of UrbanSim). For each household and individual it models long-term decision such as work and school location, household car ownership, and free parking availability at location of work. Then, the coordinated daily activity pattern model characterizes the daily patterns of individuals in a household by assigning specific tour types to each household member. These tour types include mandatory activities, non-mandatory activities, or staying at home. Lastly, ActivitySim models the frequency, location, scheduling and mode choice of tours and trips by type (Mandatory, Joint Trips, Non-mandatory, and at-work trips). Non-mandatory activities can be further categorize in social, eating out, recreational, shopping, escorting, and other discretionary. For this project, we use the model specifications from Model One, as these models have been extensively validated and calibrated[6]. Table 17 summarizes the main models in ActivitySim.

Table 17. ActivitySim Model Specification

Model	Agent	Dependent Variable	Functional Form
Mandatory Activity Location	Person	Work or School TAZ	Multinomial logit
Auto Ownership	Household	Number of vehicles	Multinomial logit
Free parking Eligibility	Person	Free parking eligibility for work trips	Binary logit
Coordinated Daily Activity Pattern	Person	Number of tours by purpose (mandatory, non-mandatory, stay at home)	Multinomial logit
Non-mandatory Activity Location	Person	Non-mandatory activities TAZs (for tours and trips)	Multinomial logit
Tour and Trip Scheduling	Tour/Trip - person	Arrival and departure time (for tours and trips)	Multinomial logit
Tour and Trip Mode Choice	Tour/Trip - person	Mode of transportation (for tours and trips - 21 alternatives)	Nested logit

Most of the policy variables examined in this research pertain to transportation policies, which are primarily incorporated into the tour and trip mode choice models. Although the functional form of the tour and trip mode choice models is similar, there are conceptual differences between them. Specifically,

[5] GitHub repository: https://github.com/BayAreaMetro/modeling-website/wiki/TravelModel

[6] A detail report of model Calibration and Validation is available at https://mtcdrive.app.box.com/s/7crr7bwhromi2au42jnpp11fqe5l24xq

a trip refers to an individual journey made by an agent, while tours are a collection of sequential trips with one primary purpose. In ActivitySim, tours represent high-level plans for the day, with home as both the starting and ending point, except for at-work-based tours. Agents may have both mandatory (e.g., school or work) and discretionary tours. The mode choice model selects the primary mode of transportation for the entire tour based on outbound and inbound trip information only. Suppose, for instance, an agent has two tours in a given simulation year: one mandatory (home-work-home) and one non-mandatory (home-shopping-home). The mode choice for the first tour may be public transit, while for the second tour, it may be drive-alone. Tours are then disaggregated into individual trips, with the first tour comprising two trips (home-work and work-home). A second mode choice model is performed for each individual trip, conditional on the tour mode choice. For example, if an agent takes public transit for the first trip, then drive-alone is not available for the second trip of the tour. This sequential modeling approach accounts for the fact that previous decisions can influence current mode choice decisions. Additionally, while tours represent one primary destination, secondary destinations can be added at the trip level. For example, a groceries trip can be added to a home-work-home tour.

In this research, most policy levers primarily influence the mode choice model and the location choice models. The following sections provide an expanded description of these models.

8.1.3.1 Location Choice Models

Location choice model defines the location where an activity will take place. The model system consists of three high-level activity types, namely home, mandatory activity, and discretionary activity, as shown in Table 18. The household location model in UrbanSim simulates the residential location of a household at the block-level. This decision depends on the characteristics of the household (e.g., age of the head, number of children, income), characteristics of the block (e.g., number of years of building, cost, proportion own/rent, proportion of single-family housing), and accessibility variable (e.g., number of jobs at 5, 10, 20 mins by single occupancy vehicles). The mandatory and non-discretionary location models in ActivitySim define activity locations outside the household residential location. These activities depend on the capacity (opportunities), the distance, and logsum-based[7] accessibility metrics.

Table 18. Location Choice models explanatory variables overview

Model	Model System	Choice	Explanatory Variables
Household Location	UrbanSim	Residential blocks with vacant residential units	Age of head, Number of Children, Number of years building, cost, proportion own/rent, proportion single family housing, ration households/units, job density, population density, income, time-based accessibilities (number of jobs at 5, 10, 20 minutes by single occupancy vehicle)
Mandatory Location (Work/School)	ActivitySim	TAZ	Capacity, Distance, Income, accessibilities (Mode Choice Logsum)
Discretionary Activity Location	ActivitySim	TAZ	Capacity, Distance, accessibilities (Mode Choice Logsum)

[7] See section 8.2.1.2 for a more detail description of logsums.

8.1.3.2 Mode Choice

The mode choice model implemented in this study is a 3-level nested logit model that includes 21 alternatives, as illustrated in Figure 36. At the first level of the nest, modes of transportation are categorized into private, non-motorized, transit, and ride-hailing. Subsequently, the private modes are further split based on occupancy and toll price, whereas the transit mode is disaggregated into walking and driving access. The utility function specification takes into account the travel times and costs associated with each alternative, as presented in Table 19, which are aggregated at the TAZ level in the skims.

Figure 36. ActivitySim Mode 3-level Nested Mode Choice Model.

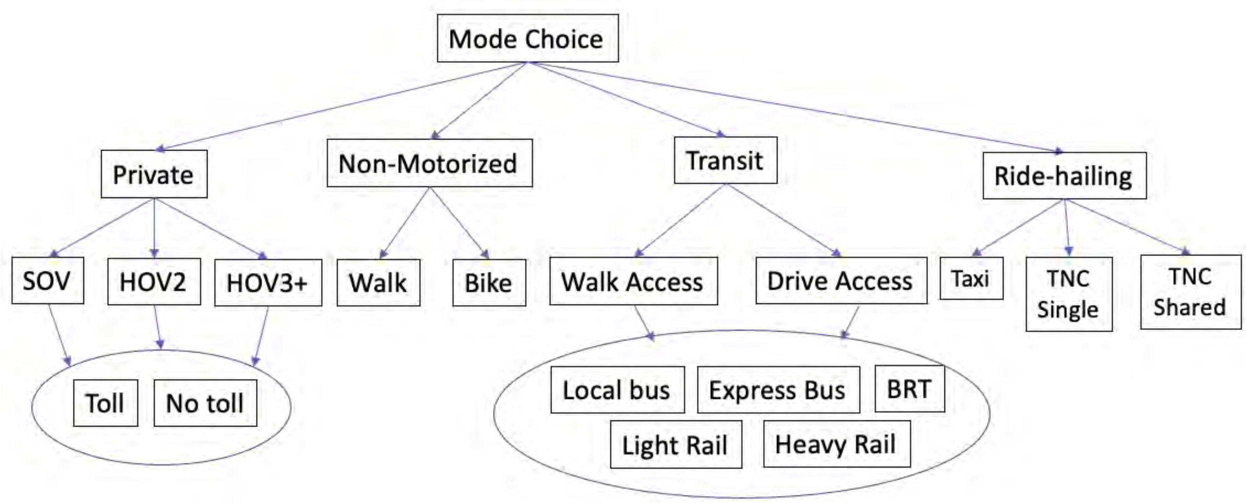


Table 19. ActivitySim mode choice model explanatory variables overview.

Mode Choice Alternatives	Explanatory Variables
Single Occupancy Vehicle Free	In vehicle time, Operating Cost, Parking Cost, Bridge Toll
Single Occupancy Vehicle Pay	In vehicle time, Operating Cost, Parking Cost, Bridge Toll, HOV Lane Toll
2-Occupancy vehicle Free	In vehicle time, Operating Cost, Parking Cost, Bridge Toll
2-Occupancy vehicle Pay	In vehicle time, Operating Cost, Parking Cost, Bridge Toll, HOV Lane Toll
3+-Occupancy vehicle Free	In vehicle time, Operating Cost, Parking Cost, Bridge Toll
3+-Occupancy vehicle Pay	In vehicle time, Operating Cost, Parking Cost, Bridge Toll, HOV Lane Toll
Walk	Distance, topology, destination density
Bike	Distance, topology, destination density
Walk Access - Local Bus	In vehicle time, wait time, transfer time, walk access/egress time, fare, destination zone density, topology
Walk Access - Express Buss	In vehicle time, wait time, transfer time, walk access/egress time, fare, destination zone density, topology
Walk Access - Bus Rapid Transit	In vehicle time, wait time, transfer time, walk access/egress time, fare, destination zone density, topology
Walk Access - Light Rail	In vehicle time, wait time, transfer time, walk access/egress time, fare, destination zone density, topology
Walk Access - Heavy Rail	In vehicle time, wait time, transfer time, walk access/egress time, fare, destination zone density, topology
Drive Access - Local Bus	In vehicle time, wait time, transfer time, drive access/egress time, fare, destination zone density, topology
Drive Access - Express Buss	In vehicle time, wait time, transfer time, drive access/egress time, fare, destination zone density, topology
Drive Access - Bus Rapid Transit	In vehicle time, wait time, transfer time, drive access/egress time, fare, destination zone density, topology
Drive Access - Light Rail	In vehicle time, wait time, transfer time, drive access/egress time, fare, destination zone density, topology
Drive Access - Heavy Rail	In vehicle time, wait time, transfer time, drive access/egress time, fare, destination zone density, topology
Taxi	In vehicle time, wait time, cost (base, per mile and per minute)
TNC Single	In vehicle time, wait time, cost (base, per mile and per minute)
TNC Shared	In vehicle time, wait time, cost (base, per mile and per minute)

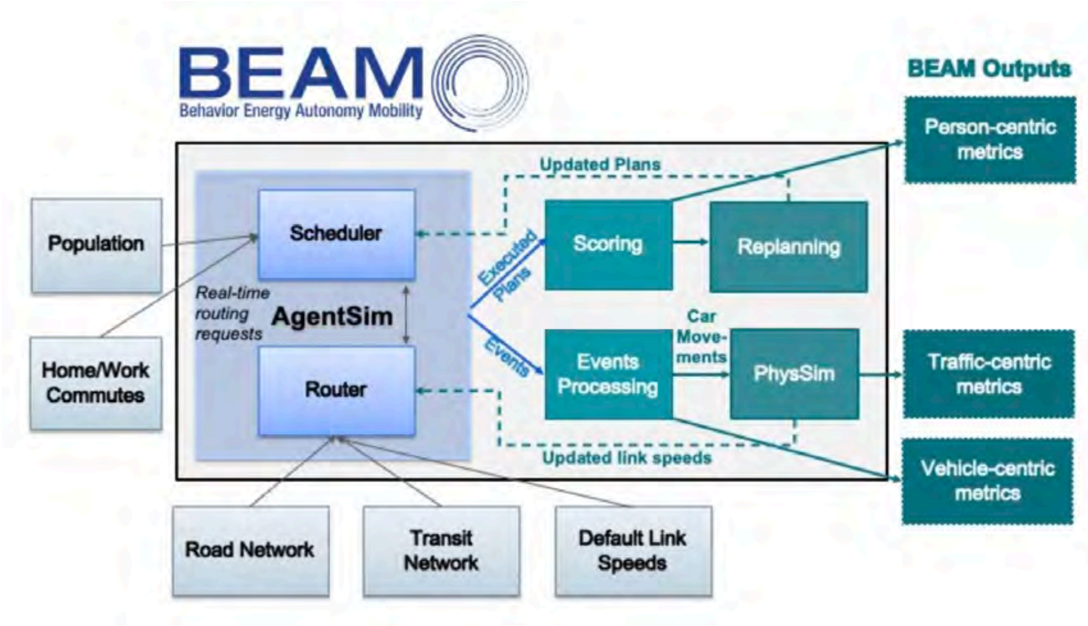
The main output of ActivitySim is the travel plan for each individual in the synthetic population, containing information on the origin, destination, purpose, time, and mode choice for each trip. The model does not capture trips originating or ending outside the modeled region, potentially leading to an underestimation of the total trips in the area. The origin and destination of each trip are aggregated to the TAZ level, while the time of day is binned into one-hour intervals. Although most trips correspond to a single agent, the model also accounts for discretionary joint trips where multiple agents travel together for a common purpose. Notably, joint trips are limited to discretionary activities and not mandatory ones.

Additional information and documentation of ActivitySim models can be found at https://activitysim.github.io. Information about the Travel Model One developed by Metropolitan Transportation Commission (MTC) can be found at https://github.com/BayAreaMetro/travel-model-one

8.1.4 Beam

The modeling framework for Behavior, Energy, Autonomy, and Mobility (BEAM) is an open-source, agent-based traffic assignment simulation software developed by the Lawrence Berkeley National Laboratory and derived in part from the MATSIM model system. BEAM allows for efficient and scalable simulation of the transportation network to understand congestion, energy, and emission implications of new mobility technologies for regional transportation systems. BEAM is currently used to evaluate and quantify strategies that ease congestion, improve mobility, and reduce pollution.

Figure 37. BEAM Modeling Framework.



Source: https://transportation.lbl.gov/beam

BEAM has three main components (1) AgentSim, (2) PhysSim, and (3) a replanning module. AgentSim has a routing engine that considers a set of possible routes for different modes of transportation. PhysSim models the network congestion using a Java Discrete Event Queue Simulator. An R5 open-source engine dynamically updates congestion and travel time, so agents are sensitive to current network conditions. The replanning module allows agents to choose different alternatives (location and mode) depending on previous days' decisions. Figure 37 shows the BEAM conceptual modeling framework.

BEAM receives activity plans from ActivitySim and simulates the network utilization given these plans. It typically respects the mode choice from ActivitySim, but it may adjust it if the chosen mode is no longer available or feasible. For example, if an agent chooses a TNC option but there are no TNC vehicles available within a reasonable time, the agent will use the internal mode choice to re-estimate the choice. To construct the skims file for UrbanSim and ActivitySim, the travel times and costs for individual trips are aggregated at the TAZ level and for different times of the day. Due to the computationally intensive nature of BEAM, a reduction in travel plans for a subset of 10% the population is implemented. To capture realistic traffic dynamics, BEAM adjusts road capacities and other available supply by scaling them down accordingly. The calibration process estimates the appropriate reduction in road capacities to ensure similar levels of congestion as observed data.

Additional information and documentation about BEAM can be found in Bae et al., (2019) https://transportation.lbl.gov/beam. Additional information and documentation on MATSIM can be found at https://www.matsim.org/.

8.2 Model Analysis, Evaluation, and Scenario Design

In this section, we introduce the fundamental theory of discrete choice models, which forms the basis of the decision-making mechanism used in our modeling framework. We will discuss the estimation of consumer surplus within the context of discrete choice models. Additionally, we will describe the Key Performance Indicators (KPIs) that will be utilized to evaluate the impact of the policy scenario, as well as the procedure employed to design three policy scenarios.

8.2.1 Discrete Choice Models

The objective of discrete choice analysis is to explain and predict the choices made by decision-makers from a finite set of alternatives, taking into account the attributes of the alternatives and the characteristics of the decision-maker[8]. These models aim to construct a probability distribution that represents the likelihood of a decision-maker choosing any of the alternatives in the set. As a result, the estimation of discrete choice models aims to derive parameters that describe the relationship between the attributes of the alternatives, the characteristics of the decision-maker, and the probability of choice.

8.2.1.1 Basics

The basic concept that enables the estimation of choice probabilities is derived from Random Utility Theory, which treats the utility of each alternative as a random variable and breaks it down into a systematic and random component. In the case of a binary choice model with only two options, the utility function for each alternative can be represented as follows:

$$
\begin{aligned}
U_{in} &= V_{in} + \varepsilon_{in} \\
U_{jn} &= V_{jn} + \varepsilon_{jn}
\end{aligned}
$$

Where U_{in} and U_{jn} are the utilities of alternatives i and j for decision-maker n. V_{in} and V_{jn} are the systematic components, which are assumed to be deterministic. Lasty, ε_{in}, and ε_{jn} are the random components. The decision process assumes a utility maximization policy, in which decision-makers choose the alternative that maximizes their utility. As the utility is assumed to be a random variable, the probability of choosing a specific alternative can be estimated as the probability of the utility of that alternative being greater than the utility of the other alternatives:

$$P_n(i) = P(U_{in} \geq U_{jn})$$

Replacing the utility by its systematic and random component, we get:

$$
\begin{aligned}
P_n(i) &= P(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}) \\
P_n(i) &= P(V_{in} - V_{jn} \geq \varepsilon_{jn} - \varepsilon_{in}) \\
P_n(i) &= P(\varepsilon_{jn} - \varepsilon_{in} \leq V_{in} - V_{jn})
\end{aligned}
$$

[8] This section is based on the reference (Ben-Akiva & Lerman, 1985)

From the above equation, it is possible to conclude that only the difference between the systematic component of the utility matters to choose one alternative over another, and not its absolute values.

The choice of distribution for the random components can lead to different models. The most used distributions for the random components are the normal distribution, which results in the Probit model, and the extreme value distribution, which results in the Logit model. In the modeling framework used in this research, it is assumed that the random components follow an extreme value distribution, resulting in all models being Logit-based. This assumption implies that the difference between the random components has a logistic distribution. As a result, the probability of choosing one alternative over the other can be expressed as:

$$P_n(i) = \frac{e^{U_{in}}}{e^{U_{in}} + e^{U_{jn}}}$$

And the probability of choosing alternative j is:

$$P_n(j) = 1 - P_n(i)$$

The specification of the systematic components aims to capture the relationships between explanatory variables and the probability distribution. These components can be represented as a linear combination of the variables, such as the attributes of the alternatives and characteristics of the decision-maker. In a mode choice model, for instance, the attributes of the alternative can be cost and travel time, while the characteristics of the decision-maker can be income and age. The weights for each variable in the linear combination can be represented as a vector of coefficients β. Thus, the systematic components can be expressed as follows:

$$V_{in} = \beta^T x_{in} = \beta_1 x_{in1} + \beta_1 x_{in1} + \cdots + \beta_k x_{ink}$$
$$V_{jn} = \beta^T x_{jn} = \beta_1 x_{jn1} + \beta_1 x_{jn1} + \cdots + \beta_k x_{jnk}$$

The estimation of discrete choice models aims to determine the magnitude of the coefficients in the utility function, which represents the marginal utility of each explanatory variable. Of the many coefficients estimated, the marginal utility of income is one of the most studied as it reflects the decision-maker's sensitivity to costs for a given choice. Additionally, the alternative specific constant (ASC) is another important coefficient that is frequently estimated. This constant acts as the intercept term in the utility function and captures any unobserved factors that may influence the decision-making process. The ASC is constant across all decision-makers regardless of the attributes of the alternative; therefore, it is often interpreted as a general preference for one alternative over another.

One of the many assumptions in logit models is the Independent of Irrelevant Alternatives (IIA), which states that adding or removing an irrelevant alternative in the choice set will not change the relative preference between remaining alternatives. This assumption is particularly problematic with alternatives that are correlated with each other. To overcome this assumption, the nested logit model groups alternatives that might be correlated into nests. In this research project, the mode choice model is a three-level nested logit model. At the first level, private, public, non-motorized, and TNC modes are grouped into a nest, as illustrated in Figure 37. The nested structure allows for correlations between alternatives within a nest while preserving the IIA assumption across nests, thus mitigating the problem of biased estimates due to correlation between alternatives.

Most of the models in UrbanSim and ActivitySim are discrete choice models, as described in Modeling Framework.

8.2.1.2 Welfare Analysis in the Context of Discrete Choice Analysis

For this research, the objective of the welfare analysis is to evaluate and compare the impacts of a policy change on the well-being of a population, measured by changes in Consumer Surplus (CS) in the mode choice model.

In the context of discrete choice model, the consumer surplus is the difference in the maximum expected utility of the choice set when a change occurs (Small & Rosen, 1981). The maximum expected utility is a metric that measures the expected benefit of a set of alternatives. In other words, it is a measure of the individual's expected utility associated with a choice situation. Mathematically, the maximum expected utility of a choice situation is calculated by the logarithmic sum of the exponential individual utilities, a term that is known as the logsums:

$$Expected\ \text{Maximum}\ utility\ (EMU) = \text{E}(\max_J U_j) = \ln \sum_J exp(U_j) + C$$

Where J is the choice set, and U_j is the systematic utility of alternative j in J. The constant value C is an unidentified parameter that represents the fact that the absolute level of the utility cannot be measured. In transportation context, the logsums are also used as a measure of accessibility, as shown in Section 8.1.3.1.

As mentioned in the previous section, a discrete choice model estimates a probability distribution for each alternative in the choice set, rather than the actual choice. During simulation, a Monte Carlo approach is utilized to randomly sample an alternative based on the resulting probability distribution. If the probability distribution changes, it is not possible to replicate the same number of trips to the same locations for all agents from two separate simulations, even if the same random seed is set. Thus, a one-to-one comparison of the CS for each person-trip across simulations is not feasible.

To overcome this problem, we estimate the average the maximum expected utility for each person-trip in a simulation, or population segment. To estimate the change in CS due to change of a policy we consider the differences between the average maximum expected utilities between two simulations and assume that the mean values of C cancel out[9]. To transform the difference of CS to monetary value we use the estimated marginal utility of income to translate the maximum expected utilities to a monetary value (Allcott, 2013; Herriges & Kling, 1997; Train, 2015). Additionally, we use an average estimated marginal utility of income for all trips because it allows useful comparison of consumer surplus across different income groups (Bills, 2013).
To summarize, the CS is the difference of the EMU divided by the marginal utility of income as follows.

$CS_n = \ln \sum_J \exp(U_j) / \alpha$represents the alternative set, C_j is the cost of the alternative, and U_j are the utilities of the alternatives in the choice set, and the parameters α is the marginal utility of income. Therefore, the difference in the consumer for a given a new policy is given by:

[9] The value C depend on the decision-maker, therefore, is reasonable to assume that the average value of C for two populations with the same characteristics is similar. As a result, this term cancels out in the consumer surplus estimation.

$$\Delta CS = CS_{baseline} - CS_{with\ Policy}$$

For this research, we conducted a welfare analysis for the mode choice model. The model results will save the logsums of the mode choice for each trip. The consumer surplus analysis will also be disaggregated by income, race, ethnicity, and area type.

8.2.2 Key Performance Indicators (KPI)

To evaluate the effectiveness of the policy scenario, our research team has identified key performance indicators (KPIs) as recommended by the California Air Resources Board, (2019). Additionally, we have incorporated the Consumer Surplus (CS) metric that was defined in Welfare Analysis in the Context of Discrete Choice Analysis. In order to optimize the analysis, CARB and our research team have selected Vehicles Miles Travelled (VMT) and CS as the two primary indicators used to gauge the responsiveness of travel demand and the well-being of the population in response to a policy change. These two KPI, have been further disaggregated by income, and race, ethnicity, and area type to better understand the impacts of the policies on various population segments. Additionally, we estimate VMT, CS and all other metrics using the entire synthetic population size. This section provides an overview of the key performance indicators used in our analysis, and a summary table is presented in Table 20.

- **Total Vehicles Miles Traveled (VMT):** This metric represents the miles traveled by all vehicles on a given day. This metric can be used as a proxy for emissions if the average vehicle emission is given. For this research, the VMT estimate includes all private driving modes, taxis, and TNC options. In the case of AVs and TNCs, the VMT estimation does include deadheading or zero-occupancy miles. One of the objectives of this research is to reduce VMT because it reduces congestion and emissions. <u>Unit of analysis: Miles</u>
- **VMT per Capita:** The VMT per capita captures the average miles driven by individual in the synthetic population. This metric is valuable because it normalizes the total VMT by the population size. This is useful when comparing scenarios for different years, where populations sizes are different. Additionally, the magnitude of VMT per capita is easier to interpret and understand for a broader population, and can be disaggregated for different population segments, without loss of interpretability. Given its importance, we disaggregate VMT per capita by disaggregating by income, and race and ethnicity, and area type. <u>Unit of analysis: miles per person</u>
- **Consumer Surplus (CS):** The consumer surplus metric aims to capture the impacts of a policy change on the well-being of a population. We measure the consumer surplus base on the mode choice model in ActivitySim, and following the procedure explain in Welfare Analysis in the Context of Discrete Choice Analysis. <u>Units: Dollars [$]</u>
- **Mode Shares:** Mode shares are a common transportation metric to measure the participation of each alternative mode in the total number of trips. This metric is normalized by the total trips, making it comparable across scenarios (and even geographies). The mode choice model implemented in this research includes 21 alternatives; however, to reduce complexity, we estimate this metric using the following categories:
    - <u>Drive Alone:</u> Private vehicle drive alone pay and free.
    - <u>Share Ride:</u> Private vehicle drive 2+ occupants pay and free.
    - <u>Public Transit:</u> Walk and driving access to local, express, and commercial bus, light rail, heavy rail, and ferry.
    - <u>Walk:</u> Walking mode
    - <u>Bike:</u> Biking model

- TNC Ride-alone: TNC with one occupant.
- TNC Shared: TNC with 2+ occupants.

Unit of analysis: percentage (%)

- **Average Travel Time:** The average travel time measures the mean travel time for all trips on each day. Given that the location choice models are sensitive to changes in the transportation system this metric measures changes in trip travel times that can be caused by changes in congestion and trip length. In general, shorter average travel times are preferable. This metric is also disaggregated by income, purpose, and transportation mode. Unit of analysis: minutes per trip.
- **Average Trips Length:** This metric estimates the mean distance for all trips. Contrary to travel time, the travel distance does not depend on the network congestion, therefore, this metric represents how far agents travel. Increase densities can result in reduced trip length because more opportunities are reachable within a given distance. Given the sensitivity of location choice models to changes in the transportation system, this metric can be interpreted as increased density. Shorter trips are preferred as they can improve efficiency, alleviate congestion, and reduce emissions. In this research, we disaggregate this metric by mode to also capture how effective each mode is depending on the travel distance. Unit of analysis: miles per trip.
- **Transit Ridership:** Public transit ridership estimates the total number of trips made in public transit for a given day. The importance of this metric is that public transit options allow for high-occupancy vehicles, one of the research objectives, therefore higher ridership is preferred. Additionally, it can be used to forecast transit revenue. Unit of analysis: trips
- **Seat Utilization:** Seat utilization measures the average private vehicle occupancy. In this research, this metric is limited to private driving modes. For shared TNC, seat utilization is not possible to estimate because the number of people in the vehicle is unknown. As this research aims to incentivize high-occupancy vehicles, increased seat usage is preferred. Unit of analysis: passengers per vehicle.
- **Household Vehicle Ownership:** This metric measures the mean number of private vehicles owned by a household. Reducing the number of vehicles per household is preferred as it has the potential to incentivize alternative transportation modes such as transit, walking and biking. These modes are characterized by high occupancy vehicles and zero-emission options, aligning with the objectives of this study. Unit of analysis: Vehicles per household

As BEAM aggregates travel time and travel to the TAZ in the PILATES framework, the research team does not have access to metrics such as congestion from the network. Therefore, we have chosen not to include this metric in our analysis.

Table 20. Key Performance Indicators (KPI)

Performance Indicator	Formula	Notation
Total VMT* [vehicle-miles]	$\sum_{N_v} dist_i$	$dist_i$: Distance of private vehicle trip i N_v: Number of private vehicle trips
VMT per Capita*, ** [vehicles-mile/person]	$\frac{\sum_{N_v} dist_i}{Pop}$	$dist_{vt}$: Distance of vehicle trip i N_v: Number of Vehicle trips Pop: Population Size
Consumer Surplus** [$]	$\ln \sum_J \exp(U_j)/\alpha$	U_j: Utility of alternative j α: Marginal utility of Income
Transit Ridership [trips]	N_t	N_t: Total Number of Trips in Public Transit Modes
Mode Shares [%]	$\frac{N_m}{N} * 100\% \; \forall\, m \in M$	M: Set of alternative modes N_m: Total number of trips with mode m N: Total number of trips
Household Vehicle Ownership [Vehicles/Household]	$\frac{\sum_H Vehicles_h}{H}$	$Vehicles_h$: Number of Vehicle for household h. H: Total Household Population.
Seat Utilization [passengers/ vehicle]	$\frac{N_1 + (2 * N_2) + (3 * N_{3+})}{N_v}$	N_1: Vehicle Trips with 1 passenger N_2: Vehicle Trips with 2 passengers N_{3+}: Vehicle Trips with 3 + passengers N_v: Total number of Vehicle trips
Average Travel Time by Purpose [mins]	$\frac{\sum_{N_p} time_i}{N_p} \; \forall\, p \in P$	P: Set of Purposes $time_i$: Time of trip i with purpose p N_p: Total number of trips with purpose p
Average Travel Time by Mode [mins]	$\frac{\sum_{N_m} time_i}{N_m} \; \forall\, m \in M$	M: Set of Modes $time_i$: Time of trip i with mode m N_m: Total number of trips with mode m
Average Travel Time by Income [mins]	$\frac{\sum_{N_j} time_i}{N_j} \; \forall\, j \in J$	J: Set of Income Categories $time_i$: Time of trip i with income j N_j: Total number of trips with income j
Average Trip Length by mode [miles]	$\frac{\sum_{N_m} dist_i}{N_m}$	$dist_i$: distance of trip i in mode m N_m: Total number of trips with mode m

* VMT includes private vehicle trips (drive alone, shared 2, and shared 3+ options) and TNC and Taxis miles.

** These metrics are disaggregated by income, race, ethnicity and area type. Income brackets are: Low (0-80k), middle (80k – 150k), and high (150k+). Race categories are Asian, Black, White, and Other. Ethnicity categories are: Hispanic and non-Hispanic. Area type categories are: Urban, Suburban and Rural.

8.3 Policy Scenario Design

The research team drafted 28 possible policy variables for this research, grouped into six main categories (pricing, parking, curb policies, operational strategies, infrastructure changes, transportation services, and land use strategies). These policies targeted the objectives of the research, which were to explore strategies to incentivize the use of zero-emission, high-occupancy, and new mobility options. A final set of 13 policy variables were selected in coordination with the CARB team, the research team, and the model framework capabilities. Table 21 contains the list of policies, and Appendix A – Policies Under Consideration, presents a more detail explanation for each of them.

CARB and the research team worked together to define a final set of policy scenarios that combine modifications to the input variables based on the results of a sensitivity analysis (see Appendix B). The objective of the sensitivity analysis was to isolate the impact of each policy variable to support the design of policy scenarios. To create these policy scenarios, the research team asked CARB to suggest policy bundles according to their priorities and needs.

This exercise resulted in the policy scenarios, as presented in Table 21. The first scenario, option one, employs a comprehensive approach by incorporating multiple strategies, including enhancing transit services, incentivizing the use of shared TNC rides, increasing the Auto Operating Cost (AOC), and increasing residential and employment densities around transit stations. In contrast to the other scenarios, option one incorporates telecommuting, with 15% of working trips expected to be telecommute. The second scenario focuses solely on transit and land use improvements, specifically increasing transit frequencies by 200%, offering free transit, and raising employment and residential densities around mass transit stations by 50%. The third scenario prioritizes pricing by increasing the cost of ride alone TNC rides, AOC and implementing a $10 cordon pricing policy, as well a 10% increase density for the Transit-Oriented development (TOD) strategy. All scenarios assume a 25% penetration rate of AVs and a 40% reduction in the value of time (VOT) for households with AVs. Baseline values for other policy variables can be found in Table 38 – Appendix E.

Table 21. Policy Scenarios Creation

ID	Policy Category	Name	Modified Scoping Plan/ CTP (Option 1)	Transit & Land Use Improvements (Option 2) Modeling Year 2045	Pricing (Option 3) Modeling Year 2045
1	**Public Transit**	Transit Frequencies	+100% (Increase in transit frequencies)	+200% (Increase in transit frequencies)	+100% (Increase in transit frequencies)
2	**Public Transit**	Transit Fare	-100% (Free Transit)	-100% (Free Transit)	-100% (Free Transit)
3	**Public Transit**	Transit in-vehicle times			
4	**Shared Rides**	TNC Price			50% (Increase in cost of TNC)
5	**Shared Rides**	Share TNC Price	50% cheaper than TNC ride alone	BAU	BAU
6	**Pricing**	Operating Cost	100% (Increase in AOC)	BAU	100% (Increase in AOC)
7	**Pricing**	Cordon Pricing			$10
8	**Pricing**	Park and Ride			
9	**Telework**	Telecommute - Option	15% of work trips*	BAU	
10	**Telework**	Telecommute - Frequency			
11	**Autonomous Vehicles**	AV Penetration Rate	25%	25%	25%
12	**Autonomous Vehicles**	AV Value of Time	-40%**	-40%**	-40%**
13	**Land Use**	TOD Residential and Employment	+25% (Increase in Density)	+50% (Increase in Density)	+10% (Increase in density)

AOC = Auto Operating Cost. BAU = Business as Usual.
* The telecommute model does not take a unique rate for telecommute. Rates for each segment were adjusted to reach this percentage.
** No suggestion was given to the AV reduction of the VOT.
For this policy result, the research team assumes a 40% reduction in the VOT for households with AV.

Based on the sensitivity analysis (see Appendix E), we compute the sum of the individual policy impacts in terms of VMT and CS as shown in Table 22. The analysis shows that the option one policy scenario is associated with a substantial reduction in VMT of 22 million, but at the cost of a loss in consumer surplus amounting of $7.0 million. The reduction in consumer surplus is mainly driven by the increase AOC, though this effect is mitigated by the positive impact of other policies, such as the improvement of transit options and the TOD strategy. Conversely, Option 2 is associated with a positive consumer surplus of approximately $5.5 million, while potentially achieving a more modest VMT reduction of 4.72 million.

Option 3 policy scenario, which primarily focuses on pricing, has the potential to reduce VMT by as much as 21 million, but results in a loss of consumer surplus of approximately $7.9 million. However, it is important to note that the sum of the individual impact of the policies is expected to differ from their aggregate effect, as we anticipate that the interactions among these policies will be greater than their individual impact.

Due to the limitations of resources and time, the research team was only able to simulate option one policy scenario up to the year 2050. The baseline population used for this simulation was that of the year 2020. To simulate the changes in the transportation system over time, the UrbanSim models were run every year, while ActivitySim and BEAM models were run every five years. Over the course of the 30-year simulation period, there were seven 5-year cycles, and each cycle took between 10 to 14 hours to complete. Therefore, running a single policy scenario simulation for the entire 30-year period could take up to 98 hours.

Table 22. Sum of Individual Impacts for the Policy Scenario - In terms of Vehicles Miles Travel (VMT) and Consumer Surplus (CS)

Policy	**Modified Scoping Plan/ CTP** (Option 1)		**Transit & Land Use Improvements** (Option 2)		**Pricing** (Option 3)	
	Total VMT [miles]	CS [$]	Total VMT [miles]	CS [$]	Total VMT [miles]	CS [$]
Transit Frequencies	-2,610,208	$1,437,340	-4,045,504	$2,057,632	-2,610,208	$1,437,340
Transit Fare	-1,020,227	$688,196	-1,020,227	$688,196	-1,020,227	$688,196
Transit in-vehicle times						
TNC Price						-$750,032
Share TNC Price	≅	≅	=	=		
Operating Cost	-19,046,287	-$11,855,256	=	=	-19,046,287	-$11,855,256
Cordon Pricing						≅
Park and Ride						
Telecommute - Option	-	+				
Telecommute - Frequency	-	+				
AV Penetration Rate	1,908,901	$2,234,097	1,908,901	$2,234,097	1,908,901	$2,234,097
AV Value of Time						
TOD	-1,185,458	$444,925	-1,315,708	$532,041	-603,775	$299,998
Total	-21,953,279	-$7,050,698	-4,472,538	$5,511,966	-21,371,596	-$7,945,657

The actual impact of the telecommute policies are not estimable as both the telecommute option and telecommute frequency models were changed to target the 15% telecommute working trips. However, we expect to see a reduction in VMT driven by the reduction in work trips; therefore, we include a negative sign to reflect that the sum of individual impacts is underestimated. For CS, we expect to see a positive impact.

8.4 Policy Scenario Analysis

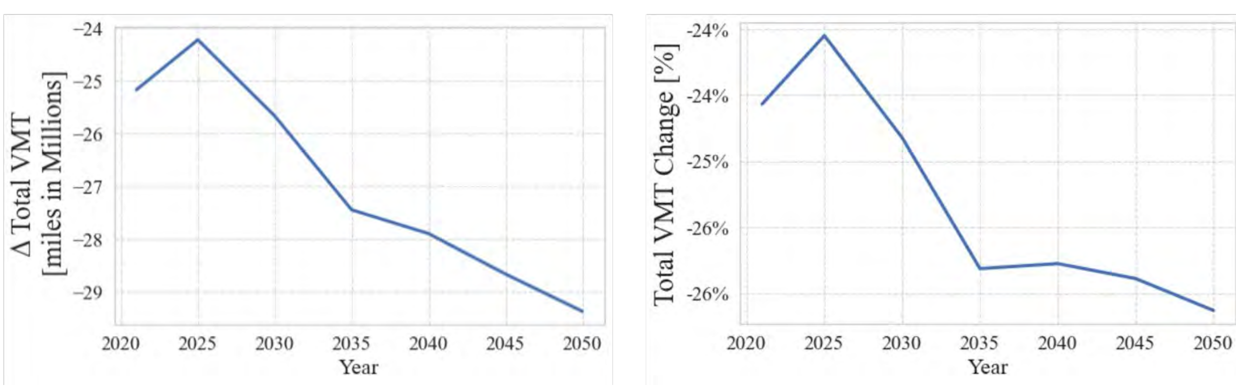
This section presents the simulation results of the policy scenario for the San Francisco Bay Area using the modeling framework described in the Modeling Framework section. The results are compared to a baseline scenario that reflects the expected travel demand evolution under current conditions, simulated up to the year 2050. To facilitate interpretation, most results are presented as both absolute and relative differences. As the simulation was conducted solely for the Option One policy scenario, which also aligns with the Scoping plan, the results and discussion focus exclusively on this particular scenario.

8.4.1 Results

Based on the policy scenario simulations, the results indicate that the option one policy is expected to generate a significant reduction in VMT by about 29 million (a 26% decline) by the year 2050, relative to the baseline as shown in Figure 38. This progress is attributable to the complementary effect of increasing AOC and improving transit, which decreases VMT. By increasing the cost of driving, individuals are motivated to consider alternative transportation modes, such as biking, walking, or public transit. At the same time, enhancing transit options can enhance the attractiveness and convenience of public transportation, reducing the need for driving. Moreover, a TOD strategy can further reduce VMT by creating more densely populated regions where home and work are in closer proximity. The findings also reveal a downward trajectory in VMT reduction from 2020 to 2050, implying the time component effect that could be explained by the TOD strategy. Collectively, these policies have a synergistic impact on reducing VMT, leading to a decline that is 33% greater than the sum of their individual impact (see Table 22).

Figure 38. Variation of Total VMT for A) Absolute difference, and B) Percentual Difference.

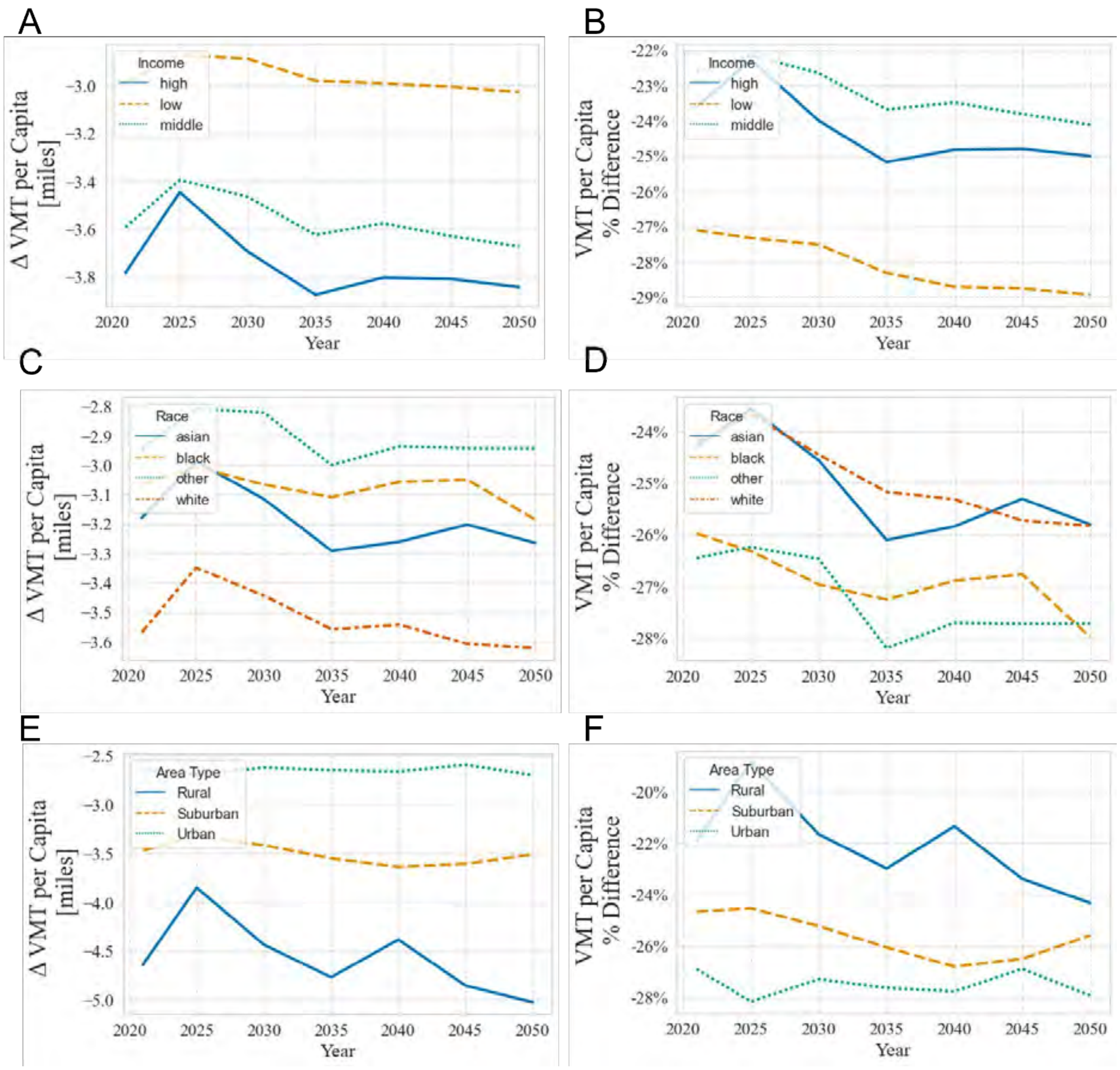
A B



Note: Estimated amounts based on a one-day simulation.

When VMT looking by population segments, low-income populations, black and other races, and urban/suburban areas exhibit a higher percentage reduction in VMT compared to other categories, despite the absolute reduction being smaller. Low-income populations experience a smaller absolute reduction of around 3 miles in VMT per capita by 2050, while middle- and high-income populations achieve a greater reduction of approximately 3.7 miles. However, the reduction in VMT per capita constitutes nearly a 30% decrease for low-income groups, whereas it represents only a 24% reduction for middle- and high-income groups (Figure 39 A and B). The results also indicate that Asians, Blacks, and other races have a smaller absolute difference in VMT reduction. However, when compared to their baseline, Blacks and other races, the reduction represents 28%, and for Asians and Whites represents 26% (Figure 39 C and D). Similarly, the results suggest that VMT reduction for urban and suburban areas is just 2.5 and 3.5 VMT, respectively, compared to 5 VMT reduction for with rural areas, however, this reduction represent 28% reduction for urban/suburban areas, but only a 24% reduction for rural areas (Figure 39 E and F).

Figure 39. Variation of VMT per capita by Income, Race and Area Type for Absolute and Relative Differences

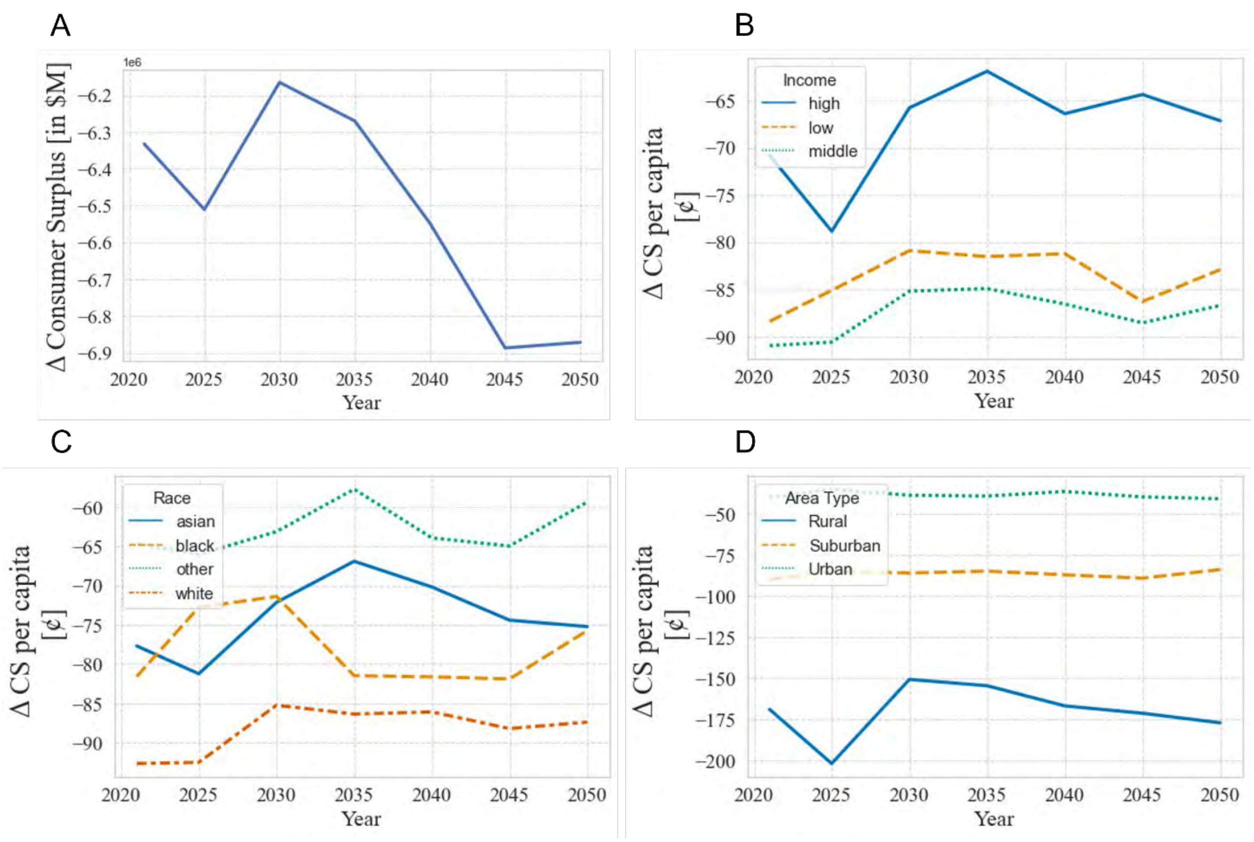


Note: Estimated amounts based on a one-day simulation.

The policy scenario option 1 estimated a reduction in consumer surplus of approximately $6.9 million by 2050 (Figure 40A). The negative impact on consumer surplus is mainly attributed to the increase in the AOC. Nevertheless, it is worth noting that the implementation of transit improvements and a TOD strategy has a mitigating effect on this negative impact. These strategies are expected to partially offset the decline in consumer surplus by improving transit waiting times and reducing transit travel costs for households.

Low- and middle-income populations experience a higher reduction in consumer surplus compared to higher income populations, with an average loss of approximately 85 cents and 65 cents respectively (Figure 40B). These results indicate a disproportionate loss in the consumer surplus for low and middle-income populations. When examining the impact of race, it appears that Asians and Blacks experience relatively similar average losses in consumer surplus at approximately 75 cents, while Whites have a higher loss at 90 cents (Figure 40C). Additionally, rural areas experience a significantly higher loss in consumer surplus compared to suburban and urban areas, with a reduction of approximately 175 cents compared 80 cents and 40 cents respectively (Figure 40C). These findings are consistent with the baseline results, which show that rural areas have a significantly higher average trip length, and therefore, greater AOC disproportionately impacts the consumer surplus of rural areas. Furthermore, it is important to note that access to public transit options in rural areas may not be enough to offset the negative impact of increasing AOC on consumer surplus, highlighting the need for careful consideration and strategic planning of policy interventions to ensure equitable outcomes.

Figure 40. Variation of Consumer Surplus (CS) per capita A) Total B) by Income, C) Race, and D) Area Type



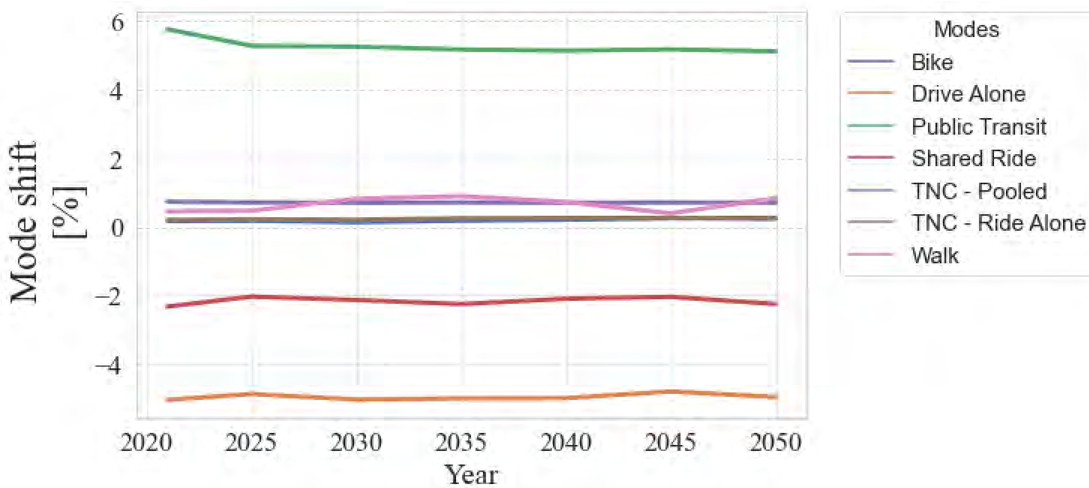
Note: Estimated amounts based on a one-day simulation.

The analysis of policy scenario shows that there is a stable mode shift across the simulation period, as illustrated in Figure 41. Notably, modes that are characterized by high occupancy, zero emissions, and new mobility options witness a greater mode share for the suggested policy scenario. For instance, the mode share for public transit is projected to increase to nearly 6% in the year 2050, indicating the largest mode shift. Furthermore, zero-emission modes such as walking and biking demonstrate a positive increase in their mode share by 0.85% and 0.25%, respectively, compared to the baseline.

Similarly, both TNC options, namely TNC ride alone and shared TNC, show an increase in their mode shares. However, the increment in shared TNC mode share (0.71%) is significantly higher than TNC ride alone (0.25%). It is worth noting that the use of private vehicles is projected to decrease considerably. For instance, the drive alone option reduces the mode share by nearly 5 points, whereas driving with two or more passengers (share ride) decreases by 2%.

The mode shift towards public transit can be attributed to the improvements made to the transit system. In contrast, the reduction in private drive mode share might be due to the increased cost of driving. Overall, the analysis underscores the potential benefits of the suggested policy scenario, such as reducing the reliance on private vehicles and promoting the use of high occupancy, zero emissions, and new mobility options.

Figure 41. Mode Shift - Baseline and Policy Scenario Option 1



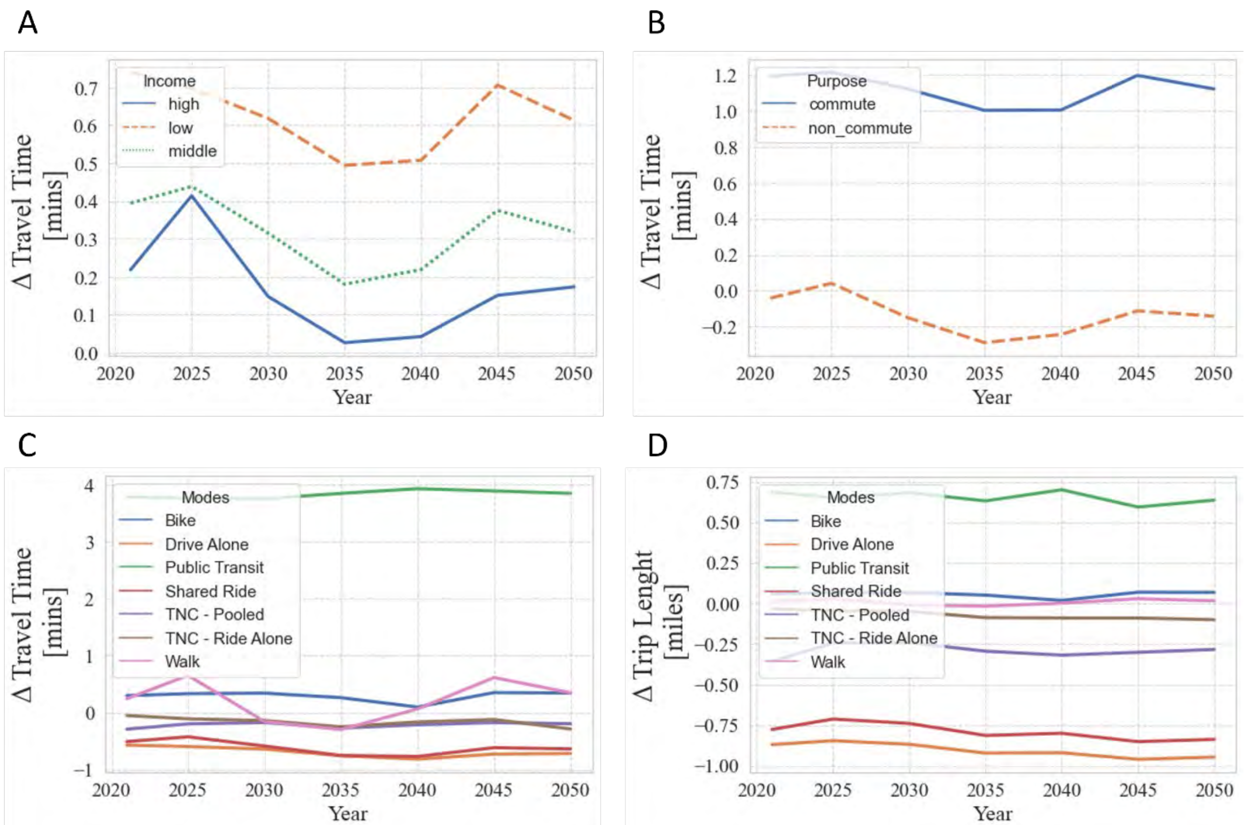
Note: Estimated amounts based on a one-day simulation.

The simulation of policy scenarios predicts a different impact in the variation of average travel times by population segments. On average, the travel time is projected to increase from 17.82 to 18.20 minutes, indicating a difference of 0.38 minutes. However, low-income populations are likely to experience greater increases in travel times, as illustrated in Figure 42A. By 2050, the difference in travel time for low-income individuals is expected to be 0.61 minutes, compared to 0.35 and 0.19 minutes for middle and high-income individuals, respectively. Moreover, there is a marked contrast between commute and non-commute travel time differences. For instance, the average travel time for commute trips is projected to increase by 1.2 minutes, whereas for non-commute trips, there is a slight decrease in travel time by 0.14 minutes (Figure 42B).

In terms of travel time by mode, public transit shows the greatest increase in travel time, which is estimated to be approximately 4 minutes (Figure 42C). This metric is largely influenced by the increased demand for public transit in the policy scenario relative to the baseline, and the fact that mode shifts have encouraged longer transit trips, as suggested in Figure 42D. Additionally, biking and walking are also projected to experience an increase in average travel time of 0.35 minutes by 2050. Overall, the simulation results suggest that the policy scenario may lead to variations in travel times, with low-income populations being more affected.

In the simulation, walking and biking modes are not affected by traffic conditions, thus the increased travel time observed in these modes may be attributed to longer trip distances. On the other hand, the average travel time for TNC modes has decreased, as indicated by a decrease of 0.28 minutes for TNC ride-alone and 0.19 minutes for TNC shared rides in Figure 42C. This reduction can be attributed to a decrease in congestion, which may be attributed to the increased use of sustainable modes of transportation. Similarly, car trips also show a reduced travel time, with a decrease of 0.63 and 0.71 minutes for shared and ride-alone private vehicles, respectively. The observed reduction in travel time for private vehicles may be attributable to a decrease in congestion as well as a reduction in the average trip length, as evidenced by Figure 42D, which indicates an average reduction of approximately one mile for private modes. The reduction of average travel length for private vehicles can result from the increased AOC, which disincentivize longer trips, in favor of public transit trips.

Figure 42. Average Travel Time Difference by A) Income, B) Purpose, C) Mode, and D) Change in Trip Length by Mode

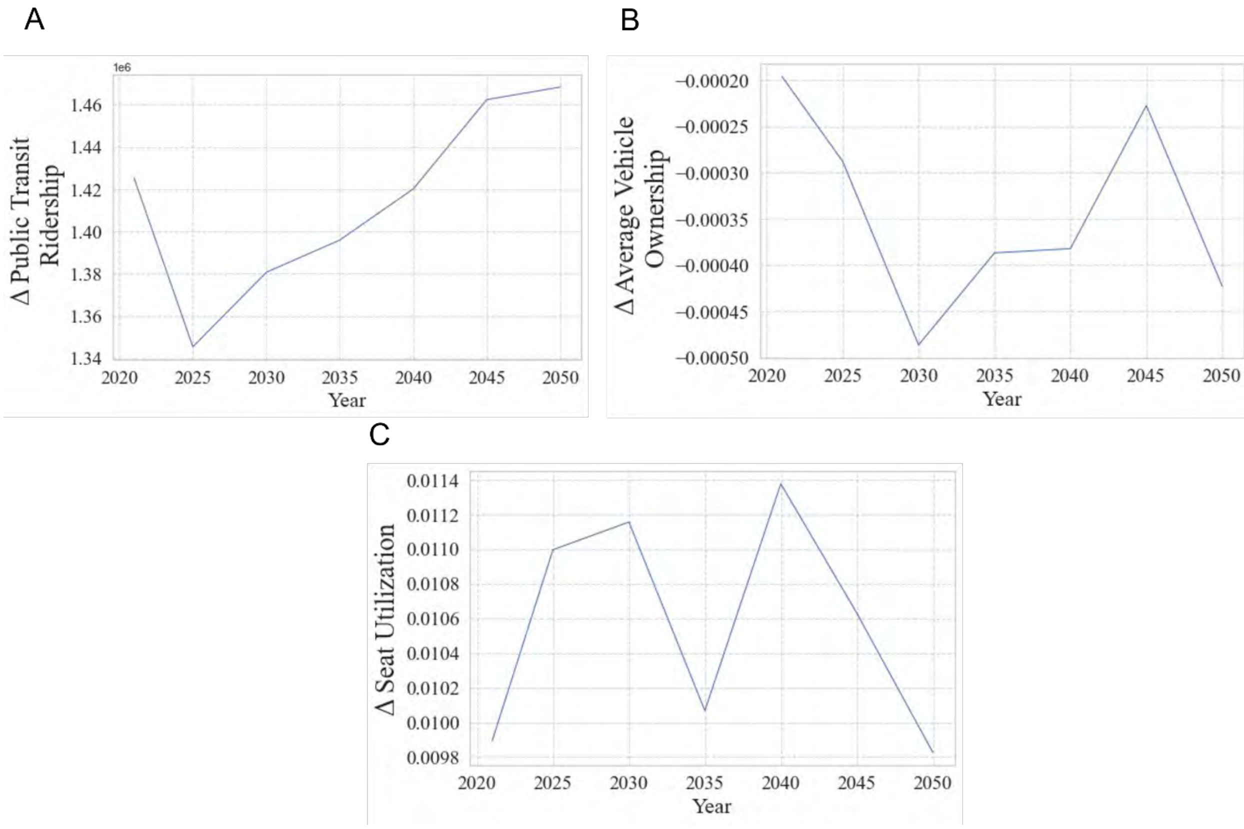


Note: Estimated amounts based on a one-day simulation.

As shown in the mode choice, the increased mode share of transit is seen in transit ridership. In the policy scenario results, transit ridership in 2050 is 3.32 million, an 80% increase with respect the baseline comparison (Figure 43A). The mode shift to public transit is mostly driven by public transit improvements in frequencies and cost, and the increased cost associated with driving a private vehicle. However, average vehicle ownership by household remains similar in the baseline and the policy scenario results (Figure 43B). While any of the policies target private vehicle seat utilization, the policy scenario results suggest a small, yet stable increase in seat utilization (Figure 43C).

The policy scenario simulation predicts a significant increase in public transit ridership of 1.46 million by 2050, as compared to the baseline scenario, which is consistent with the increase in the public transit mode choice. This trend is expected to start in 2025, with an increase in public transit ridership from 1.34 million to 1.46 million. The increase can be attributed to transit improvements such as increasing transit frequencies and offering free transit, as well as population growth. It is important to note that despite the significant increase in public transit ridership, none of the proposed policies seem to project any effect on the average vehicle ownership and seat utilization. This is evident from the plots in 11B and 11C, where the variation for these two metrics is close to zero. The findings suggest that while policies to encourage public transit usage may have a significant impact on ridership, they may not necessarily affect the overall ownership or utilization of private vehicles. Therefore, further research may be necessary to identify effective policies to reduce private vehicle ownership and promoting sharing a private vehicle ride.

Figure 43. Difference in KPI between Baseline and Policy Scenario. A) Total Public Transit Ridership, B) Average Vehicle Ownership by Household, and C) Average Seat Utilization



Note: Estimated amounts based on a one-day simulation.

To summarize, the findings from this modeling study suggest that the policy one scenario can be effective in reducing VMT by 26% and increasing the mode share of high occupancy, zero emissions, and new mobility options such as public transit, biking, walking and shared TNC rides. The increase in transit ridership by 1.46 million by 2050 is a significant achievement that can be attributed to transit improvements and population growth. However, the policy scenario also predicts a reduction in the consumer surplus estimated in $6.9 millions. The variations in VMT reduction and consumer surplus loss are not evenly distributed across population segments and geographical areas. Specifically, low-income populations and rural or suburban areas are more negatively affected than high-income populations and urban areas. These findings highlight the need for policies that are targeted towards different population segments and areas.

8.4.2 Limitations of the model

New mobility options, such as shared bikes and scooters, are increasingly gaining popularity as potential alternatives to traditional transportation modes. However, the mode choice model employed in ActivitySim does not incorporate these options as alternatives. Introducing such alternatives to the model is also challenging due to the geographical aggregation of Traffic Analysis Zones (TAZs) and the diversity of new micro-mobility modes. While the average travel time within a TAZ might be similar for driving modes and even transit, this may not hold true for micro-mobility options. The topography of the area, the type of micro-mobility option available, and other factors might lead to variations in trip duration and routes within a TAZ. For instance, in regions with hilly terrain, electric scooters or bikes may be preferred to shorten travel distances on steep inclines, while regular bikes may opt for routes with fewer hills. Further research is necessary to assess the feasibility of incorporating micro-mobility options into the mode choice model and to explore the potential impact in VMT, consumer surplus and in the travel demand behavior.

The modeling framework utilized in this research does not incorporate the penetration of electric vehicles, which could significantly impact the sensitivity to AOC. It is worth noting that electric and hybrid vehicles typically possess greater fuel efficiency, leading to a reduction in the AOC. Furthermore, the car ownership model employed in this study exclusively considers the number of vehicles a household is likely to possess, without taking into account the type of car(s) owned. As a result, the model's sensitivity to the penetration rate of new fuel efficiency technologies, which tend to be more prevalent in higher-income populations due to their novelty and high costs, is limited.

Although this study takes into account the population growth up to 2050, it does not factor in the evolution of the population within the given timeframe. As mentioned in the Modeling Framework section, to match a household control total, new agents are selected randomly from the current pool of households, therefore, maintaining their demographic distribution. Additionally, the study does not account for family events or restructuring trends that may significantly impact the decision-making process related to transportation choice. Furthermore, the models do not consider any potential changes in behavior within a population segment. In other words, a 30-year-old agent is assumed to behave similarly in both 2020 and 2050, without accounting for the possibility of behavioral shifts over time.

The policy scenario is implemented in an all-or-nothing fashion from the first year of simulation. However, certain policy variables are expected to grow from year to year. For instance, the modeling framework assumes a constant penetration rate of 25% for AVs from the first year, but a more realistic model would consider varying penetration rates over time. Similarly, the AV penetration rate in this study assumes that all vehicles within a household are AVs, and the reduction in the VOT applies to all household members. A more refined model would consider the possibility of only a portion of a household's vehicles being AVs and varying the VOT reduction for different household members based on their travel needs and preferences.

It is possible that the results of the VMT and VMT per capita estimates in this study are underestimated because the model does not factor for AV deadheading trips. Nevertheless, the reduction in trips using private vehicle modes continues to serve as a consistent indicator of the potential VMT reduction that could result from the implementation of policy scenario option one, which may also help mitigate the potential impact of deadheading VMTs. However, further research is needed to better understand the role of AVs in the context of deadheading miles, especially its cost sensitivity and how to effectively address this issue in transportation policy.

Given the limitation of the current implementation of BEAM, this study did not include a High Occupancy Toll Lane policy, which would incentivize the use of private shared rides, part of the objective of this study. Differentiated toll lanes strategies based on congestion and the number of occupancies might incentivize the average seat utilization and reduce congestion.

8.5 Discussion

The policy scenario analyzed for this research highlights the benefits of combining multiple policies. For instance, when evaluating the individual policy impacts for policies in Option One in the sensitivity analysis, it estimated a VMT reduction of 22 million miles and a loss in consumer surplus of $7 million for the base year. However, when these policies are combined in Option One, the estimated reduction in VMT is 25 million miles, and the loss in consumer surplus decreases to $6.3 million. Representing a 13% larger reduction in VMT, and a 10% smaller loss in consumer surplus for the same base year. These results also reveal a greater impact in terms of VMT and CS for low-income populations, which are more sensitive to increases in AOC. Additionally, the policy scenario results suggest that most of the mode shift will favor public transit, therefore state tax revenue collected due to VMT fees can be invested in transit to mitigate the extra loss in CS for the low- and middle-income population.

In the policy scenario option one, the daily VMT is estimated in approximately 102.4 million. Assuming that 20% of the AOC can be collected as a VMT tax (7.36 cents), this would only lead to $7.5 million in revenue. As the policy scenario analysis suggests, the majority of the mode shift is towards transit modes, indicating the need to allocate a substantial portion of VMT tax revenue to transit investments.

However, it's important to note that currently, only 15% of the gas tax is invested in transit, according to data from The California Legislature’s Nonpartisan Fiscal and Policy Advisor in 2021. Consequently, this would reduce the estimated revenue from the VMT tax to $1.12 million. Comparatively, this revenue amount is significantly lower than the daily loss in consumer surplus, which amounts to approximately $11.8 million due to the increase in AOC.

This analysis underscores the critical importance of carefully considering the revenue implications in policy decisions. While the VMT tax has the potential to generate revenue, its effectiveness in compensating for the losses in consumer surplus needs careful evaluation. Ensuring an appropriate allocation of the VMT tax revenue towards transit, in line with the observed mode shift, could play a crucial role in balancing revenue generation and maintaining consumer welfare. Further research and discussions are critical to formulate a well-informed approach to policy implementation that optimizes both revenue and consumer well-being. Assuming that only 15% of the tax revenue is invested in transit (The California Legislature’s Nonpartisan Fiscal and Policy Advisor, 2021), this estimate is reduced to $1.12 million, which is significantly lower than the $11.8 million daily loss in consumer surplus due to increase AOC.

A 25% increase in residential and employment density around transit stations was associated with a decrease in 1.2 million VMT, and a consumer surplus of $0.44 million, especially benefiting low-income population. However, the experiments in this report were limited to current mass transit stations and did not consider new mass transit lines. Given the limitations, and the small number of mass transit stations (147 stations), there is the potential to increase mass transit services to other areas with a TOD strategy. A deeper analysis of where these services and stations might locate to maximize the benefits would also be needed.

The sensitivity analysis shows that the elasticities of transit in-vehicle times to VMT and CS surplus are 0.1 and -0.2 respectively, which are the third highest elasticities after Operating Cost and the AV scenarios. In this analysis, the experiments only consider reducing the in-vehicle time, however, no explicit policy was attached to it. Short- and middle-term policies that might reduce in-vehicle transit times are exclusive bus lanes, intermittent stops, and traffic signal prioritization. However, the way the experiments were set up for this research, it is also possible to conclude that the difference in in-vehicle travel time between private driving and public transit modes is a decisive factor in the mode share. Decreasing this gap can also be achieved by increasing accessibility and connections through new transit services, which can be integrated with the expansion of the TOD policy mentioned above.

The response to autonomous vehicles and telecommute policies still carries a lot of uncertainty for the future. In this research, it is assumed that households with autonomous vehicles have a lower sensitivity to in-vehicle time and, therefore, a lower VOT. The sensitivity analysis showed that this assumption is associated with a significant increase in VMT per capita, even when the experiments did not consider deadheading VMTs, which is likely to underestimate the true VMT increase. If this assumption is true, then it is possible that in the long term, households will tend to relocate to cheaper suburban areas. Although the household location model in UrbanSim can capture relocation to suburban areas, it is not possible to determine if AV penetration leads to such relocation since the AV scenarios were tested for only one simulation year. However, strategies such as VMT fees and TOD can help mitigate this impact. VMT fees penalize longer commutes, and TOD strategies incentivize shorter and/or transit-accessible commutes. Similarly, telecommuting options might incentivize household relocations. However, while this parameter lever might reduce VMT, few benefits are associated with low-income populations.

9. Conclusion

This research explored strategies and policies to help incentivize the adoption of high-occupancy, zero-emission shared mobility and active transportation options in California. The research paid additional attention to impacts to and strategies for vulnerable populations (e.g., low-income communities). This research is critical as higher-occupancy, lower-emission, and active modes may help reduce negative transportation impacts (e.g., VMT, greenhouse gas emissions). Additionally, shared mobility modes may be able to increase the number of higher-occupancy, lower-emission, and active mode options available to travelers. This research leveraged four research tools: 1) a literature review, 2) interviews with experts from 14 organizations, 3) two focus groups with a total of 19 participants, 4) a survey from five metropolitan regions in California (n=2,354), 5) shared micromobility data analysis, and 6) the use of three modeling options to analyze various policy scenarios. Each research method informed the development and use of the subsequent research tool. For example, the literature review helped tailor the subjects covered in the expert interviews. The expert interview findings then further refined the topic areas reviewed in the focus groups.

The literature review revealed that shared mobility tends to be used by Caucasian males, aged 25 to 34 years old, with high annual incomes and levels of educational achievement. Shared mobility may result in equity concerns for select populations including people with disabilities, unbanked and underbanked and low-income households, and individuals without digital literacy. However, strategies exist that can be implemented to address these concerns. Shared mobility may also result in various impacts on the local economy, environment, modal shifts, and user health and safety, although this varies by mode. Shared mobility adoption also varies by different built environments and tends to be more widely available and used in dense, urban and lower-density, suburban environments. However, current understandings of shared mobility adoption and use may be impacted by the global pandemic. The pandemic has also increased teleworking, and this is anticipated to continue. Teleworking has resulted in distributing travel demand more consistently throughout the day. The pandemic also encouraged individuals, particularly higher income individuals, to move from higher-density areas to lower-density ones, especially in the Midwest and Northeast. Transportation demand management strategies can help address new transportation characteristics, resulting from shared mobility availability and the pandemic.

The expert interviews reiterated many of the literature review findings. The experts also noted that the pandemic altered operations for many transportation service providers (e.g., service suspensions) and ridership is returning to higher demand levels from its suppressed state. In the future, mobility operators will likely need to tailor their services to meet new needs (e.g., demand from teleworking schedules). The experts offered insights on various strategies to encourage high-occupancy, lower-emission, and active mode adoption. Generally, the experts believe that park-and-ride infrastructure may work well in some locations but are likely not a ubiquitous strategy. Infrastructure specifically for active transportation (e.g., networks of connected bike lanes) is likely necessary to support its adoption. Similarly, specific infrastructure components as well as educational campaigns are expected to be necessary to encourage EV adoption. The experts also highlighted communities that may be vulnerable to negative equity impacts including essential workers, immigrants, low-income households, racial minorities, and rural populations. Experts would like to see further research to be done on equity impacts, especially for the aforementioned populations, as well as on COVID-19 impacts and multimodal integration.

The focus group echoed the previous findings, particularly on pandemic-related changes, such as increases in teleworking and considering changing residential locations. When discussing potential strategies to encourage high-occupancy, lower-emission, and active mode adoption, they were most concerned with affordability and safety. To encourage public transit use, specifically, participants focused on addressing: safe parking availability, public health concerns, personal safety and security, and trip convenience and comfort.

The shared micromobility analysis explored potential spatial. The correlation between activity and census-based demographics suggests that micromobility was most accessible in regions that had young and middle-aged adults and greater layers of educational attainment.. With the exception of San Francisco, in most cities lower income areas had greater access to bike- and scooter- sharing. The results found that in San Francisco there is a high level of micromobility access available to wealthier populations. Overall, the results suggest that spatial inequities but are not systematic to a particular mode.

The analysis also explored the impacts of telework on overall VMT. The results find that changes in overall VMT (within the sample population) resulted from telework. These changes were presented in the context of pre-pandemic and during-pandemic behavior. The survey, given in 2021, was administered during a time of increasing recovery and opening from the lockdowns of 2020. But it was a still a time when many large-scale teleworking arrangements were in place. The analysis of the survey sample shows that the impacts of teleworking on household VMT are present, particularly among households that did not move due to teleworking. Respondents who moved in response to remote work environments experienced a considerably smaller decline in VMT than those who did not move, but were allowed to telework. The survey also found that 62% of respondents would drive in general purpose lanes to commute if HOV lanes were not available or if HOT lanes were too expensive. Other alternatives selected by respondents including using public transit (12%), teleworking (10%), joining a carpool (9%), and other strategies. These results could lend some insight to how commute patterns may shift in response to other transportation demand management policies.

Thirteen policy scenarios were created that included various components including plans, transit and land use, and pricing. The modeling results revealed that mode shifts would generally benefit public transit, and funding could be reinvested to support more price sensitive, lower-income populations. TOD strategies also had a significant impact, specifically on VMT. However, these strategies only explored current mass transit options. The models also revealed a high-elasticity of VMT per capita for transit in-vehicle time decreases. Changes like teleworking and automated vehicles are difficult to model and the future impacts are unclear.

Appendix A Shared Mobility Users and Impacts

Advancements in social networking, location-based services, wireless networks, and cloud technologies are contributing to the sharing economy (i.e., sharing, renting, or borrowing goods and services rather than owning them). Shared mobility is part of the sharing economy and is an innovative transportation strategy enabling users to gain short-term access to transportation modes on an "as-needed" basis. Table 23 summarizes commonly found shared mobility modes.

Table 23. Shared Mobility Terms and Definitions

Term	Definition
Advanced Air Mobility	A broad concept that enables consumers access to on-demand air mobility, goods delivery, and emergency services through an integrated and connected multimodal transportation network.
Carsharing	A service that provides the traveler with on-demand, short-term access to a shared fleet of motor vehicles typically through a membership and the traveler pays a fee for use. Carsharing service providers typically own and maintain the vehicle fleet and provide insurance, gasoline/charging, and parking.
Courier Network Services, or CNS or Flexible Goods Delivery	A commercial for-hire delivery service for monetary compensation using an online application or platform (such as a website or smartphone app) to connect freight (e.g., packages, food, etc.) with couriers using their personal, rented, or leased vehicles, bicycles, or scooters.
Microtransit	A technology-enabled transit service that typically uses shuttles or vans to provide pooled on-demand transportation with dynamic routing. Typically, microtransit services are operated by or provided on behalf of a government entity or nonprofit organization but privately operated microtransit programs may also exist. Variations could include fixed schedules and routes and larger or smaller vehicles.
Public Transit	A system of transportation for the public provided by public agencies.
Ridesharing	The formal or informal sharing of rides between drivers and passengers with similar origin-destination pairings.
Shared Micromobility	The shared use of a bicycle, scooter, moped, or other low-speed vehicle or device that provides travelers with short-term access on an as-needed basis. Micromobility vehicles and devices may be propelled by a variety of power sources, including human, engine, or motor. Shared micromobility includes various service models and transportation modes, such as: • *Bikesharing:* A service that provides travelers on-demand, short-term access to a shared fleet of bicycles, usually for a fee. Bikesharing service providers may own, maintain, and provide charging (if applicable) for the bicycle fleet. Users may access bicycles through annual, monthly, daily, or per-trip pricing. Bikesharing includes pedal-only and powered bicycles such as e-bikes. • *Scooter Sharing:* A service that provides the traveler on-demand, short-term access to a shared fleet of scooters for a fee. Scooter sharing service providers typically own, maintain, and provide fuel/charging (if applicable) for the scooter fleet. Service providers may also provide insurance. Generally, participants pay a fee each time they use a scooter and trips can be roundtrip or one-way. Scooter sharing includes standing and seated scooters that are solely human powered and those that are partially or fully powered by a motor or engine.
Taxis	A service that provides the traveler pre-arranged and/or on-demand access to a ride service in a motor vehicle for a fee for use. The travelers can typically access this ride by scheduling trips

Term	Definition
	in advance, by street hail, or by e-hail. Street hail is done by raising a hand on the street, standing at a taxi stand, or specified loading zone. E-hail entails dispatching a driver on-demand using a smartphone app. Taxi ride service typically uses sequential sharing (although taxi splitting—the sharing of a taxi ride and fare between two travelers—is allowed in some areas).
Transportation Network Companies, or TNCs	A service that provides the traveler with pre-arranged and/or on-demand access to a ride for fee using a digitally enabled application or platform (e.g., smartphone apps) to connect travelers with drivers using their personal, rented, or leased motor vehicles. Digitally enabled applications are typically used for booking, electronic payment, and ratings. TNCs are not allowed to street hail (on-demand does not include street hail). Concurrently shared TNC ride service is referred to as "ridesplitting." TNCs may also be used to provide goods delivery.

Source: SAE International (2021)

Shared mobility availability may be able to support reductions in single occupancy and personal vehicle-based trips and encourage trips made via higher-occupancy, lower-emission vehicles, and active modes. However, research has found that shared mobility adoption does not appear to be uniform across various demographic groups, which may cause equity concerns. Shared mobility modes may result in additional equity concerns if they exclude select populations (e.g., people with disabilities, low-income households). In addition to equity challenges, shared mobility may result in various impacts including on the economy, vehicle miles traveled (VMT) and resulting greenhouse gas emissions (GHG), individual health and safety outcomes, and modal shifts.

The literature review is separated into two halves. This half of the literature review focuses on shared mobility user demographics and impacts, while the other half summarizes travel behavior trends based on different built environments, pandemic impacts, and transportation demand management strategies. Both halves of the literature review are intended to provide relevant background information and key findings on the current state of shared mobility and travel behavior trends. The literature review focuses predominantly on carsharing, shared micromobility, and TNCs as they are some of the more well studied modes. These modes were selected specifically due to their opportunity to encourage active transportation and increase vehicle occupancies. In its entirety, the literature review includes the following sections:

Shared Mobility Users and Impacts

- **Shared Mobility Demographics:** Summary of the demographic characteristics of shared mobility users;
- **Shared Mobility Equity Impacts:** Description of the equity impacts, and strategies to address them, that may result from shared mobility; and
- **Common Shared Mobility Impacts:** A description of the common impacts carsharing, ridesharing, shared micromobility, and TNCs result in.

Trends and Policies Impacting Travel Behavior

- **Land Use and Built Environment:** Description of various land uses and their resulting impacts to shared mobility use,
- **COVID-19 Changes:** Summary of broad teleworking and housing changes resulting from the pandemic and their anticipated transportation impacts, and

- **Transportation Demand Management:** Policies and strategies to improve transportation demand management and improve transportation network efficiency.

A. 1.1 Shared Mobility Demographics

Shared mobility use may vary by demographic characteristics including gender, age, race, income, and education level. Generally, users tend to be male, Caucasian, ages 25 to 34, and with high annual incomes and levels of educational achievement. Table 24 summarizes different demographic trends regarding carsharing, bikesharing, scooter sharing, and TNC users. The table uses a metanalysis approach. This approach aggregates the results of multiple studies across the United States. The data used were the most recent at the time of each source's publication. The metadata analysis was selected because shared mobility modes and resulting studies are relatively new, resulting in inconsistently provided data (e.g., age and race but not education, information only in a select area). A metadata analysis provides a broader look at the overall shared mobility user demographics. The analysis and table findings can help detail the demographic characteristics of users of each mode, which may indicate equity concerns. Further equity concerns as discussed following the table.

Table 24. Shared Mobility User Demographics

Mode	Gender	Age	Race	Income	Education	Source
Carsharing	*Female:* 43-49% *Male:* 47-56%	*<18:* n/a *18 to 24:* 5-38% *25 to 34:* 23-48% *35 to 44:* 16-23% *45 to 54:* 11-16% *55 to 64:* 5-15% *65 to 74:* 3-11% *>75:* 1-8%	*African American:* 6-22% *American Indian or Alaska Native:* 1-2% *Asian:* 13-14% *Caucasian:* 32-89% *Hispanic:* 1-29% *Native Hawaiian or Pacific Islander:* 0-1% *Two or More Races:* 2-4% *Other:* 1-2%	*<$9,999:* 2-9% *$10,000 to $14,999:* 5-6% *$15,000 to $24,999:* 6-9% *$25,000 to $34,999:* 7- 18% *$35,000 to $49,999:* 10-19% *$50,000 to $74,999:* 14-19% *$75,000 to $99,999:* 11-15% *$100,000 to $149,999:* 7-19% *$150,000 to $199,000:* 4-21% *>$200,000:* 12-19%	*Grade School:* 1-19% *High School/GED:* 2-24% *Some College:* 5-10% Associate's Degree: 3-22% *Bachelor's Degree:* 22-43% *Master's Degree:* 15-28% *Doctorate Degree:* 4-5% *Other:* 7-8	Kim et al. (2017) Martin and Shaheen (2010) Martin et al. (2010) Martin et al. (2020) Martin et al. (2021) Shaheen et al. (2019)
Shared Micromobility - Bikesharing	*Female:* 34-45 *Male:* 55-66	*<18:* 1-3% *18 to 24:* 6-12% *25 to 34:* 26-48% *35 to 44:* 19-28% *45 to 54:* 10-23% *55 to 64:* 8-13% *>65:* 1-15%	*African American:* 1-2% *American Indian or Alaska Native: 0%* *Asian:* 3-6% *Caucasian:* 61-92% *Hispanic:* 1-5% *Native Hawaiian or Pacific Islander: 0%* *Other:* 1-5%	*<$9,999:* 1-5% *$10,000 to $14,999:* 2-3% *$15,000 to $24,999:* 3-5% *$25,000 to $34,999:* 3-6% *$50,000 to $74,999:* 19-31% *$75,000 to $99,999:* 14-20% *$100,000 to $149,999:* 12-18% *$150,000 to $199,000:* 8-12% *>$200,000:* 7-8%	*Less than High School:* 0% *High School/GED:* 1-2% *Some College:* 7-11% *Associate's Degree:* 3-4% *Bachelor's Degree:* 42-43% *Advanced Degree:* 42-46% *Other:* n/a	Hirsch et al. (2019) Shaheen et al. (2012) Shaheen et al. (2014)
Shared Micromobility - Scooter Sharing	*Female:* 19-34% *Male:* 34-81%	*<18:* 1-2% *18 to 24:* 5-21% *25 to 34:* 31-42% *35 to 44:* 25-27% *45 to 54:* 9-19% *55 to 64:* 4-16%	*African American:* 2-3% *American Indian or Alaska Native:* n/a *Asian:* 4-5% *Caucasian:* 67-79% *Hispanic:* 9-10%	*<$9,999:* 9-10% *$10,000 to $14,999:* 11-12% *$15,000 to $24,999:* 8-11% *$25,000 to $34,999:* 9-11%	*Less than High School:* n/a *High School/GED:* 7-8% *Some College:* 25-26%	City of Santa Monica (2019) Dibaj et al. (2021) National Association of City

Mode	Gender	Age	Race	Income	Education	Source
		>65: 0-2%	*Native Hawaiian or Pacific Islander:* n./a *Two or more:* 5-6% *Other:* 8-9%	*$35,000 to $49,999:* 10-15% *$50,000 to $74,999:* 14-22% *$75,000 to $99,999:* 12-14% *$100,000 to $149,999:* 17-36% *$150,000 to $199,000:* 9-10% *>$200,000:* n/a	*Associate's Degree:* n/a *Bachelor's Degree:* 65-66% *Advanced Degree:* *Other:* n/a	Transportation Officials (2019) Orr et al. (2019) Rayaprolu and Venigalla (2020) Sanders et al. (2020) Zhang and Guo (2021)
TNCs	*Female:* 40-53 *Male:* 47-60	*<18:* n/a *18 to 24:* 17-62% *25 to 34:* 25-69% *35 to 44:* 13-69% *45 to 54:* 6-10% *55 to 64:* 2-3% *>65:* 1-4%	*African American:* 3-27% *American Indian or Alaska Native:* 2-4% *Asian:* 8-23% *Caucasian:* 21-84% *Hispanic:* 10-54% *Native Hawaiian or Pacific Islander:* n/a *Two or more:* 6-14% *Other:* 5-15%	*<$9,999:* n/a *$10,000 to $14,999:* n/a *$15,000 to $24,999:* n/a *$25,000 to $34,999:* n/a *$35,000 to $49,999:* 18-19% *$50,000 to $74,999:* 19-20% *$75,000 to $99,999:* 14-15% *$100,000 to $149,999:* n/a *$150,000 to $199,000:* n/a *>$200,000:* n/a	*Less than High School:* 1-5% *High School/GED:* 8-19% *Some College:* 19-20% *Associate's Degree:* 7-42% *Bachelor's Degree:* 21-54% *Advanced Degree:* 25-27% *Other:* n/a	Circella et al. (2018) Clewlow and Mishra (2017) Gehrke et al. (2018) Grahn et al. (2019) Hampshire et al. (2018) Henao et al. (2019) Rayle et al. (2016)

A. 1.2 Shared Mobility Equity Impacts

Shared mobility adoption may be lower among vulnerable populations, particularly: 1) people with disabilities; 2) unbanked and underbanked households; 3) low-income households; and 4) individuals who are not digitally literate (Shaheen & Cohen, 2018). These demographic groups often make up disadvantaged communities. Disadvantaged communities are defined as those who most suffer from a combination of economic, health, and environmental burdens. These burdens include poverty, high unemployment, air and water pollution, presence of hazardous wastes as well as high incidence of asthma and heart disease (California Public Utilities Commission, n.d.). Shared mobility's equity impacts are further described in the following subsections.

A. 1.2.1 People with Disabilities

An estimated one in four Americans currently lives with a disability (Center for Disease Control, 2018). In the United States, by 2045, the number of Americans over the age of 65 will increase to 77% (U.S. Department of Transportation, 2016). As populations across the world age, the number of persons with disabilities will continue to increase (U.S. Department of Transportation, 2016). Shared mobility has the opportunity to lower the cost and diversify the range of assisted modes to users with cognitive and physical challenges. However, rapid technology change can create unforeseen access challenges for disabled users, if specific needs are not considered (Shaheen, Bell, Cohen, & Yelchuru, 2017). People with disabilities may face challenges including visual limitations making it hard to recognize their TNC vehicle, physical difficulties prohibiting them from operating shared micromobility devices, cognitive differences impacting their understanding and use of shared mobility apps and platforms, et cetera (Goralzik, Konig, Alciauskaite, & Hatzakis, 2022). Organizations have begun funding programs to increase transportation equity, including with shared mobility. The U.S. Department of Transportation's Intelligent Transportation Systems Joint Program Office (ITS JPO) launched the Accessibility Transportation Technologies Research Initiative (ATTRI) through a partnership with the National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR) to improve transportation accessibility in the areas of wayfinding and navigation, pre-trip concierge and visualization services, safe intersection crossings, and robotics and automation. However, studies are limited on how programs like these improve transportation accessibility.

Mandated by federal law, demand-responsive service provides support to passengers with limited mobility through dial-a-ride or paratransit services. However, these services often have limited geographic coverage, require advance scheduling, and are generally very expensive to operate on a per trip basis (compared to public transportation and other modes). Demand-responsive, shared mobility services for people with limited mobility may be one way of complying with U.S. federal requirements and potentially offering users enhanced services (e.g., reduced wait times) and at reduced cost (e.g., to the end user, public agency, or both). However, shared mobility also can raise a number of social equity concerns, particularly around the lack of demand-responsive services for passengers with limited mobility when shared modes do not offer accessible services or equivalent accessible alternatives (Shaheen S. , Cohen, Yelchuru, & Sarkhili, 2017).

A. 1.2.2 Unbanked and Underbanked and Low-Income Households

Economic inclusion can represent a notable barrier for some travelers. Many shared mobility services require debit/credit cards for payment and, in some cases, collateral for vehicles or equipment. This can be a barrier for consumers who are underbanked or unbanked (i.e., households without a bank account or debit/credit card). For example, two major TNCs – Lyft and Uber – accept payment options that include major credit and debit cards, prepaid cards, various payment platforms (e.g., Google Pay, Venmo), and direct bank account links, but not cash (Lyft; Uber). In Uber's payment information section, the company explicitly states that it is intended to be a cash free experience. Similarly, Lime, a scooter sharing company, accepts bank account-based payment services (Lime). In 2019 in the San Francisco Bay Area, the San Francisco Bicycle Coalition advocated for the local bikesharing program, Bay Wheels, to maintain a cash payment option to serve populations, such as low-income riders (Lewis, 2019). Cash payments are currently accepted for Bay Wheels riders. However, paying with cash requires the completion of one of two multistep processes: 1) using a Clipper card (the local public transit agency reusable fare card), 2) purchasing a prepaid card. To use a Clipper card, riders must go to a single location in Downtown San Francisco, even though Bay Wheels serves multiple cities in the Bay Area (e.g., Oakland, San Francisco, San Jose), to add cash to then be used to pay for Bay Wheels rides (Metropolitan Transportation Commission). If riders wish to use a prepaid card, they must go to select retail locations (e.g., drug stores, grocery stores, online), although a list of specified retailers is not available online, then load the card then use it for membership or use charges (Lyft). Information is not available as to whether or not these cash payment options have increased Bay Wheels use for unbanked and underbanked households.

To assess the inclusiveness of the banking system, the U.S. Federal Deposit Insurance Corporation (FDIC) conducts a biennial survey of household access to the bank system. In 2017, the FDIC found that 6.5% (approximately 8.4 million) of U.S. households were "unbanked" and did not have access to an account at a financial institution (Federal Deposit Insurance Corporation, 2018). The survey also found that 18.7% (approximately 24.2 million) of U.S. households were "underbanked" meaning that a household had a checking or savings account but also obtained financial products and services outside of the banking system (Federal Deposit Insurance Corporation, 2018). In addition to banking access, the survey also asked questions about access to credit card payment methods. Sixty-nine percent of households surveyed had a credit card from Visa, MasterCard, American Express, or Discover (Federal Deposit Insurance Corporation, 2018). However, the survey found that only 7.2% of unbanked households had a credit card, compared to 60% of underbanked households and 76.3% of fully banked households.

The study also found that a household's availability and use of mainstream credit products varied widely across demographic and socioeconomic groups (Federal Deposit Insurance Corporation, 2018). Generally, households that were lower income, less educated, Black or Hispanic, younger, older, or with a working-age disabled member(s) were less likely to use mainstream credit cards. The study also identified related racial and ethnic demographic differences that could have been contributing factors. For example, the study found that 36% of African American households and 31.5% of Hispanic households had no mainstream credit compared to 14.4% of Caucasian households. At all income levels, African American and Hispanic households were more likely not to have mainstream credit. The study concluded that racial and ethnic differences in bank account ownership and socioeconomic and demographic characteristics beyond income can account for some, but not all, of the racial and ethnic differences in the likelihood of limited or no mainstream credit.

Additionally, shared mobility typically employs a pay-as-you-go pricing model that can be expensive (and sometimes costlier in comparison to walking, cycling, and public transportation) (Manjoo, 2016). For example, in Helsinki, Finland, the Kutsuplus program, a municipal demand-responsive transit service in the urban core, was critiqued as having too few vehicles and too large a service area, creating higher user fees. The program had a service area of 100 square kilometers (approximately 38 square miles) with a fleet of 10 shuttles (expanding later to 15 vehicles). This resulted in higher program costs and fares with a base fare of $4.75 plus $0.60 per kilometer (about $0.97 per mile) (Shaheen & Cohen, 2018; Barry, 2013; Shared-Use Mobility Center, 2016).

Other pricing strategies, such as surge or demand-pricing, can also create affordability challenges. Proponents of dynamic pricing argue that surge pricing can help to increase supply and manage demand. However, other studies have found that uncertain roundtrip costs (e.g., the risk of surge pricing on the return leg of a journey) can make these services less desirable or reliable, particularly among low- to moderate-income user groups (Shaheen & Cohen, 2018).

A. 1.2.3 Individuals without Digital Literacy

While some shared modes can be accessed without a smartphone, shared mobility increasingly requires a smartphone and high-speed data packages to access services, multimodal aggregation, on-demand trip planning, booking, and payment. Lack of mobile Internet access can inhibit travelers from using shared modes. Since many shared mobility services are accessed by a smartphone, even the lack of familiarity with and access to mobile and web technology can preclude users from accessing the potential benefits of these services.

One notable social equity concern is the lower rate of smartphone and mobile data usage among older adults, lower-income households, and persons with disabilities; this is often referred to as the digital divide or digital poverty (Shaheen, Bell, Cohen, & Yelchuru, 2017; Shaheen & Cohen, 2018; Anderson, Perrin, & Jiang, 2018). According to a recent study by Anderson et al. (2018), 11% of Americans do not use the Internet. The percentage of Americans who do not use the Internet is notably higher among vulnerable populations including older adults, rural residents, low-income households, and individuals without a high school diploma. Of the U.S. adults who do not use the Internet, Anderson et al. (2018) found that 35% had less than a high school diploma, 34% were 65 years of age or older, 22% lived in rural communities, and 19% had an annual household income of less than $30,000 (Anderson, Perrin, & Jiang, 2018). Lack of Internet access can be a barrier to low-income and rural households who may not be able to afford or may lack mobile data coverage to access shared mobility modes. Swenson and Ghertner (2020) found that 18% of individuals who had incomes below the federal poverty line lacked internet access. Additionally, households below the federal poverty line in nonmetropolitan areas were 8% less likely to have internet access compared to similar households in metropolitan areas (Swenson & Ghertner, 2020). Alternatives such as digital kiosks, telephone services, and non-tech access (such as street hail) can help overcome these challenges. Research on ridesharing services for older adults by Freund et al. (2021) found that these services, which include service considerations like ride requests that can be made via smartphone app and phone-in options, have the potential to address equity and mobility gaps for older adults.

A. 1.3 Common Shared Mobility Impacts

In addition to adoption differences across different populations, carsharing, ridesharing, shared micromobility, and TNCs may impact societal features (e.g., vehicle miles traveled, greenhouse gas emissions), as well as individual changes (e.g., travel behavior decisions). The impacts from these modes are described in the following subsections.

A. 1.3.1 Carsharing Impacts

Carsharing provides members access to a fleet of autos for short-term use throughout the day, reducing the need for one or more personal vehicles. Carsharing tends to be more widely available in walkable, high-density mixed-use areas (Cohen, Shaheen, & McKenzie, 2008). However, evidence has shown that carsharing can fulfill various use cases in different built environment types and land uses including central business districts, new development units, and university and medical campuses (Cohen, Shaheen, & McKenzie, 2008). In lower-density areas, different carsharing business models considerations may need to be factored in, such as greater public agency involvement (Rotaris & Danielis, 2018).

A number of academic and industry studies of shared mobility have documented carsharing impacts, predominantly employing self-reported survey data. These studies collectively show the following commonly associated carsharing outcomes:

- Sold vehicles or delayed or foregone vehicle purchases;
- Increased use of some alternative transportation modes (e.g., walking, biking);
- Reduced VMT/VKT;

- Increased access and mobility for formerly carless households;
- Reduced fuel consumption and GHG emissions; and
- Greater environmental awareness.

While the environmental, behavioral, and economic impacts of carsharing services have been well studied, the magnitude of impact varies. Variations in measured impacts can be due to a variety of factors such as 1) region; 2) density; 3) built environment; 4) public transit accessibility; and 5) business model.

The vast majority of carsharing impact studies have examined carsharing's impact based on business-to-consumer (B2C) and peer-to-peer (P2P) business models. In a B2C model, a carsharing provider offers individual consumers access to a business-owned fleet of vehicles through memberships, subscriptions, user fees, or a combination of pricing models. Examples of B2C carsharing providers include Zipcar and Enterprise CarShare (roundtrip) and GIG Car Share (free-floating one-way). In a P2P model (sometimes referred to as personal vehicle sharing), carsharing providers broker transactions among vehicle owners and guests by providing the organizational resources needed to make the exchange possible. Members access vehicles through a direct key transfer from the host (or owner) to the guest (or driver) or through operator- installed, in-vehicle technology that enables unattended access. Pricing and access terms for P2P carsharing services vary, as they are typically determined by vehicle hosts listing their vehicles. The P2P carsharing operator generally takes a portion of the P2P transaction amount in return for facilitating the exchange and providing third-party insurance. Examples of P2P carsharing providers in the United States include Turo (formerly RelayRides) and Getaround.

A. 1.3.2 Impacts of Business-to-Consumer (B2C) Carsharing

According to Shaheen et al. (2019) carsharing participation may also contribute to:

- Lower vehicle miles traveled (VMT)/vehicle kilometers traveled (VKT) by as much as 67%,
- Reduced parking demand by removing as many as 11 vehicles for every carsharing vehicle and encouraging up to 23% and 44% of carsharing members to sell or avoid purchasing a vehicle respectively, and
- Increased use of other transport modes (such as cycling and walking) in lieu of vehicle travel by as much as 49% for select modes.

Further information on how these numbers vary by location, built environment type, and service characteristics can be found here.

Carsharing is also thought to lead to lower VMT/VKT by emphasizing variable driving costs, such as per hour and/or mileage charges. Reduced vehicle ownership rates and VMT/VKT can also lead to lower greenhouse has (GHG) levels, as trips are shifted to other modes (e.g., shared rides, public transit). Additionally, empirical evidence demonstrates that carsharing has a range of beneficial social impacts (Shaheen, Cohen,

& Farrar, 2019)(Shaheen, Cohen, & Farrar, 2019). For example, carsharing may offer a more cost-effective vehicle access option for lower-income households. Additionally, the anticipated lower environmental impacts from carsharing may benefit disadvantaged communities in particularly, as this population tends to be disproportionately impacted by negative environmental impacts (Shaheen, Cohen, & Farrar, Carsharing's Impact and Future, 2019)

A. 1.3.3 Impacts of Peer-to-Peer (P2P) Carsharing

A few studies have examined P2P carsharing impacts. Shaheen et al. (2018) found that P2P carsharing encourages some households to reduce, delay, or even avoid a vehicle purchase. P2P carsharing also enables hosts to reduce their ownership costs, monetize otherwise idle assets, or both. The authors surveyed 1,151 guests and hosts from three U.S. P2P carsharing companies and documented four key findings:

1. **Vehicle Ownership:** Forty-six percent of P2P carsharing members were from carless households that joined P2P carsharing to gain additional mobility. Another 20% enrolled to earn money sharing their vehicle, while 14% of respondents indicated that they held off on a vehicle purchase due to their carsharing membership. A small percentage (3%) noted that they had sold a vehicle because of their membership. . It is important to note that it is difficult to definitively identify differences between B2C and P2P vehicle ownership rates due to data limitations.
2. **Ease of Use:** Forty-eight percent of respondents felt that P2P carsharing was easier than expected to use compared to 15% who said that vehicle sharing was more challenging to employ than anticipated.
3. **Travel Mode Changes:** Most respondents reported no major change in their public transit use as a result of P2P carsharing, with 9% increasing bus ridership and 10% decreasing it. Similarly, 7% of respondents reported increasing rail use, while 8% reported a decrease. Taxi use showed a net decline among all respondents. Survey respondents that use TNCs were split, as 9% reported an increase and another 9% noted a decrease. In contrast, carpooling showed a net increase (6%) among the sample, suggesting that P2P carsharing users were likely traveling with multiple occupants.
4. **Super Sharers:** In addition, P2P carsharing was used in conjunction with other shared mobility services. Respondents reported that 14% were members of at least one other P2P carsharing service, 43% were members of at least one other carsharing organization, and 78% had used at least one other shared mobility service. Many P2P carsharing members were also frequent Lyft and Uber users, broadly suggesting that they used an array of shared mobility modes to meet their mobility needs (Shaheen, Martin, & Bansal, 2018).

Additionally, the study unveiled motivations and barriers for using P2P carsharing. For vehicle owners, key opportunities and motivations included 1) increasing revenue on existing, often underused vehicles and 2) contributing to the "sharing economy" by providing mobility access to others. Common barriers for vehicle owners included 1) concerns about their inability to use their personal vehicle when it is accessed by a guest, 2) potential vehicle damage, and complex insurance requirements that vary by jurisdiction.

For vehicle guests, key opportunities and motivations to participate in P2P carsharing were 1) accessing a wide array of vehicles, including luxury and zero- emission models and 2) avoiding the costs and hassles associated with private vehicle ownership, such as parking, maintenance, and insurance. Common barriers for vehicle owners include 1) first- and last-mile connections to access P2P carsharing vehicles, 2) key pick-up and drop-off, and 3) lack of reliable response from a car host following a sharing request. Access to/from vehicles and other challenges suggest expanding P2P carsharing outside of urban areas could be more challenging.

While P2P carsharing studies are limited, a few have supported the findings of Shaheen et al. (2019), particularly regarding VMT. A P2P carsharing study in Portland, Oregon found that overall, P2P carsharing participants' driving behavior did not significantly change. However, for 39% of drivers their driving decreased by 10% from their annual baseline due to variations in baseline higher vehicle use, higher rental activity, income constraints, and increased travel behavior flexibility (Dill, McNeil, & Howland, 2019).

Similarly, in a P2P carsharing model, vehicle owners may be incentivized to reduce their driving to make their vehicle more widely available why carsharing borrowers may reduce vehicle ownership and drive less due to the more apparent marginal vehicle costs (Dill, McNeil, & Howland, 2017).

Additionally, Clark et al. (2014) found that P2P overall increases driving mileage among carsharing participants. This is likely, in part, because individuals who are part of corporate carsharing services (i.e., businesses offer employees carsharing access) tend to make more business trips than they otherwise would. However, P2P carsharing does reduce personal vehicle travel and commuting trips for corporate carsharing members (Clark, Gifford, & Le Vine, 2014).

P2P carsharing represents a portion of carsharing, which is part of the overall suite of shared mobility options. While the study by Shaheen et al. (2018) provides insights from thorough research on P2P carsharing, the findings focus on characteristics within P2P carsharing users and compared to larger demographic trends. The findings are not compared to other carsharing users. Even though these findings are limited to P2P carsharing users, they provide useful insights on how to leverage existing resources (e.g., personally owned vehicles) to increase mobility. Additionally, P2P carsharing could increase equity in similar ways to other carsharing business models, such as by increasing more affordable vehicle access and reducing environmental impacts for all. See Table 25 for further potential impacts. The section following the table discusses shared rides, rather than shared vehicles.

Table 25. Carsharing Impacts

Impact Category	Service Name *Location* (if applicable)	Finding	Source
Environmental	**car2go** *Germany*	Over 25% of car2go members/survey respondents would forgo a vehicle purchase if car2go was a permanent service. The car2go service could potentially result in a reduction of 146 to 312 kilograms of CO_2 per participating household annually.	Firnkorn and Muller (2011)
	Europe	Carsharing is estimated to reduce the average user's carbon dioxide emissions by 40% to 50%.	Ryden and Morin (2005)
	*North America***	Carsharing resulted in an estimated an average GHG emission reduction of 34% to 41% per household or an average reduction of 0.58 to 0.84 metric tons per household.	Martin and Shaheen (2011)
	*North America**	On average, car2go carsharing reduced passenger vehicle GHG emissions by 4% (Calgary) to 18% (Washington, D.C.). Carsharing fleets that include low-emission vehicles — such as electric, plug-in hybrid, and gasoline-electric hybrid cars— can contribute to additional GHG emission decreases.	Martin and Shaheen (2016)
		One-way electric vehicle-based carsharing can offer a potential public transit connection that has lower environmental impacts. In order to full capture the potential benefits of one-way, electric carsharing, vehicle redistribution systems will need to be strategically considered.	Mounce and Nelson (2019)
		Various strategies have been employed to address one-way carsharing vehicle redistribution challenges and these may be implemented to maximize the potential carsharing environmental benefits.	Illgen and Hock (2019)
		Individuals who gave up personal vehicles due to carsharing participation can decrease their transportation-based impacts by 40%. Zero-car households who started using carsharing as at least 3% of their VMT increased their transportation-based emissions by 0.42 to 0.7%. These findings are comparable for both B2C and P2P models.	Velez (2023)
		Carsharing members also report a higher degree of environmental awareness after joining a carsharing program.	Lane (2005)

Impact Category	**Service Name** *Location* (if applicable)	Finding	Source
Modal	**Autolib** *France**	Carsharing participants removed 3 private vehicles from the road (on average), reducing overall private vehicle ownership by 23%. Both roundtrip and one-way carsharing forms reduced private vehicle use, with roundtrip carsharing having a greater reduction impact. Both carsharing forms reduced private bicycle use, and roundtrip carsharing increased bikesharing ridership. Roundtrip carsharing increased public transit use slightly. Station-based one-way carsharing reduced public transit use.	6t (2014)
	Car2go *Germany*	In a densely populated, urban area 1 shared vehicle could replace up to 24 personal vehicles.	Firnkorn and Muller (2011)
	City CarShare *San Francisco, CA*	Approximately 30% of City CarShare members (about 1,800) shed one or more personal vehicles. Two-thirds of carsharing members chose to postpone the purchase of another vehicle after using the service for 2 years.	Cervero and Tsai (2004)
	CA, Sweden	Expanding carsharing model and attribute (e.g., all-wheel drive, 7-seater vehicles) variety and availability, especially through P2P carsharing, could increase carsharing adoption and reduce personal vehicle ownership and use.	Sprei and Ginnebaugh (2018)
	*Canada***	Between 15% and 29% of carsharing participants sold a vehicle after joining carsharing programs, while 25% to 61% delayed or had forgone a vehicle purchase.	Martin et al. (2010) Communanauto (2000) Jensen (2001)
	Canada, U.S.	Roughly 25% of carsharing members sold a vehicle due to carsharing and another 25% postponed a vehicle purchase due to roundtrip carsharing availability. One carsharing vehicle replaced 9 to 13 vehicles among carsharing members (on average across this aggregate-level study).	Martin and Shaheen (2011)
	Canada, U.S.	Each roundtrip carsharing vehicle removed an average of 6 to 23 cars on roads over the course of a year.	Lane (2005)

Impact Category	Service Name *Location* (if applicable)	Finding	Source
			Martin et al. (2010) Zipcar (2005).
	Canada, U.S.	Across five cities in the United States and Canada, about 2% to 5% of participants sold a vehicle after joining carsharing and 8% to 10% on average delayed or had foregone a vehicle purchase. Each free-floating one-way carsharing vehicle removed seven to 11 vehicles from the road.	Martin and Shaheen (2016)
	*Europe***	A roundtrip carsharing vehicle reduced the need for 4 to 10 privately owned vehicles.	Ryden and Morin (2005)
	Italy	Adoption of carsharing could increase by 10% by diverting personal vehicle trips. Carsharing adoption could also crease active transportation and public transit adoption.	Chicco and Diana (2021)
	Netherlands	B2C and P2P carsharing adopters may vary in the frequency in which they use carsharing and public transit ; B2C adopters tend to use carsharing for more regular trips but use active transportation or public transit for other trips.	Munzel et al. (2019)
	Portland, OR	About 37% of families in poverty live in a census block group that contains at least one P2P vehicle, but only 13% live in a census block that has a roundtrip carsharing vehicle. In parts of East Portland, which is a lower-income area of Portland, P2P vehicles are the only type of carsharing vehicles available. P2P carsharing will likely have more pronounced impacts on below-median income consumers than above-median income users.	Dill et al. (2014).
	Switzerland	Free-floating carsharing can reduce personal vehicle use by 6%.	Becker et al. (2018)
	U.S.	Carsharing resulted in a slight overall decline in public transit use. Carsharing members tended to increase their use of alternative modes (e.g., walking). Modal impacts may vary by location-specific variations including urban density, public transit service and availability, sociodemographics, and cultural norms.	Martin and Shaheen (2011)
	*U.S.***	About 11% to 26% of carsharing participants sold a personal vehicle. Nearly 12% to 68% carsharing participants postponed or entirely avoided a car purchase.	Lane (2005)

Impact Category	**Service Name** *Location* (if applicable)	Finding	Source
			Martin et al. (2010) Arlington County Commuter Services (2012)
Societal	*North America***	Carsharing households saved an average of $154 US to $435 US per month in contrast to private vehicle use.	Shaheen et al. (2012)
	City CarShare *San Francisco, CA*	Almost 30% of carsharing members got rid of one or more vehicles after joining the carsharing service. Approximately 2/3 of carsharing members opted not to purchase another vehicle.	Cervero and Tsai (2004)
	U.S.	Low-income households and college students can also benefit from participation in carsharing programs.	Kyeongsu (2015) Stocker et al. (2016)
	U.S.	Households can gain or maintain access to vehicles without bearing the full costs of car ownership. Depending on the location and the organization operating the carsharing program, the maximum user mileage where carsharing is more cost effective (in comparison to owning or leasing a personal vehicle) between 6,200 and 10,000 miles.	Shaheen et al. (2006)
VMT/VKT	**Autolib** *France**	One-way station-based carsharing recorded an 11% VKT reduction.	6t (2014)
	*Canada, U.S.***	Carsharing VMT/VTK reductions, on average, ranged from 7.6% to 80% of a member's total VMT/VKT.	Shaheen et al. (2006)
	*Canada, U.S.**	VMT reductions ranged from 6% (in Calgary, Alberta) to 16% (in Vancouver, British Columbia and Washington, D.C.) for free-floating one-way carsharing in the United States and Canada. (This percentage reduction considers an estimate of the total driving by households on average, as derived from annual VMT/VKT responses and broader driving reductions computed for the population.)	Martin and Shaheen (2016)

Impact Category	**Service Name** *Location* (if applicable)	Finding	Source
	*Canada, U.S.***	Roundtrip carsharing reduced VMT/VKT from 27% to 43% in the United States and Canada.	Martin and Shaheen (2011)
	*Europe***	VKT reductions ranged from 28% to 45% on average.	Shaheen and Cohen (2007)

*One-way carsharing

**Roundtrip carsharing

A. 1.4 Ridesharing

Empirical and anecdotal evidence indicates that ridesharing (e.g., carpooling and vanpooling) provides numerous societal benefits, such as:

- Reduced vehicle miles/kilometers traveled and congestion mitigation,
- Reduced energy consumption and emissions, and
- Reduced parking and roadway infrastructure demand.

One impact commonly associated with ridesharing is a reduction in VMT/VKT. VMT/VKT is a travel demand metric that measures the sum of the number of miles traveled by each vehicle. Employee-based trip reduction (EBTR) and transportation demand management (TDM) programs are recognized as best practices to support VMT reduction goals. However, many of these programs lack performance monitoring and assessment and only a handful of empirical studies have examined the VMT impacts of these policies.

A. 1.4.1 Individual Impacts of Ridesharing

Studies suggest that ridesharing is a flexible strategy that can be employed by many users. Although research is limited, ridesharing participants frequently benefit from pooling in a number of ways. Individually, ridesharing users can benefit from:

- Cost savings (through shared travel costs),
- Travel time savings from high occupancy vehicle (HOV) lane access and preferential parking at destinations, and
- Reduced commute stress (through shared driving responsibilities).

Table 26. Ridesharing Impacts

Impact Category	Finding	Source(s)
GHG Emissions	In China, ridesharing could reduce CO_2 emissions by 46.2 thousand tons and NO_X emissions by 253.7 tons.	Yu et al. (2017)
	Ridesharing can save fuel and reduce greenhouse gas (GHG) emissions by increasing vehicle occupancy. Carpooling could save 33 million gallons of gasoline daily if each average commuting vehicle carried one additional passenger (PACommutes, 2016).	Minett and Pearce (2011)
	Enacting policies to increase pooling is the most effective strategy to reduce energy consumption besides driving prohibitions.	Noland et al. (2006)
	Adding one additional passenger added to every 100 vehicles could result in a potential fuel savings of 0.80 to 0.82 billion gallons of gasoline per year in the United States. If one additional passenger was added to every 10 vehicles there could be a potential annual fuel savings of 7.54 to 7.74 billion gallons per year in the United States.	Jacobson and King (2009)
	Individual carpoolers reduce personal annual commute GHG emissions by approximately 4% to 5% after joining an employer trip reduction program.	Hillsman et al. (2001)
	Adding one passenger to every 10 vehicles could result in a savings of 68 million tons of GHG emissions annually in the United States.	Jacobson and King (2009)
	Employing information and communication technology (ICT), such as app-based carpooling, to optimize roadway performance could abate 70 to 190 million metric tons of carbon dioxide emissions annually.	The Global e-Sustainability Initiative (2008)
Societal	Casual carpooling users between the ages of 25 and 34 in Houston, Texas were more likely to make commute trips (96%) versus noncommute trips (80%). HOV lane users tended to belong to larger households with over 60% of carpools comprising family members.	Burris and Winn (2006)
	Carpooling can provide job access to households with lower incomes and households with more workers than vehicles.	Tomer (2016)
	Ridesharing users tend to have lower incomes, and Hispanics and African Americans carpool more than other racial and ethnic groups.	Liu and Painter (2012)

Impact Category	Finding	Source(s)
	Ridesharing may serve an important role in enhancing mobility in low-income, immigrant, and nonwhite communities where travelers are more likely to be unable to afford personal automobiles and obtain driver's licenses.	
	Some ridesharing users can have longer commute distances and therefore have higher commute costs. Ridesharing can be an important cost-saving travel strategy for commuters. Carpool participants were more likely to have lower incomes and be the second worker in a household.	Teal (1987)
	According to a 1998 survey, approximately 9,000 commuters (6,000 riders and 3,000 drivers) used casual carpooling each weekday morning in the San Francisco Bay Area.	Metropolitan Transportation Commission (1999)
	Commuters who participate in ridesharing frequently have access to preferential parking and HOV lanes, which also contribute to pooling's convenience and time savings. Casual carpooling can result in travel time savings, cost savings, and convenience as key motivators to share a ride.	Burris and Win (2006) Maltzman and Beroldo (1987) Reno et al. (1989) Beroldo (1990)
	Convenience, time savings, and monetary savings were key motivators to carpool.	Shaheen et al. (2016)
	In Washington D.C. and Northern Virginia, driver departure flexibility was a primary reason for driving instead of riding as a carpool participant. The top reason for choosing to be a rider was the desire to save on gasoline cost, followed by a preference to do other things during the drive. About 60% of casual carpooling participants in Washington D.C. and Northern Virginia only participated as passengers, 12% only as drivers, and 28% as both passengers and drivers.	Oliphant (2008)
VMT/VKT	Employees participating in a TDM program had 4.2% to 4.8% lower VMT than employees at the same worksite who did not participate. Total VMT declined by 1.33% annually on all roadways and annual freeway VMT was reduced by 1.07% for the four central counties in metropolitan Seattle when TDM measures were implemented.	Hillsman et al. (2001)
	VMT in Washington was reduced by 1.6% from carpooling over the course of the study.	Interagency Commute Trip Reduction Board (2011)
	TDM programs can reduce VMT for workplace commutes by 4% to 6% (or approximately 1% regionally).	Boarnet et al. (2014)

Impact Category	Finding	Source(s)
	Employees of locations with TDM measures in place had an average VMT reduction of 6%.	Lagerberg (1997)

A. 1.5 Shared Micromobility Impacts

Although before-and-after studies documenting shared micromobility impacts are limited, a few North American programs have conducted user surveys to record program outcomes. These studies suggest that a number of social, environmental, and behavioral impacts are attributable to shared micromobility, and an emerging body of empirical evidence supports many of these relationships—although more research is needed as studies on dockless modes (bikesharing and scooter sharing) are limited. In general, impact studies of shared micromobility tend to demonstrate the following outcomes:

- Assistance with bridging gaps in the transportation network and encouraging multimodal journeys;
- Increased use of some alternative and nonmotorized modes of transportation (e.g., walking and biking);
- Potential for reduced fuel consumption and GHG emissions;
- Opportunities to burn calories (Freed, 2014); and
- Greater environmental awareness.

Table 27 and Table 28 describe the economic, environmental, health, modal, and environmental impacts of bikesharing and scooter sharing, respectively.

Table 27. Bikesharing Impacts

Impact Category	Service *Location*	Finding	Author
Economic	**Nice Ride Minnesota** *Minneapolis and Saint Paul, MN*	Users spent an average of $1.25 per week on new economic activity that would likely have not occurred without the bikesharing system; this resulted in approximately $29,000 of new economic activity per season in the Twin Cities. Bikesharing stations may: 1) increase accessibility to station areas, 2) users may alter destinations or make additional trips, and 3) users spend more money in the immediate vicinity around bikesharing kiosks.	Schoner (2012)
Environmental	**Bluebikes** *Boston, MA*	In 2018, 267,000 users completed more than 1.7 million trips, traveled 2.1 million miles, and offset three million pounds of GHG emissions.	Bluebikes (2019)
	Fort Work BCycle *Fort Worth, TX*	In 2017, approximately 15,000 unique riders completed 59,000 trips covering 266,000 miles, which offset 251,000 pounds of GHG emissions.	Camareno and Brennan (2017)
Health	**Bluebikes** *Boston, MA*	In 2018, users expended nearly 159 million calories riding on bicycles in 2018.	Bluebikes (2019)
	Capital Bikeshare *Washington, D.C.*	Approximately, 31.5% of Capital Bikeshare users reported reduced stress, and about 30% indicated they lost weight due to bikesharing use. However, a key limitation of bikesharing health impact assessment studies is that they do not examine potential negative health impacts associated with ridership, such as the costs associated with increased exposure and risks related to injuries and collisions.	Alberts et al. (2012)
	CitiBike *New York City, NY*	Between 2013 and 2018, users burned 4.5 billion calories between 2013.	Motivate (2018)
Modal	**Capital Bikeshare, Nice Ride** *Washington, D.C.; Minneapolis and Saint Paul, MN*	In Minneapolis-Saint Paul modal changes in response to bikesharing included: • 15% of people shifted toward rail while 3% shifted away from it, • 38% of respondents shifted toward walking while 23%, and • 15% of respondents increased their use of buses compared to 17% that decreased it. In Washington, D.C. modal changes in response to bikesharing included: • 47% of people shifted away from rail than to it (7%),	Shaheen et al. (2012)

Impact Category	**Service** *Location*	Finding	Author
		• 31% of respondents shifted away from walking than to it (17%), and • 5% of respondents increased bus ridership compared to 39% that decreased it.	
	Bike Share Toronto, BIXI Montreal, Capital Bikeshare, Nice Ride *Toronto, Ontario; Montreal, Quebec; Washington, D.C.; Minneapolis and Saint Paul, MN*	Shifts toward public transportation in response to bikesharing tend to be more prevalent in lower-density regions on the urban periphery, suggesting that station-based bikesharing may serve as a first- and last-mile connector in smaller metropolitan regions with lower densities and less robust public transit networks. In larger metropolitan regions with higher densities and more robust public transit networks, station-based bikesharing may offer faster, cheaper, and more direct connections compared to short distance transit trips. Public bikesharing may be more complementary to public transportation in small and medium metropolitan regions and more substitutive in larger metropolitan areas, perhaps providing relief to crowded transit lines during peak periods	Shaheen and Martin (2015)
	Citi Bikeshare *New York City, NY*	Every thousand bikesharing docks along a bus route are associated with a 1.69% to 2.42% reduction in daily unlinked bus trips on routes in Manhattan and Brooklyn (with and without controlling for bicycle infrastructure, respectively)	Campbell and Brakewood (2017)
Safety	**Bay Wheels, Capital Bikeshare, Nice Ride** *San Francisco Bay Area, CA; Washington, D.C.; Minneapolis and Saint Paul, MN*	The number of bicycle collisions was generally rising in bikesharing regions, but this increase was very likely due to bicycle activity growth in all regions. Between 2006 and 2013 the following trends were noted: • In Washington, D.C. the estimated number of people commuting to work by bicycle increased 162%, while bicycle collisions increased 121%. • In San Francisco, the estimated number of bicycle commuters increased 98%, and collisions increased 40%. • In Minneapolis-Saint Paul, collision rates remained relatively flat (a 1% increase), while bicycle commuters increased an estimated 65%. Identifying comparative safety outcomes is challenging for researchers to determine. If trips were diverted from automobiles, buses, or rail, then the risk to individual bikesharing users as well as overall transportation safety could be expected to increase—based on statistics of the per-trip fatality rates of bicycle ridership in comparison to car, bus, or train travel.	Martin et al. (2018)

Impact Category	Service *Location*	Finding	Author
	Bike Share Toronto, BIXI Montreal, Capital Bikeshare, Nice Ride *Toronto, Ontario; Montreal, Quebec; Washington, D.C.; Minneapolis and Saint Paul, MN*	Operators with more than 1,000 bicycles have an average collision rate of 4.33 crashes per year, with rates decreasing among operators with smaller fleets.	Shaheen et al. (2012)
	Capital Bikeshare *Washington, D.C.*	Only 6% of short-term users wore helmets, while 37% of annual users wore helmets.	Buck et al. (2013)
	Nice Ride, Capital Bikeshare *Minneapolis and Saint Paul, MN; Washington, D.C.*	A high number of respondents in four North American cities never wear helmets: • 62% in Montreal, • 50% in Minneapolis-Saint Paul, • 45% in Toronto, and • 43% in Washington, D.C.	Shaheen et al. (2014)

Table 28. Scooter Sharing Impacts

Impact Category	Service *Location*	Finding	Author
Environmental		An average value of lifecycle global warming impacts of 202 grams (g) CO2-eq/passenger-mile, driven by materials and manufacturing (50%), followed by daily collection of scooters for charging (43%). The potential to reduce lifecycle emissions through a variety of scooter collection and charging approaches such as: 1) using fuel-efficient vehicles for collection (yielding 177 g CO2-eq/passenger mile), 2) limiting scooter collection to those with a low battery state of charge (164 g CO2-eq/passenger-mile), and 3) reducing the driving distance per scooter for e-scooter collection and distribution (147 g CO2-eq/passenger-mile).	Hollingsworth et al. (2019)

Impact Category	Service *Location*	Finding	Author
		However, when scooter sharing use replaces average personal automobile travel, there is almost universally a net reduction in environmental impacts.	
Modal	**Bird Rides Inc., Lime, Skip Transport** *Portland, OR*	Over the course of the four-month pilot in Portland, 700,369 scooter trips were made (averaging approximately 5,885 per day) covering a total of 801,888 miles (averaging 1.15 miles per a trip). Approximately 34% of local users would have used a motor vehicle had scooter sharing not been available. Roughly 19% of respondents would have driven a personal vehicle, and 15% stated they would have used a for-hire service, such as a taxi, Uber, or Lyft in the absence of scooter sharing. Among visitors, 48% would have used a motor vehicle (driving or a for-hire service) without the availability of scooter sharing. Around 6% of local users sold a vehicle, and 16% considered selling a vehicle due to standing electric scooter sharing. Nearly 43% percent of respondents said they would have either walked (37%) or ridden a bicycle (5%), if scooter sharing had not been available. However, scooter sharing added some vehicular trips to retrieve and redistribute scooters throughout the day.	Portland Bureau of Transportation (2018)
Safety	**Bird Rides Inc., Lime, Skip Transport** *Portland, OR*	During the pilot period, the study identified 176 scooter-related emergency room visits compared to 16 during the same period a year earlier (prior to the pilot). On average, emergency room visits increased from less than one a week prior to the pilot to approximately 10 a week during the pilot period. The study also suggests that scooter-related emergency room visits accounted for approximately 5% of total traffic crash injury visits during the pilot. Of the entire sample of scooter-related emergency visits, 83% did not involve another mode compared to 13.6% involving a motor vehicle and 2.8% including a pedestrian. Only one collision (0.6%) was reported involving two scooters. Intoxication was reported in 16% of the collisions. PBOT staff observations suggest that approximately 90% of riders do not wear helmets. PBOT received over 1,600 complaints of illegal sidewalk riding, representing approximately 27% of public comments. These complaints generally indicated that sidewalk use made pedestrians and persons with disabilities feel unsafe.	Portland Bureau of Transportation (2018)

Impact Category	Service *Location*	Finding	Author
	Los Angeles, CA	Over 1-year period between September 2017 and August 2018, 249 patients sought medical treatment at two medical center emergency rooms. The mean age of patients was 33.7 years, and 58% of patients were male. Ninety-two percent were injured as riders compared to 8% as nonriders. Approximately 11% of patients were under 18 years of age, and less than 5% reported wearing a helmet. Roughly 5% of patients were intoxicated at the time of their medical treatment. Of the emergency room visits, only 6% (15 reports) were admitted patients, and only two cases (less than 1%) were admitted to the intensive care unit.	Trivedi et al. (2019)

A. 1.6 Transportation Network Company Impacts

TNCs provide prearranged and on-demand transportation services for compensation, which connect drivers of personal vehicles with passengers. Smartphone applications are used for booking, ratings (for both drivers and passengers), and electronic payment. TNCs can provide both pooled services, sometimes referred to as ride-splitting, and non-pooled services. In a pooled service, a TNC ride serves separate parties with similar routes. In a non-pooled service, a TNC ride serves only one party. TNCs differ from taxicab services in that taxis are permitted to pick-up street hails where TNCs are not in most jurisdictions (Shaheen & Cohen, 2018). As TNCs have gained popularity, policymakers, advocates, and researchers have sought to understand how these services are changing travel behavior and affecting the environment.

A number of studies assessing the impact of TNC services on modal shift have found that passengers are either substituting a trip they formerly made with another transportation mode (public transit, driving, walking, biking, etc.) or making a new trip they otherwise would not have made without the availability of TNC services (i.e., induced demand). There are conflicting conclusions regarding the extent to which TNCs compete with public transit. While some studies conclude that TNCs are largely not substituting for public transit trips (Hampshire, Simek, Fabusuyi, Di, & Chen, 2017; Feigon & Murphy, 2018; Clewlow & Mishra, 2017), several others suggest that a significant portion of travelers do substitute TNCs for public transit, biking, and walking (Martin, Shaheen, & Stocker, 2021; Gehrke, Felix, & Reardon, 2017; New York City Department of Transportation , 2017; Henao, 2017; Rayle, Dai, Chan, Cervero, & Shaheen, 2016; Alemi, Circella, Handy, & Mokharian, 2018). Past surveys show that the degree to which TNCs substitute for other travel modes varies by city and the built environment. Denser cities such as New York City, Boston, San Francisco, and Washington, D.C. exhibited some of the highest proportions of passengers who would have used public transit for their last TNC trip had TNCs been unavailable.

It is important to note that aggregated cross-city studies may obscure city-specific differences in TNC impacts. Also, studies may frame the question aimed at analyzing modal shift differently. Some ask in a general manner what transportation mode travelers might have taken instead of a TNC, while others may ask what mode travelers would have used for their last TNC trip. Depending on how this question is presented, responses may be less representative. The results of existing modal shift studies are shown in Table 29, along with the survey question asked in each study.

Broadly, TNC impacts can be summarized in terms of the impacts on public transportation ridership, automobile ownership, and VMT/VKT and GHGs. Each of these impacts are summarized in Table 29. Specific information on the modal impacts of TNCs can be found in Table 30.

Table 29. TNC Impacts

Impact Category	Finding	Source(s)
Personal Vehicle Ownership	About 9% of respondents sold one or more household vehicles due to TNCs.	Clewlow and Mishra (2017)
	About 5% of respondents in Atlanta, 12% in the San Francisco Bay Area, and 21% in Washington, D.C. either postponed a purchase, decided not to purchase, or sold a personal vehicle due to TNCs.	Feigon and Murphy (2018)
	About 9% of respondents acquired a personal vehicle due to the Uber service suspension in Austin, Texas. Another 9% considered purchasing one but ultimately did not. Although Lyft and Uber were not operating in Austin from mid-2016 to mid-2017, other smaller TNC services continued to operate in their place. An even larger portion of respondents may have acquired a personal vehicle, if all TNC services had exited the region.	Hampshire et al. (2017)
Public Transportation	Uber acted as a complement for the average public transit agency in 196 U.S. Metropolitan Statistical Areas, increasing ridership by 5% after 2 years.	Hall et al. (2018)
	Between 2010 to 2016 in six U.S. cities (Chicago, Illinois; Washington, D.C.; Los Angeles, California; Nashville, Tennessee; Seattle, Washington; and San Francisco, California) there was no relationship between the peak-hour TNC trip share and changes in public transit ridership in these cities.	Feigon and Murphy (2018)
	A greater portion of respondents would have used public transit (bus and rail) than would have driven or rode in a personal vehicle, if TNCs were not available in San Francisco and Washington D.C.	Martin et al. (2021)
	The entry and presence of TNCs cumulatively decreased heavy-rail ridership by 1.29% per year and bus ridership by 1.70% per year.	Graehler et al. (2018)
	Passengers with lower incomes and those who possess a weekly or monthly transit pass were more likely to have substituted TNC services for public transit. Relatively low TNC service cost, low TNC trip times, poor weather, and the unavailability of public transit were also predictive of public transit substitution.	Gehrke et al. (2017)
VMT/VKT and GHG Emissions	Usage rates among taxis and TNC vehicles declined in New York City between 2013 and 2017, while the number of unoccupied taxi and TNC vehicles increased by 81% over this time period. The total taxi and TNC weekday mileage in the central business district (CBD) increased by 36% from 2013 to 2017.	Schaller (2017)

Impact Category	Finding	Source(s)
	After accounting for mileage declines in yellow cabs and personal vehicles, TNCs and other on-demand ride services (including Uber, Lyft, Via, Gett, and Juno) contributed 600 million additional miles of vehicle travel to the city's roads between 2013 and 2016. These additional miles equate to an estimated 3.5% increase in citywide VMT and a 7% increase in VMT in Manhattan, western Queens, and western Brooklyn in 2016.	
	In San Francisco and Los Angeles, the VMT produced by Lyft and Uber was larger than the VMT reductions that occurred due to passenger behavior and vehicle ownership changes. In Washington, D.C., the balance of impacts resulted in a net VMT and GHG reduction. These differences may reflect land use and built environment factors that led to lower VMT traveled by TNCs. The potential substitution effect of TNCs in place of personal vehicle ownership suggests that between 2016 to 2017, TNCs may have contributed to a reduction in individual vehicle registrations of 1.7% to 4.2%.	Martin et al. (2021)
	TNC trips made up 15% of average weekday vehicle trips within San Francisco and 9% of average weekday person trips within the city. TNCs represented 20% of average weekday intra-San Francisco VMT (trips that originate and end within city limits only) and 6.5% of total VMT (including regional trips starting or ending within city limits) on an average weekday. Around 20% of all TNC miles were deadheading (or zero-occupancy travel) miles.	San Francisco County Transportation Authority (2017) San Francisco County Transportation Authority (2018)

Table 30. TNC Mode Substitution Impacts*,†,‡

Study	Rayle et al.* (2016)	Henao* (2017)	Gehrke et al.* (2017)	Clewlow and Mishra† (2017)	Feigon and Murphy‡ (2018)	Hampshire et al.** (2017)	Alemi et al. ‡‡ (2018)	NYCDOT ‡‡ (2017)
Location	San Francisco, CA	Boulder and Denver, CO	Boston, MA	7 U.S. Cities††	7 U.S. Cities††	Austin, TX	CA	New York City, NY
Drive (%)	7	33	18	39	34	45	66	12
Public transit (%)	30	22	42	15	15	3	22	50
Taxi (%)	36	10	23	1	8	2	49	43
Bike or walk (%)	9	12	12	23	18	2	20	15
Would not have made the trip (%)	8	12	5	22	1	-	8	3
Carsharing/car rental (%)	-	4	-	24	4			
Other/other (%)	10	7	-		42/2	6/0		
TNC (%)								

^Survey question: "If Lyft and Uber were not available, how would you have made your most recent trip instead?"

*Survey question: "How would you have made ***your last trip***, if TNC services were not available?"

†Survey question: "If TNC services were unavailable, ***which transportation alternatives would you use for the trips*** that you make using TNC services?"

‡Survey crosstab and question, for respondents that use TNCs more often than any other shared mode: "How would you make ***your most frequent (TNC) trip*** if ridesourcing was not available?"

**Survey question: "How do you currently make trips like the last one you took with Uber or Lyft, now that these companies no longer operate in Austin?"

††The impacts in these studies were aggregated across Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle, and Washington, D.C.

‡‡These studies allowed multiple responses to the question: "How would you have made your most recent TNC trip (if at all), if these services had not been available?" Therefore, the percentages add up to more than 100%, making it challenging to directly compare it to the other studies.

A. 1.7 Key Takeaways

The key takeaways from this literature review are summarized in the following bullet points.

- **Demographics:** Shared mobility users tend to be male, Caucasian, aged 25 to 34 years old, and with high annual incomes and levels of educational achievement.
- **Equity Impacts:** Shared mobility may result in various equity impacts, particularly for vulnerable populations.
    - **People with Disabilities:** Various shared modes may be able to offer more accessible transportation services (e.g., larger service area, on-demand scheduling option). However, they may exacerbate accessibility challenges if they do not offer accessible services or equivalent accessible alternatives.
    - **Unbanked and Underbanked and Low-Income Households:** Certain required payment methods (e.g., credit/debit cards) and structures (e.g., pay-as-you-go) may exclude certain populations from using the associated shared mobility option. These challenges may be particularly true for select demographic groups (e.g., minority populations).
    - **Individuals without Digital Literacy:** People who are not digitally literate may face difficulties accessing and navigating smartphone-based transportation modes.
- **Common Shared Mobility Impacts:** Different shared mobility options may result in various impacts including on the economy, environment/GHG, modal choices, VKT/VMT, and society. These impacts may vary based on characteristics like the population density of the service area and service model.
    - **Carsharing:** Carsharing may encourage participants to forgo vehicle purchases and/or decide to sell a vehicle. Additionally, carsharing may lower VKT/VMT and associated GHG emissions, while improving mobility and lowering the full cost of vehicle use.
    - **Ridesharing:** Similarly, ridesharing may lower VKT/VMT and associated GHG, while increasing mobility, particularly for more vulnerable populations.
    - **Shared Micromobility:** Bike-sharing and scooter sharing may increase economic activity within their service areas, encourage people to shift to certain forms of public transit (e.g., buses), lower transportation emissions, and offer health benefits.
    - **Transportation Network Companies:** The impacts of TNCs varies greatly by location and built environment characteristics. Many TNC-focused studies are not conclusive and there is evidence that TNCs may increase VKT/VMT and associated GHG, while in other cases lowering it. TNCs may also encourage modal shifts (e.g., away from personal vehicles and public transit).

Appendix B Trends and Policies Impacting Travel Behavior

In addition to varying user demographics and impacts, shared mobility use may be altered by different transportation trends. For example, shared mobility tends to be available in two predominant built environment types: 1) Higher-Density, Urban; and 2) Lower-Density, Suburban areas. Additionally, impacts from the global pandemic are impacting shared mobility and the broader transportation industry. The pandemic is resulting in greater teleworking capabilities and adoption rates (which vary by different demographic groups), transportation changes (e.g., modal shifts), and housing changes (e.g., increased suburbanization). Transportation demand management strategies may be able to help address resulting changes from these transportation trends. This second half of the literature review is separated into four sections: 1) Land Use and Built Environment, 2) COVID-19 Changes, 3) Transportation Demand Management Strategies, and 4) Key Takeaways.

B. 1 Land Use and Built Environment

Various land use patterns and built environment types can impact travel patterns in various ways including altering congestion patterns and influencing transportation priorities (e.g., longer hours of public transit operation) (Polzin & Choi, 2021). Most shared mobility services have been deployed and for use cases in two built environment types: 1) higher-density, urban environments, and 2) lower-density, suburban environments. Higher-density, urban environments tend to have a high concentration of jobs, mixed-used developments, and multimodal transportation networks and are often the location of central business districts (Shaheen, et al., 2020). Lower-density, suburban environments are typically less urbanized and have high-levels of low-density residential uses, fewer jobs than residences, and segregated land uses (Shaheen, et al., 2020).

These built environment types often impact what shared modes are available and the frequency in which and how they are used (e.g., as part of a multimodal trip, replacement for a personal vehicle). Most research has focused on shared mobility use in two predominant areas – higher density, urban and lower-density, suburban areas. The following subsections discuss shared mobility in these regions. However, it is important to note that the COVID-19 pandemic is increasing suburbanization and consequently reducing the importance of brick-and-mortar retail spaces, office developments, and restaurant and lodging options (Polzin & Choi, 2021). The pandemic is also illustrating travel behavior trends in various land uses (e.g., lower public transit use in central business districts in urban areas, continued personal vehicle use in suburban retail locations). Travel volumes in rural and non-metropolitan areas have been more resilient than travel behavior trends in more urban environments (Polzin & Choi, 2021). These changes may alter future land uses and shared mobility use patterns.

B. 1.1 Higher-Density, Urban Areas

Although shared mobility can potentially increase mobility and fill transportation gaps in various land uses and built environment types, shared modes tend to be more frequently available and used in higher density, mixed-use urban areas. For example, Hu et al. (2018) found that carsharing is more popular in areas with mixed land uses and high population density, number of adults (i.e., individuals between 15 and 65 years of age), and number of males. The study found that carsharing users tend to be 81% adults and 53% male. Additional land use characteristics that support carsharing use include more designated carsharing parking spaces, longer surrounding business hours, and fewer nearby transit-based carsharing locations where carsharing vehicles tend to be oversupplied (Hu, Chen, Lin, Xie, & Chen, 2018). Khan and Machemhal (2017) and Stillwater et al. (2009) also found that carsharing locations near public transit stops and stations positively and significantly increased carsharing demand. Similarly, Brown (2020), Conway et al. (2018), and Lee et al. (2016) found that ridesharing tends to occur in lower-income, high density areas.

Higher density, mixed-use environments may also encourage TNC availability and use (Circella, Alemi, Tiedeman, Handy, & Mokhtarian, 2018; Conway, Salon, & King, 2018; Hasnine, Hawkins, & Habib, 2021). For example, in major U.S. cities, 21% of adults use TNCs (Clewlow & Mishra, 2017). Approximately 29% of TNC users who live in more urban neighborhoods use TNCs regularly (Clewlow & Mishra, 2017). Additionally, Schaller Consulting (2018) found that 70% of U.S. TNC trips, specifically made via Lyft and Uber, occur in nine densely populated metropolitan areas (Boston, Massachusetts; Chicago, Illinois; Los Angeles, California; Miami, Florida; New York City, New York; Philadelphia, Pennsylvania; San Francisco, California; Seattle, Washington; Washington, D.C.). Locations with greater density of employment opportunities and services, public transit stops and stations, roads, and complete pavements can also encourage TNC use (Yu & Peng, 2019; Shokoohyar, Sobhani, Nargesi, & Ramezanpour, 2020; Grahn, Harper, Hendrickson, Quan, & Matthew, 2019).

Shared micromobility use also tends to be higher in locations with higher population density, higher incomes, a younger population, and more mixed land uses – specifically commercial areas and public spaces (Jing, Hu, & Lin, 2021; Shaheen, Martin, Cohen, & Finson, 2012). Bikesharing services, in particular, are more likely to be used when devices and stations are located near dense public areas with high levels of economic development and recreational activity opportunities (He, Song, Liu, & Sze, 2019). Bikesharing users also tend to rely more on bicycle infrastructure more than bicyclists using personally owned devices (Jing, Hu, & Lin, 2021). Additionally, scooter sharing ridership appears to be higher in urban areas and around universities; neighborhoods with mixed land uses; locations with connected streets; and locations with high population, employment, intersection, and public transit stop and station density (Huo, et al., 2021; Bai, Jiao, Chen, & Guo, 2021; Jiao & Bai, 2020). Research by Caspi et al. (2020) on scooter sharing in Austin, Texas similarly found that scooter sharing use almost exclusively occurred in the central part of the city. Scooter sharing use was higher in locations with high employment rates, places of interest (e.g., museums, stadiums) ample amounts of bicycle infrastructure, and large student populations (Caspi, Smart, & Noland, 2020; Hawa, Cui, Sun, & El-Geneidy, 2021). Locations with a variety of dining, drinking, shopping and recreational activities may also encourage scooter sharing use (Bai, Jiao, Chen, & Guo, 2021). Public transit ridership may be higher in locations with mixed-land uses, particularly retail opportunities within 0.25 miles of public transit stops or stations (Johnson, 2003).

B. 1.2 Lower-Density, Suburban Areas

While shared mobility is typically used in higher-density areas, there are still use cases and opportunities for high ridership in lower-density locations. These areas may be better suited for select shared modes. For example, carsharing, especially peer-to-peer models, may be able to fill transportation gaps and improve mobility in lower-density areas (Shaheen, Marin, & Hoffman-Stapleton, 2019). Carsharing locations near public transit hubs, colleges and universities, and shopping centers tend to be used more frequently (Hu, Chen, Lin, Xie, & Chen, 2018). Areas with higher percentages of zero car households are more likely to participate in carsharing (Khan & Machemehal, 2017). Carsharing is also more popular in suburban locations with high parking fees (e.g., downtown business districts) (Khan & Machemehal, 2017). Similarly, ridesharing may be more popular in lower-density locations with designated spaces (e.g., pick-up and drop-off zones), mixed uses, and select built environment features (e.g., lighting)

(Shaheen, Darling, Broader, & Cohen, 2021). Similarly, taxis, rather than TNCs, serve more riders in suburban and rural areas (Schaller Consulting , 2018). Some lower density areas may support select shared micromobility trip types. McKenzie (2019) found that shared micromobility trips tend to occur in recreational/public land uses (40.6%), then commercial areas (36.3%), and finally residential locations (23.1%).

B.2 COVID-19 Changes

Land use is not the only variable that can impact shared mobility use. The COVID-19 pandemic has spurred various changes to education, industries, travel behavior, and workplaces. Two areas of pandemic-related changes may drastically impact transportation: 1) the increase in teleworking capabilities (and resulting business model and workplace redesigns), and 2) housing changes (e.g., moving from urban to suburban areas). However, the impact of these changes may vary by sociodemographic characteristics. The following subsections discuss teleworking and housing changes and their respective transportation impacts in greater depth.

B.2.1 Telework

Pabilonia and Vernon (2020) define teleworking (also referred to as telecommuting, working from home, and working remotely) as “a formal or informal arrangement allowing workers to work from home or a location other than their traditional workplace.” Prior to the onset of the COVID-19 pandemic in March 2020, teleworking was typically promoted as a tool to help employees with work-life balances (Pabilonia & Vernon, 2020). In 2018, only about 5% of U.S. workers teleworked (TRIP, 2021). However, social distancing measures implemented to help protect public health led many workplaces to offer and/or require employees to telework. While initial teleworking efforts may have been mandated or necessary, many workers are now opting to telework. Parker et al. (2022) found that in February 2022, approximately 61% of U.S. workers who were able to telework chose to. Of individuals who are currently teleworking, about 78% would like to continue (Parker, Horowitz, & Minkin, 2022). In the future, about 60% of employees with jobs that can be completed via teleworking would like to telework most or all of the time (Parker, Horowitz, & Minkin, 2022). However, approximately 60% of U.S. workers do not have jobs that can be completed via teleworking (Parker, Horowitz, & Minkin, 2022).

B.2.2 U.S. Teleworking Demographics

The U.S. workers who are able to telework vary by factors including demographic makeup, occupation, industry, and geographic region. Research by Bick et al. (2020) revealed that highly educated, higher-income, Caucasian individuals were more likely to be able to shift to telework and maintain employment after the onset of the global pandemic. Day et al. (2020) also found that individuals who were teleworking were likely to be employed through the pandemic and containment of the COVID-19 virus. Further information on the demographic makeup of individuals able to telework can be found in Table 31.

Table 31. Ability to Telework by Demographic Characteristics

Category	Characteristics	Ability to Telework
Gender	Female	48-52%
	Male	39-40%
Age	15 to 24 years	22-24%
	25 to 54 years	46-48%
	55 years and older	47-49%
Race/Ethnicity	Black	34-40%
	Hispanic	29-30%
	Non-Hispanic white	47-49%
Marital Status	Married	48-50%
	Not Married	34-39%
Children	Have children	42-51%
	No children	44-45%
Educational Attainment	Less than a high school diploma	11-17%
	High school diploma	25-30%
	Some college or associate's degree	37-43%
	Bachelor's degree and higher	68-71%
Job Status	Full time	46-48%
	Part time	29-32%

Source: Day et al. (2020)

Bick et al. (2020) also identified demographic characteristics of individuals who teleworked every day in February and May 2020. These findings are summarized in Table 32. The percentages represent the percent of the population able to telework.

Table 32. Teleworking Rates in February and May 2020

Category	Characteristic	Date	
		February 2020	May 2020
Total Work Force	Percentage of employed	8%	35%
Gender	Female	9%	39%
	Male	8%	32%
Race/Ethnicity	Black	7%	25%
	Hispanic	5%	23%
	White	10%	39%
Children	No children	10%	36%
	Have children	6%	34%
	Youngest child under 13 years old	5%	33%
Educational Attainment	High school or less	8%	15%
	Some college	8%	25%
	College degree or higher	8%	50%
Income	Less than $50k	8%	18%
	$50k - $100k	7%	31%
	More than $100k	10%	46%

Source: Bick et al. (2020)

Dalton and Groen (2022) examined the business side of teleworking. They found that about 33% of U.S. businesses increased telework capabilities. This was particularly true of establishments who offered flexible or staggered work hours. These businesses increased their teleworking capabilities by 57%. Teleworking ability also varied by occupation. Table 33 provides information on the ability of individuals in various occupations to telework.

Table 33. Ability to Telework by Occupation

Category	Occupation	Ability to Telework
Administrative and Professional	Administrative and office	59-62%
	Business, financial, and management	86-88%
	Professional and related	63-65%
Agriculture	Farming, fishing, forestry	0%
Labor	Construction and extraction	0%
	Installation, maintenance, and repair	1-4%
	Production	0-4%
	Material moving and transportation	0-1%
Miscellaneous	Sales and related	30-32%
	Services and related	8-13%

Source: Day et al. (2020)

However, ability to telework may not be determined by occupation, but other factors such as tasks and activities (e.g., need for fixed equipment) (McKinsey Global Institute, 2020). As a result, Dalton and Groen (2022) examined teleworking rates by occupation. Across all sectors approximately 13% can telework full time, 9% can telework part time, and 78% can rarely or never telework (Dalton & Groen, 2022). The McKinsey Global Institute (2020) found that individuals in finance, management, professional services, and information sectors had the highest ability to telework. Teleworking capabilities in different industries also impacted employment rates. Information collected by Day et al. (2020) showed that from February to April 2020, employment decreased by 21% in industries where teleworking was not possible, compared to an 8% decrease in industries that could offer teleworking options.

B.2.3 Transportation Impacts from Telework

Teleworking changes may impact transportation by altering travel behavior decisions, peak congestion time, etc. Bick et al. (2020) analyzed differences in commute patterns after the onset of the global pandemic, when people started teleworking. These commute frequency rates are summarized in Table 34.

Table 34. Commute Frequency in February 2020

Commute Frequency	February 2020 (n=3,587)	May 2020 (n=2,565)
Daily	75%	51%
Some Days	16%	14%
Telework Everyday	8%	35%

Source: Bick et al. (2020)

Teleworking is anticipated to impact transportation in numerous ways. Prior to the pandemic, about 58% of people primarily traveled for work. However, this percentage decreased to 30% during the pandemic (Abdullah, Dias, Muley, & Shahin, 2020). Increases in teleworking led to many transportation changes, such as greater e-commerce use, particularly for home deliveries (TRIP, 2021). Additionally, teleworking altered travel patterns and peak congestion times. Stiles and Smart (2021) found that people who shift to telework typically decrease their daily travel duration and increase their likelihood of avoiding peak hour travel. Supporting research has found that teleworking drastically decreases trips at peak commute times (e.g., 8 AM and 6 PM), particularly during morning commutes, and maintains travel demand at lower, but more consistent, levels throughout the day (Liu, Miller, & Scheff, 2020; Stiles & Smart, 2021; Goulias, Su, & McBride, 2020). Roughly 80% of teleworkers make at least one trip during their workday, accruing more VMTs and numbers of trips than traditional commuters (Goulias, Su, & McBride, 2020). Teleworkers also typically have less predictable trips in which they visit multiple locations (Goulias, Su, & McBride, 2020).

Teleworking Impacts in Washington, D.C.

Table X summarizes different modal splits in Washington, D.C. commutes in 2019 and 2022.

Table X. Washington, D.C. Commute Mode Split

Mode	Year	
	2019	*2022*
Telework	10%	48%
Drive alone	58%	41%
Public Transit	24%	8%
Active Transportation	3%	2%
Carpool/Vanpool	5%	2%

Source: LDA Consulting (2022)

The research by LDA Consulting (2022) also found that public transit commuters in the Washington, D.C. area were less satisfied with their commutes, likely due to longer trip times due to longer vehicle headways and increased commute difficulties (e.g., fewer timed transfers). In 2022, Washington, D.C. commuters were less aware of commute resources, like carpooling platforms (LDA Consulting, 2022).

Teleworking is anticipated to continue impacting public transit ridership and VMT, especially in downtown areas and job centers (TRIP, 2021; National Academies of Science, Engineering, Math, 2022). At the beginning of the pandemic, many public transit agencies introduced service cuts and reroutes to address pandemic impacts (e.g., low ridership, unavailable drivers) (Sutcliffe & Bahnam, 2021). Research has found that these service changes disproportionately impacted individuals with limited mobility options, including those facing socioeconomic challenges, such as Latinx, female, and non-binary riders (He, Rowangould, Karner, Palm, & LaRue, 2022). Research by the National Capital Region Transportation Planning Board (2021) on public transit service in Washington, D.C., found that marginalized populations tended to have more public transit service access than the general population, but only about 41 to 55% of marginalized individuals had access to high-frequency public transit service (i.e., 15-minute headways), compared to 62 to 68% of the general population. DeWeese et al. (2020) found that some communities applied service changes uniformly throughout their service hours, potentially disproportionately impacting low-income areas. However, some communities, such as San Francisco, California and Portland, Oregon, strategically implemented service cuts to minimally impact vulnerable populations (DeWeese, et al., 2020).

Telecommuting Impacts in Chicago, Illinois

Research by the Argonne National Laboratory (2022) found that in Chicago, Illinois if individuals' concern regarding COVID-19 transmission continued and individuals teleworked at least one day per week, the city would witness a public transit ridership decrease, 22% decrease in vehicle speed, and an 8.5-minute increase in travel time (from individuals choosing to take personal vehicles rather than shared modes). Research in New York City had similar findings. The regional shelter-in-place order, and subsequent increases in teleworking, led to drastic declines in public transit ridership and vehicular traffic (94% and 72% of pre-pandemic levels, respectively) (Gao, Bernardes, & Bian, 2020). As pandemic recovery continues, residents are more likely to have longer commutes originating from further, suburban destinations (Chicago Metropolitan Agency for Planning).

According to the American Public Transportation Association (2022), after being dramatically impacted by the pandemic (e.g., shelter-in-place orders, teleworking capabilities) public transit ridership has increased to 70% of pre-pandemic levels. Ridership recovery has varied by mode and the modes ranked by order of greatest to least ridership recovery include: demand responsive transit, bus services, heavy rail, light rail, and commuter rail (American Public Transportation Assocation, 2022). Currently, public transit ridership is predominantly serving essential workers and lower-income households. Public transit recovery is largely dependent on service delivery (e.g., service hours) and reliability and is impacted by external factors (e.g., surrounding economic recovery) (American Public Transportation Assocation, 2022).

Changing travel patterns resulting from teleworking increases have encouraged public transit operators to prioritize maintaining core operations and meeting freight and essential workers' needs (Deloitte, 2020). However, altering public transit priorities and schedules has been impacted by difficulties rehiring public transit operators and other staff. This may make returning public transit services to pre-pandemic levels (e.g., hours of operation, arrival frequency) challenging (Mack, Agrawal, & Wang, 2021). Based on lessons learned from the pandemic, the Community Transportation Association of America (2022) recommends the following steps to encourage public transit ridership even as teleworking continues:

- Leverage services to meet new needs (e.g., access to public health services),
- Make fare payment more equitable (e.g., free transit rides for eligible passengers),
- Improve service frequency and reliability,
- Enhance employment outreach and employee retainment,
- Redesign routes to better meet traveler's needs (e.g., routes on less congested streets for faster trip times), and
- Expand demand responsive services.

Telework has led to physical workplace changes, such as downsizing and relocations, which are also likely to impact future teleworking and travel patterns. Dalton and Groen (2022) found that of the 6% of establishments that have relocated since the pandemic's onset, 58% increased teleworking, compared to the 32% of establishments that did not relocate. Similarly, establishments that plan to relocate by March 2023 increased teleworking by 50%, compared to a 32% increase in teleworking for establishments not planning to relocate.

Some research anticipates that after COVID-19 is contained, as much as 15 to 25% of Americans will telework in some capacity (Polzin & Choi, 2021). Teleworking capabilities can increase teleworking services including remote learning, telemedicine, electronic banking, and online platforms for religious and social activities, amplifying travel behavior changes (Polzin & Choi, 2021).

Other factors, such as shifts to lower emission vehicles and high gas prices, may also impact travel behavior going forward by encouraging the use of EVs or more cost effective, shared modes (Nehiba, 2021). Teleworking may also impact EV charging locations by encouraging the use of more neighborhood-based chargers (e.g., at strip malls) and encouraging building and land owners to replace a few parking spaces with EV chargers (McDonald, 2020). As COVID-19 is contained, these changes might promote and popularize increased biking and walking, which has been cited as a way to safely return to pre-pandemic mobility (Habib & Hasan Anik, 2021).

B.2.4 Housing Changes

COVID-19 encouraged individuals to move from dense urban areas to lower density suburban areas. This shift was influenced by teleworking considerations (e.g., appeal of larger homes with more space for home offices, need for strong internet connections and reliability), recreational access (e.g., backyards, proximity to parks), and improved safety and security (e.g., lower neighborhood crime, in building security systems) (Nanda, Thanos, Valtonen, Xu, & Zandieh, 2021; TRIP, 2021). Increasingly, Americans are moving to places that are warmer, healthier, smaller, less dense, with greater access to better healthcare facilities and smaller schools, and that have more highly educated populations, lower taxes, and less regulation (Taylor, 2020). Data trends illustrate moves to the Midwest and Northeast over the Southeast and West Coast, in part because of greater home availability and affordability (J.P. Morgan, 2021; Polzin & Choi, 2021; Mondragon & Wieland, 2022).

Some moving trends varied by demographic characteristics. Approximately 37% of young adults (aged 18 to 29 years old) moved. Moving was more common by Hispanics (28%), than Asian (24%), Caucasian (20%), and Black (19%) adults (Cohn, 2020). Individuals who are "untethered" (i.e., can telework, have no school-aged children, rent rather than own their home, have no spouse or have a spouse who can also telework) are more likely to move (Patino, Kessler, & Holder, 2021). Common reasons for moving include reduced COVID-19 contraction risk (28%), closed college campuses (23%), desire to be with family (20%), money-related reasons (10%), and job loss (8%) (Cohn, 2020). In late 2020, approximately 14 to 23 million Americans had or were planning to move due to the greater options that teleworking provided (TRIP, 2021). Between 7% and 12% of households were planning on moving explicitly due to increased options from teleworking. Within this group, about 7% were planning on moving to an area that had greater teleworking options and 3% were moving because of a household member's ability to telework (UpWork, 2020).

Typically, individuals moving during the pandemic shifted from central urban areas into outlying, more suburban and rural regions where larger square footage residences are more available (Kikuchi, 2021; Popken, 2020). This is, in part, because individuals in larger, more expensive urban environments appeared to be unwilling to pay premium prices for amenities that were not available during the pandemic (e.g., museums, theatres) (Dowell, 2021). Americans are particularly interested in locations like Atlanta, Georgia; Austin, Texas; Las Vegas, Nevada; Phoenix, Arizona; and Sacramento, California (Popken, 2020). The pandemic and teleworking capabilities also resulted in people moving to and working from "vacation towns" (e.g., Ocean City, New Jersey; Key West, Florida) (Dowell, 2021). People are looking for amenities including affordability; yard and greenspace; and room for teleworking, remote learning, and home workouts (Popken, 2020). Researchers anticipate that people will continue placing greater value on community amenities (e.g., parks, stadiums), rather than home amenities (e.g., swimming pools) (Gascon & HaaS, 2020). Home ownership, particularly by young adults, increased during the pandemic (Kikuchi, 2021). This was likely enabled by the ability to move to more affordable locations.

B.2.4.1 Transportation Impacts from Housing Changes

Household location can impact various transportation decisions including vehicle ownership, commute length, and mode choice (Lerman, 1976). Often, people make tradeoffs regarding transportation levels of service compared to other variables (e.g., neighborhood quality) (Wesibrod, Ben-Akiva, & Lerman, 1980). Historically, commute time has been a dominant determinant of residential location (Levine, 2007). However, increasing teleworking opportunities is likely to change this. For example, changes in housing location to various built environment types could drastically impact car ownership rates and travel behavior decisions (Scheiner & Christian, 2021). Currently, most U.S. EV chargers are located in urban areas, but trends like increasing suburbanization could encourage greater EV charging availability in these locations to better meet drivers' needs (International Energy Agency, 2022). Increasing suburbanization increases vehicle use and decreases use of public transit, biking, and walking. Inversely, moves to more urban environments result in decreases in personal vehicle use and increases in public transit, biking, and walking (Scheiner & Christian, 2021).

Additionally, changing residential preferences, particularly the ratio of housing options to jobs, can alter commute distances, trip types (e.g., chained trips), and VMT (Peng, 1997). Having higher job-housing balances can substantially decrease travel and VMT (Cervero & Duncan, 2008). Lower VMTs may increase the opportunity for alternative modes (e.g., shared micromobilty) to serve as transportation options. Lastly, housing pattern changes could alter necessary infrastructure projects (e.g., EV charging options), changes tax bases that maintain capital projects, and create new demands (e.g., for scooter sharing options) (Polzin & Choi, 2021).

B.3 Transportation Demand Management

Transportation demand management (TDM) strategies can be used to instigate or mitigate the trends and policies such as those described in this document. TDM is defined as a set of strategies that increase transportation network efficiency by shifting single-occupancy vehicle trips to shared rides and modes or to non-peak periods (Seattle Department of Transportation, 2017). Generally, TDM strategies help shift travelers to higher-occupancy and/or lower emission modes (e.g., bikesharing) and by doing so increase mobility and decrease congestion and subsequent environmental impacts. Table 35 summarizes various TDM strategies and provides examples.

Table 35. TDM Strategies and Examples

Strategy	Description	Example
Allocated Space	Provide space exclusively for select modes (e.g., high-occupancy vehicle lanes that can also be accessed by electric vehicles)	In San Francisco, California, the city closed 2.2 miles of Market Street (a main thoroughfare) to private vehicles, including TNCs, to prioritize active and shared modes (San Francisco Public Works, 2021). Early findings reveal that the project increased the number of bicyclists on Market Street by 25% and improved public transit times by 12% (SFMTA, n.d.).
Employer Benefits	Work with employers to encourage employees to take modes including carsharing, public transit, ridesharing, and shared micromobility	Amazon encourages their employees to bike to work by facilitating bike leases, allowing employees to expense bikesharing costs, providing two complimentary bike tune ups per year, and offering bike parking at the office. The goal is to reduce Amazon's emissions and adhere to the company's climate goals (Amazon Staff, 2021).
Incentives	Incentivize modes other than personal vehicles (e.g., free public transit passes, priority parking for ridesharing)	The California Clean Mobility Options Voucher Pilot Program awarded roughly $20 million to 21 stakeholders (e.g., Cahuilla Band of Indians, Imperial County Transportation Commission) to provide funding for shared modes in different communities (Clean Mobility Options, 2022). The program works to fill clean transportation gaps via zero-emission modes and improve community mobility (Clean Mobility Options, 2022).
Infrastructure	Provide supportive infrastructure for shared modes (e.g., shared micromobility docks, TNC loading zones)	In 2018, Santa Monica, California installed 19 corrals and four docks for shared micromobility parking (Linton, 2018). Santa Monica is using the shared micromobility infrastructure to manage device storage and availability (Linton, 2018).
Integration	Integrate various modes (e.g., seamless fare payment, multimodal trip planning platforms) to encourage the use of alternative modes	San Diego, California is in the process of developing mobility hubs that co-locate various transportation services including public transit, shared micromobility, and TNCs (San Diego Association of Governments, 2021). San Diego is hoping that the

Strategy	Description	Example
		mobility hubs will support multimodal trips and decrease personal vehicle use (San Diego Association of Governments, 2021).
Marketing	Provide information about various alternatives to single-occupancy vehicles	Los Angeles, California has a transportation plan that includes digital marketing strategies for various shared and technology enabled modes (Hand, 2016). These considerations in Los Angeles's transportation plan help distribute program information and decrease personal vehicle trips (Hand, 2016).
Pricing	Increase the price of high emission, single-occupancy vehicles (e.g., parking fees, tolls)	In the San Francisco Bay Area, express lanes can be accessed for free for high-occupancy vehicles (HOV) and eligible electric vehicles, and for a fee by single-occupancy vehicles (FasTrak). The HOV/EV lanes improve public transit service reliability and trip times by reducing congestion and encouraging carpooling (The Bay Link, 2022).
Policies	Implement policies and regulations that support lower-emission, higher-occupancy modes	CARB adopted regulation that requires TNCs to begin electrifying their fleets in 2023 (California Air Resources Board, 2021). This regulation is part of CARB's efforts to reduce greenhouse gas emissions (California Air Resources Board, 2021).
Parking	Prioritize parking for higher-occupancy, lower-emission modes	In San Jose, California, vehicles that are registered in the city, have obtained a valid State of California Carpool lane sticker (ensuring that the vehicle meets emission requirements), and pay a $40 program fee can park free at all city parking meters, four city-operated parking garages, and city parks and recreation facilities (Park San Jose, 2022). The program was designed to encourage EV adoption and use (Kadah, 2022).
Ridematching	Leverage platforms and other resources to pair travelers with various options to meet their travel needs (e.g., ridematching)	In the San Francisco Bay Area, the merge platform allows travelers to make a profile then match with other travelers to facilitate carpools (merge). The platform's goal is to encourage carpooling to increase vehicle occupancies and decrease congestion and travel times throughout the Bay Area (merge).
Zoning	Develop regions to increase density, mixed-use development, and shared mobility options	In 2021, California Governor Newsom signed into law a bill allowing more dwelling units (i.e., increasing density) in areas currently designated for single-family zoning, with priority in areas near public transit (Sheyner, 2021). The law increases

Strategy	Description	Example
		density to encourage public transit ridership (Sheyner, 2021).

Source: Institute for Transportation and Development Policy (2017), Federal Highway Administration (n.d.), RideAmigos (n.d.), Schaller Consulting (2018), Washington State Department of Transportation (n.d.)

B.4 Key Takeaways

- **Land Use and the Built Environment:** Built environment types can significantly impact shared mobility availability/access and adoption.
    - **Higher-Density, Mixed-Use Urban Areas:** These locations have higher use rates of shared modes such as public transit, carsharing, bikesharing, and TNCs. This may be due to the greater density of shared mobility facilities and services in mixed-use urban areas, creating a conducive environment for increased use of shared mobility.
    - **Lower-Density Suburban Areas:** These built environment types also provide opportunities for using shared mobility. Smaller-scale, locally oriented shared vehicle modes such as carsharing near popular public areas or taxis (as opposed to TNCs) can help cover the longer distances in suburban areas, many of which are not pedestrian-friendly.
- **Teleworking:** Prior to March 2020, telework was typically promoted as a tool to improve employee work-life balance. However, not every worker was able to transition to telework during the pandemic. When looking at telework rates by occupation, across all sectors, 78% can rarely or never telework, and only approximately 13% can telework full time. Non-Hispanic white individuals with high education and high income were more likely to be able to shift to telework and maintain employment during the pandemic.
    - **Telework Transportation Impacts:** In general, increased telework has shifted travel behavior away from peak hour commutes and toward a more even distribution throughout the day, therefore maintaining a similar volume of VMT but reducing congestion. Telework has also reduced the need to travel to a specific workplace, although teleworkers tend to travel more frequently and unpredictably than traditional commuters.
- **Housing Changes:** Individuals who moved during the pandemic typically moved from high-density, urban areas to lower-density suburban or rural areas. A significant proportion of these individuals moved in order to take advantage of teleworking options but may have also wanted to enjoy expanded outdoor space and amenities away from urban cores. Individuals who moved during the pandemic leaned toward the Midwest and the Northeast, where there are more affordable housing options. However, individuals who moved were more likely to be “untethered”, with much more flexibility to telework and relocate.
- **Transportation Demand Management:** Various TDM strategies (e.g., space allocation, incentives) can be implemented to address the changing transportation landscape from impacts, such as shared mobility use and increased teleworking. These TDM strategies can encourage increased vehicle occupancies, shifts toward shared modes, lower VMT, and improved environmental impacts.

Appendix C Expert Interview Protocol

Thank you for taking the time to speak with us today. This research is supported by the Transportation Sustainability Center (TSRC) at UC Berkeley and the California Air Resources Board (CARB) and should take about an hour. Your answers will help inform future strategies and policies implemented by CARB to encourage multi-passenger trips and the use of more efficient vehicles.

1. Before we begin, can you describe a little about your position at (INSERT ORGANIZATION)?

C.1 COVID-19 – Impacts and Telework

The outbreak of COVID-19 in early 2020 resulted in a variety of impacts in the US and throughout the world.

1. How is your organization responding, or planning to respond to, the COVID-19 pandemic?
2. How do you think organizations' experience with telework during COVID-19 will impact the transportation network throughout the recovery process?
3. How do you think telework will impact transportation after a vaccine is widely deployed?

C.2 COVID-19 – Housing Affordability

COVID-19 has caused people to move for a variety of reasons including increased affordability, greater access to greenspaces, etc.

1. For some people housing has become more affordable (e.g., by moving to less dense areas, rent decreases). How do you think this will impact transportation choices?
2. For other people, housing has become less affordable (e.g., income or hour reductions). How do you think this will impact transportation choices?
3. As residential densities shift, what changes are required to the transportation system to meet needs?

C.3 Shared Rides – Pooled Rides

During the COVID-19 pandemic, guidelines from the Center for Disease Control discouraged the use of pooled rides. As we recover from COVID-19, CARB and other agencies are looking for ways to increase trip occupancy, through means such as pooled rides.

1. What do you think are some of the best strategies for supporting pooled or shared rides?
2. In light of COVID-19, what would increase trust in pooled rides?
3. What incentives can support shared rides?
4. What infrastructure changes may need to be made to support shared rides?
5. What do you think are some of the biggest contributors to health and safety challenges for shared rides?

C.4 Shared Rides – Public Transit

Public transit is one of the highest occupancy modes of travel.

1. What strategies can be used to encourage public transit use in California?
    a. Has your organization implemented any strategies to encourage shared rides?
2. Do you think park-and-ride facilities can support the use of public transit?
    a. What strategies could support the use of park-and-ride facilities?
    b. What challenges do you think park-and-ride facilities could present?
3. In light of COVID-19, what is needed to increase trust in public transit?
4. What do you think are some of the biggest contributors to health and safety challenges for public transit?
5. What incentives may encourage public transit use?
6. Are there infrastructure changes that should be implemented to support public transit use?
7. What changes to the payment process would allow for more seamless ridership between transit and other mobility modes?

C.5 Pricing

Incentives, or disincentives, may play a critical role in encouraging the use of shared rides, including public transit.

1. What pricing strategies (e.g., reduced toll costs for high-occupancy vehicles) would be most effective to support shared rides?
2. Are there any programs or resources that may need to be adapted to support these strategies?
3. What design and implementation tools can allow for equity to be embedded in the process from the beginning?
4. What evaluation tools or other strategies can be used to help ensure that pricing strategies have equitable impacts?

C.6 Electrification

In addition to shared rides, CARB wants to encourage the use of zero-emission travel.

1. What do you think are some of the biggest challenges to the widespread awareness and adoption of low-emission vehicles?
    a. Do you think these challenges vary by demographic characteristics, such as population density, income, or age?
2. How do you think zero-emission or electric vehicles can best be supported? Infrastructure? Incentives?
    a. *If they respond infrastructure:* What infrastructure changes do you think need to be made to support higher occupancy and lower emission modes? More charging stations for electric vehicles?

    b. *If they respond incentives:* What incentives do you think would be the most effective in California? Where incentives are most useful to allow for broader access to transportation and mobility options leveraged?

C.7 Active Transportation

In many areas of the United States, COVID-19 encouraged the use of active transportation. However, some areas also witnessed an increase in collisions and fatalities.

1. How do you think we could support the use of active transportation (e.g., land use changes, infrastructure changes)?
2. What do you think are some of the biggest contributors to health and safety challenges for active transportation?
    a. Do you think these challenges vary by mode or operational characteristics, such as time of day?
    b. Do you think these challenges vary by built environment factors, such as surrounding land uses?
3. What strategies or policies do you think could address these challenges?

C.8 Social Equity

As CARB works to increase mobility, it is important to consider the options for low-income and disadvantaged communities - those with a combination of economic, health, and environmental burdens.

1. What unique barriers to mobility options do you think these groups face?
2. What strategies do you think would support increased access for these groups?
3. What environmental justice challenges do you think low-income and disadvantaged communities face?
4. What strategies do you think could address these challenges?
5. What racial justice challenges do you think these groups face?
6. What strategies do you think could address these challenges?

C.9 Closing

1. Is there anything else you would like to add?
2. Would you mind if we contacted you with any follow up questions or for clarification?

Appendix D Policies Under Consideration - Modeling

The research team drafted 28 possible policy variables for this research, grouped into six main categories (pricing, parking, curb policies, operational strategies, infrastructure changes, transportation services, and land use strategies). These policies targeted the objectives of the research, which were to explore strategies to incentivize the use of zero-emission, high-occupancy, and new mobility options. A final set of 13 policy variables were selected in coordination with the CARB team and the research team, considering model framework capabilities, as presented in Table 36.

Table 36. Final Set of 13 Policy Variables

ID	Policy Category	Name
1	Public Transit	Transit Frequencies
2	Public Transit	Transit Fare
3	Public Transit	Transit in-vehicle times
4	Shared Rides	TNC Price
5	Shared Rides	Share TNC Price
6	Pricing	Operating Cost
7	Pricing	Cordon Pricing
8	Pricing	Park & Ride
9	Telework	Telecommute - Option
10	Telework	Telecommute - Frequency
11	Autonomous Vehicles	AV Penetration Rate
12	Autonomous Vehicles	AV Value of Time
13	Land Use	TOD Residential and Employment

This appendix describes in more detail each policy variable, the mechanics of how the input variables are modified in the modeling framework presented in the Modeling Framework section, elasticities found in the literature when applicable, a description of the test ranges used in the analysis (Appendix B), and possible policy implications.

D.1 Transit Frequencies

We hypothesize that increasing transit frequency will increase ridership by reducing the average waiting and transfer times. The implementation of the mode choice model in ActivitySim has an in-vehicle time coefficient, and other time-related variables, such as waiting and transfer times, use the same coefficient modified by a multiplier. In ActivitySim, short waiting times (10 minutes or less) increase the time coefficient sensitivity by two, whereas long waiting times (greater than 10 minutes) maintain the same in-vehicle time sensitivity, consistent with reported time multipliers in the literature (Abrantes & Wardman, 2011). These coefficients suggest decision-makers are more sensitive to short waiting and transfer times, meaning that reduced waiting times increase the probability of selecting public transit modes. Additionally, a literature review on this topic suggests that increasing frequencies by 1% increases ridership by 0.5% (Handy et al., 2013)

As mentioned before, changes in transit frequencies impact the average waiting and transfer times at transit stations. Waiting and transfer average waiting times are the model inputs we modify for this sensitivity test. In BEAM, the public transit network schedules transit routes according to the General Transit Feed Standard (GTFS); buses follow the scheduled arrival and departure time and are not affected by dynamic traffic congestion. Additionally, BEAM takes the ActivitySim person's departure time, meaning that the model does not represent when a person plans to leave a location based on the public transit expected arrival time. Given the current implementation of the model system, and to simplify the implementation of this policy scenario, we use the average waiting time and the average transfer time skims matrix as a proxy for transit frequencies. Modes affected by this sensitivity test are local bus, light-rail, express bus, bus rapid transit, and heavy rail, in both walk and drive access. CARB and the research team were primarily interested in exploring improved frequencies at the beginning of this project, which began before the start of the COVID-19 pandemic. However, after the pandemic began in 2020, many transit agencies have seen a sharp ridership decline, which has resulted in reduced frequencies and bus services. As a result, the sensitivity test includes scenarios that reduce frequencies in addition to those that increase them.

In the above scenario, riders leave the current location at a planned time regardless of the transit schedule. While this is a common behavior for frequencies less than 10 minutes, it might not be realistic for frequencies greater than 10 minutes. In reality, travelers tend to arrive at the transit stop closer to the scheduled time, which implies that the current implementation may overestimate the actual waiting times and, consequently, underestimate the demand for transit.

D.2 Transit Fare

The decision-making process of travelers is heavily influenced by the trade-off between travel time and cost. As such, if the cost of a particular mode of transportation decreases while the travel time remains constant, it is anticipated that there will be an increase in demand for that mode. For instance, research suggests that a 1% reduction in transit fares is associated with an increased ridership between 0.17% and 1% (Handy et al., 2013). Furthermore, Tod Litman, (2022)reviews the literature on transit fare elasticities and recommends the use of a range of -0.2 to -0.5 for transit ridership for short-term ranges. The broad range of elasticities is because studies disaggregate elasticities by transit mode and trip lengths. Uneven impact across population segments, however, has been explored to a lesser extent. Gillen, (1994)reported an elasticity of 0.19 for individuals earning less than $5000 and -0.28 for those earning more than $15000. These findings are unexpected, as lower-income populations are generally considered more price-sensitive than higher-income groups, which would lead to a higher absolute elasticity. We hypothesize that decreasing transit fare will increase ridership, but elasticity for lower-income populations is greater than for higher-income because of higher price sensitivity among lower-income travelers.

In the model system, transit fares are an input variable reflected in the GTFS. BEAM configuration files include a transit fare tuning multiplier that reflects changes in the transit fare. These changes are reflected in the skims, which contain the average transit fare for every Origin-Destination pair at different times of the day. ActivitySim reads the skims with the modified transit fare, which are used in the tour and trip mode choice model. Transit fares are modified for all transit modes (local bus, light-rail, express bus, bus rapid transit, and heavy rail, in both walk and drive access).

For this research project, CARB and the research team are interested in exploring policies that subsidizes the transit fare in ranges from 25% and 50%. Additionally, the study investigates the potential impact of a 100% reduction discount, which corresponds to a free transit policy. Furthermore, CARB and the research team explore the sensitivity of increased transit fares resulting from factors such as increased operation cost of transit and reduced federal or state funding.

D.3 Transit In-Vehicle Time

Improving transit speeds reduces total in-vehicle time, which incentivizes the use of public transit by increasing the speed of transit compared to driving and other modes, holding price and other mode attributes constant. Therefore, we hypothesize that increased transit speeds increase ridership. In the mode choice model, the travel time coefficient is negative, which reflects that lower in-vehicle times increased the probability of transit modes. Previous research suggests that reducing the time spent on the vehicle by 1% is associated with ridership increases between 0.4% and 0.9%, depending on the transit mode (Handy et al., 2013). Similarly, differential impact across population segments has been less explored.

Improved speeds for bus systems can be attained with different policy strategies, such as priority signaling, exclusive bus lanes, and intermittent bus stops. While a better approach would be to test the sensitivity of each of these strategies, the model system does not yet offer such detailed capabilities. Therefore, for this sensitivity analysis, we modify the average in-vehicle times for all transit modes and every Origin-destination pair as a proxy. In coordination with the CARB team, the elasticity of this policy is only tested for a -10% and -25% variation, as any policy that might result would incentivize improved speeds.

D.4 TNC Price and Shared TNC Pricing

Transportation Network Companies (TNCs) are a relatively new mode of transportation that became popular in the last decade with companies such as Uber and Lyft. This new option has two main alternatives, which are ride-alone or pooled/shared. In the ride-alone option, a person orders a ride through their phone and does not share the ride with any other user. In contrast, in the pooled options, for the possibility of a lower cost, the app matches riders with similar trajectories in one ride. The pool option, therefore, incentivizes higher vehicle occupancy. For this research, we hypothesize that lower TNC prices for shared rides with respect to ride-alone options increase the mode share of pooled rides. Given that the mode share of TNC is still relatively low, we do not expect to capture a significant reduction in VMT when TNC prices are lowered. Elasticity studies for TNC prices are limited. Middleton et al., (2021) suggest that a $1/mile price difference between ride-alone and pooled rides results in a VMT change of -0.06% for the San Francisco Region. Other studies estimate a price elasticity on demand of -0.84 in Egypt (Christensen & Osman, 2021), and between -0.42 to -0.50 for a 1.5 surge price factor in the United States (Cohen et al., 2016).

For this sensitivity analysis, we consider the price of ride-alone and pooled rides as two sensitivity tests. Taxis, while included in the mode choice model in ActivitySim, are not included in any of the sensitivity test. For both tests, we modify the cost per mile, per minute, base fare, and minimum fare by the same percentage in the tour and trip mode choice. For the sensitivity analysis, we vary TNC price from $\pm 50\%$ and $\pm 25\%$.

D.5 Operating Cost

In the model system, the operating cost is associated with the cost of driving a private vehicle. One of the few policies that could impact the operating cost is the gas tax, which is 53.9 cents per gallon (assuming a vehicle efficiency of 27mpg, this translates to 2 cents per mile). However, improved vehicle efficiency and the penetration of EVs might put gas tax revenue at risk. In 2017, a California VMT pilot conducted by the California State Transportation Agency and California Department of Transportation (Caltrans) suggest a

VMT fee of 1.8 cents per mile, which is assumed to be a revenue-neutral rate (California State Transportation Agency, 2017). In a Portland pilot program, daily VMT was reduced by 2.9 miles with a VMT charge of 1.2 cents per mile (Boarnet et al., 2014; Guo et al., 2011). We hypothesize that an increase in operating costs will reduce the total vehicle miles traveled and increase the mode share for public transit systems and pooled TNC rides.

For the purpose of this study, we modify the average operating cost per mile for driving modes. Currently, the model has an operating cost of 18.29 cents per mile which includes gas and other maintenance cost but not the cost of purchase. The ranges for the sensitivity test were coordinated with the CARB team, and they vary from a 100% increase to a 50% decrease. This range is selected to test potential VMT fees policy, but also increase fuel efficiency and greater electric vehicle electrification. The VMT fees impact all private modes, as well as TNCs and Taxis.

D.6 Cordon Pricing

A cordon pricing strategy aims at reducing congestion by charging a fee to drive into a pre-defined zone such as a downtown area. While the main objective of this policy is to reduce congestion, especially in busy financial districts, international experiences also suggest increased public transit use. In Singapore, the reduction of vehicles entering the cordon area was 24%, and the increase in public transit use was between 25% and 34% (Bhatt et al., 2008). The same report states that in London, vehicles accessing the charging zone were reduced by 18%, and public transit use increased by 40%. Similarly, in Stockholm, the congestion pricing reduced city-wide VMT by 1% and increased transit use by 9%. Therefore, our hypothesis is that an increased price to the cordon price will increase the mode share of public transit.

The baseline scenario for the congestion pricing policy is based on a current San Francisco County Transportation Authority (SFCTA) proposal. A baseline with no congestion pricing would not allow estimating an elasticity because the reference value is zero. Even estimating arc elasticities, the percentage increase for all scenarios would always be 200% regardless of the price change, which would result in meaningless elasticities.

The cordon is defined by the smaller zone (shown in a darker shade in Figure 44) in the San Francisco downtown area. The cost is set to $6.5. Additionally, the hours of operations are approximated to 6 am to 11 am (AM period) and 4 pm to 8 pm (PM period) to match the time period embedded in the skims data. The cost is applied to every driving mode, including TNCs and Taxis, for those trips whose destination is a zone within the cordon. Trips starting and ending in the zone or going through the zone are not charged. Trips that go through the zone are not charged if they only use the highway system, they would be charged otherwise. The current implementation does not consider discounts for households living within the cordon area, toll bridge, or base on income. For the sensitivity analysis, the upper and lower bounds range from a 25% increase to a 50% reduction. Since the experiments use a baseline charge of $6.5, the results do not test the effectivity of the congestion pricing policy but rather the impact on different price strategies.

Figure 44. Proposed Cordon Areas

Source: https://www.sfcta.org/downtown

More information about the cordon pricing strategy in the San Francisco Bay area can [be found here: https://www.sfcta.org/downtown](https://www.sfcta.org/downtown)

D.7 Park & Ride

The Park & Ride strategy refers to the availability of parking spaces close to public transit access with the purpose of increasing public transit access by private vehicles. Other potential benefits of this strategy are avoiding congestion in busy financial districts, reducing the cost of parking at the destination, and reducing VMT in private vehicles. In the San Francisco Bay Area, parking availability at most mass transit stations is already available, however, high demand and limited parking spaces have increased parking prices at some stations. For instance, West Oakland's daily fare is $12.40; the reserved monthly pass is $311.05 per month (Bay Area Rapid Transit, 2022). For this sensitivity analysis, we test different prices for park and ride options at mass transit stations. We hypothesize that lower parking prices increase public transit mode shares and reduce VMT. In the literature, parking price sensitivities are tested for general off-street parking prices but not for park and ride strategy.

The current implementation of the model system does not consider the cost of parking for drive-to-transit modes. Therefore, to test price sensitivity, the baseline scenario includes a $3.0 per day cost, the BART average parking cost. Since the main interest is to make mass transit more available, we only include this cost to drive to heavy rail options, which include BART and Caltrain. The model framework also assumes infinite parking, therefore capacity constraints are not considered. For the sensitivity analysis, the variation in the parking cost at mass transit stations is from a 50% increase to a 50% reduction.

D.8 Telecommute

Telecommuting is the possibility of performing work activities in places different from the workplace, such as from home. While telecommuting alone may not directly impact the use of sustainable transportation options such as high-occupancy, zero-emission, and new mobility options, the travel restrictions put in place during the COVID-19 pandemic have greatly increased the adoption of telecommuting as a viable alternative to commuting. As of 2022, 60% of workers who are able to work remotely continue to do so (Pew Research Center, 2022), a substantial increase from the 23% reported in the 2017 NHTS (Federal Highway Administration, 2017). However, the impact of a high penetration rate of telecommuting on VMT and other transportation metrics remains unclear. As the COVID-19 pandemic is still evolving, there is great uncertainty about the future of telecommuting, which is why CARB, and the research team are interested in quantifying its potential impact. We hypothesize that a greater percentage of the population with the option of telecommuting reduces total VMT and VMT per capita.

A previous implementation of the model system did not include a telecommute model. This capability was added to ActivitySim for the purpose of this research project. The telecommuting capability consists of two main models that answer two questions: (1) Does a worker have the option of telecommuting, and (2) What is the weekly frequency of telecommuting given that telecommuting is an option? The first question separates workers who might not be able to perform their jobs outside the workplace (e.g., essential health work professionals, constructing workers, retail, etc.) and those who can perform their job outside the workplace, and their employer allows telecommuting for all or some days per week. The research team used the San Francisco Bay Area subsample from NHTS 2017 data to estimate these two models. The models are implemented as stochastic models predicting the outcomes using simulation based on pre-determined rates. It is important to note that this model only applies to worker agents residing in the study area and not to students, unemployed individuals, retirees, or people residing outside the study area. The estimated rates for these models can be found in Appendix 0.

For the sensitivity analysis, this research divide telecommutes into two tests. The first one varies the rates at which workers have the option of telecommuting (called telecommute – option) by $\pm 50\%$. The baseline for this model is the NHTS 2017 rates. The second varies the weekly frequency of telecommuting for workers who have the option of telecommute (called telecommute – frequency). Regarding the latter, the CARB team acknowledges recent changes in telecommuting patterns due to the COVID-19 pandemic, and thus considers a baseline that is 100% higher than the rate suggested by NHTS (2017). Specifically, a recent study by the Pew Research Center (2022) reports that the average number of telecommute days per week is 2.72, compared to 0.77 days per week in the NHTS survey. Although the telecommuting rate is still heavily influenced by the pandemic, the CARB team believes that the baseline should reflect the significant changes observed in telecommuting behavior, and therefore has adjusted the baseline accordingly.

To build the scenarios of analysis for the telecommute – Weekly Frequency model, we use the average number of days per week of telecommute in the NHTS 2017 as the lower bound and increase it by 50%, 100%, 200%, and 300% for the other scenarios, as shown in Table 37. For the purpose of this study, the baseline is set to 1.5 days of telecommute per week, which is twice the rate in the 2017 NHTS. Then, for each scenario, the research team modified the probability distribution in the baseline to match the increased average. In the baseline scenario, we lowered the percentage of workers with the option to telecommute who would still choose to commute for work from 46.7% to 30.4%. At the same time, we raised the percentage of workers who would telecommute 4 to 5 days per week from 2.5% to 16.6%. The upper-bound scenario assumes that all workers with the option to telecommute would telecommute at least once per week, with 56.2% telecommuting at least 4-5 days per week. Our conservative scenario falls between the lower bound and baseline, while the aggressive scenario falls between the baseline and upper bound.

Table 37. Upper and Lower Bounds for the Telecommute Weekly Frequency Model

	Lower bound	Conservative	Baseline	Aggressive	Upper Bound
Days Per Week (Average)	2017 Rates (NHTS)	50% Increase	100% Increase	200% Increase	300% Increase
0	47.60%	39.00%	30.40%	14.80%	0.00%
1	39.60%	39.60%	39.60%	39.60%	36.60%
2.5	10.40%	10.40%	10.40%	7.20%	7.20%
4.5	2.50%	11.00%	19.60%	38.40%	56.20%
Average Number of Days Per Week	0.77	1.15	1.54	2.31	3.07

D.9 Autonomous Vehicles Penetration Rates and Value of Time

Autonomous vehicle technology has advanced in the last few decades and is expected to continue doing so in the near future, to the point that fully autonomous vehicles are expected in the next decade or two (Todd Litman, 2017). However, the penetration of autonomous vehicles will change in response to the evolving cost and availability of the technology. There is substantial uncertainty around the exact magnitude of penetration rates given the unknown pace of future technological progress, changes in costs, regulatory changes, future population preferences for adoption, and the behavioral changes that might generate. A study of the I-80 corridor in Iowa stated a conservative and aggressive AV penetration rate, which varies 2050 penetration from 100% in the aggressive scenario, to 50% in the conservative scenario (Iowa DOT, 2017). Given the high degree of uncertainty, it is particularly appropriate to study the adoption of AV technology using alternative assumptions.

As the adoption of AVs becomes increasingly likely, researchers are investigating the potential behavioral changes that may result. One such change is a decrease in the VOT attributed to AVs due to a reduced sensitivity to travel times. With the elimination of the need to drive, passengers can utilize their travel time for other activities, such as work or leisure, while still enjoying the benefits of driving, such as shorter travel times and greater flexibility. While other transportation modes also eliminate the need to drive, they may not offer the same level of time savings or flexibility, as models account for different time sensitivities, such as waiting, walking, and transfer times. Furthermore, other factors, such as bus crowding (Tirachini et al., 2013) may counterbalance the benefits of in-vehicle time sensitivities.

However, the magnitude in which VOT changes is uncertain. Multiple studies have tried to quantify it by using stated preference surveys, real-life experiments, and simulations. Kolarova et al., (2018) used stated preference surveys to estimate a 40% reduction in the VOT across multiple income levels. In addition, Correia et al., (2019) employed stated preferences to estimate a 26% reduction in the VOT for AVs that provide a working environment compared to conventional cars, as well as a similar VOT for AVs that offer a "leisure interior". Harb et al., (2018), revealed preferences data (a study conducted using a chauffeur as a proxy for AVs) estimated a reduction of 60% in the VOT. Therefore, we hypothesize that a decreased VOT and greater AV penetrations increase the total VMT and VMT per capita.

For the purpose of the sensitivity analysis, the research team divides AV scenarios tests into two (1) AV penetration rates and (2) VOT reduction. The baseline scenario does not consider AV penetration or VOT reduction. For the first scenario, we use CARB inputs to vary AV penetration from 5% to 50%. For these tests, we assume a VOT reduction of 40%. To test VOT reduction sensitivity, we used lower and upper limits suggested by the literature, which vary from 10% and 60% reduction. In the model, AV penetration rates are randomly assigned to households, and we assume an all-or-nothing allocation, meaning if a household is flagged with an AV, all vehicles in the households are AVs. Consistently, the VOT will be changed for all household members as well.

It is also worth noticing that the current implementation of the mode choice model has the VOT and the time-sensitivity (β_t) coefficient as inputs. The model, then, estimates a cost-sensitivity (β_c) coefficient depending on the household VOT following this relationship $\beta_c = \beta_t/VOT$. While this approach makes the decision-making process sensitive to income characteristics, it is not appropriate to reduce the VOT variable, as the model will keep the time-sensitivity coefficient constant and increase the cost-sensitivity parameter. For this research, we leave the cost-sensitivity parameter constant and modify the time-sensitivity to match the target value of time reduction.

D.10 Transit-Oriented Development

Transit Oriented Development (TOD), which combines land use and transportation planning, aims to increase access to opportunities by developing areas around transit stations. Cervero & Kockelman (1997) state that potential benefits of TODs are the reduction of motorized trips and especially solo driving; the shortening of motorized trip length; and the increase of non-motorized trips like cycling and walking, all of which are the objectives of this research. The literature reports strong effects of TODs on travel behavior. Cervero & Kockelman (1997) found that residents of a TOD development use transit 1.4% to 5.1% more than a non-TOD resident. Similarly, Cervero (2007) studied 26 TOD housing projects in California and reported that the transit mode share of residents living within half a mile from a transit station was 27%, in contrast to 7% of residents living within half and mile and three miles. This finding suggests that proximity to mass transit stations plays a crucial role in promoting transit and reducing the need to drive, thereby decreasing vehicle miles traveled (VMT). Based on this observation, we hypothesize that increasing the density of development around mass transit stations will lead to an increase in the transit mode share and a reduction in VMT per capita.

For the sensitivity analysis, we modify the residential and employment capacities half a mile around mass transit stations (BART and Caltrain). The capacity is a block-level input variable for UrbanSim models, which determines the maximum development for each block. The building location model is sensitive to the increased capacity and the likelihood of developing new real estate increases. However, increasing capacities does not immediately increase densities, since real estate supply responds to market opportunities over many years. Therefore, the research team runs the sensitivity test from 2020 to 2035. The land-use portion of the modeling (UrbanSim) runs every year; however, the travel demand model (ActivitySim) and network assignment (BEAM) run every five years. The upper and lower limits were defined to increase capacities, ranging from 10% to 50% increase in both residential and employment capacities.

Appendix E Sensitivity Analysis

The objective of the sensitivity analysis is to isolate individual impacts of the policies variables suggested in Appendix A to explore their relative influence and quantify their elasticity on key metrics. These policies allow for the exploration of hypothetical future scenarios through the combination of technological, behavioral, and economic changes, as well as policy levers that can significantly alter the transportation system.

In general, sensitivity tests were designed to vary from +50% to -50%, in 25% steps. The CARB team suggested limits outside these boundaries to explore the elasticities of more aggressive policies. An example is free to transit fare policy, where transit fare reduces by 100%. The tests for the sensitivity analysis are summarized in Table 38. To evaluate the induvial impact of the policy variable, we estimate the arc elasticities for the KPI described in Key Performance Indicators (KPI).

Table 38. Sensitivity Analysis Tests

Policy Variable	Model Variable (proxy)	Forecasting Horizon	Baseline level	Test
Transit Frequencies	Average waiting time	One year (2021)	Current Transit Frequencies	200% 100% -25% -50%
Transit Fare	Transit Fare	One year (2021)	Current Transit Fare	50% -25% -50% -100%
Transit Speeds	Transit in-vehicle times	One year (2021)	Current Transit in-vehicle times	-10% -25%
TNC Price	TNC Prices	One year (2021)	Base: $2.20 Minimum: $7.20 Per mile: $1.33 Per Minute: $0.24	50% 25% -25% -50%
Share TNC Price	Share TNC Prices	One year (2021)	Base: $2.20 Minimum: $3.0 Per mile: $0.53 Per Minute: $0.10	50% -10% -25% -50%
Operating Cost	Operating cost per mile	One year (2021)	18.29 cents	100% 50% -25% -50%
Cordon Pricing	Price to access cordon perimeter	One year (2021)	No Cordon Pricing	50% 25% -25% -50%
Park & Ride	Parking price for driving options (only for mass transit)	One year (2021)	Average of $3/day	50% 25% -25% -50%
Telecommute Option	Telecommute option rates	One year (2021)	2017 NHTS Model (see Appendix F)	50% 25% -25%

Policy Variable	Model Variable (proxy)	Forecasting Horizon	Baseline level	Test
				-50%
Telecommute Frequency	Telecommute Frequency rates	One year (2021)	+100% 2017 NHTS Model (see Appendix F)	NHTS 2017 50% 200% 300%
AV Penetration Rate	AV penetration rates	One year (2021)	0% Penetration rate	5% 10% 25% 50%
AV Value of Time	AV value of time	One year (2021)	Current Value of Time for Non-AV - AV Penetration rate of 25%	-10% -20% -40% -60%
TOD Residential and Employment	Residential and Employment capacities ½ mile around mass transit stations	2035	Current Residential and Employment Capacities	10% 25% 50%

This appendix is structured as follows: E.1 Elasticity Estimation outlines the methodology used to estimate arc elasticity. E.2 Baseline Results presents the baseline results. Lastly, E.3 Results shows the results for various KPI, including Vehicles Miles Traveled (VMT), Consumer Surplus (CS), mode shares, travel times, and others.

E.1 Elasticity Estimation

The elasticity measures the percentage change in one output of interest in response to a percentage change in one input variable. It is a particularly helpful metric for policy evaluation because it provides a standardized way to interpret the scale of sensitivity of an output to a change in a specific input, and it is widely used in economic analysis. More formally, elasticity is of input variable x on y is defined by:

$$\varepsilon = \frac{\partial y / y}{\partial x / x}$$

In this case, the policy variable is the input variable, and the key performance indicators are the output of interest. To estimate the elasticity from the sensitivity analysis, we use arc elasticity estimation. In the arc elasticity estimation, the percentage change of the output variable and the policy variable is estimated with respect to their corresponding midpoint, as follows:

$$\%\ Change\ in\ KPI_i = \frac{KPI_{i,base} - KPI_{i,exp}}{KPI_{i,base} + KPI_{i,exp} / 2}$$

$$\%\ Change\ in\ Policy\ Variable_j = \frac{PV_{base} - PV_{exp}}{PV_{base} + PV_{exp} / 2}$$

$$\varepsilon_{i,j} = \frac{\%\ Change\ in\ KPI_i}{\%\ Change\ in\ Policy\ Variable_j}$$

Where $\varepsilon_{i,j}$ is the arc elasticity of KPI_i with respect to the policy variable j. To estimate a final elasticity, we average the estimated elasticity for each test. The range of the elasticity estimate is from negative infinitive to positive infinity, although most estimated elasticities are between 10 and -10. A positive elasticity means that an increase in the input variable results in an increase in the output variables. A negative elasticity, on the other hand, reflects an inverse relationship; the output variable decreases, and the input variable value goes up. Notice that if the Policy Variable in the baseline is zero, then the percent change would always yield to 200%, regardless of the value of the policy in the experiment.

For many policies, estimating the percentage change of the policy variables is not always possible because a unique factor is applied to modify the policy variable. For instance, the cost of transit is different for each O-D pair. Hence, a uniform factor was applied to adjust all the values, either by increasing or decreasing them. For such cases, the corrected percentage change to estimate the arc elasticity is defined by:

$$\%\ Change\ in\ Policy\ Variable_j = \frac{2 * (factor - 1)}{(factor + 1)}$$

E.2 Baseline Results

For the sensitivity analysis tests, we use the baseline results from Table 39. The baseline one results are used to compare TNC price, share TNC price, cordon pricing, Park & Ride policies and telecommute models. The baseline two results are used to compare Transit Frequencies, Transit Fares, Transit in-vehicle times, and AV scenarios. The TOD scenario uses a different baseline result because the forecasting period is the year 2035. For the other input variables, a discrepancy in the transit fare magnitude was corrected for baseline two, resulting in a different baseline result. Since the objective of the sensitivity analysis is to isolate the impact of each input variable, we do not anticipate that the discrepancy in the transit fare magnitude has a significant impact in the elasticity estimate of other policies, therefore we kept the elasticity estimations that use the baseline one results. To ensure the integrity and accuracy of our research findings, we validate the decision to retain the previous results.

Table 39. Baseline Results for Baseline 1, Baseline 2, and Baseline TOD Shares

KPI	Demographic Attribute	Category	Baseline 1	Baseline 2	Baseline TOD
Ridership			1,951,653	1,626,553	2,089,347
Vehicle Ownership			1.89	1.89	1.88
Seat Utilization			1.32	1.32	1.32
Total VMT			119,115,247	120,506,735	128,901,277
	Average		15.86	16.04	15.94
	Income	Low	13.03	13.21	13.14
		Middle	18.19	18.37	18.31
		High Income	18.25	18.44	18.25
	Race	Asian	15.14	15.42	15.24
		Black	13.96	14.18	14.10
VMT Per Capita		other	13.08	13.24	13.18

KPI	Demographic Attribute	Category	Baseline 1	Baseline 2	Baseline TOD
		White	16.99	17.15	17.07
	Ethnicity	Hispanic	13.24	13.35	13.31
		Non - Hispanic	16.61	16.81	16.70
	Area Type	Urban	11.72	11.93	11.76
		Suburban	16.25	16.31	16.51
		Rural	23.92	24.41	24.41
Average Travel Times	Income	Low	17.18	16.91	16.96
		Middle	18.54	18.39	18.32
		High Income	18.43	18.26	18.20
	Purpose	Commute	19.12	18.80	18.96
		Non-commute	16.71	16.61	16.43
	Mode	Bike	11.63	11.76	11.72
		Drive Alone	18.83	18.80	18.53
		Drive Shared	16.48	16.43	16.15
		Public Transit	28.35	27.22	28.53
		TNC - Pooled	13.91	13.85	13.53
		TNC - Ride Alone	11.44	11.36	10.93
		Walk	13.96	14.35	14.37
Mode Shares	Mode	Bike	1.40%	1.47%	1.40%
		Drive Alone	44.59%	45.29%	44.64%
		Drive Shared	32.48%	32.99%	32.49%
		Public Transit	7.60%	6.33%	7.55%
		TNC - Pooled	1.30%	1.31%	1.32%
		TNC - Ride Alone	3.37%	3.41%	3.45%
		Walk	9.26%	9.20%	9.16%
Mode Shares	Mode	Bike	2.35	2.35	2.34
		Drive Alone	8.09	8.09	8.14
		Drive Shared	6.16	6.16	6.20
		Public Transit	5.52	5.52	5.98
		TNC - Pooled	5.87	5.87	5.90
		TNC - Ride Alone	3.75	3.75	3.75
		Walk	0.72	0.72	0.72

There are several potential explanations for the differences in vehicle miles traveled (VMT) across different population segments. For example, low-income populations tend to have a lower average trip per person compared to high-income groups (NuStats, 2013), which may contribute to the observed differences in VMT. Additionally, urban areas tend to have lower VMT per capita (Cervero & Murakami, 2010), which might be explain by higher accessibility to jobs and opportunities, resulting in shorter travel times. Furthermore, commute trips are more strongly affected by congestion since they tend to occur during peak travel times.

E.3 Results

The section below displays the outcomes of the sensitivity analysis. According to Castiglione et al., (2003), results that range between 2% and 0.5% are attributable to the stochastic element of the models. For the outcomes presented in this appendix, it is assumed that results with variations of less than 0.5% are due to random factors and do not represent a significant signal for the model. The results for VMT and CS are presented in tables for all experiments. However, to simplify the results by population segment, average elasticity is plotted for each policy. This is because the elasticity estimation trend is relatively stable regardless of the percentage variation of the policy scenario.

E.3.1 VMT and VMT per Capita

Table 40 presents the sensitivity analysis results for the VMT metric. The analysis assesses the impact of various policies on the total VMT difference with respect to the baseline scenario. Elasticities for most policies are relatively stable regardless of the percentage change in the policy variable. The highest absolute elasticity on VMT is associated with operating cost and transit in-vehicle times. A 1% increase in auto operating cost predicts a reduction in VMT between 0.24% and 0.18%, while reducing transit in-vehicle times by 1% is associated with a 0.11% reduction in VMT. Increasing transit frequencies and reducing transit fare are also associated with less VMT, with absolute elasticities of approximately 0.02 for both. Greater telecommute rates are associated with a decrease in VMT, with a 1% increase in telecommute rates leading to a 0.05% decrease in VMT. The TOD scenario has a negative elasticity of 0.04, suggesting that a 1% increase in residential and employment density around mass transit stations is associated with a 0.04% reduction in VMT. Finally, the cordon pricing and park & ride policies test do not show any signal, as results vary less than 0.5% (approx. 600k VMT). For TNC scenarios, only changes of $\pm 50\%$ result in significant VMT change.

When examining the impact of policies on VMT elasticities by population segments, the results indicate significant variations, as shown in Figure 45. For example, the VMT elasticity for operating cost varies by income, race, and area type. Low-income populations show the highest VMT elasticity with operating cost at 0.24, while middle and high-income populations have lower elasticities at 0.17 and 0.16, respectively. Additionally, black populations exhibit a 22% higher elasticity than white and Asian populations, and the Hispanic population's elasticity is 9% higher than that of non-Hispanics. Elasticities for area type are relatively similar, but urban areas exhibit a 7% greater elasticity than rural areas.

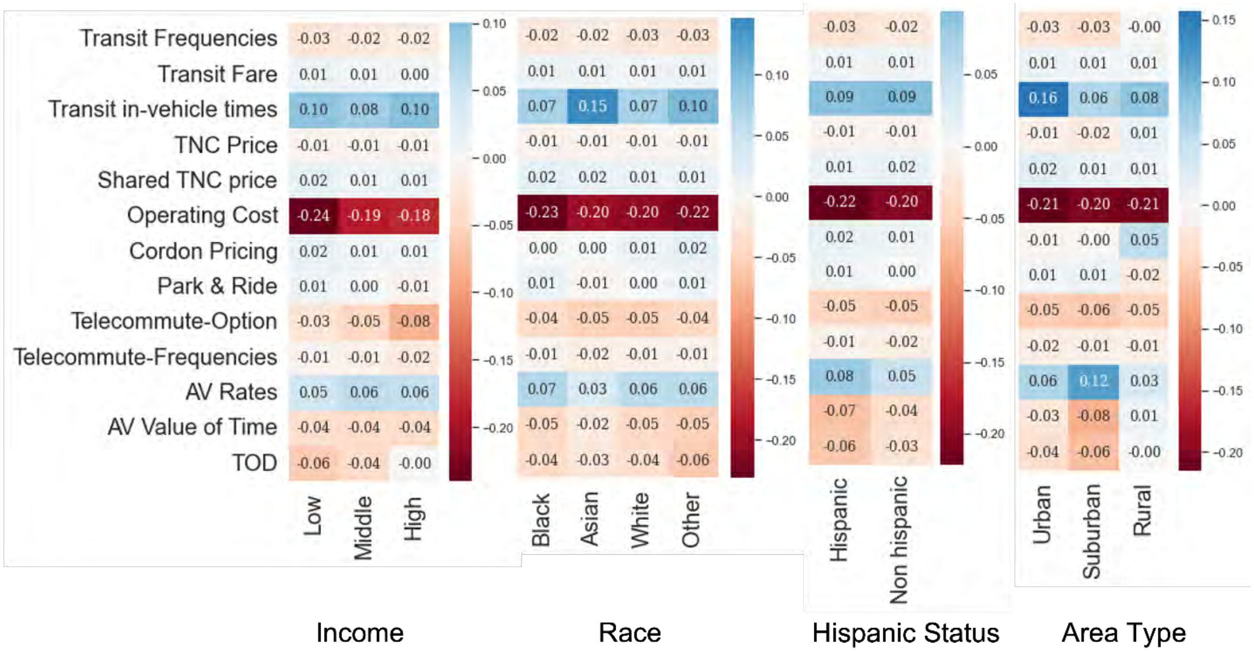
Regarding the TOD strategy, the analysis indicates a significant negative elasticity of -0.04 and -0.06 for low- and middle-income populations, respectively, but almost zero for high-income populations, as presented in Figure 45. This suggests that the TOD strategy has a positive impact on low- and middle-income populations. The elasticity for black populations is almost twice that of white populations, and the elasticity for Hispanics is also twice as high as for non-Hispanics. Similarly, the telecommute-option policy shows an elasticity 2.5 times higher for high-income populations than for low-income populations, indicating a disproportionate benefit for higher-income populations. However, the impacts of this policy are relatively similar in terms of race, ethnicity, and area type. Finally, transit in-vehicle times are almost two times more elastic in urban areas than in suburban or rural areas, with an elasticity of 0.15 compared to 0.08, respectively.

Table 40. Total VMT Sensitivity Analysis Results for All Policies

Policy	Description	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Transit Frequencies	Difference	-4,045,504	-2,610,208	309,032	1,688,911
	Elasticity	-0.03	-0.03	-0.01	-0.02
	% Change	(200%)	(100%)	(-25%)	(-50%)
Transit Fare	Difference	997,314	-166,882	-422,243	-1,020,227
	Elasticity	0.02	0.00	0.01	0.00
	% Change	(50%)	(-25%)	(-50%)	(-100%)
Transit in-vehicle times	Difference	-1,443,203	-2,517,114	N/A	N/A
	Elasticity	0.11	0.07	N/A	N/A
	% Change	(-10%)	(-25%)	N/A	N/A
TNC Price	Difference	-638,793	-218,655	-249,814	1,549,152
	Elasticity	-0.01	-0.01	0.01	-0.02
	% Change	(50%)	(25%)	(-25%)	(-50%)
Shared TNC price	Difference	1,722,436	410,225	163,988	-914,075
	Elasticity	0.04	0.02	-0.00	0.01
	% Change	(50%)	(25%)	(-25%)	(-50%)
Operating Cost	Difference	-19,046,287	-10,159,506	6,625,370	13,950,223
	Elasticity	-0.24	-0.21	-0.19	-0.18
	% Change	(100%)	(50%)	(-25%)	(-50%)
Cordon Pricing	Difference	747,447	-6,368	-270,095	-303,443
	Elasticity	0.03	-0.00	0.01	0.00
	% Change	(25%)	(10%)	(-25%)	(-50%)
Park & Ride	Difference	537,510	-427,533	-347,075	-389,830
	Elasticity	0.01	-0.02	0.01	0.00
	% Change	(50%)	(25%)	(-25%)	(-50%)
Telecommute-Option	Difference	-2,669,144	-1,275,157	1,927,974	3,670,347
	Elasticity	-0.06	-0.05	-0.06	-0.05
	% Change	(50%)	(25%)	(-25%)	(-50%)
Telecommute-Frequencies	Difference	1,927,669	923,698	-865,433	-3,271,217
	Elasticity	-0.01	-0.01	-0.01	-0.03
	% Change	(-100%)	(-50%)	(100%)	(200%)
AV Rates	Difference	-182,394	996,897	1,908,901	4,247,856
	Elasticity	-0.03	0.09	0.07	0.09
	% Change	(5%)	(10%)	(25%)	(50%)
AV Value of Time	Difference	1,143,144	613,714	1,908,901	2,518,128
	Elasticity	-0.09	-0.02	-0.03	-0.02
	% Change	(-10%)	(-20%)	(-40%)	(-60%)
TOD	Difference	-603,775	-1,185,458	-1,315,708	N/A
	Elasticity	-0.05	-0.04	-0.03	N/A
	% Change	(10%)	(25%)	(50%)	N/A

For each policy, the first row shows the difference with respect to the baseline, the second row shows the elasticity estimation, and the third row shows the percentage change corresponding to the scenario.

Figure 45. Per Capita VMT Elasticities by Income, Race, Hispanic status, and Area Type



E.3.2 Consumer Surplus (CS)

The sensitivity analysis results for the CS metric are shown in Table 41. The results indicate that increasing transit frequencies by 100% and 200% leads to an increase in CS of $2 million and $1.4 million, respectively, and providing free transit results in an increase of $688k in CS. Decreasing transit-in-vehicle times by 10% results in an increase of $755k in CS. The elasticity of transit policies to CS ranges from 0.01 to 0.2, being in-transit time the more elastic policy. The elasticity for TNC services is varies from -0.02 to 0.11, being the ride-alone option more elastic in general. For instance, a 50% reduction in TNC ride alone option is associated with a CS of $1.8 million, while the same reduction for the share TNC is only associated with a CS of $0.5 million.

For the telecommute option model, an increase of 50% leads to an increase in CS of $1.2 million. The CS also increases as the penetration rate of AVs increases, and the VOT decreases. For instance, 25% penetration rate for AVs, with a 40% reduction in VOT due to AV ownership, results in $2.2 million in consumer surplus. Additionally, increasing residential and employment density by 25% around transit stations results in a consumer surplus of $444k. However, cordon price and park & ride policies have a limited impact on consumer surplus, with the variation being less than 0.5% threshold. Finally, the study finds that the operating cost policy is the most elastic to consumer surplus, and a 100% increase in the AOC results in a loss of consumer surplus of approximately $11.8 million. Considering the stochastic nature of the model, fluctuations of CS values within the range of +-$250,000 can be attributed to model stochasticity, which suggests that these variations might not be significant.

Table 41. Consumer Surplus (CS) Sensitivity Analysis Results for All Policies

Policy	Description	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Transit Frequencies	Difference	\$2,057,632	\$1,437,340	\$190,854	\$-228,318
	Elasticity	-0.06	-0.06	0.02	-0.01
	% Change	(200%)	(100%)	(-25%)	(-50%)
Transit Fare	Difference	\$-488,435	\$178,423	\$303,282	\$688,196
	Elasticity	0.03	0.02	0.01	0.01
	% Change	(50%)	(-25%)	(-50%)	(-100%)
Transit in-vehicle times	Difference	\$755,704	\$975,293	N/A	N/A
	Elasticity	0.20	0.10	N/A	N/A
	% Change	(-10%)	(-25%)	N/A	N/A
TNC Price	Difference	\$-750,032	\$-316,661	\$1,129,603	\$1,851,894
	Elasticity	0.05	0.04	0.11	0.08
	% Change	(50%)	(25%)	(-25%)	(-50%)
Shared TNC price	Difference	\$-773,859	\$-152,798	\$150,782	\$529,621
	Elasticity	0.06	0.02	0.02	0.02
	% Change	(50%)	(25%)	(-25%)	(-50%)
Operating Cost	Difference	\$-11,855,256	\$-6,558,161	\$3,788,742	\$8,078,616
	Elasticity	0.51	0.47	0.38	0.35
	% Change	(100%)	(50%)	(-25%)	(-50%)
Cordon Pricing	Difference	\$-205,931	\$206,028	\$70,104	\$8,554
	Elasticity	0.03	-0.06	0.01	0.00
	% Change	(25%)	(10%)	(-25%)	(-50%)
Park & Ride	Difference	\$-121,300	\$235,339	\$35,570	\$58,892
	Elasticity	0.01	-0.03	0.00	0.00
	% Change	(50%)	(25%)	(-25%)	(-50%)
Telecommute-Option	Difference	\$1,120,831	\$698,094	\$-913,217	\$-1,683,719
	Elasticity	-0.08	-0.09	-0.09	-0.07
	% Change	(50%)	(25%)	(-25%)	(-50%)
Telecommute-Frequencies	Difference	\$-426,910	\$-528,642	\$320,304	\$1,471,868
	Elasticity	-0.01	-0.02	-0.01	-0.04
	% Change	(-100%)	(-50%)	(100%)	(200%)
AV Rates	Difference	\$643,655	\$910,480	\$2,234,097	\$4,374,857
	Elasticity	-0.37	-0.27	-0.28	-0.31
	% Change	(5%)	(10%)	(25%)	(50%)
AV Value of Time	Difference	\$314,083	\$1,054,204	\$2,234,097	\$3,560,044
	Elasticity	0.08	0.13	0.13	0.12
	% Change	(-10%)	(-20%)	(-40%)	(-60%)
TOD	Difference	\$299,998	\$444,925	\$532,041	N/A
	Elasticity	-0.09	-0.05	-0.04	N/A
	% Change	(10%)	(25%)	(50%)	N/A

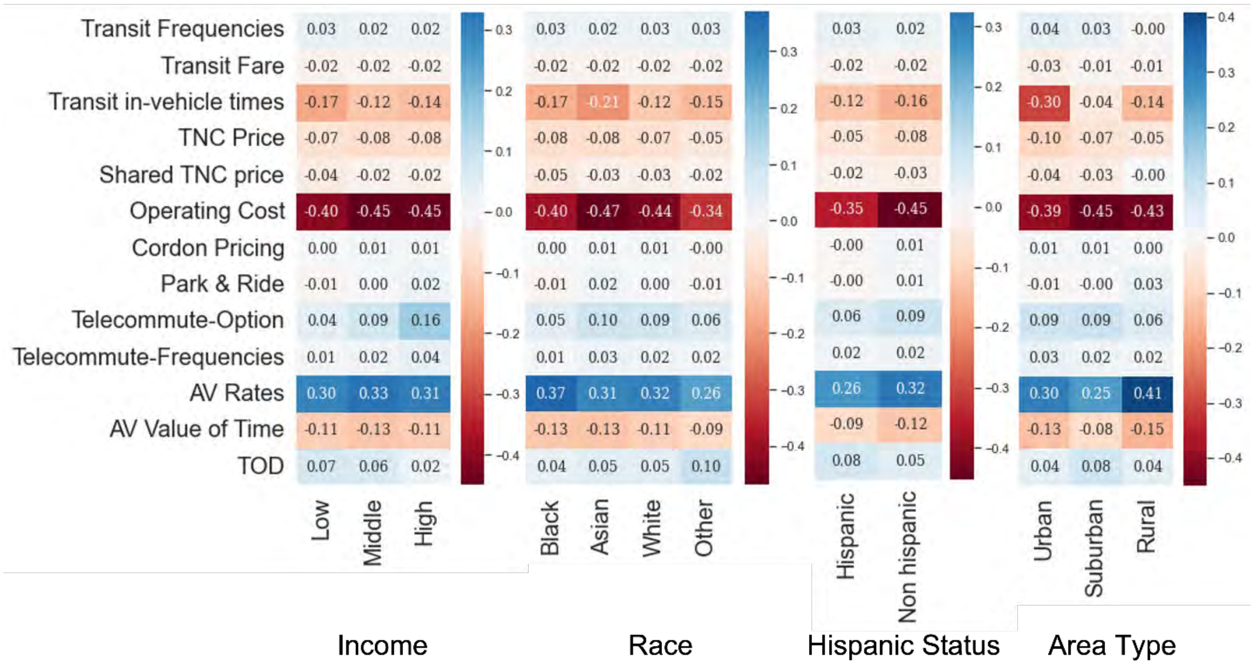
For each policy, the first row shows the difference with respect to the baseline, the second row shows the elasticity estimation, and the third row shows the percentage change corresponding to the scenario.

AV scenarios also have a positive impact on consumer surplus. AV penetration rate and VOT of AV have elasticities of 0.27 and -0.14, respectively. At increased AV penetration and reduced VOT, trips with the same length will experience an increase in the consumer surplus driven by the reduced in-vehicle time sensitivity. Since the AV assignation is random across the population, differential impacts across income, race, and ethnicity are relatively small. For the telecommute option and frequency, a similar trend is shown, with consumer surplus elasticities of 0.08 and 0.02, respectively. However, the benefits are disproportionally shared by high-income populations. It is important to notice that for telecommute scenarios, the increased consumer surplus is given by not making a trip. Since trips are usually considered a disutility, not making a trip increases the consumer surplus. Lastly, a 1% increase in TNC ride-alone prices is associated with a decrease in consumer surplus of 0.08%. Nevertheless, other policies such as park & ride, cordon pricing, and share TNC prices show almost no elasticity to consumer surplus.

The impact of transportation policies on consumer surplus varies by income, race, and location, as shown in Figure 46. The CS for low-income is more sensitive to transit in-vehicle times, with an elasticity of 0.14 compared to 0.08 for middle- and high-income populations. Similarly, the elasticity of transit in-vehicle times to CS is approximately 37% higher for Asians, Blacks, and other races than White. This result suggests that low-income, and Asian & Black populations are mostly benefit for reduced transit in-vehicle times. Low and middle-income populations are also more sensitive to changes in consumer surplus in response to TOD strategies. A 1% increase in residential and employment density around mass transit stations is associated with a 0.07% increase in consumer surplus for low- and middle-income populations, while high-income populations experience only a 0.02% increase. However, the benefits of the telecommute option are disproportionately shared by high-income, non-Hispanic in suburban areas.

The elasticity of consumer surplus to operating cost also varies based on income, race, and location. For middle- and high-income populations, the elasticity is -0.45, indicating that a 1% increase in operating costs leads to a 0.45% decrease in consumer surplus. In contrast, the elasticity for low-income populations is 9% lower at -0.40. Among different races, Asians have the highest elasticity at -0.47, while Blacks and other races have lower elasticities of -0.40 and -0.34, respectively. Finally, rural, and suburban areas have higher elasticities of -0.43 and 0.45, respectively, indicating that they are more sensitive to changes in operating cost compared to urban areas with an elasticity of 0.39.

Figure 46. Consumer Surplus per Capita Elasticities by a) Income Category, B) Race, C) Hispanic Ethnicity, and D) Area Type



E.3.3 Mode Shares

According to the sensitivity analysis results, improving public transit can lead to an increase in ridership. Specifically, increasing transit frequencies, decreasing transit fare, and reducing transit travel times by 1% are associated with a 0.29%, 0.15%, and 1.80% increase in ridership, respectively. Moreover, it was observed that as transit ridership increases, the demand for other modes of transportation decreases. For instance, a decrease of 1% in in-transit in-vehicle times, for instance, was associated with a decrease in walking and biking by 0.24% and 0.48%, respectively.

In term of TNC policies, a 1% cost increase in the TNC ride alone option leads to a 1.27% reduction in demand for this service, while the share TNC pooling option increases by 1.09%. In contrast, a 1% decrease in the cost of share TNC results in a 1.71% increase in demand, with only a 0.24% reduction in demand for ride alone services. These findings suggest that there is a trade-off between ride-alone and pooling services for TNCs, and pricing strategies can significantly impact mode choices.

The results in Figure 47 also indicate that there is a negative relationship between AOC and private transportation modes such as ride alone and share rides. Specifically, a 1% increase in AOC leads to a reduction of private modes by 0.07%. Conversely, there is an increase in demand for other transportation modes. Notably, biking and transit demand experienced an increase of 0.34%, and walking of 0.12%.

Figure 47. Mode Share Elasticity by Policy Variable

An increase in telecommute models is linked to a rise in TNC trips. For example, a 1% increase in the telecommute-option model leads to a 0.11% increase in TNC ride-alone and TNC pooled options, which may indicate a preference for these options for discretionary trips. In addition, the telecommute option shows a negative elasticity of -0.05 on public transit modes, indicating a decrease in their usage as telecommuting rates increase.

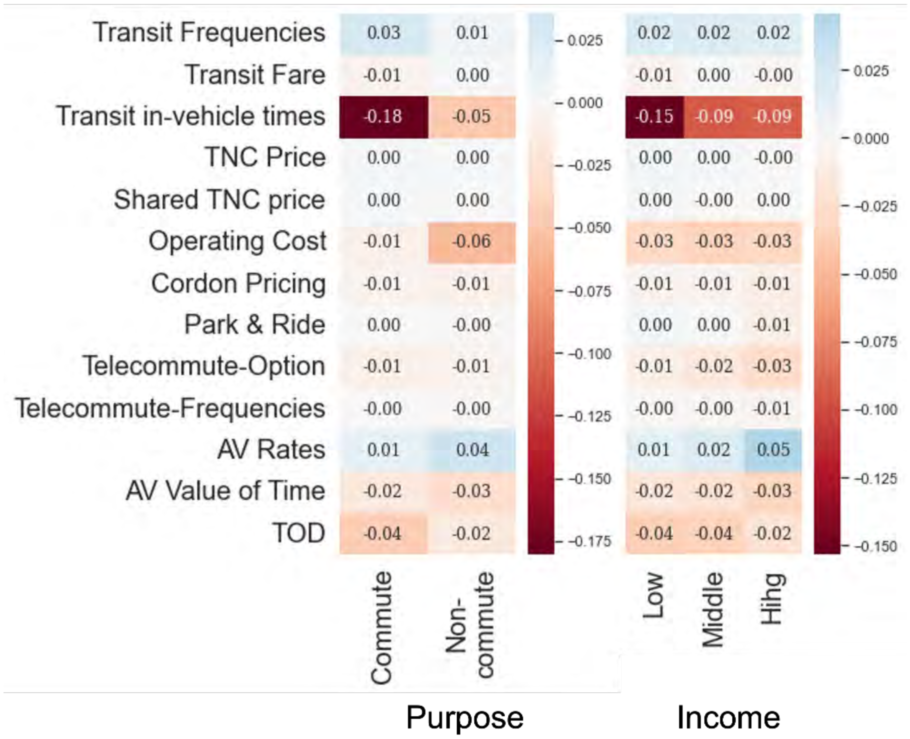
Increasing the penetration rate of AVs is associated with an increase in driving and a reduction in participation in other modes. The elasticity for ride-alone and share rides is 0.02 and 0.01, respectively. Additionally, a 1% increase in AV penetration is linked to a reduction in demand for biking, transit, share TNC rides, and walking by 0.16%, 0.15%, 0.13%, and 0.12%, respectively.

The TOD strategy indicates that increasing residential and employment densities by 1% is associated with a 0.01% increase in biking and a 0.34% increase in walking, underscoring the importance of this policy not only for zero-emission modes, but also for the investments required to support these modes and the development of the necessary infrastructure. Moreover, it decreases the demand for driving modes and TNC options. However, it also seems to reduce the mode choice for public transit services.

E.3.4 Travel Times

For most policy variables, the elasticity of travel time is less than 0.05, except for transit in-vehicle times (Figure 48). While an improvement in travel times would be expected as a result of this policy, our findings indicate the opposite. Transit in-vehicle times elasticities are -0.18 and -0.05 for commute and non-commute trips, respectively. When examining the elasticity by income, high- and middle-income groups exhibit a 40% lower elasticity than low-income (0.09 versus 0.15). This result suggests that reduced transit in-vehicle times incentivizes longer trips in transit, which is confirm by the positive elasticity of transit in-vehicle times in average trip length (Figure 50).

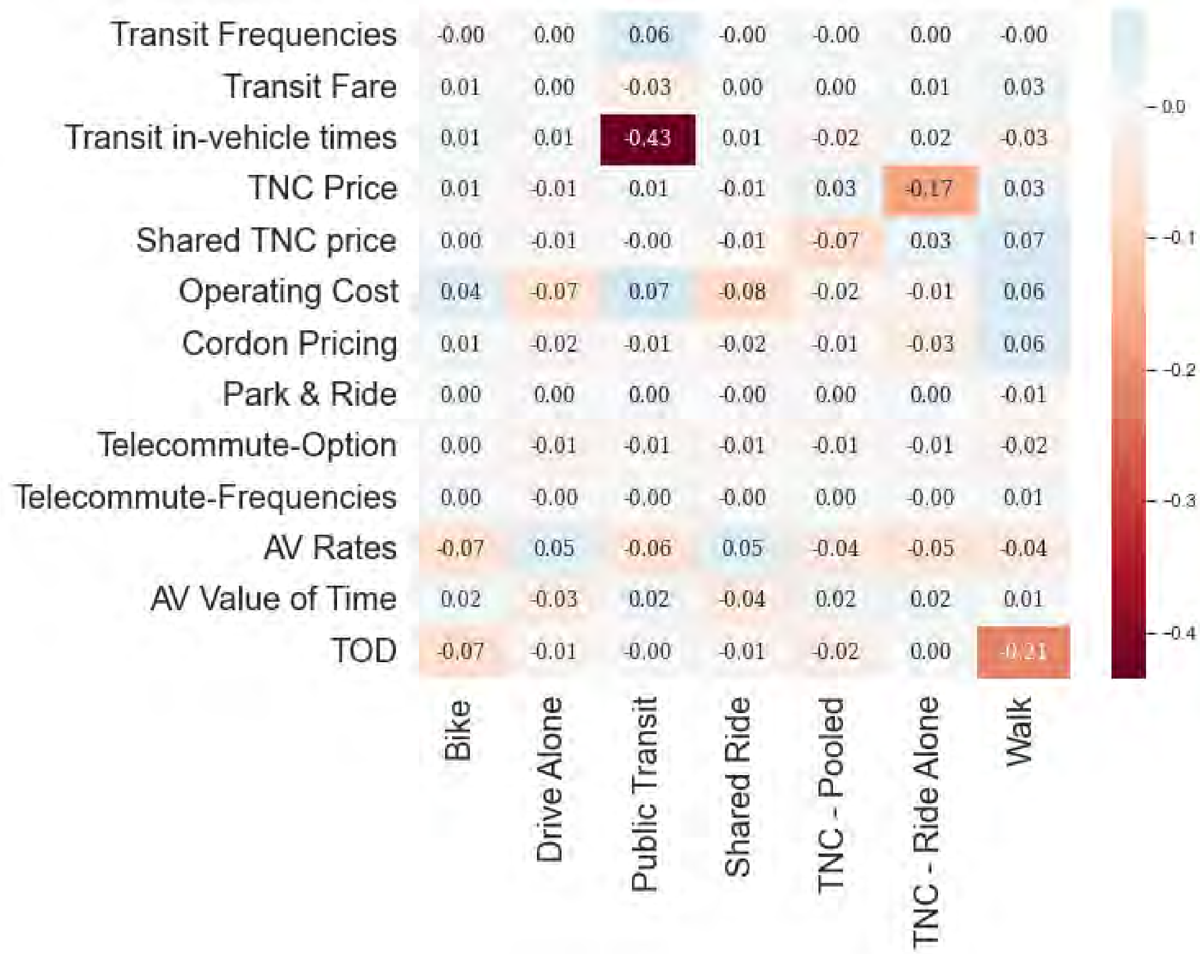
Figure 48. Average Travel Time Elasticities by Policy Variable and Trip Purpose and Income



The sensitivity analysis also shows that the elasticity of travel time to operating cost is significantly higher for non-commute trips compared to commute trips. However, for a TOD strategy, the elasticity is higher for commute trips. While we expected that commute and non-commute trips would benefit from a reduction of congestion, increased operating costs might also reduce the length and proportion of non-mandatory trips. Increasing residential and employment capacities around transit stations reduces commute travel times more than discretionary trips. This differential impact suggests an increased accessibility to job opportunities driven by increased density. The result is expected as the probability of reducing commute distances increases, given the increase in residential and employment densities around mass transit stations.

AV penetration rate and AV value of time also have an impact on the average travel time. For both policies, the results suggest a higher elasticity for non-commute trips and high-income populations. Similarly, it increases the average travel time and travel distance for driving modes, as suggested by Figure 49.

Figure 49. Average Travel Time by Mode



Our analysis also indicates that the elasticities for travel distance by mode are reflected in travel times by mode, but not in the same proportion. For instance, reducing transit in-vehicle times by 1% leads to a 0.66% increase in trip distance and a 0.43% increase in public transit travel times. Similarly, a 1% increase in operating costs results in a 0.12% increase in transit trip length and a 0.07% increase in travel time. Since speed is a function of distance over time, lower increases in travel time and higher increases in travel distance result in higher speeds. Therefore, it is possible to conclude that policies that discourage the use of private cars and incentivize the use of public transit can improve congestion by improving speeds. It is worth noting that for all policies examined, the average travel time and average travel length for both biking and walking options have equal elasticates. This finding is not surprising given that these two modes of transportation are typically not affected by congestion.

Figure 50. Average Trip Length by Mode

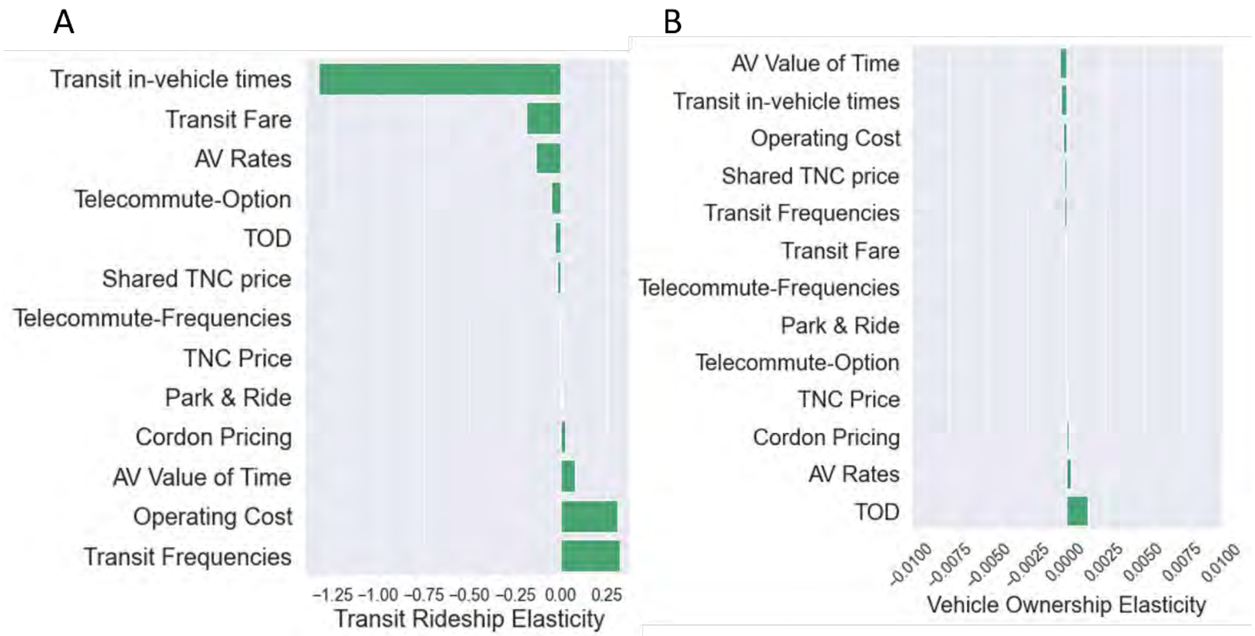
E.3.5 Other KPI

Our sensitivity analysis indicates that an increase in transit frequencies, a reduction in transit fares, and transit in-vehicle times are all positively associated with an increase in public transit ridership, as presented in Figure 51A. However, it shows that transit in-vehicle times have a more significant elasticity than the other two policy variables. A 1% decrease in transit in-vehicle times is predicted to result in a 1.32% increase in ridership, whereas a 1% increase in transit frequencies and a 1% decrease in transit fares are predicted to result in only a 0.32% and 0.19% increase in ridership, respectively.

The non-transit-related variable that is most elastic to ridership is operating cost, with an elasticity of 0.31. This finding is consistent with the public transit mode share elasticities presented in Figure 47, and suggest that increasing AOC is associated with mode shift to public transit modes.

Vehicle ownership has virtually no elasticity to any of the policies examined, with elasticities ranging from -0.0007 to 0.0012.

Figure 51. Policy Variable Impacts on A) Transit Ridership Elasticity and B) Average Vehicle Ownership



Appendix F Telecommute Models

<u>Telecommute as an Option:</u> Rate-based model to estimate what workers have telecommute as an option. This model was estimated using the Bay Area Subsample in the NHTS 2017.

Table 42. Telecommute as Option Rates

Job Sector	Income Category	Age Category	Base Year WFH Option Rate - NHTS
Sales or Service, Clerical or Administrative, Support, Manufacturing, Construction, Maintenance, or farming	0k - 50k	less than 25	0.0%
		25 - 45	9.5%
		45+	9.7%
	50k - 150k	less than 25	0.0%
		25 - 45	20.2%
		45+	13.5%
	150k+	less than 25	0.0%
		25 - 45	34.3%
		45+	30.0%
Professional, Managerial or Technical	0k - 50k	less than 25	23.3%
		25 - 45	30.2%
		45+	18.1%
	50k - 150k	less than 25	32.4%
		25 - 45	39.7%
		45+	26.3%
	150k+	less than 25	22.0%
		25 - 45	54.9%
		45+	40.8%

Estimated from NHTS 2017

<u>Frequency of telecommuting:</u> Models the weekly frequency of telecommuting given that telecommuting is an option. This model was estimated using the Bay Area Subsample in the NHTS 2017.

Table 43. Telecommute Frequency

Frequency Rates	Baseline NHTS - 2017
0 Days/week	0.476
1 Day/Week	0.396
2-3 Days/week	0.104
4+ Days/week	0.025

Estimation process and exploratory data analysis can be found here:
https://github.com/ual/activitysim/blob/main/carb/jupyter_notebooks/WFH_rates.ipynb

Appendix G Sensitivity Analysis Test

During the sensitivity analysis, the research team identified a discrepancy in the transit magnitude fare in the modeling framework PILATES[10]. As a result of addressing the discrepancy, the baseline results changed, making it inappropriate to compare the new baseline with previously conducted tests that reflect the discrepancy. Therefore, sensitivity runs associated with the discrepancy would need to be re-run.

However, due to the high computational costs associated with re-running the analysis, the team decided to keep the results unchanged for the policies that had been run until that point (highlighted in green and orange in Table 44). The rationale behind this decision was that we did not anticipate a significant impact of the fare magnitude error on the elasticity estimation results of other policies. Additionally, re-running the entire analysis would have resulted in at least a month's delay in the project timeline.

Nevertheless, to ensure the integrity and accuracy of our research findings, we validate the decision to retain the previous results. Therefore, the purpose of this appendix is to evaluate whether the fare magnitude error during the PILATES run has a substantial impact on the sensitivity analysis results and the conclusions drawn in Appendix E Sensitivity Analysis. We re-ran the sensitivity analysis for two policies and compared the results with the corrected PILATES version. Table 44 provides an overview of the policies examined in the present research project. The table highlights in green the two policies being tested in this appendix, and in orange, the policies excluded. Other rows represent the policies for which the corrected version of PILATES was used. Given the time and resources constraints, the policies highlighted in orange will not be re-run.

Table 44. List of Sensitivity Review Policies

Policy Variable	Forecasting Horizon	Baseline level	Corrected in Pilates	Test	Corrected in Pilates	Included in Policy Scenario
Transit Frequencies	One year (2021)	Current Transit Frequencies	NO	200% 100% -25% -50%	NO	YES
Transit Fare	One year (2021)	Current Transit Fare	YES	50% -25% -50% -100%	YES	YES
Transit Speeds	One year (2021)	Current Transit in-vehicle times	YES	-10% -25%	YES	NO
		Base: $2.20		50%		

[10] PILATES is the modeling framework that integrates the land use model *UrbanSim*, the activity-based model *ActivitySim*, and the network assignment model *BEAM*.

Policy Variable	Forecasting Horizon	Baseline level	Corrected in Pilates	Test	Corrected in Pilates	Included in Policy Scenario
TNC Price	One year (2021)	Minimum: $7.20 Per mile: $1.33 Per Minute: $0.24	NO	25% -25% -50%	NO	NO
Share TNC Price	One year (2021)	Base: $2.20 Minimum: $3.0 Per mile: $0.53 Per Minute: $0.10	NO	50% -10% -25% -50%	NO	YES
Operating Cost	One year (2021)	18.29 cents	NO	100% 50% -25% -50%	NO	YES
Cordon Pricing	One year (2021)	No Cordon Pricing	NO	$7.15 $6.50 $4.80 $3.20	NO	NO
Park & Ride	One year (2021)	Average of $3/day	NO	50% 25% -25% -50%	NO	NO
Telecommute Option	One year (2021)	2017 NHTS Model (see Appendix F)	NO	50% 25% -25% -50%	NO	NO
Telecommute Frequency	One year (2021)	+100% 2017 NHTS Model (see Appendix F)	NO	NHTS 2017 50% 200% 300%	NO	YES
AV Penetration Rate	One year (2021)	0% Penetration rate	YES	5% 10% 25% 50%	YES	YES
AV Value of	One year (2021)	Current Value of Time for Non-AV /	YES	-10% -20%	YES	YES

Policy Variable	Forecasting Horizon	Baseline level	Corrected in Pilates	Test	Corrected in Pilates	Included in Policy Scenario
Time		AV Penetration rate of 25%		-40% -60%		
TOD Residential and Employment	2035	Current Residential and Employment Capacities	YES	10% 25% 50%	YES	YES

Highlighted in green are the selected policies to verify that the discrepancy does not significantly affect the elasticities estimated with the transit fare magnitude discrepancy. The column "Corrected PILATES run" references the policies run with the corrected version. Highlighted in orange are the policies that will not be re-run.

G.1 Methodology

To assess the changes in elasticities resulting from variations in the transit fare magnitude, we re-ran the sensitivity analysis for two policies: "Transit Frequencies" and "Operating Cost." The former policy pertained to public transit and had previously shown low elasticities, while the latter is indirectly related to transit and demonstrated higher elasticities. Both policies are also included in the final policy scenario run.

In this study, we estimated the arc elasticities for all Key Performance Indicators, some of which were categorized by income, race, and transportation mode, resulting in 51 elasticities per policy. A pair-wise difference of the elasticities for the corrected and uncorrected simulation results are compared and analyzed. To evaluate the statistical significance of the of the pair-wise difference, we conducted a one-sample t-test. The null hypothesis posits that the mean of the pair-wise difference distribution is zero, while the alternative hypothesis states that the mean of pair-wise difference distribution deviates significantly from zero. We reject the null hypothesis if the p-value associated with the t-ratio is less than 0.05.

We estimated the arc elasticity. In the arc elasticity estimation, the percentage change of the output variable and the policy variable is estimated with respect to their corresponding midpoint, as follows:

$$\%\ Change\ in\ KPI_i = \frac{KPI_{i,base} - KPI_{i,exp}}{KPI_{i,base} + KPI_{i,exp}/2}$$

$$\%\ Change\ in\ Policy\ Variable_j = \frac{PV_{base} - PV_{exp}}{PV_{base} + PV_{exp}/2}$$

$$\varepsilon_{i,j} = \frac{\%\ Change\ in\ KPI_i}{\%\ Change\ in\ Policy\ Variable_j}$$

Where $\varepsilon_{i,j}$ is the arc elasticity of KPI_i with respect to the policy variable j. To estimate a final elasticity, we average the estimated elasticity for each test. The range of the elasticity estimate is from negative infinitive to positive infinity, although most estimated elasticities are within 10 and -10. A positive elasticity means that an increase in the input variable results in an increase in the output variables, while a negative value indicates an inverse relationship between the output variable and the input variable. Specifically, as the input variable increases, the output variable decreases.

G.2 Results

The findings of the Transit Frequency policy are presented in Figure 52. The policy's elasticity remains relatively inelastic, ranging from -0.1 to 0.3. It is worth noting that the sign of the elasticities might change depending on the metric being evaluated, even within the same policy. For instance, increasing transit frequencies results in a negative elasticity for VMT, but a positive elasticity for consumer surplus. Figure 52A depicts the distributions, which exhibit a significant resemblance, albeit the corrected elasticity shows a sharper peak in proximity to zero. Figure 52B shows that the pair-wise difference distribution is concentrated around zero and is bounded between ±0.06, indicating that the elasticities of the two tests are reasonably similar. To test the null hypothesis that the mean of the pair-wise difference is zero, we conducted a t-test, yielding a t-statistic of 1.45 and a p-value of 0.15, indicating insufficient evidence to reject the null hypothesis.

Figure 52. Sensitivity Test for Transit Frequency Policy with A) Distribution of Elasticities for Corrected and Uncorrected Simulation Results and B) Pair-Wise Elasticity Difference Distribution

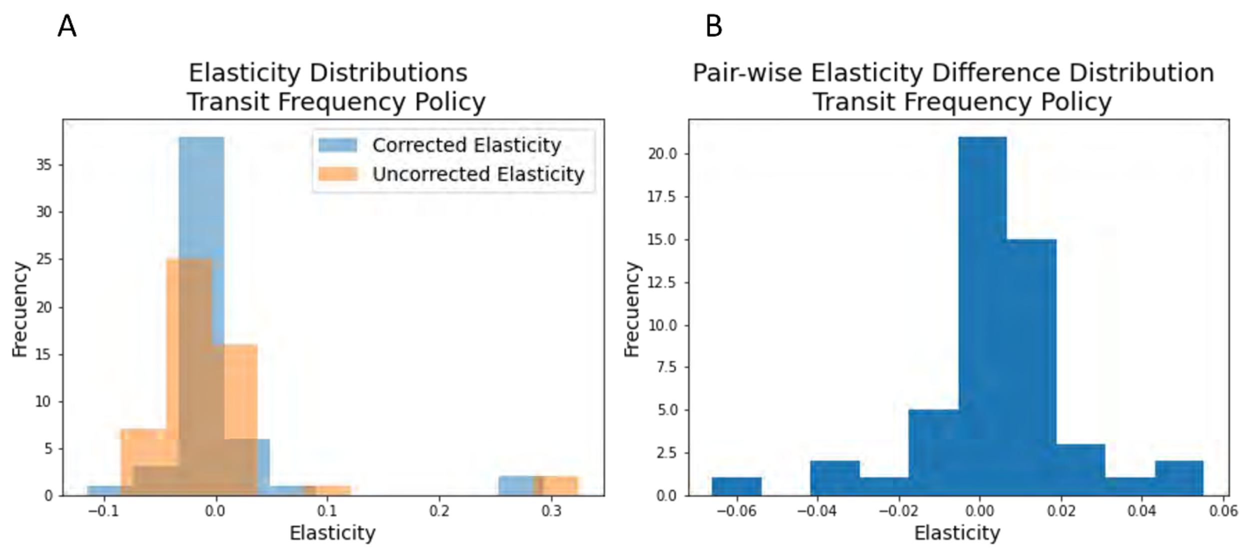
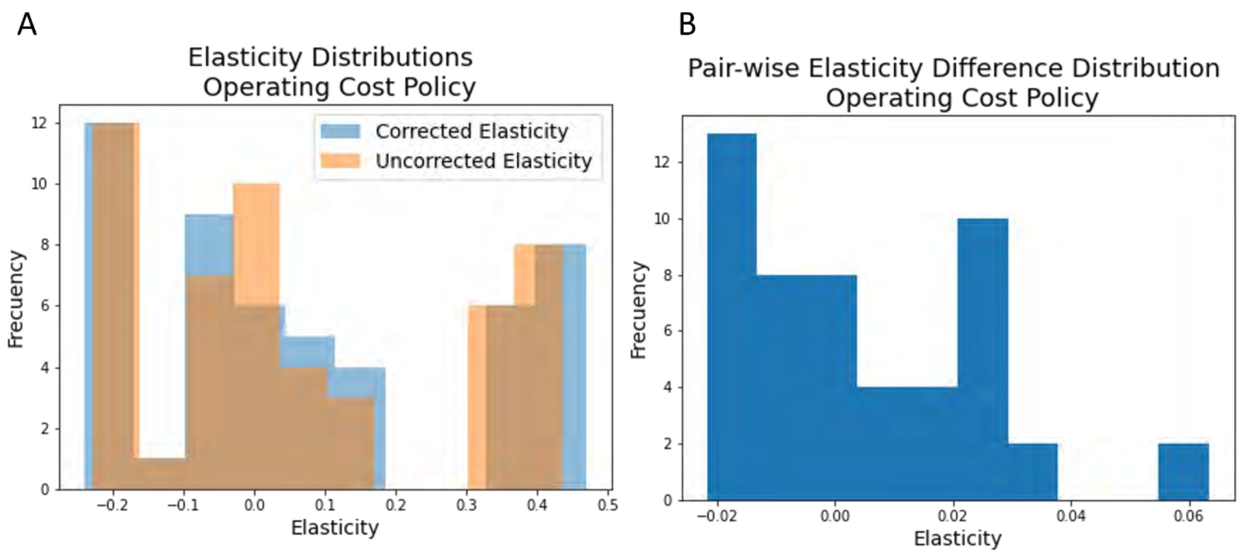


Figure 53 presents the elasticity results of the Operating Cost policy, derived from two sensitivity analyses. The distributions of elasticities in the two tests, as depicted in Figure 53A, are comparatively similar, with elasticities ranging from -0.2 to 0.45. The variation in the elasticity sign is related to the estimated elasticity. For instance, increasing operating cost results in a negative elasticity for VMT, but a positive elasticity for transit ridership. Notably, the pair-wise elasticity difference distribution in Figure 53B appears to be center around zero and oscillating between -0.02 and 0.06, even though it does not appear to follow a normal distribution. The corresponding t-statistic for this distribution is 1.72, with a corresponding p-value of 0.09, also suggesting that there is not enough evidence to reject the null hypothesis.

Figure 53. Sensitivity Test for Operating Policy Cost by A) Distribution of Elasticities and B) Pair-Wise Elasticity Difference Distribution



G.3 Conclusion

Based on the sensitivity analysis conducted in this appendix, it is evident that the variation in transit fare magnitude does have some impact on the elasticity estimates for other policies. However, the degree of change observed is not statistically significant, indicating that it is unlikely to alter the conclusions stated of the sensitivity analysis in Appendix E Sensitivity Analysis. The distribution of elasticity differences suggests that the discrepancy in transit fare magnitude has only a minimal impact on the elasticity estimates of other tested policies. Therefore, it can be concluded that the Transit Frequency policy and Operating Cost policy remain and have no substantial differences in their elasticities despite the variation in transit fare magnitude.

It is important to note that for the results in the policy scenario in Policy Scenario Analysis , the modeling framework runs the corrected version of PILATES.

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