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Report for the California Strategic Growth Council

Photo: Greg Linhares, City of Oakland

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Bridging the Income and Digital Divide with Shared Automated Electric Vehicles

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EXECUTIVE SUMMARY

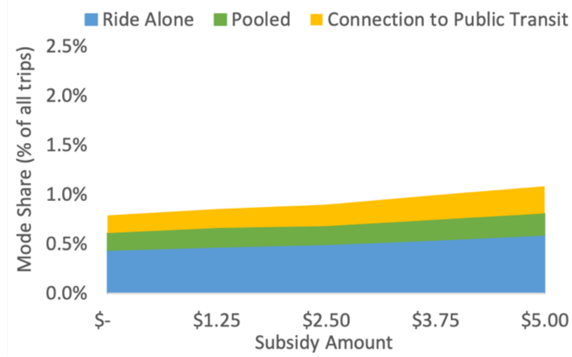
Shared mobility services, including carsharing, bikesharing, scooter sharing, and transportation network services (TNCs) (also called ridesouring and ridehailing), offer flexible, on-demand alternatives to personal auto use that can also supplement public transit and active modes of transportation. While early adoption of shared mobility services has primarily been led by younger individuals with higher levels of income and education (Shaheen et al., 2017), recent evidence suggests that lower-income people of color (POC) without access to personal vehicles are among the heaviest users of TNC services (Lazarus, et al., 2020, Brown, 2018). Lower-income POC are using TNCs for essential trip purposes, including commuting and accessing healthcare, groceries, and public transportation (Lazarus, et al., 2020). It is widely anticipated that vehicle automation and electrification may further enhance the affordability of shared on-demand services as well as reduce the negative environmental and safety impacts of road transportation in general(Greenblatt and Shaheen, 2015).

Pooling, in which multiple passengers traveling along similar paths are matched and transported in the same vehicle, has been projected to reduce the congestion and emissions impacts of shared automated vehicle (SAV) fleets (Viegas et al., 2016; WEF and BCG, 2018; Greenblatt and Shaheen, 2015; Greenblatt and Saxena, 2015). Yet prior to the COVID-19 pandemic, which spurred the suspension of many existing pooled on-demand ride services, the rate of pooled ride requests among users of the TNC services Lyft and Uber was relatively low, resulting in negligible impacts to overall vehicle occupancies (CARB, 2019; Schaller, 2018; Shaheen and Cohen, 2019). In 2018, only about 30 percent of TNC users surveyed across four metropolitan regions in California considered requesting a pooled ride more than half the time they used TNCs (Lazarus et al., 2021). Ultimately, the ability to fully leverage the potential societal benefits offered by the three revolutions in urban transportation (electrification, automation, and sharing) relies heavily on the ubiquity of individuals willing to pool rides as well as an equitable distribution of the benefits that innovative mobility offers.

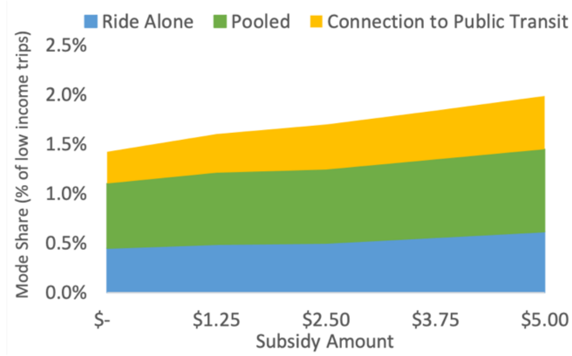
This research investigates strategies to improve the mobility of low-income travelers by incentivizing the use of electric SAVs (SAEVs) and public transit. We employ two agent-based simulation engines, an activity-based travel demand model of the San Francisco Bay Area, and vehicle movement data from the San Francisco Bay Area and the Los Angeles Basin to model emergent travel behavior of commute trips in response to subsidies for TNCs and public transit. Sensitivity analysis was conducted to assess the impacts of different subsidy scenarios on mode choices, TNC pooling and match rates, vehicle occupancies, vehicle miles traveled (VMT), and TNC revenues. The scenarios varied in the determination of which travel modes and income levels were eligible to receive a subsidy of \$1.25, \$2.50, or \$5.00 per ride. Four different mode-specific subsidies were investigated, including subsidies for 1) all TNC rides, 2) pooled TNC rides only, 3) all public transit rides, and 4) TNC rides to/from public transit only. Each of the four mode-specific subsidies were applied in scenarios which subsidized travelers of all income levels, as well as scenarios that only subsidized low-income travelers (earning less than \$50,000 annual household income). Simulations estimating wait times for TNC trips in both the San Francisco Bay Area and Los Angeles regions also revealed that wait times are distributed approximately equally across low- and high-income trip requests.

Key Findings

We find that subsidizing TNCs and public transit by $1.25 to $5.00 per ride can incentivize greater usage of these modes with broad implications that vary across the subsidies explored. Figure 1 and Figure *2* display the sensitivity of a) overall mode share and b) low-income mode share to subsidies for all TNC rides and pooled TNC rides, respectively. Widespread savings in the consumer costs of all TNCs, as are expected from the rollout of SAEV technology, were found to increase the overall TNC mode share in the San Francisco Bay Area by an estimated 2,100 daily trips in response to the first $1.25 of TNC fare reduction and an estimated 10,000 daily trips at the $5 subsidy level. With the majority of new trips being shifted away from public transit and active modes, there were little additional environmental benefits from such scenarios beyond those achieved by the SAV or SAEV technology itself. Travelers shifting from public transit and active modes to TNCs benefited from faster travel times, although they incurred increased travel costs on the order of $20 per trip, on average. Using a fixed fleet size, the BEAM San Francisco Bay Area Model estimates that such growth in TNC adoption produces a net increase in revenues after subtracting subsidies.



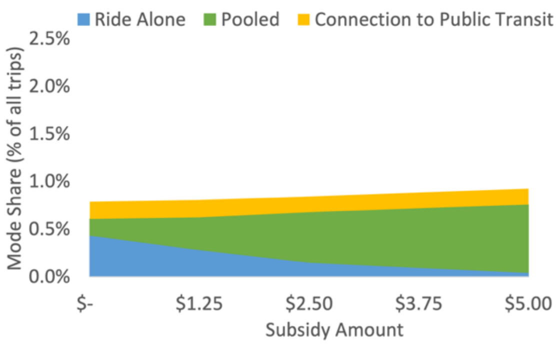
a) Overall TNC mode share



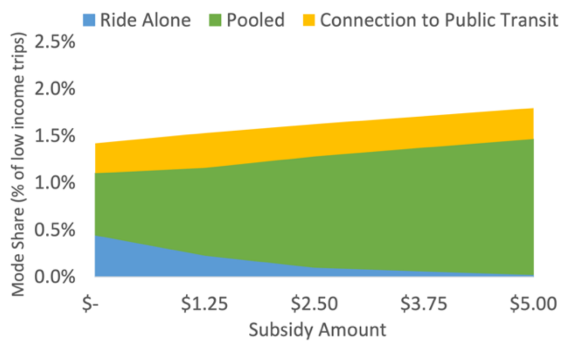
b) Low-income TNC mode share

Figure 1. Sensitivity of TNC mode share to subsidies for all TNC rides, all income

The results suggest that further reduction of the price of pooled TNCs is necessary to achieve higher utilization of SAEVs. Subsidies targeted only for pooled TNC rides resulted in substantial mode shifts from ride-alone to pooled TNCs with travel time increases of just three minutes, on average. At the lowest subsidy level ($1.25/ride), the overall mode share of pooled TNCs doubled, while at the highest level ($5/ride), the portion of ride alone TNCs fell to almost zero across income levels. The pooling match rate, or the portion of pooled TNC ride requests that are successfully matched, increased with respect to the pooling request rate (the portion of TNC ride requests that are for pooled service). Subsidies for pooled TNCs for all riders more than tripled the overall pooled TNC request rate, resulting in a 260% increase in the match rate from 12% to 32% at the $5 level and 19% increase in the ratio of TNC person miles traveled (PMT) to VMT. While subsidies for pooled TNCs targeting low-income riders achieved similar mode shifts among the subsidized population, they resulted in smaller increases in the pooled match rate and PMT to VMT ratios, reflecting the network effects of widespread adoption on the efficiency of pooled on-demand services. Lower pooled request rates across the region in the scenarios subsidizing only low-income travelers reduced the likelihood that requested pooled rides were actually matched, thus limiting the potential benefits of offering such a subsidy.



a) Overall TNC mode share



b) Low-income TNC mode share

Figure 2. Sensitivity of TNC mode share to subsidies for pooled TNC rides, all income levels

Subsidies for public transit were the most effective in reducing regional VMT by eliciting substantial mode shifts away from personal vehicle use. A subsidy of just $1.25 resulted in about a 12% increase in overall public transit use (+1.8% mode share) with primary sources of mode shifts coming from driving alone, followed by biking, walking, and riding alone in a TNC. At the $5 subsidy level, a 26% increase in overall public transit mode share resulted in a 2.8% reduction in total VMT across the San Francisco Bay Area. On average, travelers shifting to public transit in the $5 subsidy scenario increased travel times by about 18 minutes, although those that shifted from TNCs incurred travel time increases of about one hour, on average.

Recommendations for Future Work

We conclude with a discussion of recommendations and considerations for further research for the development of equitable strategies to effectively manage demand for SAEV services. This research suggests that subsidies for pooled on-demand mobility services can promote mobility while improving the efficiency of these services. Although widespread adoption of pooled services is integral in generating the network effects needed for sustainable service, targeted strategies are needed to support populations that have been historically disadvantaged by the exclusivity of a car-centric transportation system.

Further investigation of the effects of pricing and subsidy structures on policy outcomes is recommended. This research suggests that while revenue increases can offset subsidies in some situations, a feebate structure for transportation pricing—in which fees are applied to ride-alone service to cover the costs of pooling subsidies for particular populations—may be particularly effective for incentivizing all travelers to pool while supporting disadvantaged communities in overcoming the financial barriers of on-demand mobility. While a single income level was employed in this study to determine eligibility for the simulated subsidies region-wide, further research is also needed to investigate the potential benefits of a more targeted eligibility structure based on additional criteria (e.g., home or work location, housing burden).

This study suggests that SAEV services are capable of achieving equal distributions of wait times across low- and high-income trip requests in both the San Francisco Bay Area and Los Angeles regions. Further investigation is recommended to inform the development of regulations that ensure an equitable distribution of on-demand mobility service levels using indicators such as wait times and travel costs. The California Public Utilities Commission recently implemented such a regulation for the level of service provided by TNC wheelchair accessible vehicles by establishing response time standards specific to each geographic area of the state (CA Pub Util Code § 5440.5). Such policies may be integral in mitigating for the potentially inequitable consequences of pricing strategies that induce travelers with greater price sensitivity to choose modes with worse levels of service.

Further research is needed to extend the findings of this study to a broader array of trip contexts including other essential and leisure trip purposes, geographic regions, and time periods (e.g., weekend travel, emergency/evacuation scenarios). Importantly, the models and scenarios investigated in this study should also be revisited once the lasting behavioral effects of the COVID-19 pandemic become increasingly evident.

INTRODUCTION

Automobile ownership has historically been a major determinant in access to job opportunities and other aspects of a high quality of life across most urban regions of the United States, particularly for those living outside of the urban core or in areas otherwise poorly served by public transit (Blumenberg and Pierce, 2016; Brown, 2017). Shared mobility services, including carsharing, bikesharing, scooter sharing, and transportation network services (TNCs) (also called ridesouring and ridehailing), offer flexible, on-demand alternatives to personal auto use that can also supplement public transit and active modes of transportation. Vehicle automation and electrification are expected to further improve the affordability of shared on-demand services and reduce the negative environmental and safety impacts of road transportation in general(Greenblatt and Shaheen, 2015). However, the potential societal benefits of these three revolutions in urban transportation (electrification, automation, and sharing) rely heavily on the ubiquity of individuals willing to pool rides in addition to the assurance that these benefits are equitably distributed across the population.

Pooling, in which multiple passengers traveling along similar paths are matched and transported in the same vehicle, has been projected to reduce the congestion and emissions impacts of shared automated vehicle (SAV) fleets (Viegas et al., 2016; WEF and BCG, 2018; Greenblatt and Shaheen, 2015; Greenblatt and Saxena, 2015). Pooling can be carried out in many forms, including: 1) app-based pooling services that typically match commuters and facilitate nominal reimbursements of drivers by passengers or employers (e.g., Waze Carpool, Scoop), 2) pooled TNC services that match on-demand ride requests that are typically offered at a discount to ride alone service (e.g., Lyft Shared rides, Uber Pool), and 3) microtransit services which pool rides in larger vehicles such as vans or shuttles using either fixed or dynamic routes and either fixed or dynamic schedules (e.g., Via, Bridj, Chariot). Public health concerns amid the COVID-19 pandemic prompted many companies to constrain or suspend pooled ride services starting in February 2020.

Yet even prior to the COVID-19 pandemic, the rates of pooled ride requests among users of the TNC services Lyft and Uber were relatively low, resulting in negligible impacts to overall vehicle occupancies (CARB, 2019; Schaller, 2018; Shaheen and Cohen, 2019). In 2018 in New York City, for example, only about 22 percent of requested Lyft Line (now Lyft Shared) rides and 23 percent of Uber Pool rides resulted in matched trips (Schaller, 2018). Another study across the state of California in 2018 found that the average vehicle occupancy of ride-alone and pooled TNC trips were about the same, at about 1.55 passengers per vehicle (CARB, 2019). In a survey distributed across four California metropolitan regions in 2018, Lazarus, et al. (2020) find that only about 30 percent of TNC users consider requesting a pooled ride more than half the time they use TNCs, although heavy TNC users - those that use TNCs more than three days per week - are significantly more likely to consider pooling than less frequent users. The study also finds that commute trips are the most attractive TNC trip purpose for pooling and quantifies significant differences in the time and price tradeoffs of low- and high-income TNC users, finding that high-income users (earning $100,000 or more) are among the least likely to pool rides.

While early adoption of shared mobility services has primarily been led by younger individuals with higher levels of income and education (Shaheen et al., 2017), recent evidence suggests that lower-income people of color (POC) without access to personal vehicles are among the heaviest users of TNC services (Lazarus, et al., 2020, Brown, 2018). In particular, lower-income POC are using TNCs for essential trip purposes, including commuting and accessing healthcare, groceries, and public transportation (Lazarus, et al., 2020). Lower income TNC users have a lower value of in-vehicle time than other users, resulting in a greater willingness to accept the travel time increases inherent in pooled rides in return for cost savings. As a result, subsidization and promotional offers for pooled rides and rides connecting to public transit are attractive strategies to promote pooling among heavy users while improving the affordability of on-demand services for disadvantaged populations.

This research investigates strategies to improve the mobility of low-income travelers by incentivizing the use of SAEVs and public transit. Sensitivity analyses of several subsidy scenarios were conducted using agent-based simulation models of the San Francisco Bay Area and the Los Angeles regions, revealing key opportunities to increase TNC vehicle occupancies while supporting low-income communities in accessing affordable on-demand shared mobility and public transit services. Regional-level outcomes of the subsidies are examined, including the sources and characteristics of modal shifts to subsidized modes, the impacts of increased pooling request rates on pooled match rates, TNC vehicle occupancies and the portion of VMT attributed to travel without passengers (deadheading) as well as the tradeoffs in the amounts of subsidy incentives distributed versus additional TNC revenue generated. In the following section, we provide an overview of the methodological approach of this study. Results of model calibration and sensitivity analyses are presented next, followed by a discussion of key findings, study limitations, and conclusions.

METHODOLOGICAL OVERVIEW

This study employs two agent-based simulation models for the analysis of the sensitivity of regional travel behavior to policy initiatives that could expand the benefits of the "Three Revolutions" in mobility (shared, electric, and connected/automated vehicles) for low-income groups. The Behavior Energy Automation Mobility framework (BEAM) model, described more fully in the Appendix, was selected for assessing active transportation and social equity impacts of pricing policies. An existing activity-based travel model for the nine county San Francisco (SF) Bay Area implemented in BEAM was used, which includes multi-modal travel behavior and automated electric fleet operations for both ride-alone and pooled on-demand ride services (e.g., Uber and Uber Pool, Lyft and Lyft Shared Rides). The model simulates the travel decisions of a synthetic population of individuals, each with designated socio-demographic attributes, vehicle ownership, and activity plans determining home and work locations and desired commute travel times. BEAM emphasizes within-day planning with the inclusion of a discrete choice model that dynamically determines the mode choices of simulated travelers according to the state of the transportation system during the simulation.

We introduced additional heterogeneity into this model (e.g., sensitivity of demand with respect to income, age, vehicle ownership) with the implementation of a multinomial logit model estimated from a general population stated preference (SP) survey of four metropolitan regions in California (Los Angeles, Sacramento, San Diego, and the SF Bay Area) that was conducted in Fall 2018 (Lazarus et al., 2020). The heterogeneous model was calibrated in order to align the commute mode shares of each of three income groups in the BEAM SF Bay Area model to those reported by the 2017 National Household Travel Survey for the same region (NHTS, 2017) (see Figures A3 and A4).

SAEV fleet operations in the SF and Los Angeles (LA) metropolitan areas were more extensively analyzed using a separate agent-based fleet simulation model, Routing and Infrastructure for Shared Electric vehicles (RISE) (Bauer et al, 2018) that models the repositioning, matching, and charging of automated electric fleets of on-demand vehicles (see Appendix for further information). TNC trip data for the SF Bay Area was taken from BEAM outputs, including the origin, destination, time of day, travel distance and duration of all ride-alone and pooled TNC ride requests. In order to extrapolate emergent TNC travel behavior observed using the SF Bay Area model to the LA region, a model was trained to reproduce SF Bay Area data with a standard machine learning algorithm, then extrapolated to LA. We recorded the wait time and deadheading distance for each trip,and compared the operational results by socioeconomic status of the passengers.

Sensitivity Analysis

The BEAM SF Bay Area model was applied in sensitivity analysis of four different subsidy schemes for shared mobility, including subsidies for: 1) all TNC trips, 2) pooled TNC trips, 3) all public transit trips, and 4) TNC trips connecting to public transit. Each subsidy was applied for: 1) all travelers, and 2) low-income travelers (earning less than $50,000) only. In total, 24 subsidy scenarios were run in the SF Bay Area model, including all combinations of the 4 eligible modes, 2 eligible target groups, and 3 subsidy levels shown in Table 1. The subsidies factored into the simulation at the mode choice stage, during which the estimated costs of eligible trips were discounted by the subsidy amount up to the cost of the trip[1].

Eligible Modes	Target Groups	Subsidy Levels
All TNC rides Pooled TNC rides All public transit rides TNC rides to/from public transit	All incomes Low-income (less than $50,000 annual household income)	$1.25/ride $2.50/ride $5.00/ride

Table 1. Sensitivity analyses performed

Travelers' eligibility for low-income subsidies was determined based on household income, with all travelers in households earning less than $50,000 annually being eligible for the subsidies. This income level is commensurate with the eligibility requirements of low-income membership and discount programs for several shared mobility services in California (e.g., Bike Share for All, LimeAccess) in which qualifying users must show enrollment in a local, state, or federal

[1] If an eligible trip cost less than the subsidy amount, the trip would be free and no additional subsidy would be provided to the traveler.

low-income assistance program such as CalFresh, the Supplemental Nutrition Assistance Program, or SNAP, or discounted utility programs. As shown in

Figure 3, the California state income limits vary considerably by county, with 2-person households earning \$50,000 per year being considered very low-income in five out of the nine SF Bay Area counties. In Marin, San Francisco, San Mateo, and Santa Clara counties, 2-person households earning \$50,000 per year are considered extremely low-income. While a single income level was employed to determine eligibility for the simulated subsidies region-wide, further research is needed to investigate the potential benefits of a more targeted eligibility structure based on additional criteria (e.g., home or work location, housing burden).

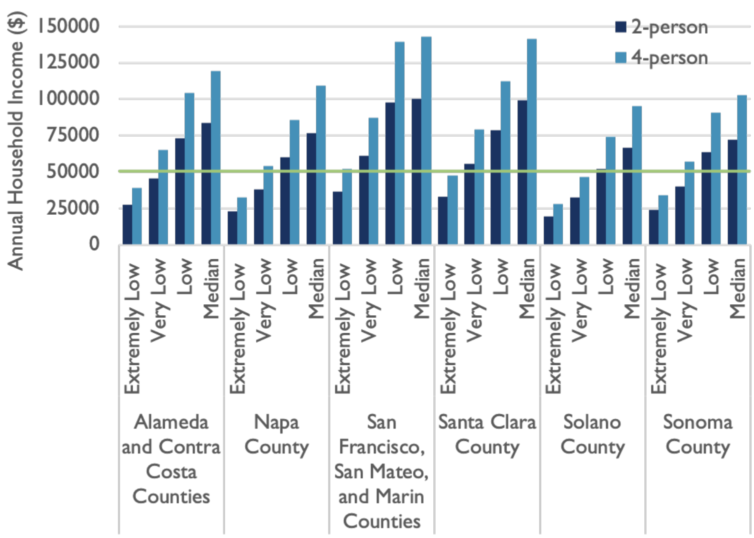


Figure 3. 2020 California State Income Limits (HCD, 2020)

Simulation outputs from BEAM including all mode choices and vehicle movements were processed and analyzed to produce estimates of regional commute mode shares, trip characteristics (e.g., cost, duration, length, vehicle occupancy), and outcomes from TNC operations (e.g., revenue, deadheading miles, occupied miles). In addition, the distributions of TNC trips produced by sensitivity analysis in the BEAM SF Bay Area model were input to RISE to test for differences in the TNC service levels and enable the extrapolation of the behavioral responses to the subsidies in a model of the LA Basin. Sensitivity analyses of TNC subsidies and level of service restrictions that specified a minimum wait time for rides requested by low-income travelers were run for LA using RISE.

RESULTS

In this section, the results of the sensitivity analyses in the SF Bay Area and LA regions are presented. We begin with a discussion of the baseline simulation results produced by the calibrated BEAM SF Bay Area model, in which key metrics used throughout the study are introduced given the context of available reference data for the region. The results of sensitivity analysis of ride-alone and pooled TNC subsidies provided to all income levels are presented next, followed by a comparison across both types of TNC subsidies when provided to all versus just low-income riders. The following subsection presents the results of public transit subsidies, including those provided for all public transit rides and those targeting TNC connections to public transit. Finally, we present the results of sensitivity analyses of pooled TNC subsidies and wait time restrictions run using RISE.

Baseline SF Bay Area Simulation Results

In the baseline scenario, TNC trips made up about 0.8% of all trips in the BEAM SF Bay Area model. Pooled ride requests accounted for about 22% of those trips, although only about 12% of requested pooled rides were successfully matched. Given that the BEAM model simulated independent travel decisions not including coordination among travelers of the same household or workplace, all TNC ride requests were constrained to one passenger per request. This resulted in an average occupancy across all TNC rides of about 1.01 passengers per TNC ride the average occupancy of pooled TNC rides was about 1.07 passengers per ride. The geographic distribution of TNC trip requests in the baseline scenario is displayed in Figure 4 below. City origin-destination pairs for which requested pooled TNC rides were successfully matched across two or three trip requests are shown in the figure with orange and magenta lines, respectively. In addition, larger orange and magenta circles are shown in cities for which pooled TNC ride requests for trips starting and ending in the city were successfully matched.

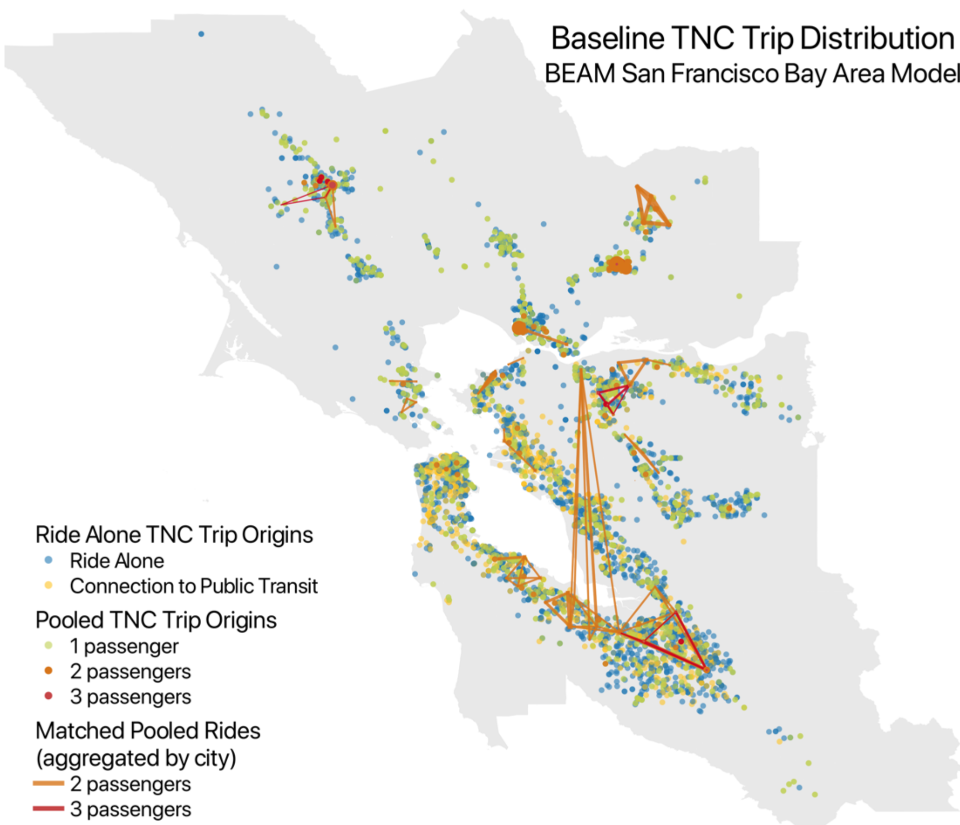


Figure 4. Distribution of TNC trips in the SF Bay Area Baseline Scenario

The width of the lines representing matched pooled TNC trips are weighted by the number of matched rides with the same origin-destination city pair and number of passengers. Larger circles denote matched pooled trips within the same city.

Estimates of TNC pool request and match rates, average overall TNC occupancy, and average pooled TNC occupancy from six studies in the United States, summarized in Table 2, suggest that the calibrated BEAM SF Bay Area model produced a reasonable baseline. In comparing the BEAM model outputs to these metrics, it is important to keep in mind that the BEAM model included only solo commuter trips. Since the dynamics of companion travel are not represented, the average overall and pooled TNC occupancies estimated by the BEAM model should be interpreted as the average number of ride requests per vehicle. The pooled request rate of 22% is greater than all but one estimate from the literature, which was conducted using the activity data of all Lyft trips in LA from September to November 2016 (Brown, 2019). It is possible that the pooling rate of 29% found by the Brown (2019) study is biased due to the fact that only Lyft activity data was included in the study, whereas other TNC services (i.e., Uber) were included in the other studies which estimated lower pooling rates.

Study (year published)	Study Region, Year	Data Collection Method	TNC Pool Request Rate	TNC Pool Match Rate	Average Overall TNC Occupancy	Average Pooled TNC Occupancy	Dead-heading Percentage
Rayle et al. (2016)	San Francisco, CA, 2015	Intercept survey	n/a	n/a	2.1	n/a	n/a
Henao and Marshall (2018)	Denver, CO, 2016	Intercept survey	13%	15%	1.36	n/a	40.8%
Brown (2019)	Los Angeles, CA, 2016	Activity data	29%	n/a	n/a	n/a	n/a
Gehrke et al. (2018)	Boston, MA, 2017	Driver trip diaries	20%	n/a	1.52	1.4	n/a
Schaller (2018)	New York City, 2018	Activity data	n/a	22-23%	n/a	n/a	41%
Circella et al. (2019)	CA, 2018	Survey (last trip)	15%	n/a	1.9	n/a	n/a
CARB (2019)	CA, 2019	Driver trip diaries	12% (CA) 9% (Bay Area)	n/a	1.54 (CA) 1.56 (Bay Area)	1.57 (CA) 1.46 (Bay Area)	38.5%
BEAM SF Bay Area Model			22%	12%	1.01*	1.07*	67.5%

Table 2. TNC Pooling Metrics

**The BEAM model does not simulate travel among companions (i.e., traveling with a friend/relative/other for the same trip).*

The baseline match rate for the BEAM SF Bay Area model is notably lower than the most recent estimate of the match rate in New York City using activity data (Schaller, 2018), although it is only slightly lower than that of Denver. The discrepancy may be due to the regional scope of the SF Bay Area Model which spans nine counties with varying employment density (see Appendix, Figure A6). Within-county trips generally have the highest pooled match rates while the counties with greatest public transit access (e.g., San Francisco, Alameda, Contra Costa, San Mateo, Santa Clara) have the lowest TNC pooled request rates among within-county trips albeit with match rates ranging from about 20% to 75% (see Appendix, Figures A6).

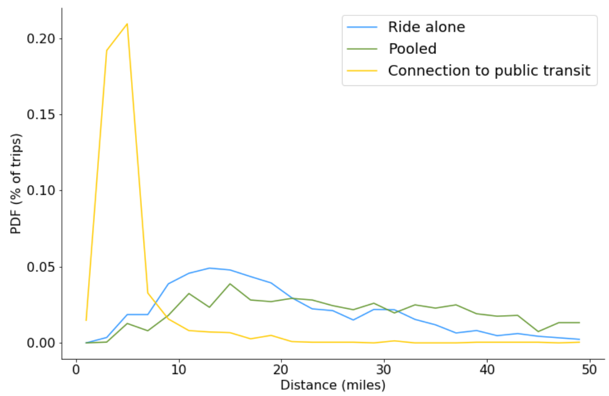
The CARB (2019) study employed self-recorded trip diaries from 31 drivers across the state of California, nine of which were serving the SF Bay Area. Of the 737 trips recorded by the SF Bay Area drivers (about one quarter of the trips in the CARB study), the pooling request rate was about 9%, with an average occupancy of 1.56 passengers per TNC ride and an average of 1.46 passengers per pooled ride. Notably, the Gehrke et al. (2018) study also found that the average occupancy of pooled rides was less than that of all TNC rides. This may reflect a key difference in the trip characteristics of ride alone and pooled TNC trips. More research is needed in this area; however, the authors stipulate that TNC users may be less likely to request a pooled ride when making a trip with one or more companions (e.g., traveling with a friend, relative, coworker, etc.). Travel companions already benefit from a reduced per-person fare since they can share the cost of a ride and thus may prefer the privacy and convenience of a private ride. The financial incentive of a pooled ride, which charges a discounted rate in return for the possibility of a longer travel time is likely to be more salient for a solo rider than for travel companions.

The portion of TNC VMT attributed to deadheading is considerably higher in the baseline scenario compared to the estimates from Denver, New York City, and California (Henao and Marshall, 2018; Schaller, 2018; CARB, 2019). This may be due to a number of parameters in the TNC fleet configuration, including the TNC fleet size and parameters of the algorithms governing the repositioning of TNC vehicles throughout the simulation. The calibration of such parameters were not undertaken for the purposes of this study, though they are of great interest for future work. It is also important to note that the TNC fleet size was kept fixed across all sensitivity analysis scenarios in the BEAM SF Bay Area Model.

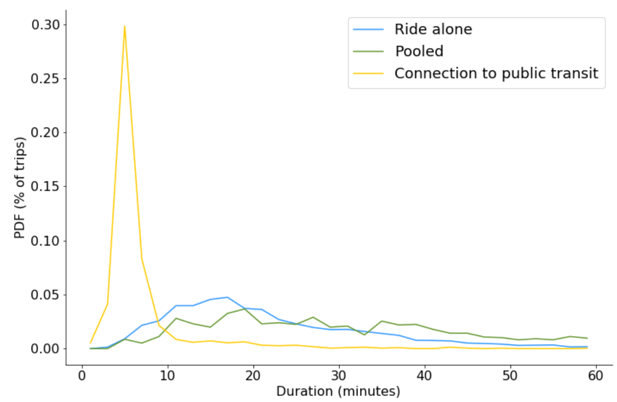
Summary statistics of the baseline TNC trip characteristics are presented in Table 3, including mean and median trip distance, duration, and cost. The overall average TNC trip distance was about 20 miles per trip in the baseline BEAM SF Bay Area model. On average, pooled TNC trips in the baseline were about 10 miles and 12 minutes longer than ride-alone trips. TNC trips connecting to public transit were much shorter, averaging about 5 miles in distance and 7 minutes in duration. Including the transit leg, TNC trips connecting to public transit averaged about 32 miles and 68 minutes. Figure 5 shows the distributions of trip distances, durations, and costs of TNC trips in the baseline, demonstrating a high variance in ride-alone and pooled TNC trip characteristics. By comparison, CARB (2019) estimates that the statewide average TNC trip distance is about 12 miles and SFCTA (2017) estimates that the average TNC trip distance for trips within the City of San Francisco is about 2.6 miles. The baseline model produced a slightly higher estimate of the average trip distance for inter-county trips in San Francisco, at about 3.8 miles per trip (see Appendix, Figure A7). The average cost of pooled TNC trips was generally higher than that of ride alone trips, reflecting the greater distance of pooled TNC trips in the baseline simulation. The distribution of the costs of TNC connections to public transit was bimodal, with about one third of these trips costing between \$5 and \$15 and another third between \$20 and \$30 in total. On average, low-income travelers (earning less than \$50,000) made less expensive ride-alone and pooled TNC trip trips than other travelers, with average ride-alone and pooled TNC trip costs of about \$34 and \$43 among low-income TNC users compared to costs of about \$38 and \$55 among TNC users earning more than \$50,000.

	Ride Alone TNC	Pooled TNC	TNC Connection to Public Transit	Overall
Distance (miles)				
mean	21	31	5	20
median	18	28	4	16
standard deviation	13	18	4	16
Duration (min)				
mean	23	35	7	22
median	19	30	5	18
standard deviation	15	21	5	18
Cost ($)				
mean	37	46	20	35
median	32	42	21	29
standard deviation	20	24	9	21

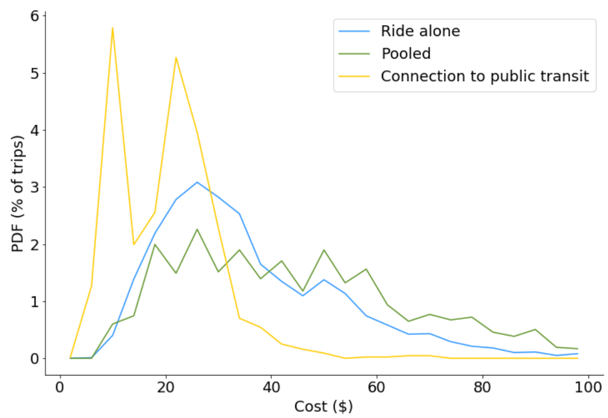
Table 3. Baseline TNC Trip Characteristics by Type of TNC Ride Service



a) TNC trip distance



b) TNC trip duration



c) TNC trip cost

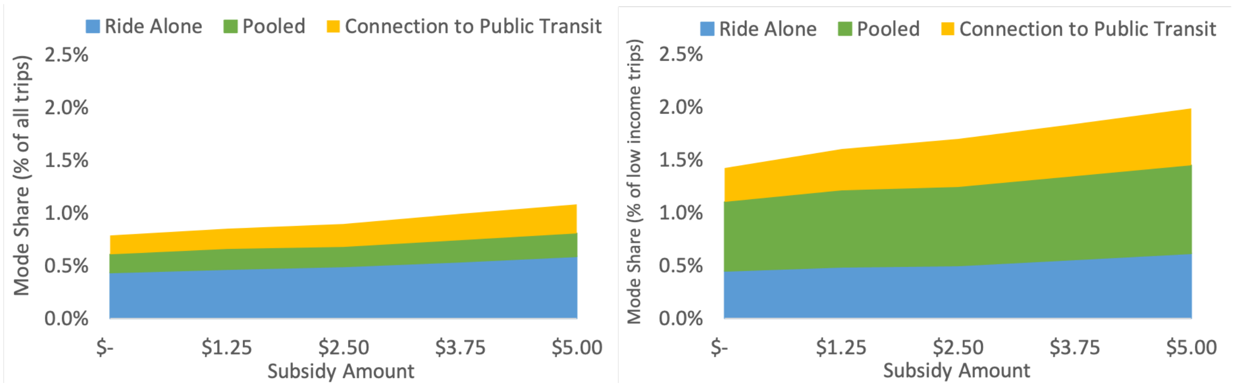
Figure 5. Distribution of TNC Trip Distance and Duration by Service Type

Sensitivity Analysis of Subsidies for TNCs in the San Francisco Bay Area

This section presents the results of the sensitivity analysis of TNC subsidies using the BEAM model of the SF Bay Area (see Table 1).

Subsidies for All TNC Rides

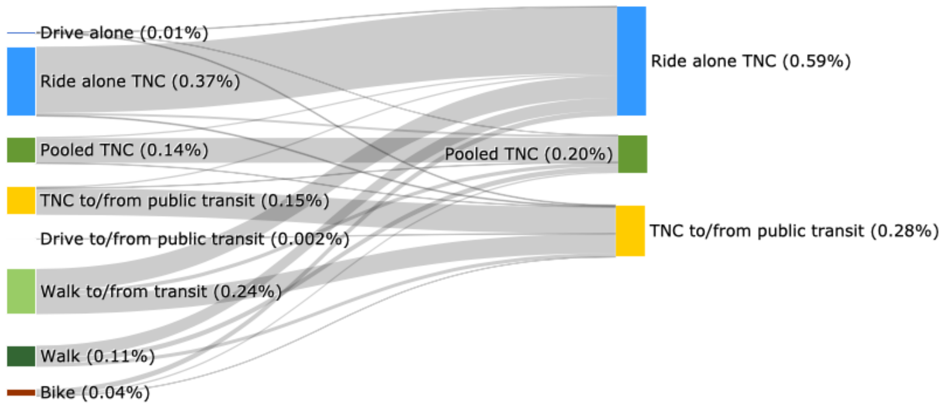
The provision of subsidies for all TNC rides regardless of service type produced slight overall mode shifts on the order of fractions of a percent of the total number of trips across the region (see Figure 6a). However, when considering that there are a total of 3.9 Million commuters in the SF Bay Area (ACS, 2019), the 0.06% increase in overall TNC commute mode share resulting from a $1.25 subsidy for all TNC rides would result in an estimated 2,100 new daily TNC trips in the region, while at the $5 subsidy level, the total increase in TNC mode share of 0.29% would amount to an estimated 10,000 new daily trips. Travelers earning between $50,000 and $100,000 per year exhibited the largest mode shifts, with increases of 0.3% in ride-alone and 0.1% in TNC public transit connection mode shares at the $5 subsidy level. Though small in absolute terms, these increases constitute a 46% and 73% increase in the baseline mode shares of ride-alone TNCs and TNC connections to public transit, respectively, among this group. Notably, neither the middle- nor high-income groups exhibited increases in pooled TNC trips in response to the general decrease in TNC prices. In contrast, low-income travelers increased usage of all three TNC trip types (ride-alone, pooled, and public transit connections) (see Figure 6b). Up until the $2.50 subsidy level, the greatest mode shift among low-income travelers was to TNC connections to public transit (+0.14%), followed by pooled TNCs (+0.08%) and ride-alone TNCs (+0.06%). The additional subsidy at the $5 level induced a slightly greater increase in ride-alone TNC mode share (+0.11%) than in the mode shares of pooled (+0.09%) and TNC connections to public transit (+0.08%).



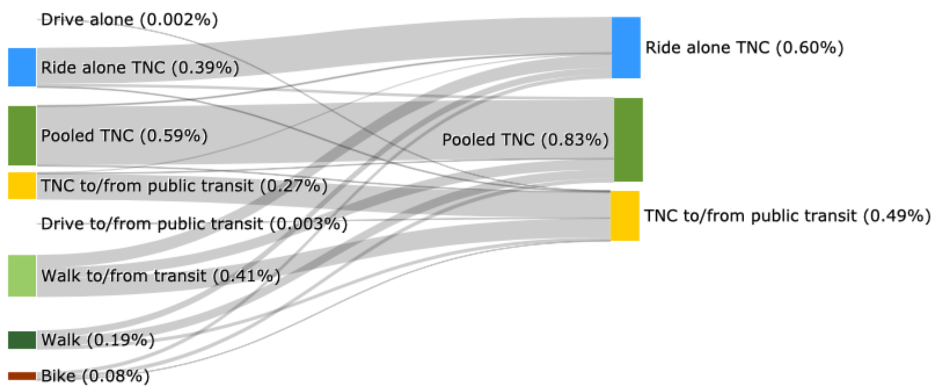
a) Overall TNC mode share b) Low-income TNC mode share

Figure 6. Sensitivity of mode share to subsidies for all rides, all income levels

The primary sources of the mode shifts to TNCs in response to subsidies for all TNC rides were from walking, biking, and walking to/from public transit (see Figure 7). Notably, driving alone and driving to/from public transit hardly changed in response to subsidies for all TNCs. As the subsidy level increased, former public transit users made up a greater share of the mode shift to ride-alone TNCs, with about half of new ride-alone TNC trips at the $5 subsidy level being shifted from public transit accessed by foot and about 30% from walking. While trip characteristics vary widely, travelers shifting from walk to/from public transit to ride-alone TNCs saved an average of about 65 minutes, amounting to about an 80% decrease in travel time in the $5 TNC subsidy scenario. On average, these travelers spent $19.05 more traveling by ride-alone TNC in the $5 TNC subsidy scenario compared to using public transit in the baseline scenario.



a) Overall mode shifts

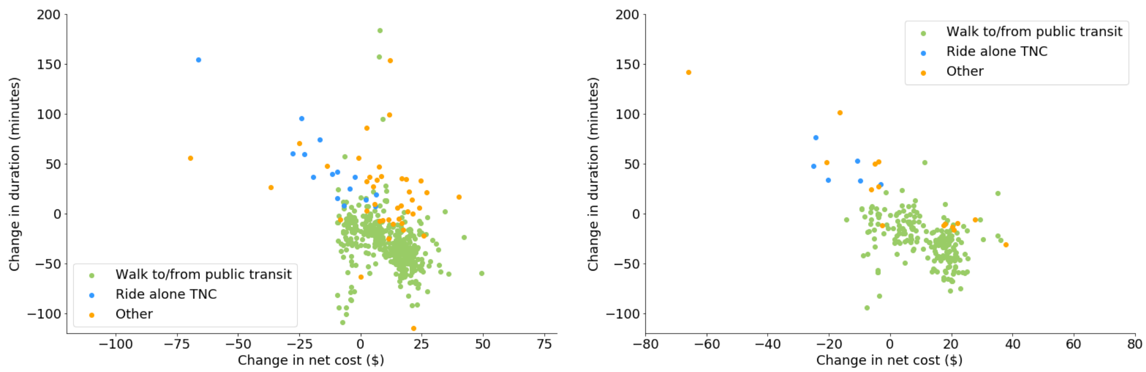


b) Low-income mode shifts

Figure 7. Mode shifts to TNCs from $5 subsidies for all rides, all income levels
Bars on the left show mode share that shifts from each mode used in the baseline simulation to TNC modes used in the scenario described above. Trips with no change in mode used or those that shifted to non-TNC modes are not shown.

Mode shifts to pooled TNCs, which were almost entirely among low-income travelers, were more heavily drawn from former walking trips, with about 40% of new pooled TNC trips at the $5 subsidy level being shifted from walk trips, about 30% from public transit trips accessed by foot, and about 15% from ride-alone TNCs. Low-income travelers shifting to pooled TNCs from walking to/from public transit at the $5 subsidy level saved even more time than those shifting to ride-alone TNCs while increasing spending by about the same amount, with average time savings of about 70 minutes and an average increase in trip cost of about $21. In contrast, middle- and high-income travelers that made this shift had commutes that were about 5 miles shorter, on average, resulting in average time savings of 50 minutes and about $13 in cost increases.

Across all subsidy levels and income groups, about 70 to 80% of the increases in TNC connections to public transit were from travelers that formerly walked to/from public transit. As shown in Figure 8, the majority of travelers that shifted from walking to/from public transit to using TNCs to access public transit increased net trip cost in return for a decrease in trip duration. On average, travelers in the middle- and high-income groups making this shift in the $5 TNC subsidy scenario saved about 24 minutes while low-income travelers saved about 12 minutes. All groups spent about $11 more, on average.

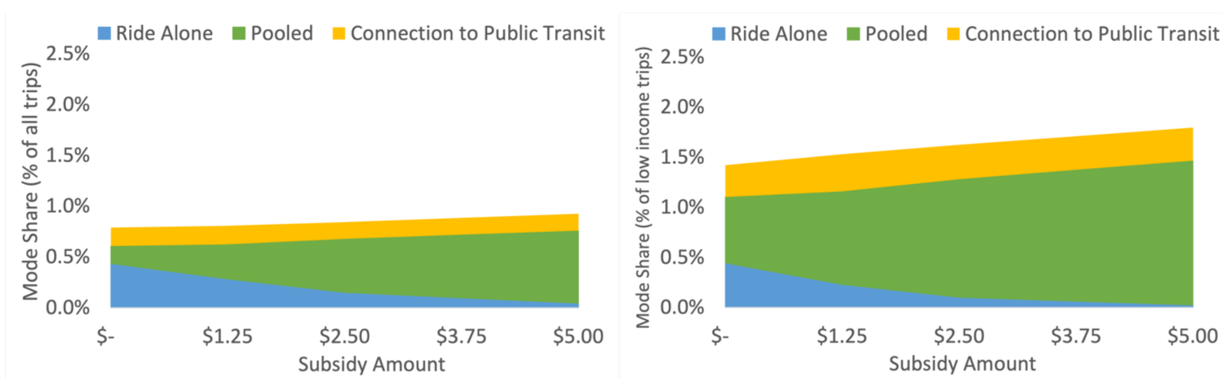


c) Middle- and high-income b) Low-income

Figure 8. Distribution of the change in trip duration vs net cost of new TNC connections to public transit in the scenario with pooled $5 subsidy for all riders
(change = scenario value - baseline value)

Subsidies for Pooled TNC Rides Only

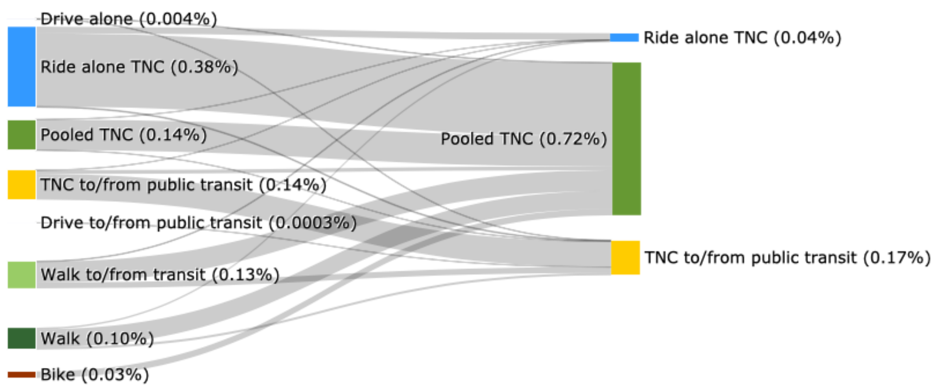
Restricting the TNC subsidies to pooled rides dramatically increased the mode shifts to pooled TNCs (see Figure 9). At the lowest subsidy level of $1.25, the overall mode share of pooled TNCs doubled, with about a 40% increase in the pooled TNC mode share among the lowest income group and about a 270% increase among the middle- and high-income groups. At the $5 subsidy level, the pooled TNC mode share among low-income travelers doubled to about 1.4% while those of middle- and high-income travelers increased from 0.1% to 0.9% and from 0.02% to 0.35%, respectively. Ride-alone mode share decreased as the subsidy for pooled rides increased, reaching one tenth of the overall baseline mode share at the $5 subsidy level.



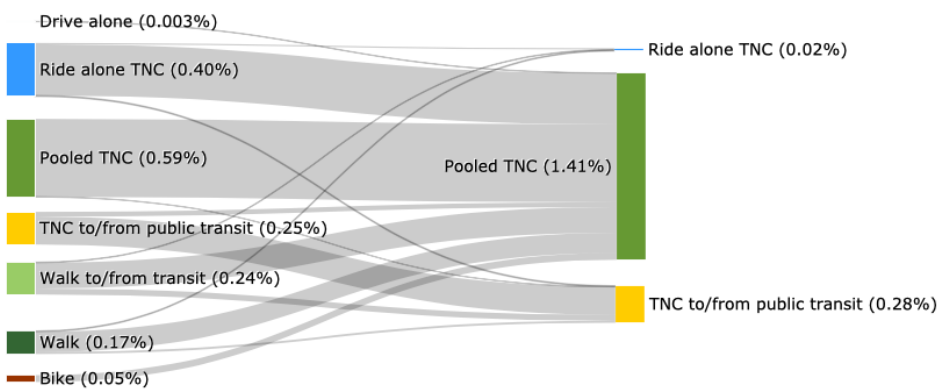
d) Overall mode share b) Low-income mode share

Figure 9. Sensitivity of mode share to subsidies for pooled rides, all income levels

Across all income groups, the primary source of mode shifts to pooled TNCs in response to subsidies for pooled TNCs only was from ride-alone TNCs, followed by walking and public transit accessed by foot (see Figure 10). About 60 to 65% of the mode shift to pooled TNCs among travelers earning more than $50,000 was from ride-alone TNCs. In comparison, ride-alone TNC trips accounted for about 45% of the mode shift to pooled TNCs among the lowest income group, which had higher rates of mode shift from walking and public transit (see Figure 10b). On average, travelers shifting from ride-alone to pooled TNCs increased travel time by about 3 minutes and saved about $4.47 in the $5 pooled TNC subsidy scenario, across all income groups. The travel time savings and cost increases for travelers shifting from walking to/from public transit to pooled TNCs were about the same as in the scenarios with all TNCs subsidized.



a) Overall mode shifts



b) Low-income mode shifts

Figure 10. Mode shifts to TNCs from $5 subsidies for pooled rides, all income levels

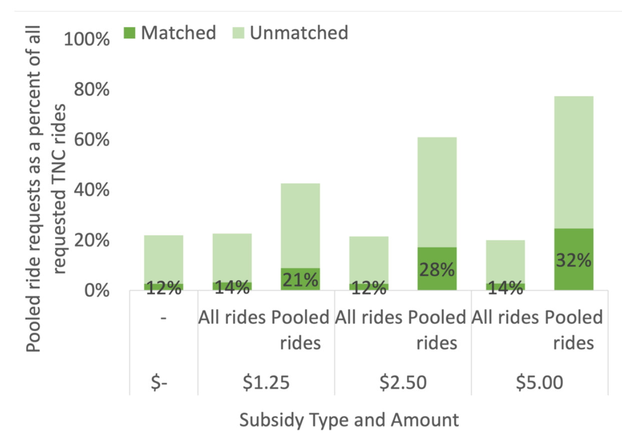
The bars on the left show the mode share that shifts from each mode used in the baseline simulation to TNC modes used in the scenario described above. Trips with no change in mode used or those that shifted to non-TNC modes are not shown.

Subsidies for Low-Income TNC Riders Only

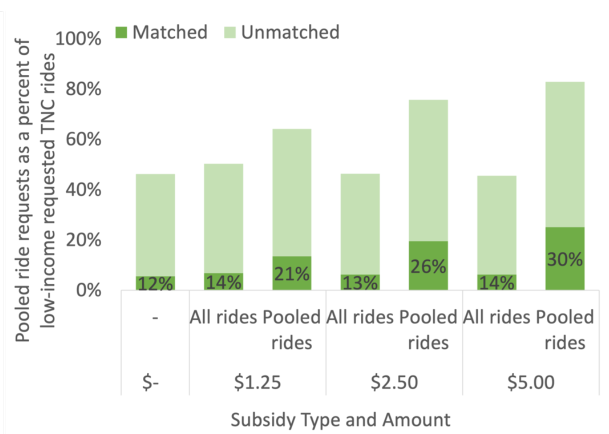
Subsidies for all TNC rides targeted to low-income riders only elicited a slightly larger mode shift to ride-alone TNCs than when the same subsidies were provided to all riders (+0.19% compared to +0.17%). In addition, they resulted in a slightly lower rate of mode shift to pooled TNCs (+0.16% compared to +0.18%). On the other hand, subsidies for pooled TNC rides only elicited a smaller shift to pooled TNC rides when the subsidies were only provided to low-income riders than when they were provided to all riders. The greater increase in pooled TNC mode share among low-income travelers in scenarios in which all TNC riders were subsidized may reflect economies of scale achieved by the widespread increase in demand for pooled TNC use in those scenarios. We will explore the interrelated effects of pooled TNC request rates on pooled matching rates next.

Comparison of All TNC Subsidies

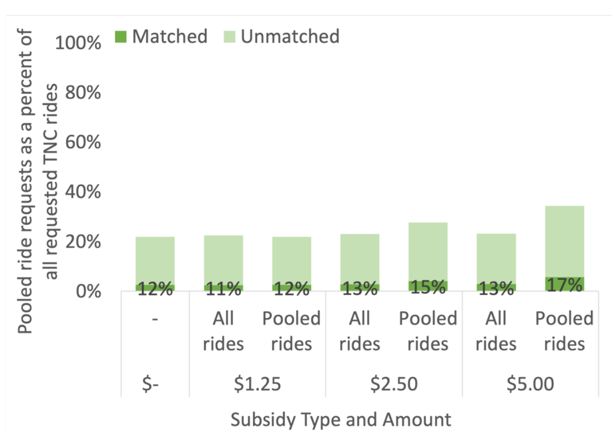
Figure 11 shows the sensitivity of the pooled TNC request and match rates for scenarios with all income levels subsidized (panels a-b) and with only low-income riders subsidized (panels c-d). Panels a and c show the pooled TNC request and match rates across all trips while panels b and d show the pooled TNC request and match rates among low-income trips only. Across all subsidy scenarios, the pooled request rate, or the percentage of TNC ride requests that are for pooled service, directly reflects the mode shifts previously discussed. Overall, we see that pooled TNC match rates (shown as labels in Figure 11) increased with respect to the pooled request rate. Subsidies for all TNC rides have a comparatively small effect on both pooled TNC request and match rates, as they increased both ride-alone and pooled ride requests at about the same rates. In contrast, subsidies for pooled TNCs for all riders more than triple the overall pooled TNC request rate, resulting in a 260% increase in the match rate from 12% to 32% at the $5 level. The pooled request and match rates among low-income riders also increased, though by smaller amounts (170% and 150% increase, respectively).



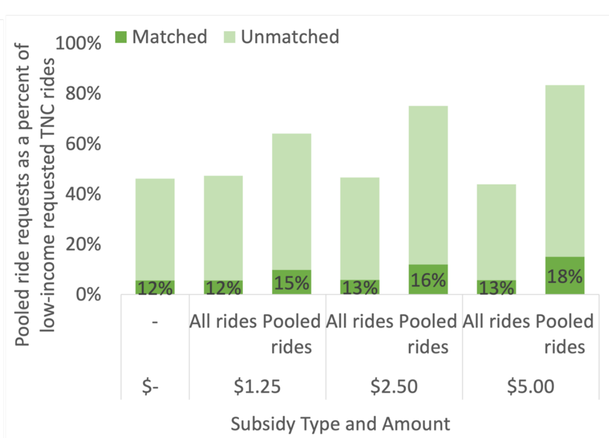
a) All rides, all income levels subsidized



b) Low-income rides, all income levels subsidized



c) All rides, low-income only subsidized



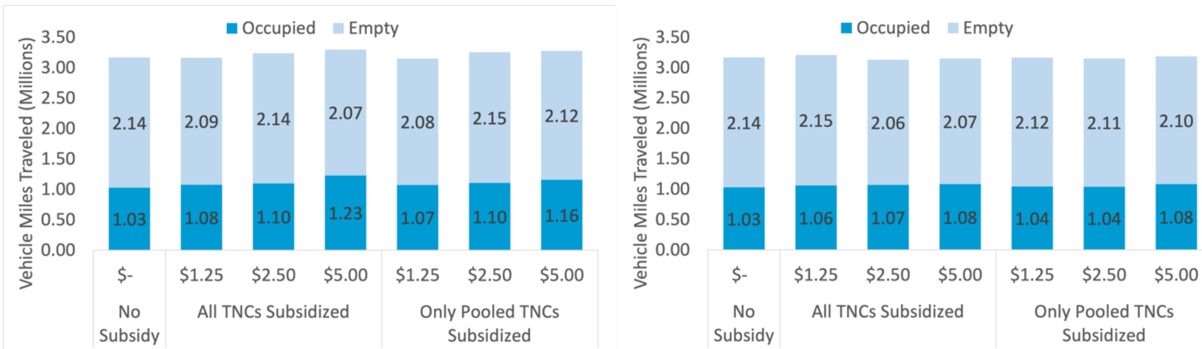
d) Low-income rides, low-income only subsidized

Figure 11. Pooled TNC Request and Match Rates by Subsidy Type and Amount
(Request Rate: pooled TNC requests as a percent of all TNC requests; Match Rate (shown on each bar): matched pooled TNC requests as a percent of all pooled TNC requests)

Pooled TNC request rates among low-income TNC users increased by about the same amount regardless of whether subsidies were provided to all income levels or were targeted to low-income travelers only. However, lower pooled request rates across the region in the scenarios subsidizing only low-income travelers reduced the likelihood that requested pooled rides were actually matched. The pooled match rates among low-income travelers were significantly lower in scenarios with only low-income TNC riders subsidized compared to those subsidizing all riders (see Figure 11b and 11d, respectively). The pooled TNC match rate among low-income travelers increased from 12% to 30% when subsidies were provided to pooled TNC riders of all income levels. However, when the same subsidy was restricted to just low-income travelers, the match rate increased by less than half as much, reaching about 18% at the $5 subsidy level.

The overall average occupancy of TNC rides increases with respect to the pooled match rate, as does the average occupancy of pooled TNC rides. Consistent with the discussion above, subsidies for all TNCs, whether restricted to low-income riders or not, did not impact the average occupancies of TNC rides in general nor those of pooled TNC rides. When all riders were offered $5 subsidies for pooled TNC rides, the average occupancy of all TNC rides increased by 12% from 1.01 ride requests per ride in the baseline to 1.14 requests per TNC ride. The average occupancy of pooled TNC rides increased by 13% from 1.07 to 1.20 requests per pooled TNC ride at the $5 subsidy level for pooled TNC rides, all riders. More modest increases were achieved by the subsidies for only low-income pooled TNC riders, which resulted in average occupancy rates of 1.03 requests per ride across all TNC rides and 1.08 across pooled TNC rides at the $5 subsidy level.

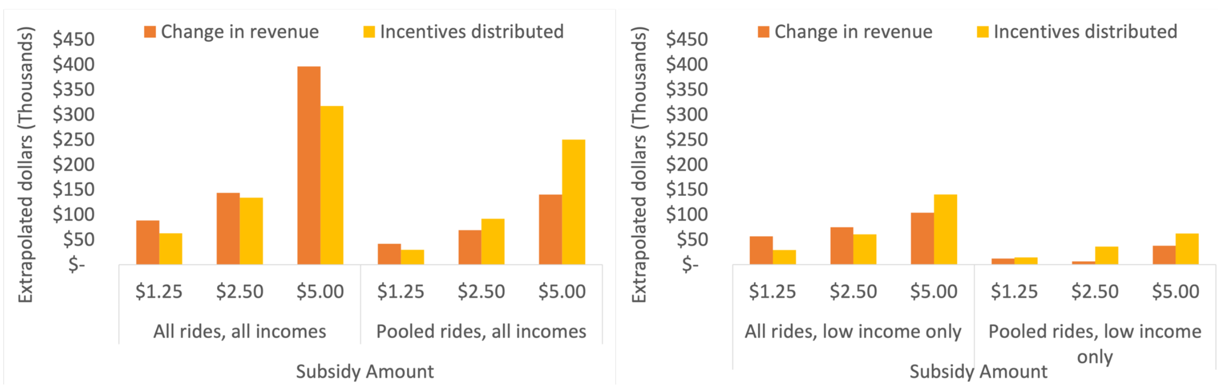
Although we found that total TNC VMT increased as demand for TNCs increased, the portion of TNC VMT attributed to deadheading generally decreased across the subsidy scenarios. Figure 12 below shows the total extrapolated VMT by TNCs, with the breakdown of occupied and empty VMT labeled for each subsidy scenario. When all income groups were subsidized, total TNC VMT increased by about 4.2% from the baseline at the $5 subsidy level for all TNC rides and by about 3.5% from the baseline at the $5 level for pooled TNC rides. The portion of total VMT that were empty miles decreased from about 67.5% in the baseline to about 62.8% and 64.8% at the $5 subsidy levels for all rides and pooled rides, respectively. In contrast, subsidization for low-income riders only resulted in little variation in the total TNC VMT and smaller improvements in the portion of empty miles out of total TNC VMT, which decreased to about 65.7% and 66.0% in response to $5 subsidies for low-income riders using all TNCs and just pooled TNCs, respectively.



a) All income levels subsidized b) Low-income only subsidized

Figure 12. Extrapolated TNC Vehicle Miles Traveled by Subsidy Scenario with All Riders Subsidized

Additional TNC revenue is generated from the increased adoption of TNCs, across all subsidy types and levels (see Figure 13). When all TNC rides and income levels are subsidized, the amount of additional revenue generated exceeds the total amount of incentives distributed, across all subsidy levels (+$25,000, +$9,000, and +$79,000 at the $1.25, $2.50, and $5.00 levels, respectively). This is also true at the $1.25 and $2.50 subsidy levels for all rides, low-income only, and at the $1.25 level for pooled rides, all incomes. In other scenarios, the costs of incentives distributed exceed the additional revenue generated.



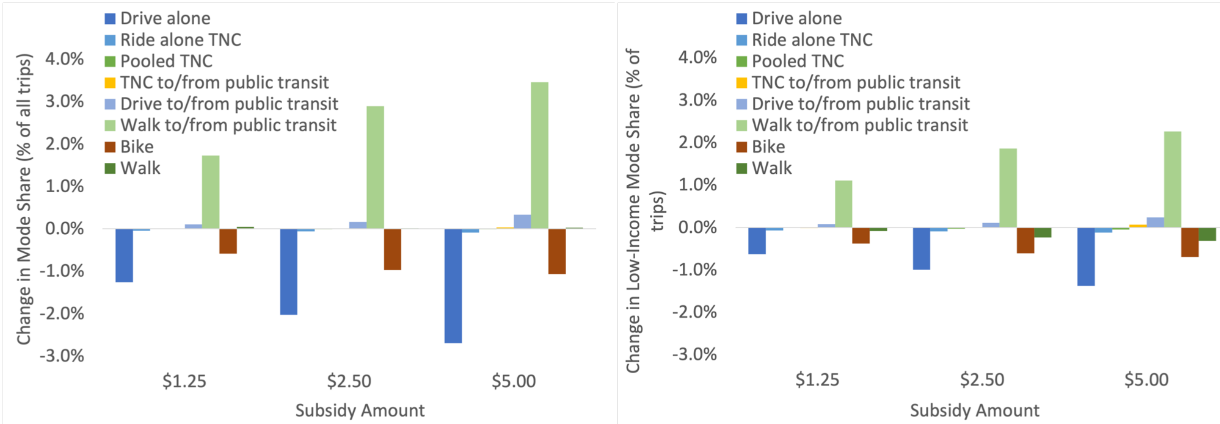
a) All income levels subsidized b) Low-income only subsidized

Figure 13. Extrapolated Total Change in TNC Revenue and Total Incentives Distributed by Subsidy Type and Amount

Overall, some subsidy types paid for themselves whereas others did not. Nonetheless, for those with net costs, there could still be a social benefit from these subsidies, such as increasing low-income mobility, use of public transit, and/or decreased driving. However, further study will have to occur before policy decisions can be made about which types of subsidies to pursue.

Subsidies for Public Transit

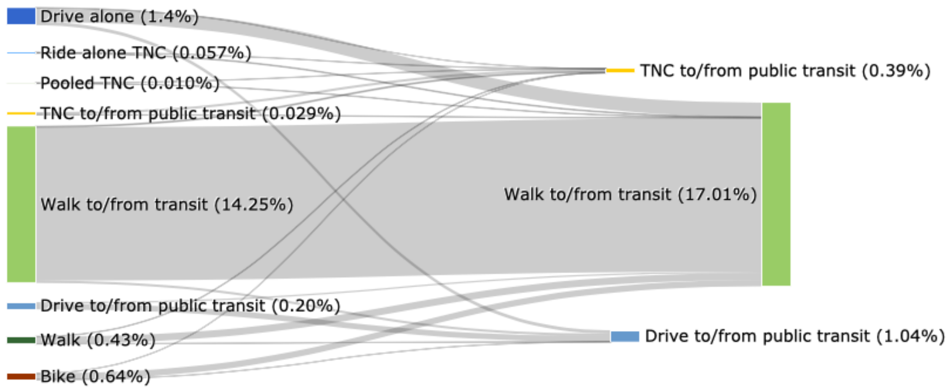
Public transit subsidies were investigated with both the all income levels and low-income only eligibility structures. In addition to a subsidy provided for all public transit rides regardless of access/egress mode, subsidies targeted specifically for TNC connections to/from public transit were analyzed.



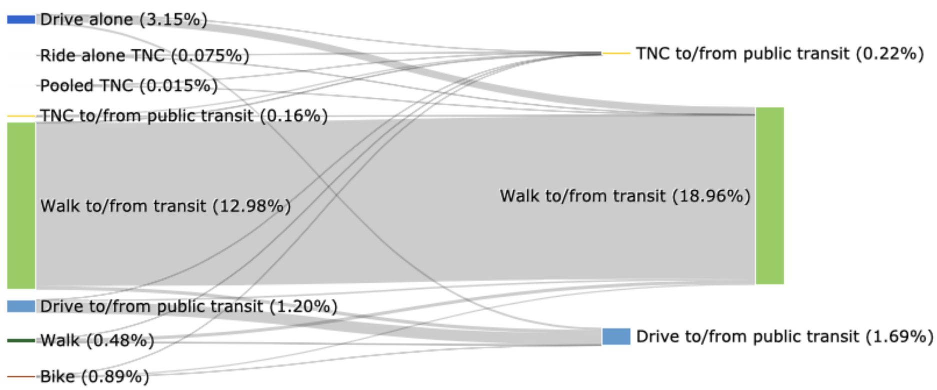
a) Change in overall mode share b) Change in low-income mode share

Figure 14. Change in Mode Share by Public Transit Subsidy Level

Subsidies for public transit rides result in larger magnitudes of mode shifts than do TNC subsidies. When the subsidies are made available to all travelers, the $1.25 level results in about a 12% increase in overall public transit use (+1.8% mode share). The increase at this level is primarily in public transit trips accessed by foot (+1.7%), with a slight increase in those accessed by personal vehicle (+0.11%) and an even smaller increase in the amount of public transit trips accessed by TNCs (+0.003%). The rate of mode shift to public transit accessed by foot tapers off as the subsidy level increases, with total public transit mode share increasing by another 1.2% at the $2.50 subsidy level and 0.8% at the $5 subsidy level. Mode shifts among low-income travelers are smaller than those of the overall population, with an increase in overall public transit mode share 1.2% at the $1.25 subsidy level, and additional increases of 0.8% and 0.6% at the $2.50 and $5 subsidy levels, respectively. The mode shifts of low-income travelers follow a similar pattern as the overall population, with an initial increase of +1.1% in the mode share of public transit accessed/egressed by walking and +0.08% in the mode share accessed/egressed by driving a private vehicle. However, the low-income mode share of public transit trips accessed by TNCs is relatively unaffected by the subsidies. Figure 15 summarizes these mode shifts at the $5 subsidy level across the a) overall population and b) low-income population.



a) Overall mode shifts



b) Low-income mode shifts

Figure 15. Mode shifts to Public Transit from $5 subsidies for Public Transit Rides, All Income Levels

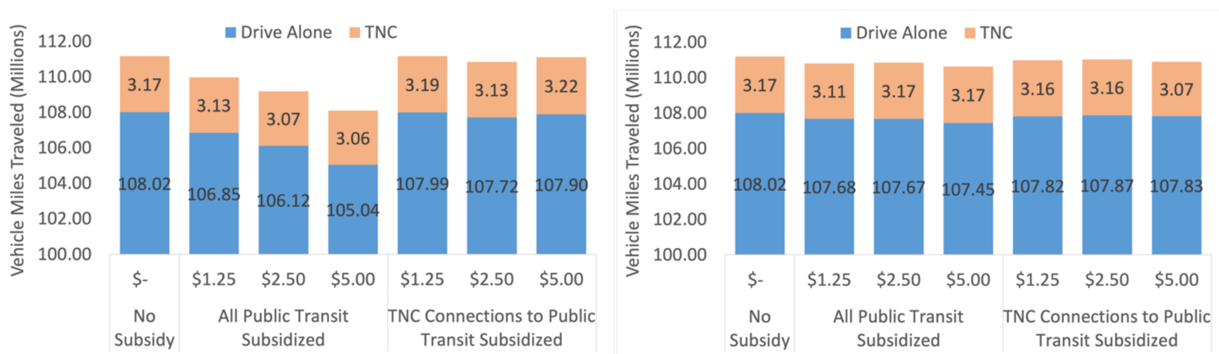
The bars on the left show the mode share that shifts from each mode used in the baseline simulation to public transit used in the scenario described above. Trips with no change in mode used or those that shifted to non-public transit modes are not shown.

The primary sources of the mode shifts to public transit are from drive alone, followed by biking, walking, and ride alone TNC. Across all subsidy levels, about 60% of all new walk to/from public transit trips were shifted from drive alone. That portion is smaller among low-income travelers (about 45%), for which about one quarter of the increase in walk to/from public transit mode share was shifted from walking and about 4% from ride alone and pooled TNCs. Among the middle-income group, only about 20% of induced walk to/from public transit mode share were shifted from walking and about 2% were from ride alone and pooled TNCs. These portions were even smaller among the highest income group, which exhibited the largest mode shifts from biking to public transit accessed/egressed by foot across all income groups. At the $5 subsidy level, about one quarter of new walking to/from public transit trips among this group were shifted from biking, compared to 10% and 20% among the middle and low-income groups, respectively. Across all income groups, about 5% of new walk to/from public transit trips were shifted from travelers shifting their access/egress mode from driving to walking.

On average, travelers shifting to public transit in the $5 subsidy scenario increased travel times by about 18 minutes. Those experiencing the largest travel time increases were travelers shifting from drive alone, ride alone and pooled TNCs, with increases of about 22, 66, and 68 minutes, respectively. Trips shifted from TNCs to public transit tended to be longer, covering distances of about 30 miles, on average. In contrast, the average drive alone trip that shifted to public transit was about half as long.

Subsidies provided only to trips using TNCs to access/egress public transit produced the largest increases in this mode, across all subsidy types. However, the overall mode share of public transit varies only slightly in response to such a subsidy, as about 60 to 70% of the mode shifts to public transit accessed/egressed by TNC are from travelers who formerly walked to/from public transit, across all income and subsidy levels. Another 15 to 20% of the mode shifts are from former walking trips, and about 10 to 15% are from ride alone TNC trips.

The mode shifts to public transit induced by subsidization result in notable decreases in total VMT by private vehicles, as shown in Figure 16. Figure 16a demonstrates the impact on VMT of the 4.5% reduction in drive alone mode share at the $5 subsidy level for all transit riders, which results in a 2.8% reduction in drive alone VMT. Overall VMT also decreases by about 2.8% in this scenario, with a 3.4% reduction in TNC VMT. Public transit subsidies for low-income riders only produce smaller reductions in VMT, with a 0.53% reduction in drive alone VMT and a 0.51% reduction in overall VMT at the $5 subsidy level for all public transit rides for low-income only. As discussed previously, subsidies targeted for TNC connections to/from public transit result in relatively small mode shifts which are reflected in the minor reductions in VMT shown in Figure 16.



a) All income levels subsidized b) Low-income only subsidized

Figure 16. Extrapolated Total Vehicle Miles Traveled by Subsidy Type and Amount

Sensitivity Analysis of Pooled Subsidies and Wait Time Restrictions Using RISE

Results from sensitivity analysis of TNC subsidies using RISE are shown in Figure 17. Across all subsidy scenarios, wait time and deadheading time and distance are slightly lower for low-income riders than high-income riders. The differences in both deadheading time and distance decrease slightly when all trips are subsidized, likely due to relatively more high-income trips. Fleet size (not shown in figure) generally increases with increasing subsidy, from 636 vehicles with no subsidy to 675 vehicles when all trips are subsidized.

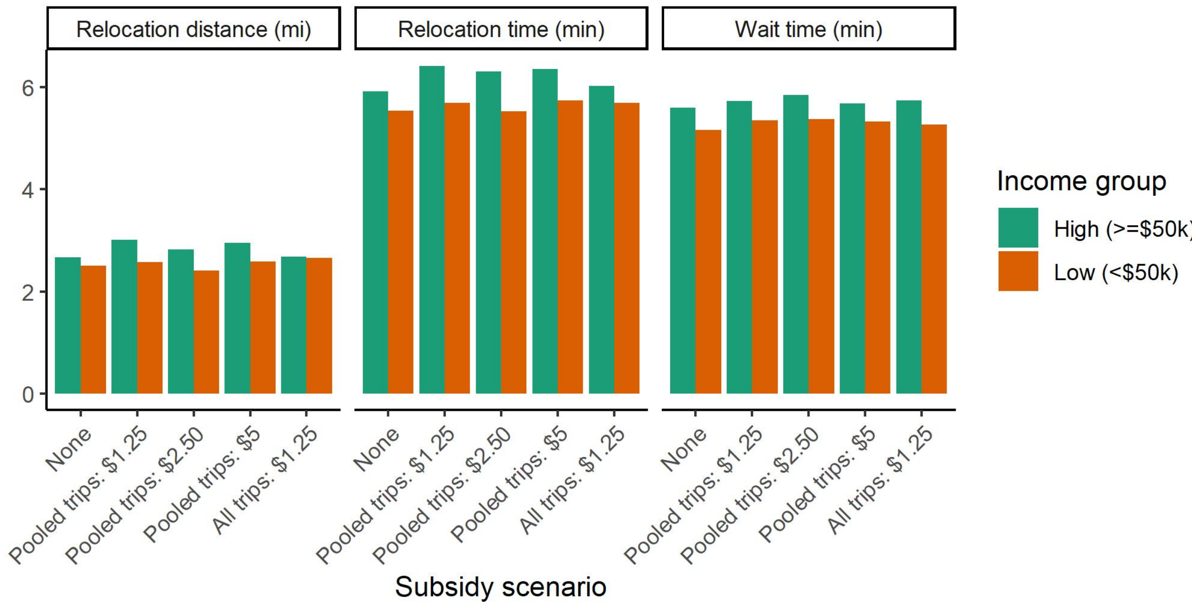


Figure 17. Simulation results for a range of subsidy scenarios in the SF Bay Area

This result suggests that there is little difference in wait times with income. These findings are consistent with those of Brown (2019) using activity data in Los Angeles. Thus, if discrepancies in wait times occurred, they would likely be due to discrimination, for example if drivers are reluctant to enter low-income neighborhoods. In this case, the fleet operator would need to focus more vehicles in low-income areas and implement some sort of cross-subsidy to ensure equal wait times for all rider demographic groups.

To analyze the impact of such a policy, we conducted simulations in which the maximum allowed wait time is lower for low-income riders than high-income riders. As shown in Figure 18 and Table 3, results suggest that it is feasible to decrease average wait times for low-income riders to under five minutes while increasing fleet size by less than 5%. The deadheading (i.e., empty) distance per trip increases for low-income riders, but this impact is offset by a decrease in empty distance for high-income riders, such that the overall deadheading ratio (the ratio of empty distance to total vehicle miles traveled) remains roughly constant.

Table 3 also shows the results for restricting wait times in low-income neighborhoods ("Geographic" restrictions), which could be employed if it is impractical to restrict wait time based on individual income ("Individual" scenarios). While geographic restrictions are somewhat less efficient at reducing low-income rider wait time, they still show the potential to significantly reduce wait time at the cost of a small increase in fleet size.

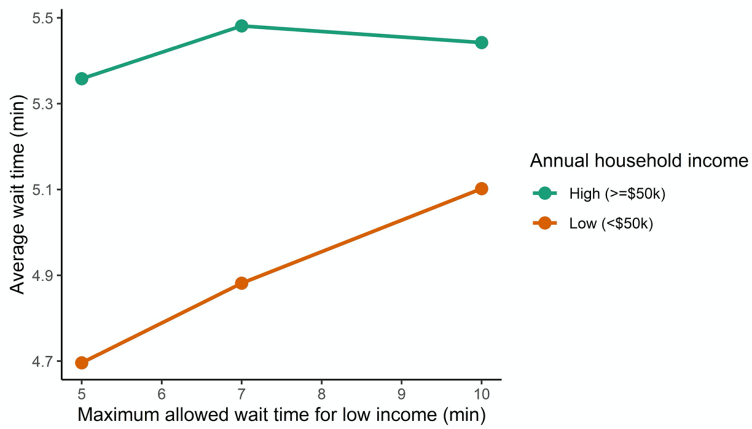


Figure 18. Impact on wait times and fleet size of reducing maximum allowed wait time for low-income riders

Maximum wait time (low-income)	Restriction type	Fleet size	Wait time (low-income)	Wait time (high-income)	Empty miles per trip (low-income)	Empty miles per trip (high-income)	Overall deadhead-ing ratio
10	Geographic	629	5.10	5.44	2.93	2.57	0.205
7	Geographic	655	4.83	5.31	3.47	2.18	0.201
5	Geographic	666	4.82	5.13	3.85	2.09	0.208
10	Individual	629	5.10	5.48	2.63	2.72	0.205
7	Individual	646	4.88	5.13	3.18	2.64	0.208
5	Individual	654	4.70	5.36	3.28	2.38	0.202

Table 3. Simulation results for San Francisco Bay Area.

Results for Los Angeles are consistent with the Bay Area: in the base scenario, wait time is no higher for low-income riders than for high-income riders, and wait times for low-income riders can be decreased by over a minute on average by reducing the maximum allowed wait time from 10 minutes to five minutes, by increasing the fleet size by less than 3%. The deadheading ratio also increases by less than 3% in the scenario where wait time is capped at five minutes for low-income riders. In practice, this wait time reduction arises from requiring low-income trips to be served by vehicles that are already idle. In the base scenario, 46% of all trips are assigned to vehicles that are occupied at the time of the request, with an average of five minutes left in their previous trip. In contrast, when maximum wait time for low-income riders is reduced to five minutes, only 14% of low-income trips are served by currently occupied vehicles, with an average of two minutes left in their previous trip. This flexibility in routing arises from the fact that at any given time during the simulations, there are at least five times as many vehicles available as there are trip requests. Even if routing is much less flexible in reality, this result suggests that TNC companies should be able to provide equal levels of service even if drivers exhibit significant discrimination towards marginalized groups.

Maximum wait time (low-income)	Fleet size	Wait time (low-income)	Wait time (high-income)	Empty miles per trip (low-income)	Empty miles per trip (high-income)	Overall deadheading ratio
10	5225	5.19	5.22	1.02	1.01	0.118
7	5303	4.02	5.27	1.36	0.91	0.120
5	5375	3.67	5.18	1.51	0.86	0.121

Table 4. Simulation results for Los Angeles metropolitan area.

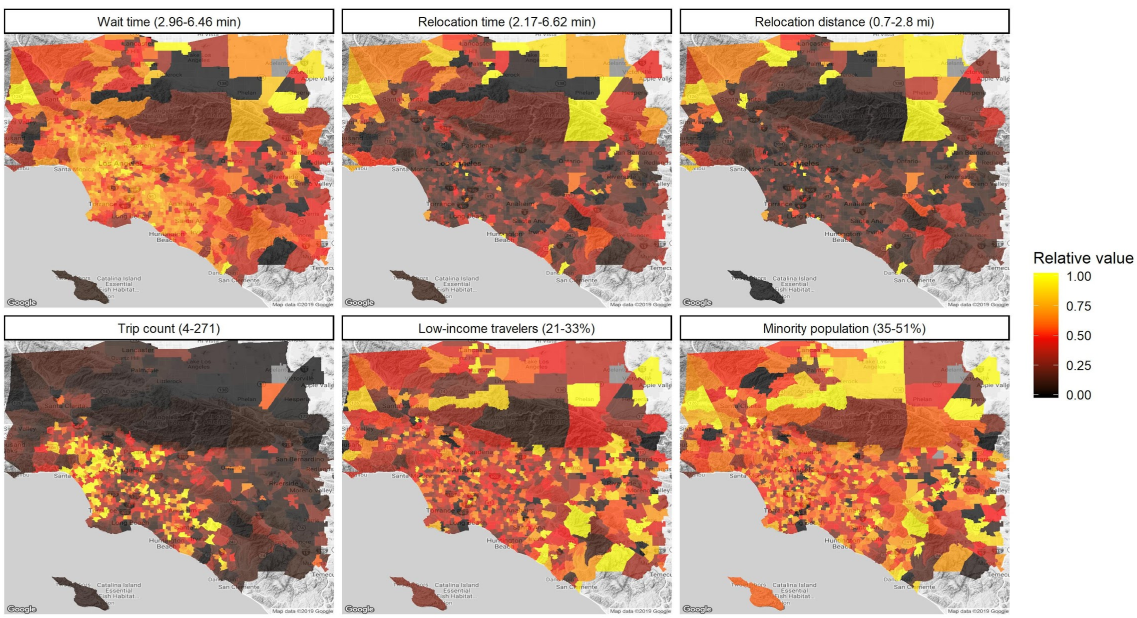


Figure 19. Comparative results for Los Angeles base simulation showing the 5th-95th percentile range of each statistic

GENERAL DISCUSSION

The models and survey data used in this study represent travel patterns and preferences prior to the COVID-19 pandemic. While the results indicate that pooled TNC and public transit adoption can be incentivized with $1.25 to $5 subsidies, the long-term impacts of the pandemic on travel behavior and willingness to share rides may have a significant effect on the outcomes of the subsidization strategies investigated in this study. Persisting health concerns are likely to skew behavior toward single-party rides, and fewer TNC rides in general compared with lower-risk transport modes such as private vehicles, active transit, and micromobility. The relative perception of health risks from pooling a ride with another passenger in comparison to riding alone in a TNC vehicle with a driver is yet to be determined. Perceptions of safety may increase following a full rollout of vaccines, yet this is also still unknown. Nonetheless, pooled TNC, app-based pooling, and microtransit services all offer reduced contact in comparison to traditional public transit services. Thus the opportunity to mitigate higher rates of auto ownership and single occupant vehicle use by promoting pooled rides persists. In the longer-term horizon, monetary incentives may play an important role in reintegrating public transit into daily travel.

The study results demonstrate the considerable time savings offered by TNC services in comparison to public transit. While the subsidies explored reduce the financial barrier to accessing on-demand mobility, the increases in travel costs for those shifting from public transit and active travel modes to TNCs are significant, particularly for lower income travelers. At scale, microtransit services that offer flexible on-demand shared ride services in larger vehicles such as passenger vans and shuttles may offer a more favorable tradeoff between operational costs and levels of service than either pooled TNCs or fixed route public transit, particularly for service to or from lower density areas.

The results across different types of public transit subsidies suggest that direct subsidization of public transit is more effective in reducing single occupant vehicle use and VMT than subsidies for TNCs, including targeted subsidies only for pooled rides or TNC connections to public transit. Although not included in the BEAM model, pooled TNC trips connecting to public transit would likely increase the benefits of subsidizing first/last mile TNC trips to public transit by increasing pooled match rates and overall TNC vehicle occupancy. Incentivization of the use of other first/last mile modes such as bicycles, e-bicycles, e-scooters, and mopeds are of interest for further investigation.

The model results indicate that revenues outweigh subsidy costs primarily when provided for all rides, all incomes, as well as for all rides, low-income levels at the $1.25 and $2.50 levels while subsidizing pooled rides results in revenues outweighing subsidy costs only at the $1.25 subsidy level for all incomes. These results stand in contrast to our model findings that the greatest increase in pooled TNC rides result from targeted pooled-only subsidies, which exhibit up to an 80% increase in pooled match requests under a $5.00 subsidy. We also found that subsidizing all rides had roughly the same effect on low-income riders as subsidies targeting low-income rides only. However, there was a greater increase in pooled mode share among low-income travelers in scenarios in which all TNC riders are subsidized, which may reflect economies of scale achieved by the widespread increase in demand for pooled TNC use in those scenarios. Overall, it appears that subsidies targeting pooled rides generally do not pay for themselves. This is not necessarily a failure, however; to achieve a social benefit (increasing shared rides and thereby reducing vehicle traffic as well as travel times among riders who might otherwise use a slower form of transit such as walking or biking) might require some expenditure of public funds. It appears that revenues are at least half as large as the subsidies in most of the cases in Figure 13 where revenues do not exceed costs; for instance, in the pooled ride, all riders $5.00 subsidy level. This suggests that subsidies could be substantially offset by revenues, lowering public spending to achieve a desirable social outcome.

STUDY LIMITATIONS

This study is primarily constrained by the scope and limitations of the models used. Geographically, the two major metropolitan regions that are the focus of this study, Los Angeles and the San Francisco Bay Area, are the two largest and most dense regions of the state of

California. Each of these regions has a unique distribution of land use, transportation, population, and employment, with a large degree of within-region variation. While neither region can be considered a typical urban environment, various sub-regions within the San Francisco Bay Area, in particular, provide insight into the relative responses of commuters with a variety of personal and trip characteristics as well as varied access to transportation.

Commute trips compose a large portion of peak road travel in most urban areas and thus contribute importantly to the negative impacts of personal vehicle use which can be mitigated by the strategies explored in this study. However, there are a multitude of other trip purposes which are not considered, including essential trips to access healthcare, childcare, food, and other services, as well as recreational trips. Given the finding that pooled TNC match rates benefit directly from greater pooled request rates, application of pooling subsidies across the full spectrum of trip purposes is likely to further improve the outcomes of such strategies. The likelihood to request a pooled ride varies significantly across trip contexts (Lazarus, et al., 2020), so responses to pooling incentives are likely to vary considerably across spatial and temporal dimensions. In addition, within-household planning and other forms of pooling among acquaintances were not modeled. As discussed previously, this affects the interpretation of TNC vehicle occupancies, which represent the number of ride requests served per vehicle as opposed to the expected number of passengers per vehicle. Further research is needed to investigate the implications of emergent travel behavior in response to pooling incentives with a broader scope of travel patterns and geographies.

Several aspects of the transportation system and travel behavior were kept fixed in the BEAM San Francisco Bay Area model to limit the number of confounding variables in the sensitivity analysis. These included the size and composition of the TNC vehicle fleet and all characteristics of vehicle charging and parking supply. Unlike RISE, which optimizes the size of the TNC fleet in order to maintain service levels, TNC fleet parameters are fixed within each BEAM simulation run. Additional sensitivity analysis would be needed to further investigate the behavioral effects of scaling the TNC fleet up or down in tandem with the subsidies that were investigated in this study. Likewise, the impacts of vehicle charging and parking supply were not explicitly investigated in the BEAM model, though they are prominent features of the RISE model.

Finally, there are a multitude of other subsidy types and structures that may be studied using the methodology of this study. The three subsidy levels that were employed in the study were determined following initial testing in the BEAM San Francisco Light model, which only simulated trips within San Francisco county. The various effects of the subsidies are found to taper as the subsidy level increases, suggesting that higher subsidy levels would have decreasing marginal effects as demand for the incentivized modes saturates further.

CONCLUSIONS

The subsidization of TNCs and public transit with $1.25 to $5.00 can incentivize greater usage of these modes with broad implications that vary across the subsidy types and structures explored. The baseline simulation (without subsidies) produced a TNC pooled request rate of 22% and a pooled match rate of 12%, which are consistent with results obtained by other studies. The sensitivity analysis of subsidies for all TNC rides regardless of service type illuminates potential outcomes of widespread cost savings that are expected from the rollout of SAV technology. The results suggest that uniform decreases in the consumer costs of TNCs across all service types would increase TNC mode share in the San Francisco Bay Area by about 0.06% or about 2,100 daily trips in response to a $1.25 reduction in TNC fares and about 0.29% or 10,000 daily trips in response to a $5 reduction in TNC fares. Of those trips, about half are ride-alone, 30% are connections to public transit, and the remaining 20% are pooled, resulting in a slight decline in the pooled request rate and almost no effect in the pooled match rate. With almost no shift from driving alone to TNCs, there are little to no additional environmental benefits from such scenarios beyond those achieved by the SAV or SAEV technology itself. Travelers shifting from public transit and active modes to TNCs benefit from faster travel times, although they incur increased travel costs on the order of $20 per trip, on average. Using a fixed fleet size, the BEAM San Francisco Bay Area Model estimates that such growth in TNC adoption produces a net increase in revenues minus subsidies distributed.

Comparison of the scenarios subsidizing all TNC services to those subsidizing only pooled TNC rides demonstrates that further reduction of the price of pooled TNCs is necessary to achieve higher utilization of SAEVs. Subsidies for pooled TNC rides only result in substantial mode shifts from ride-alone to pooled TNCs with travel time increases of just three minutes, on average. At the lowest subsidy level ($1.25/ride), the overall mode share of pooled TNCs doubled, while at the highest level ($5/ride), the portion of ride alone TNCs fell to almost zero across income levels. Subsidies for all TNC rides targeted only to low-income riders elicited a slightly larger mode shift to ride-alone TNCs and a slightly smaller shift to pooled TNCs than when the same subsidies were provided to all riders. However, the pooled match rate for low-income riders was only half as large when pooled-ride subsidies were targeted to low-income riders only as when applied to all riders, indicating a potentially important role of the network effect in creating economies of scale for pooled TNC service. Subsidies for TNC rides were smaller than the generated revenues when subsidies were applied to all rides and income levels, as well as to low-income riders below the $5 subsidy level, and to pooled rides at all income levels below the $2.50 subsidy level. Such subsidies were therefore deemed cost-effective. However, other types of subsidies generated less revenues than they cost. Nonetheless, there could be societal value for these subsidies, such as increasing low-income mobility, use of public transit, and/or decreased driving. Further study will have to occur before policy decisions can be made on which types of subsidies to pursue.

For the San Francisco Bay Area, differences in wait times, relocation times, and relocation distances are nearly identical across income levels and subsidies explored; in fact, they are slightly lower for low-income riders. As a result, any actual differences, if they were to occur, would likely result from discrimination, not network constraints. To correct for potential discrimination, wait times for low-income riders can be kept to under 5 minutes by lowering the maximum wait time from 10 to 5 minutes. This is accomplished by increasing the fleet size by less than 5%. Simulation results for Los Angeles were nearly identical to the San Francisco Bay Area in terms of wait times and relocation times/distances. However, to correct for potential discrimination, lowering the maximum wait time from 10 to 5 minutes resulted in average wait times decreasing by more than one minute, increasing the fleet size by less than 3% and the fraction of trips served by idle vehicles from 54% to 86%.

Further investigation of the effects of pricing and subsidy structures on policy outcomes is recommended. This research suggests that while revenue increases can offset subsidies in some situations, a feebate structure—in which fees are applied to ride-alone service to cover the costs of low-income pooling subsidies—may be particularly effective for incentivizing travelers of all income levels to pool while supporting lower-income travelers in accessing on-demand mobility. Such a subsidy structure may employ a broad definition of pooled modes that includes traditional public transit service, microtransit, and traditional carpooling, particularly if payment is integrated across services in the form of a mobility-as-a-service (MAAS) platform.

Subsidization programs for pooled on-demand mobility and public transit may be modeled after existing programs in other sectors, including those providing subsidized utilities, food, and healthcare access. Several shared micromobility services already offer low-income membership programs using enrollment in local, state, or federal aid programs such as CalFresh or Medicaid as proof of eligibility. In California, the Low Income Rate Assistance (LIRA) and California Alternate Rates for Energy (CARE) programs, which offer assistance to low-income residents for paying their water and energy bills, respectively, have established a precedent for the subsidization of public goods. It may be worthwhile to explore the potential of such programs to provide transportation subsidies in future research.

Further work is also needed to extend the findings of this research to a broader array of trip contexts including other essential and leisure trip purposes, geographic regions, and time periods (e.g., weekend travel, emergency/evacuation scenarios). Importantly, the models and scenarios investigated in this study should be revisited once the lasting effects of the COVID-19 pandemic on travel behavior become increasingly evident. While some findings may hold, considerable changes in trip patterns and traveler preferences will likely affect the efficacy of incentives on mode shifts to pooled modes.

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APPENDIX

BEAM Overview

The BEAM model is an agent-based simulation developed by the Lawrence Berkeley National Laboratory (LBNL) and University of California Berkeley Institute of Transportation Studies (ITS) (cite). The model uses census or survey data to generate a synthesized population of individuals and their corresponding households endowed with a home location, socio-demographic characteristics (e.g., gender, age, income, vehicle ownership), and a daily activity plan that determines the time and location of activities that individuals travel to throughout the simulation. A multi-modal network for cars, bikes, pedestrians, and public transit is integrated in the model, with travel speeds in the road network estimated at the link level based on the length, speed limit, and capacity of each link and the flow of vehicles on the links at any time in the simulation. Public transit operations are simulated using a fixed schedule and TNC service is optimized using a centralized algorithm that manages fleet repositioning, assignment to ride requests, and matching of pooled ride requests.

Mode Choices in BEAM

Prior to initiating a trip from one activity to another (e.g., from home to work or vice-versa), the BEAM model evaluates the estimated travel time and cost of each mode available to the individual trip maker at that time in the simulation, including: walking, biking, driving alone, riding alone in a TNC, pooling in a TNC, walking to/from public transit, biking to/from public transit, and riding alone in a TNC to/from public transit. The traveler chooses one option based on a probability distribution estimated using a discrete choice model (e.g., multinomial logistic regression, nested logistic regression). Based on the principles of utility maximization, the model predicts the likelihood that an individual chooses one particular alternative from a finite set of mutually exclusive alternatives. The utility equation implemented in BEAM is of the form defined in Equation 1., below:

Equation 1. Homogeneous Mode Choice Utility Equation - BEAM Representation

$$U_{i,t,m} = ASC_m + \beta_{cost}X_{cost,i,t,m} + \beta_{in-veh,t,m} \cdot X_{in-veh,t,m} + \beta_{wait,t,m} \cdot X_{wait,t,m} + \beta_{transfer} \cdot X_{transfer,t,m} + \varepsilon$$

Where the variable terms $X_{cost,i,t,m}$, $X_{in-veh,t,m}$, $X_{wait,t,m}$, and $X_{transfer,t,m}$correspond to the estimated cost, in-vehicle time, wait time and number of transfers for individual i making trip t using mode m. The termASC_m is an alternative-specific constant (ASC) that represents the preference for a particular mode if all other parameters were equal. Finally, the equation includes an extreme-value distributed error term, ε, representing unknown factors un-represented by the other variables.

In this study, the mode choice model is represented using a multinomial logit equation of the form defined in Equation 2, below:

Equation 2. Multinomial Logit Model

$$P_{i,t,m} = Prob(U_{i,t,m} \geq U_{j,t,m} \forall j \in C_{i,t}) = \frac{e^{\mu(V_{i,t,m})}}{\sum_{j \in C_{i,t}} e^{\mu(V_{j,t,m})}}$$

Where $V_{i,t,m} = U_{i,t,m} - \varepsilon$ is the deterministic portion of the utility equation and $C_{i,t}$is the set of mode alternatives available to individual i making trip t. Following the assumption that the variances of the error terms are homoscedastic (i.e., have equal variance), the scale parameter μ is conveniently constrained to a value of one (Ben-Akiva and Lerman, 1985).

Introducing heterogeneity to the BEAM mode choice model using SP survey data

A heterogeneous mode choice model was implemented in the BEAM framework by introducing additional parameters to the utility function that represent the sensitivity of TNC mode choices to trip destination (home or work) and individual characteristics of the trip-maker, including: age, income, and car ownership. The model coefficients were estimated using data from an online general population SP survey distributed from August to December 2018 to residents in the Los Angeles, Sacramento, San Diego, and the San Francisco Bay Area metropolitan regions. The survey included a series of four to five SP mode choice experiments in which respondents were asked to indicate their preferred option among three TNC ride services for a specified trip, as presented:

- Ride-alone TNC: a service such as UberX/ Lyft Classic where travelers request a direct, door-to-door ride for themselves.
- Door-to-door shared ride (TNC): a service such as Uber Pool/ Lyft Shared rides (formerly Lyft Line) where travelers request a door-to-door ride for themselves and the route may deviate to pick up or drop off one to three additional passengers riding along a similar route.
- Indirect shared ride (TNC): a service such as Uber Express Pool that is identical to the door-to-door shared ride, except the traveler is assigned pickup and dropoff locations that might require them to walk several minutes to and from the origin and destination locations designated in the ride request. Indirect shared rides may have one to five additional passengers.

Respondents were asked to imagine that they were making a trip from a specified origin (home or outside from home) to a specified destination (home, a restaurant/bar, an event (e.g., sports event, theater, concert), the airport, a recreational/social activity (e.g., a park, the beach, etc.), or a public transit station with a specified time constraint (no, some, or plenty of time to spare). The alternative-specific attributes for each transportation option were presented in a table format including the: 1) estimated wait time, 2) estimated walking time to or from the pickup or dropoff locations, 3) estimated in-vehicle time, 4) estimated total time, 5) estimated cost, and 6) expected range of additional passengers. For more information regarding the design and implementation of the survey please see Lazarus, et al. (2020) and Shaheen et al. (2021).

A total sample of 10,912 SP choice experiments from 2,398 individual respondents were collected and included in a discrete choice analysis for the present study. In contrast to the previous study, the model specification was constrained by the availability of parameters in BEAM. Parameters corresponding to travelers' attitudes and perceptions toward sharing and their usual weekly travel profiles, (i.e., the frequency with which they drive, use public transit, etc.) and the time since they first began using TNCs were not included in this model, as this individual-level data is not represented in BEAM. One exception is the inclusion of the parameter indicating a medical condition or handicap. Although the BEAM model did not distinguish travelers by this characteristic, the parameter was found to be highly significant by Lazarus, et al. (2020) and thus improves the performance of the model in estimating the coefficients for all other variables. Thus, rather than exclude the variable, it is included and all travelers in the BEAM model are treated as though they have no medical condition or handicap. Similarly, the coefficients corresponding to indirect pooled rides and the other three metropolitan regions are included in the model although only door-to-door pooled ride service and the San Francisco Bay Area are modeled in BEAM. Thus the coefficients corresponding to indirect pooled rides and to trips occurring in Los Angeles, Sacramento, and San Diego are not used in the simulation.

The resulting heterogeneous utility function is defined in Equation 3, with the description, estimated coefficients, and significance of each parameter presented in Table A1 below.

Equation 3. Heterogeneous Mode Choice Utility Equation - Standard Form

$$U_{i,m,t} = ASC_m + \beta_{cost,i} \cdot X_{cost,i,t,m} + \beta_{in-veh,m,i} \cdot X_{in-veh,t,m} + \beta_{wait,i} \cdot X_{wt,t,m} + \beta_{transfer} \cdot X_{transfer,t} + \beta_{origin,m} \cdot X_{origin,t} + \beta_{dest,i,m} \cdot X_{dest,t} + \beta_{age,i,m} \cdot X_{age,i,m} + \beta_{income,i,m} \cdot X_{income,i,m} + \beta_{car-owner,i,m} \cdot X_{car-owner,i}$$

Description	**Ride Alone TNC**	**Door-to-Door TNC**
Alternative-specific constant	0	-1.058***
Trip cost ($)	-0.027***	
In-vehicle travel time (minutes) - Less than $35,000)	-0.012**	
In-vehicle travel time (minutes) - $100,000 or more	-0.039**	
Wait time (minutes)	-0.055***	
Origin: Home	0	
Origin: Somewhere other than home	0	0.054
Destination: Home	0	
Destination: Restaurant/Bar	0	0.314**
Destination: Airport	0	0.227*
Destination: Transit Station	0	0.387*
Destination: Work	0	0.445***
Destination: Social/Recreational Activity	0	0.155*
Time Sensitivity: Some/Plenty of time to spare	0	
Time Sensitivity: No time to spare	0	-0.363***
Gender: Male	0	

Gender: Female	0	-0.007
Age: Under 30 years old	0	
Age: 30 to 50 years old	0	-0.148**
Age: 50 to 70 years old		-0.269
Age: 70 years or older		-0.236*
Employment: Unemployed/Retired	0	
Employment: Employed	0	-0.198**
Income: Less than $35,000		0.457**
Income: $35,000 to $100,000	0	
Income: $100,000 or more	0	0.170
Medical condition/handicap: None	0	
Medical condition/handicap: Some	0	0.427***
Vehicle owner	0	0.251**

*: p-value < 0.1; **: p-value < 0.01; ***: p-value < 0.0001

Table A1. Heterogeneous Mode Choice Model

The model results are consistent with the findings reported in Lazarus, et al. (2020), where the reader may find further analysis and interpretation of the full model. The following discussion of the model focuses on the parameters corresponding to the BEAM San Francisco Bay Area model, as other parameters do not affect the present study. The estimated coefficient for the ASC for pooled TNC is negative, reflecting a general preference for ride-alone TNCs. TNC mode choices in the San Francisco Bay Area are significantly more sensitive to the estimated wait time of a trip than to the estimated time in the vehicle. In addition, travelers earning less than $100,000 are significantly less sensitive to in-vehicle time than those earning more than $100,000. Dividing the coefficient estimates for wait and in-vehicle times by that of cost, the model estimates that the value of TNC wait time is about $120/hour, while the value of in-vehicle time is about $86/hour for travelers earning more than $100,000 per year and about $25/hour for all other travelers.

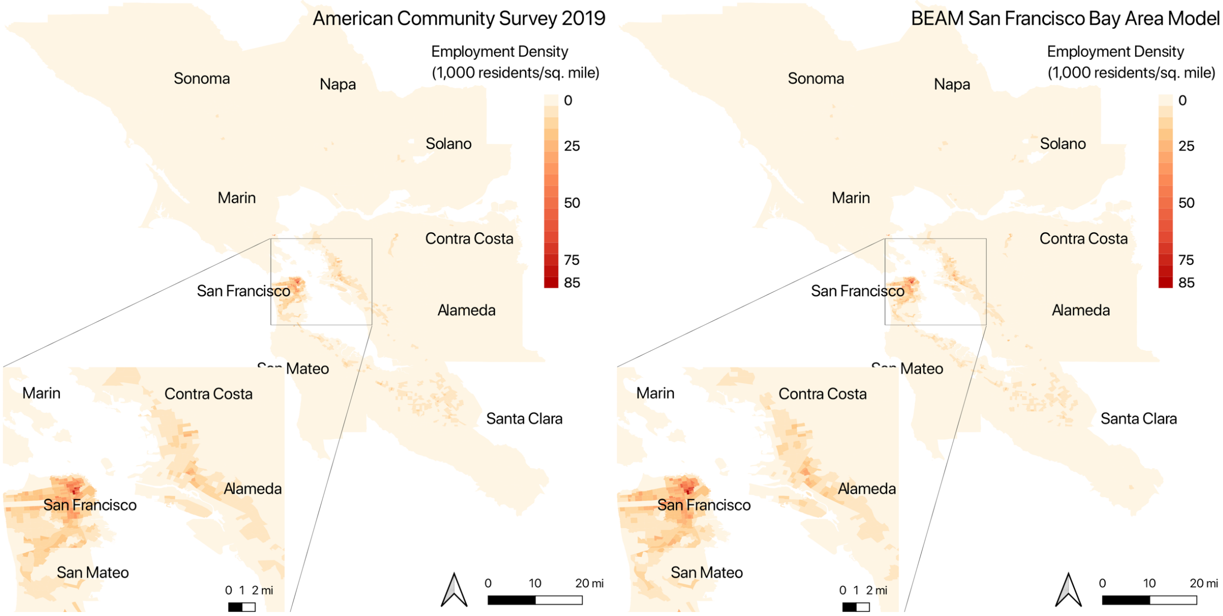
The coefficient estimates for trip origin suggest that, while travelers are more likely to choose an indirect pooled TNC when starting a trip from somewhere other than home, trip origin does not have a significant effect on likelihood to choose a door-to-door pooled ride. However, travelers are the most likely to choose a pooled TNC when traveling to work. In the San Francisco Bay Area, travelers are also significantly more likely to choose a pooled ride when making a TNC trip to a public transit station. The model reflects the sensitivity of travelers to the reliability of pooled rides, as the coefficient estimates corresponding to having 'no time to spare' are significant and negative. However, since mode choices in BEAM generally occur with plenty of time to spare, this variable does not have an effect in the present study. The remainder of the variables correspond to traveler characteristics, finding that in the San Francisco Bay Area, travelers under the age of 30, unemployed/retired or earning less than $35,000, with a medical condition/handicap, and that own/lease a vehicle are the most likely to choose a door-to-door pooled TNC over a ride-alone TNC option.

In order to implement the above model in the BEAM framework, the coefficients corresponding to ride-alone and door-to-door pooled rides were added to the utility equations for TNCs in the BEAM mode choice model. Since no additional parameters were initially introduced for the other modes, the resulting mode choice model necessitated considerable calibration, as described below.

BEAM Model Calibration

The primary model employed in this study is an activity-based travel model of the nine-county San Francisco Bay Area: San Francisco, San Mateo, Santa Clara, Alameda, Contra Costa, Solano, Napa, Sonoma, and Marin Counties. The model includes a simplified road network of about 70,000 nodes and 180,000 links wherein local roads are aggregated in order to reduce the computational burden of the simulation. Public transit services across the region are simulated using open-sourced General Transit Feed Specification (GTFS) data from each agency, and TNC service is simulated with TNCs managed by a single operator with a demand-following repositioning algorithm.

Although admittedly incomplete, the BEAM model in its currently available form focuses solely on commute trips, with each agent making two trips per day: one from home to work and another from work to home. While the total number of commuters in the San Francisco Bay Area is about 3.9 Million (US Census, 2019), the model employs a randomly-sampled sub-population of about 325,000 commuters. The population synthesis, including the generation of individuals, households, home and work locations, and preferred activity start times, was conducted externally from BEAM, using UrbanSim, a regional land use and transportation model that simulates housing and employment choices (Waddell, 2002). The distribution of employment density per census tract as reported in the 2019 American Community Survey (ACS) (U.S. Census, 2019) and modeled in BEAM are displayed in Figure A1 a and b, respectively. As shown, the distribution of the synthesized population in the BEAM model is generally similar to that of the actual population, with greatest density in the City of San Francisco and in the urban centers of the East and South Bay.



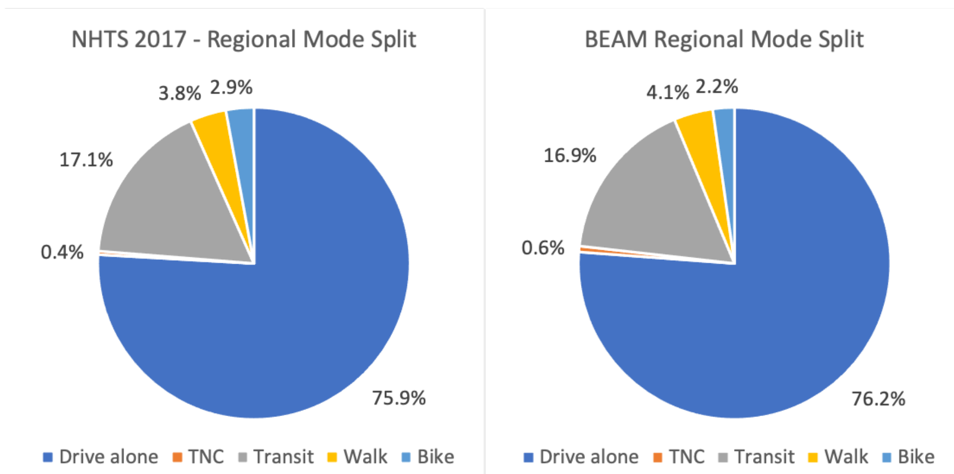
a) American Community Survey (2015) b) BEAM San Francisco Bay Area Model

Figure A1. Employment Density per Traffic Analysis Zone in the San Francisco Bay Area

The methodological approach for scenario calibration and sensitivity analysis using BEAM was developed and tested using a model of the City and County of San Francisco, called "BEAM SF Light." Functionally, the San Francisco model is a subset of the San Francisco Bay Area model consisting of the same road and public transit network. A sample of 50,000 commuters was generated from the synthetic population used in the San Francisco Bay Area BEAM model. Commuter data collected by SFMTA in the 2019 Travel Decision Survey (TDS) (SFMTA, 2019) was used to determine the sampling distribution per zip code based on the portion of residents living or working in the City of San Francisco.

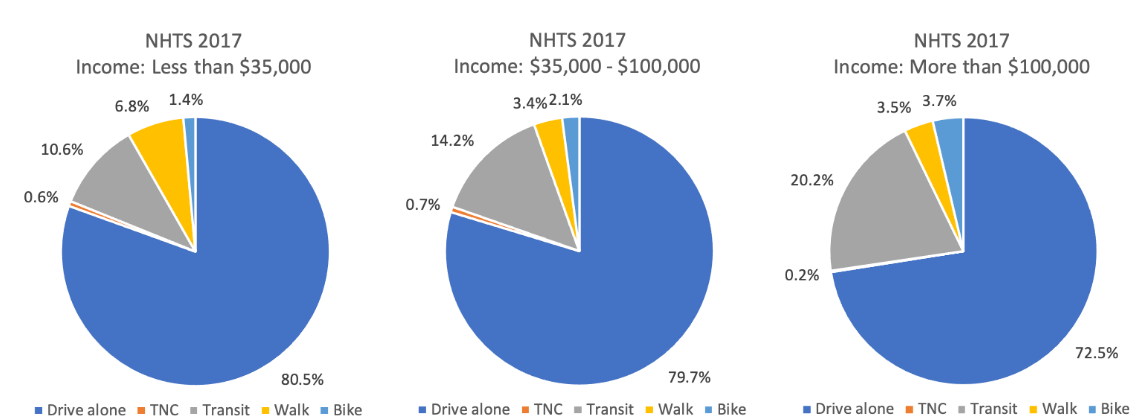
The mode choice model was calibrated with the objective of minimizing the mean squared error (MSE) of the simulated mode split as measured by census data. The first phase of calibration was conducted using the BEAM SF Light model and the commute mode share reported by the 2019 TDS as the target mode split. The ASCs of the model were modified in consecutive runs of the BEAM SF Light model, until the MSE of the mode split reached about 0.0015. At this stage, the simulated mode shares among each of three income groups (earning less than \$35,000, \$35,000 to \$100,000, and more than \$100,000) were compared to those estimated from the 2019 TDS, revealing significant disparities in the mode shares disaggregated in this way. In particular, by using only the overall mode share as a calibration target, the TNC mode share among the lowest and middle income groups in the simulation were about triple and double those of the population, respectively, while the TNC mode share among the highest income group in the simulation was only about a third of that of the population. Furthermore, transit mode share was skewed toward the highest income group with the transit mode share of the low-income group in the simulation equaling just 20% of that of the low-income population. This resulted in an MSE of 0.012 for the income-specific mode shares.

In order to address these discrepancies, additional parameters were introduced in the mode choice model to represent heterogeneity in the sensitivity of demand for other modes with respect to income. These include the parameters for in-vehicle time by income group, income group, and the trip transfer penalty (denoted with an asterisk in Table A2). These parameters were modified in another sequence of simulation runs until the MSE of income-specific mode shares was reduced to about 0.00099 and that of the overall regional commute mode split was reduced to 0.000019. The resulting mode choice model was then run in the full BEAM San Francisco Bay Area model and the same two steps were taken using the 2017 NHTS to estimate the commute mode splits for the San Francisco Bay Area (USDOT, 2017). At the end of the full calibration process, the MSE of the income-specific mode shares in the final calibrated model was 0.00086 and that of the overall regional commute mode split was 0.000013. As shown in Figure A2, the calibrated BEAM San Francisco Bay Area model has slightly higher mode shares of driving alone, TNC, and walking than reported by the NHTS 2017 and slightly lower mode shares of transit and bike use. Compared to the income-specific mode shares of the population (see Figure A3-A4), the low- and middle-income groups in the calibrated BEAM model have lower drive alone mode share and higher transit mode share.



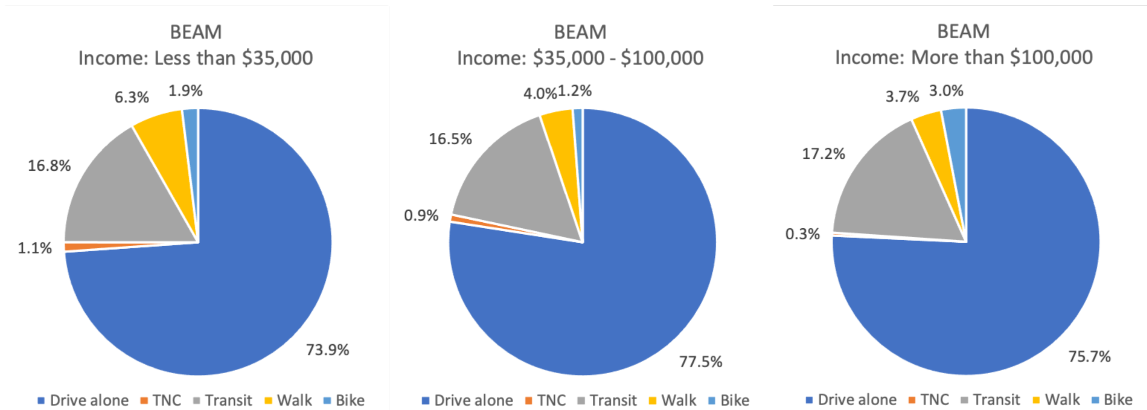
a) Population (NHTS, 2017) b) BEAM San Francisco Bay Area Model

Figure A2. Regional Commute Mode Split in the a) Population and b) Simulation



a) Low-income b) Middle-income c) High-income

Figure A3. Commute Mode Split by Income Group in the Population (NHTS, 2017)



a) Low-income b) Middle-income c) High-income

Figure A4. Commute Mode Split by Income Group in the BEAM San Francisco Bay Area Model

The final coefficient values of the calibrated mode choice model are presented in Table A2. Coefficients that were altered during the calibration process are denoted with asterisks. The coefficients for walk and bike time were set to 1.5 and 2.5 times the coefficients for in-vehicle time corresponding to pooled TNCs, respectively. In addition, parameters distinguishing the sensitivity of demand with respect to income across modes were introduced to the model to increase the mode shares of driving, walking, and biking among low-income travelers as well as that of biking among low-income travelers.

	Drive Alone	Ride Alone TNC	Pooled TNC	TNC to/from Transit	Walk to/from Transit	Drive to/from Transit	Walk	Bike
Alternative-specific constant*	0.000	-0.259	-0.491	0.137	0.334	0.096	0.444	0.246
Trip cost ($)	-0.027							
In-vehicle travel time (minutes) - Less than $35,000)*	-0.012						-0.017	-0.029
In-vehicle travel time (minutes) - $100,000 or more*	-0.023						-0.035	-0.058
Wait time (minutes)	n/a	-0.023					n/a	
Transfer*	n/a			0.038			n/a	
Destination: Home	0							
Destination: Work	0		0.444	0				

Age: Under 30 years old	0					
Age: 30 to 50 years old	0		-0.148	0		
Age: 50 to 70 years old	0		-0.269	0		
Age: 70 years or older	0		-0.236	0		
Income: Less than $35,000*	0.209	-0.104	0.000		0.139	0.07
Income: $35,000 to $100,000*	0					
Income: $100,000 or more*	0		0.075			0.07
Vehicle owner	0		0.251	0		

**: coefficients adjusted during calibration*

Table A2. Calibrated Mode Choice Model Parameters

RISE Overview

RISE is an agent-based fleet simulation model first described in Bauer et al (2018). The model routes vehicles to trips and to charge over the course of a simulated set of trip demand (typically an average weekday), given data inputs for travel times between each origin-destination pair. Trips that aren't served within a chosen threshold (typically 10 minutes) are lost; however, the number of vehicles can be dynamically adjusted to ensure that a desired maximum wait time is achieved. The user chooses the relocation strategy for rebalancing the fleet and how vehicles decide to charge, as well as number of chargers and charging speed. Charging locations are determined by minimizing the total distance to all trips. Battery range can be fixed or estimated endogenously by increasing vehicles' battery range whenever needed to serve a trip. The simulation repeats until the fleet's average battery range and state of charge at the end of the simulation period are within 5% of the values at the beginning of the period. Outputs include the distance traveled by each vehicle both with and without a passenger, the energy supplied by each charger, and the wait time and operating cost associated with each trip.

To simulate fleet operations in the San Francisco and Los Angeles metropolitan areas, we obtained data from StreetLight Data on trip volumes, travel distances and durations between each origin and destination zone (roughly the size of a traffic analysis zone, or TAZ). Given that these data are presented as distributions, additional pre-processing steps were required, and during the simulation each travel time and distance is determined by taking a random draw from the appropriate distribution. For more details on this process, see Sheppard et al. (2021).

Vehicles were assumed to have 300-mile range, with a number of 50-kW chargers estimated based on the trip data such that each charger is occupied for four hours per day on average. The number of vehicles available to serve trips at any given time was determined by the trip data, assuming all trips must be served within a 10-minute wait time. We recorded the wait time and "deadheading" (travel without passengers) distance for each trip, and compared the operational results by socioeconomic status of the passengers.

San Francisco Bay Area to Los Angeles

Trip data for the Bay Area was taken from BEAM outputs. To extrapolate trip data for Los Angeles, we developed a machine learning model based on the StreetLight Data for each city, along with Census data for the nearest census tract to each zone, including income, age, and population (see Table A3 for description of all variables and relative importance). The response variable was the number of trips between each zone-pair by hour of the day. The model was trained to reproduce San Francisco data with a standard machine learning algorithm based on decision trees, then extrapolated to Los Angeles based on the corresponding features in each zone. The final model for predicting BEAM outputs in the Bay Area had a mean squared error of 0.033. As suggested by Figure A5, the model accurately reproduces the broader spatial pattern of trip counts across the Bay Area.

Variable	Relative importance	Fraction of predictive power
StreetLight trip density	1.00	0.16
StreetLight trip count	0.99	0.16
Straight-line distance	0.74	0.12
Hour of day	0.56	0.09
Fraction vehicles with vehicle scarcity (origin zone)	0.46	0.07
Average driving time	0.38	0.06
Fraction non-white travelers	0.33	0.05
Population (origin zone)	0.33	0.05
Average driving distance	0.28	0.04
Population density (destination zone)	0.18	0.03
Area (origin zone)	0.18	0.03
Population density (origin census tract)	0.17	0.03
Population (destination census tract)	0.15	0.02
Population (destination zone)	0.15	0.02
Fraction low-income travelers	0.13	0.02
Population (origin zone)	0.12	0.02
Fraction vehicles with vehicle scarcity (origin zone)	0.10	0.02

Area (destination zone)	0.04	0.01
Area (destination census tract)	0.03	0.00
Area (origin census tract)	0.03	0.00

Table A3. Trip extrapolation model results

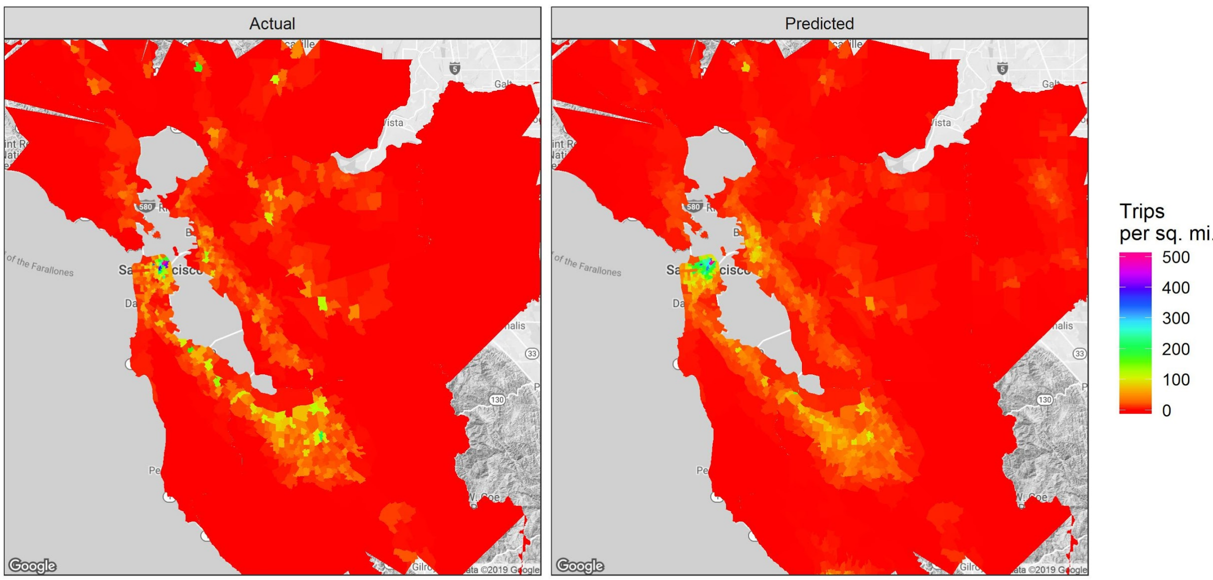


Figure A5. Left: outputs of BEAM for ridehailing trips per square mile in each zone; Right: outputs from the machine learning model.

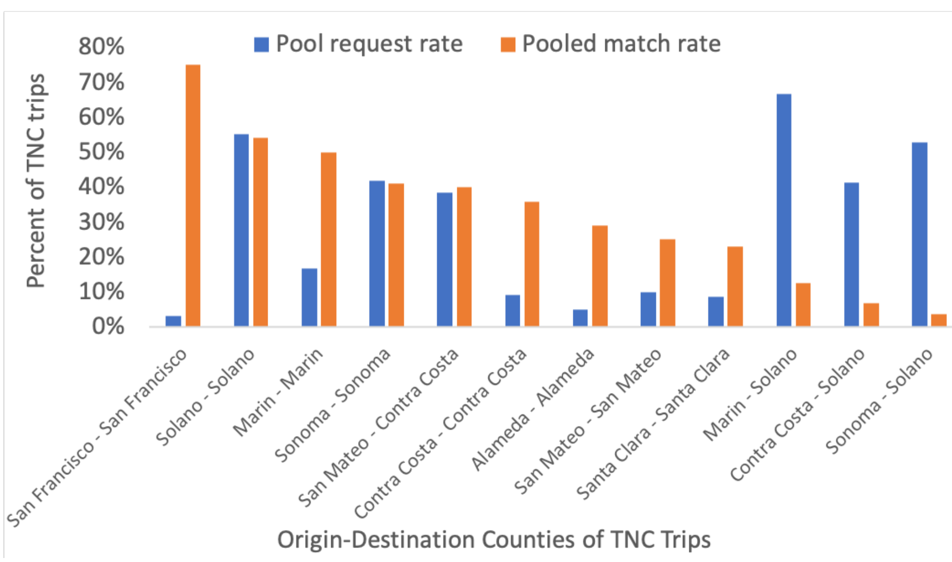
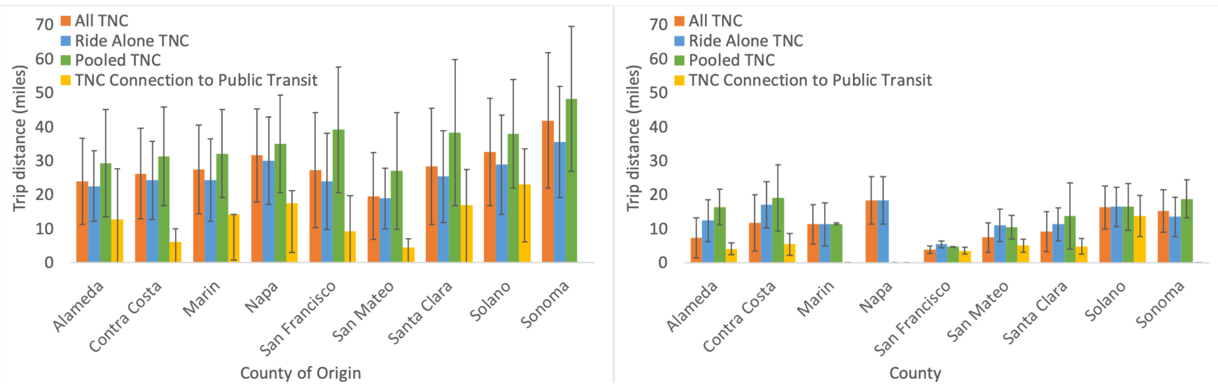


Figure A6. Baseline Distributions of the TNC Pooled Request Rate and TNC Pooled Match Rate By Origin-Destination County Pairs With Non-Zero Pooled Match Rates



a) Inter-County Trips by County of Origin b) Intra-County Trips by County

Figure A7. Mean TNC Trip Distance by County and Type of TNC Ride Service
Error bars represent the standard deviation of trip distance in the corresponding county.

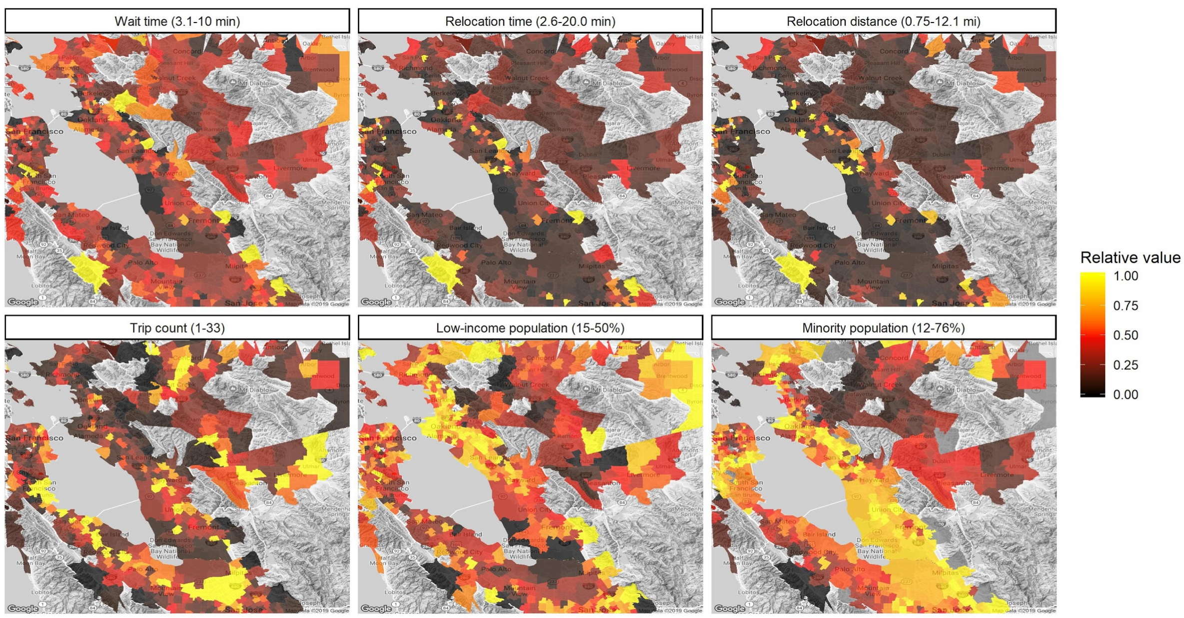


Figure A8. Comparative results for San Francisco Bay Area base simulation in RISE showing the 5th-95th percentile range of each statistic. Trip counts are outputs for ridehailing from BEAM, and low-income and minority statistics represent shares of total travelers in StreetLight Data.