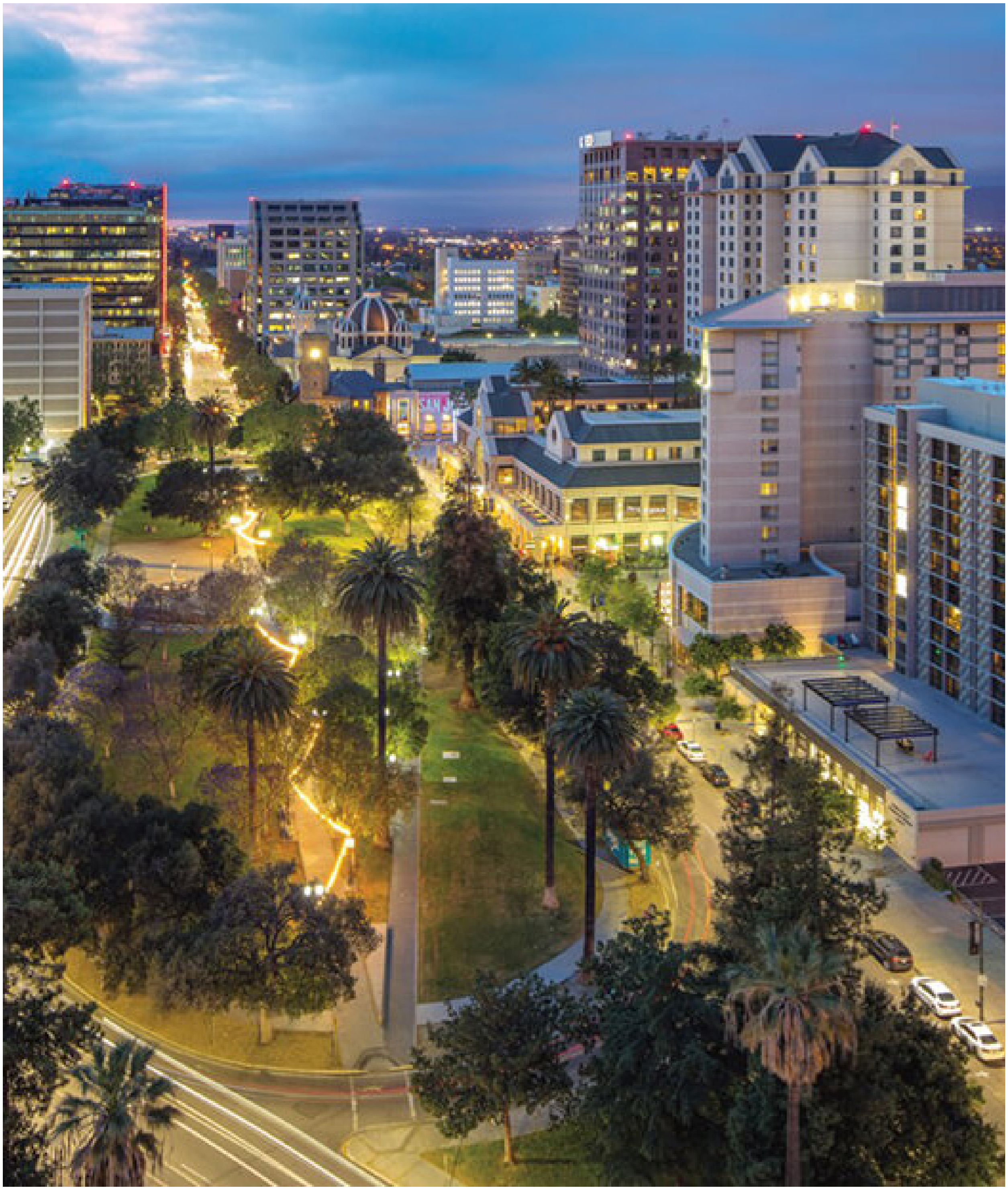

San Jose
Travel Forecasting Report

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Introduction

Abstract

A thriving, populous city as San Jose, California, is the ideal environment for exploring transportation implications from working from home trends given the strong presence of the tech sector. Although this industry had pioneered in these practices many years before, it is undeniable how the Covid-19 pandemic accelerated a transition to remote activities when possible, needed, or desired. The analysis expects to forecast not only reductions in Vehicle Miles Traveled (VMT) and/or ridership, but also to see some uneven distribution of travel changes because of how jobs and their associated industries are concentrated across the territory. Additionally, results and implications will be also mindful of inequalities of other kinds, regardless of the location: namely low income, no vehicle ownership, and unemployment / inactivity at the household level.

San Jose Metropolitan Statistical Area (MSA)

San Jose, located in the heart of Santa Clara Valley in California, is the most populous city in Northern California and the third most populous city in the state (according to 2020 Census, 1,013,240 inhabitants, with a decennial growth rate of 7.1%). It is also the largest city by area in Northern California, and the major city of its MSA, the San Jose-Sunnyvale-Santa Clara Metropolitan Statistical Area (MSA), having roughly half of its population.

The metropolitan region is ranked second for the most expensive rent by the National Low Income Housing Coalition. The median home price is $1.3 million and buyers' income is at least $203,000 for affordability. This is strongly related to San Jose's location in Silicon Valley. The high growth in the tech sector in the past decades, driven by large employers such as Apple and Google, contributed to a rise in the average annual salary to $83,960 (as of 2021, this was 1.57x the national average). The tech sector also provided a quick recovery from the recession brought by the pandemic.

As for transportation, the average commute time is 26-28 minutes for most of San Jose with the southern tip being the highest, of 33 minutes or more. The central city of San Jose has the highest rate of use of transit and lowest use of personal vehicles for commuting of all the MSA zip codes. Despite the presence of biking and pedestrian activities in the central city, San Jose is still highly dependent on automobiles for commuting with over 80% of car usage. The average vehicle ownership varies from 1.8 to 2.2 with higher ownership of 2.3 cars per household or greater in certain areas to the southeast of the city and concentrated areas around Rockspring with no vehicle ownership. The proportion of commuters who cycle to work ranges from 0.1% to 1.5%, constituting a small share. Lastly, most of the transit service is concentrated in between the central city and Santa Clara along the Airport.

Methodology

Using census tracts, the number of employees were considered according to broad categories of industries: 'basic jobs', 'service jobs', and 'retail jobs'. Employees were added up since LEHD OnTheMap data suggested the share of employees working at their same tract (and thus implying no interzonal travel) was negligible, so theoretically possible overlaps have been disregarded in practice.

Service jobs were considered, as opposed to retail jobs or basic jobs, as suitable for working from home. This definition is a simplification, since belonging to an industry does not imply by itself the type of task that is performed (which is what actually would define suitability for remoteness). The assumption is that in quantitative terms, the effects are canceled (the service jobs that are not suitable for WFH compensate basic and retail jobs that are). It is acknowledged, however, that spatial distribution might experience some noise because of this.

Under a hypothesis of upcoming paradigms of working from home on a twice-a-week basis, employees would not commute to their workplace during 40% of the week. Considering the object of this travel forecasting exercise is an average weekday, this is equivalent to reducing 40% of the workforce + positions in the industry any given day (assuming WFH choice is uniform along the week, e.g., ignoring any biases towards Fridays). It must be acknowledged, however, that this reduction is not only related to the pandemic's aftermath: probably some of these workers were already remote once a week, for example, meaning that some percentage points of 40% have not been recently added, but rather existed. Demographic data also accounts for employees who worked from home as a default, and this information is taken into account as well prior to defining the baseline and the alternative scenario.

An additional implication of the exercise is that for commuting purposes, employment suitable for WFH disappear, but projected behavior for these workers will not be equivalent to that of an unemployed, and might imply other kinds of travel. These workers are not completely deleted, but just unobservable in terms of commuting, and reinterpreted with regards to other activities.

Zones

Summary

The target zones, defined as the census tracts belonging to the San Jose MSA (Metropolitan Statistical Area) have been analyzed for the suggested topics: mainly household, income, vehicle ownership, and employment-related census variables. On top of this diagnosis, the proposed alternative scenario accounts for deepened working from home trends as compared to a pre-pandemic baseline (sources are from 2019, namely the 2019 US ACS 5-yr. estimates). After defining assumptions about the nature and the future of those trends, the phenomenon is expected to reduce the network's number of commuters, *a priori* without affecting employment (at least directly), which would seem unprecedented at a large scale. It was known that the expected impact would be uneven both spatially and across industries, which in turn would correlate to income groups and other socioeconomic dimensions.

ACS variables

The scope of the analysis of census data was related to the broad income (Figures 1 and 3) and vehicle ownership distributions (Figure 2), while also showing the spatial distribution of the most vulnerable tail: where households not owning a vehicle (Figure 5), not featuring any workers (Figure 6), or earning less than 10 thousand dollars a year (Figure 7) are concentrated. Summarized statistics of how tracts are precisely distributed according to these vulnerability indicators are also provided (Figure 4).

LEHD variables

As for labor-related variables, census block-level data were collapsed into census tract-level data, which were in turn joined to their ACS counterpart. A dual approach of labor supply (employees at each location and from each industry) and labor demand (job positions at each location and from each industry) was conducted. One challenge at this point was the possibility of positions belonging to local residents, since summing employees and jobs per tract might had overestimated the metric because of their potential overlap. For a perfect overlap (all local workers work within their tracts, and/or all local jobs are undertaken by tract residents), the correct approach would have been to compute the maximum value between labor demand and labor supply counts. As if it were not enough, an infinite continuum of intermediate Venn diagram combinations could have been the most accurate answer instead, requiring either additional (but extremely sensitive) assumptions, or further evidence.

By using LEHD OnTheMap for observing a small but representative random sample of the defined zones, it held true that the proportion of workers who happened to live at the same tract, or of residents who happened to work at the same tract, was completely negligible. The simplification of having purely independent supply and demand was then a feasible and compelling option: for modeling purposes, jobs generated at a census tract would attract trips from elsewhere, and residents from the tract having an occupation would similarly generate outbound trips according to their magnitude. This assumption also made working from home trends more visible, given that they would clearly divert from the norm (being the only workers who do not travel to other defined zones).

WFH assumptions

Among the employees and jobs available at the LEHD database, industries suitable to working from home practices were defined as those identified as *Service Jobs* (as opposed to *Basic* or *Retail Jobs*). Reasons for this selection were intuitive, based on stereotypical positions and tasks performed by each sector.

Zones

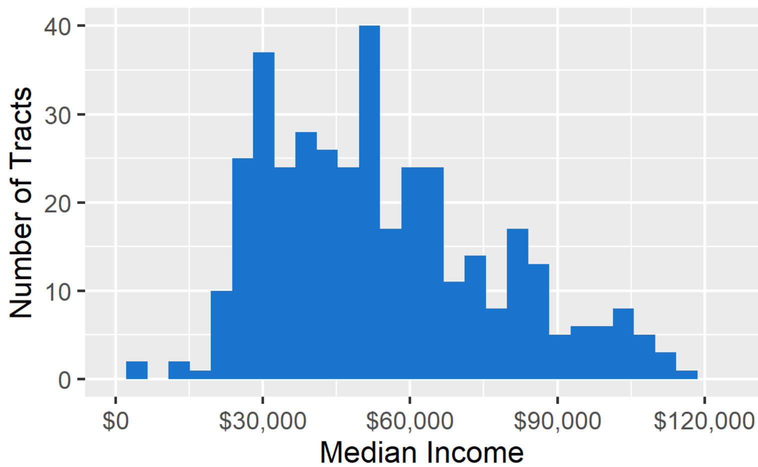


Figure 1 - Distribution of the median income across tracts.

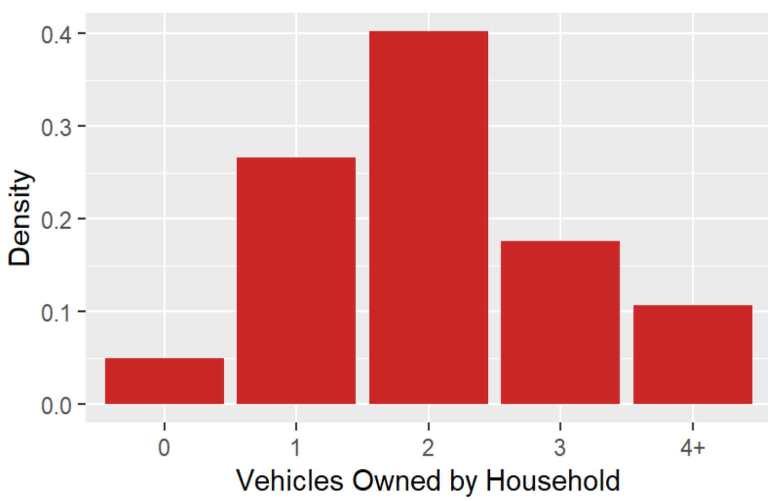


Figure 2 - Distribution of vehicle ownership across tracts.

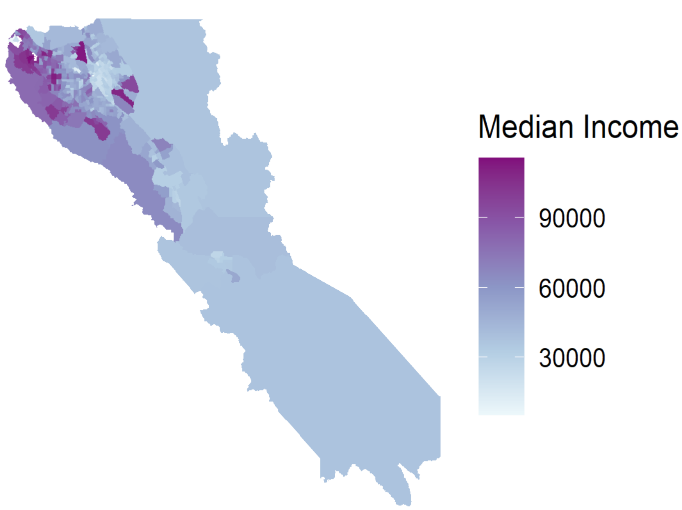


Figure 3 - Spatial distribution of median income by tract.

The future trend for these compatible jobs was set in the following way: given that trips will be estimated for the average weekday, and that a two days per week WFH regime seems an upcoming norm, not commuting on two out of five weekdays is equivalent to reducing the number of commuters on the average day by the same proportion: 40% less workers would travel to their jobs and back. Employees who had declared having been already working from their homes as the default regime in 2019 were assigned to the same group.

Alternative scenario: Implications

Before zooming into bias and skewness brought by the uneven distribution of the involved industries, a first implication to be mindful of is that the baseline only includes data about those who worked from home permanently, and thus overlooks any possibly existing weekly regime (e.g., flexible Fridays where WFH is an option). For that reason, the number of commuters in the sectors suitable for working from home is set to drop by 40% with regards to the total number of workers who did not work from home permanently. However, part of this percentage was not commuting even before the pandemic. For example, if the average worker had been favored by this regime once a week, the current twice-a-week assumption would mean 40% of the workers are not on the streets commuting, but only half of them (each weekday is equal to 20 percentage points) are derived from the most recent trends, whereas the other half had been removed from commuting networks in the last decades due to technology and modern habits, and it would be inaccurate to attribute them to post-pandemic customs.

After clarifying the initial interpretations, an additional choropleth (Figure 5) shows where employees and positions that could disregard commuting are more concentrated (those suitable for WFH as a percentage of the total number of employees and positions altogether). On top of the correlation with income and its distributive impact, suitability was found to also be concentrated near Downtown San Jose. This poses some limits to hypothetical overall social benefits derived from reducing long-distance trips: travel time and fuel saved, or avoided externalities like emissions, might not be as large as expected.

Finally, a weighted scatter plot (Figure 9) shows a positive correlation between census tracts' ability to work from home and their median incomes. This would not necessarily harm the poorest census tracts, but the reduction of any trip saturation would be rather limited to the richer ones. What is an additional concern is reflected by the weights: thicker points indicate higher percentages of households not owning a vehicle. Not surprisingly, most of them are located at the bottom of the income distribution, where WFH is not able to help in mitigating the demand for mobility. Nevertheless, the potential alleviation of traffic, transit, and transportation in general for the richest sectors thanks to post-pandemic working from home trends should make public resources available to be instead invested in the poorer communities who most need it.

Vulnerability Ratios

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
ratio_no_veh	417	0.049	0.049	0	0.02	0.034	0.064	0.387
ratio_no_worker	417	0.19	0.074	0.028	0.143	0.176	0.231	0.551
ratio_lt_10k	417	0.029	0.025	0	0.012	0.024	0.038	0.198

Figure 4 - Summary statistics for the whole MSA, focusing on the distribution of the most vulnerable population across the census tracts.

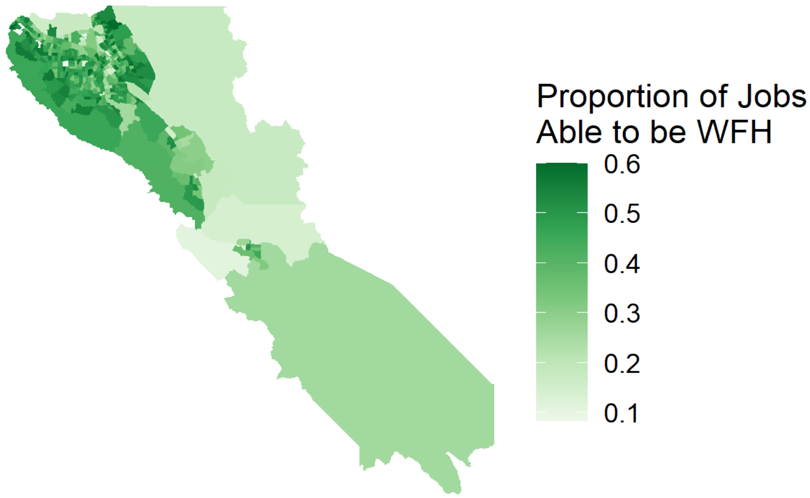


Figure 5 - Proportion of jobs that would be suitable for working from home according to this paper's definition. Recall Figure 3 and how similar their highlighted census tracts are. Additionally, Downtown San Jose concentrates most of the jobs suitable for the analyzed regime.

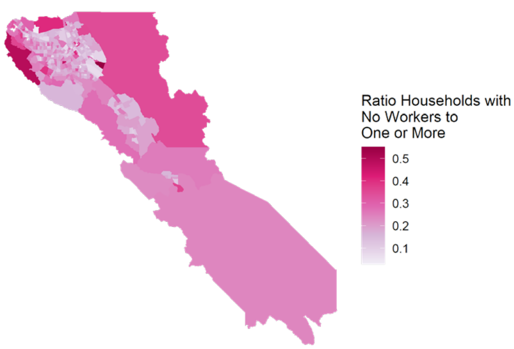


Figure 6 - Ratio of households not having any workers. Spatial correlation is not that clear, and senior households could offer an explanation for high values while not necessarily being problematic.

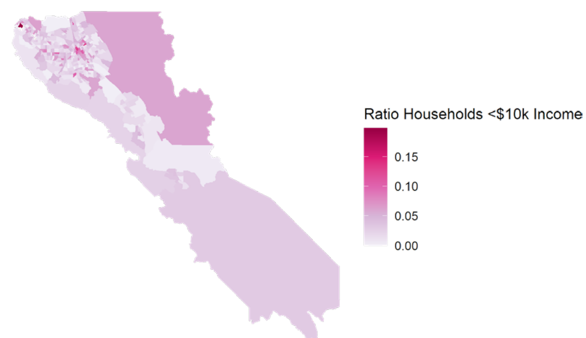


Figure 7 - Share of households with an annual income under USD 10k. Some centric and peripheral tracts show the highest values, whereas the furthest outskirts are not particularly poorer from this perspective.

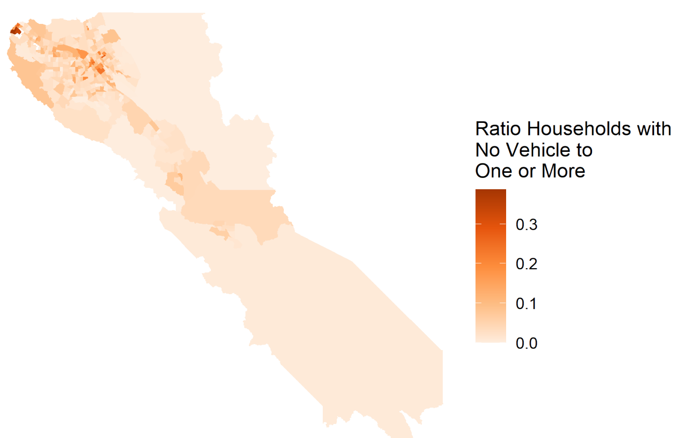


Figure 8 - Share of households not owning any vehicles. One outer census tract draws particular attention, but the ratio seems to be higher near Downtown San Jose.

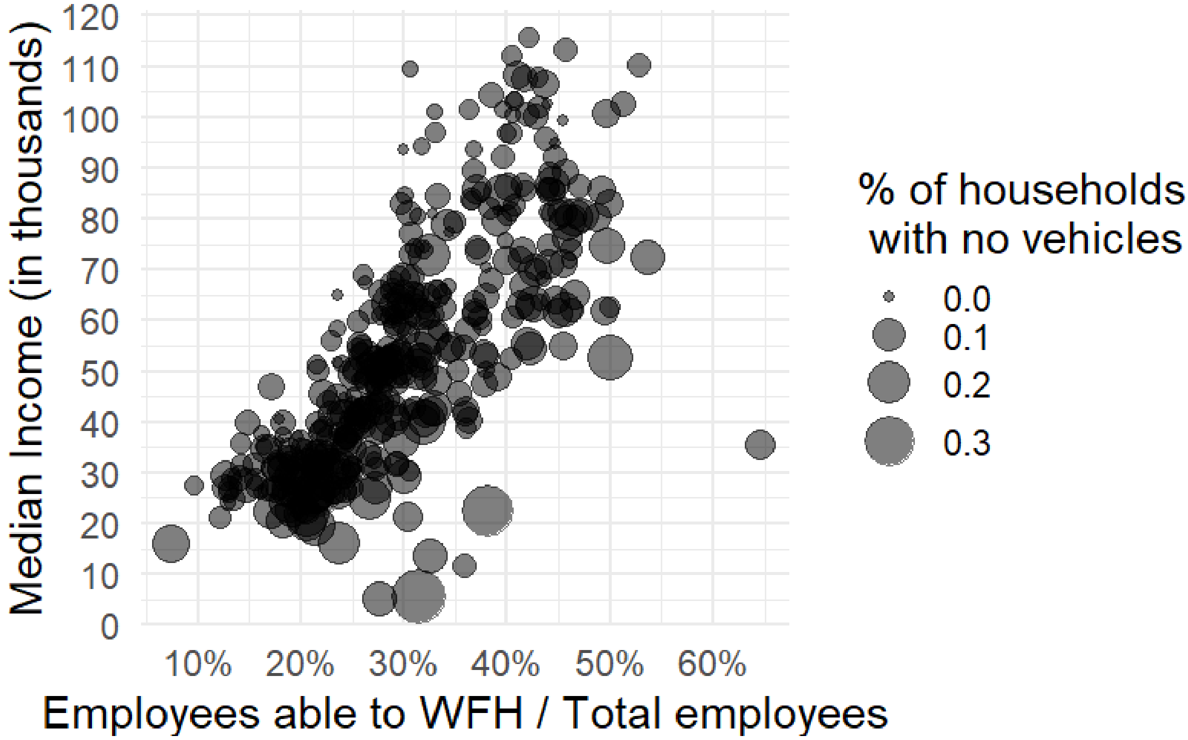


Figure 9 - WFH suitability versus median income. The positive correlation is undeniable, and the large circles at the bottom (tracts with many households not owning vehicles and not able to work from home) suggest possible scopes for future policymaking.

Networks

Overview

The proposed alternative for this analysis does not change the street or transit networks; the proposed changes affect the population only. The skims generated for the existing scenario are therefore identical to those generated for the alternative scenario.

The skims presented below for travel by car, transit, bicycle, and foot have calculated the time it takes to travel from each of the census tracts in the San Jose MSA to the tract in San Jose with the highest number of jobs, as this likely indicates the area with the greatest inflow and outflow of commuters daily.

The results of the four skims are shown below. The size of the two-hour travel area varies by mode, with cars having the largest area, followed by transit, bicycles, and pedestrians. Travel by car is the only mode in which a traveler can reach every zone in under two hours.

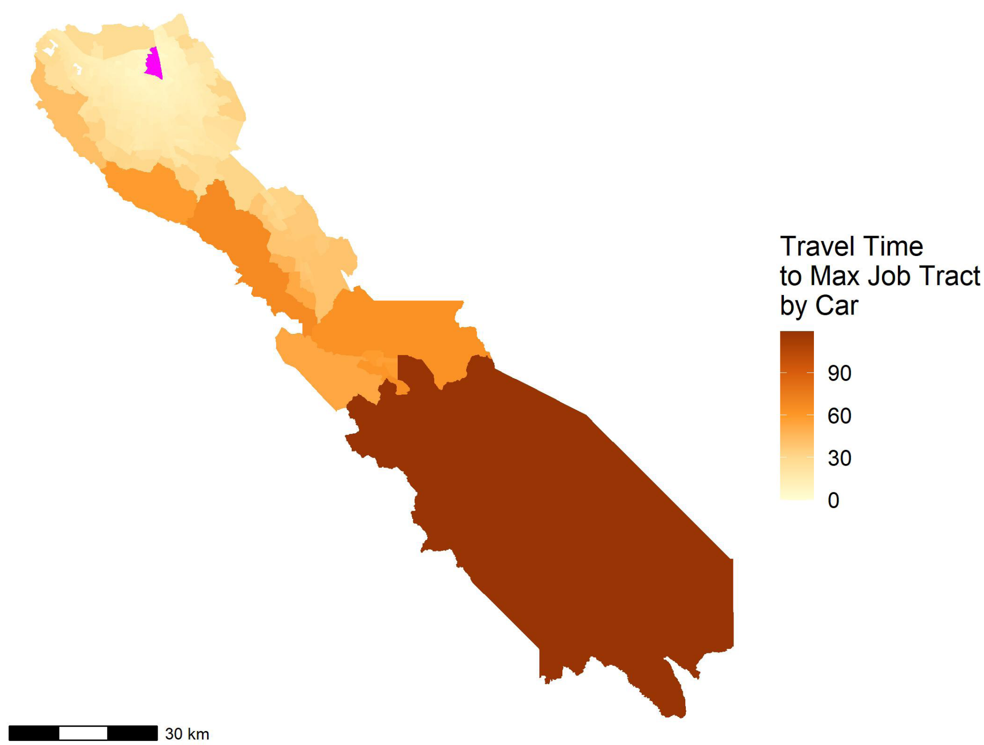


Figure 10 - Car Travel Time.

Figure 11 - Transit Travel Time.

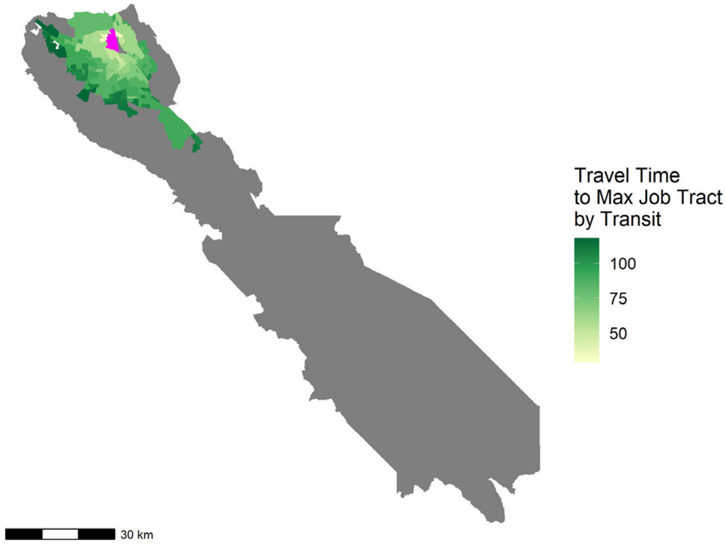


Figure 12 - Bike Travel Time.

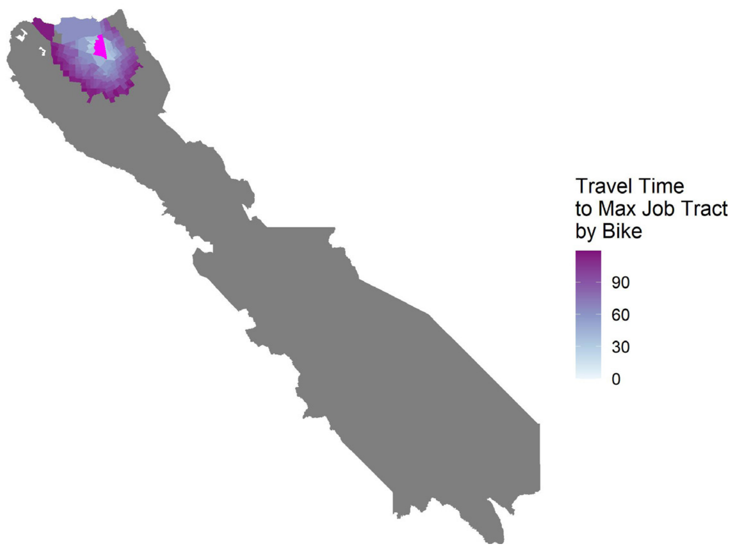
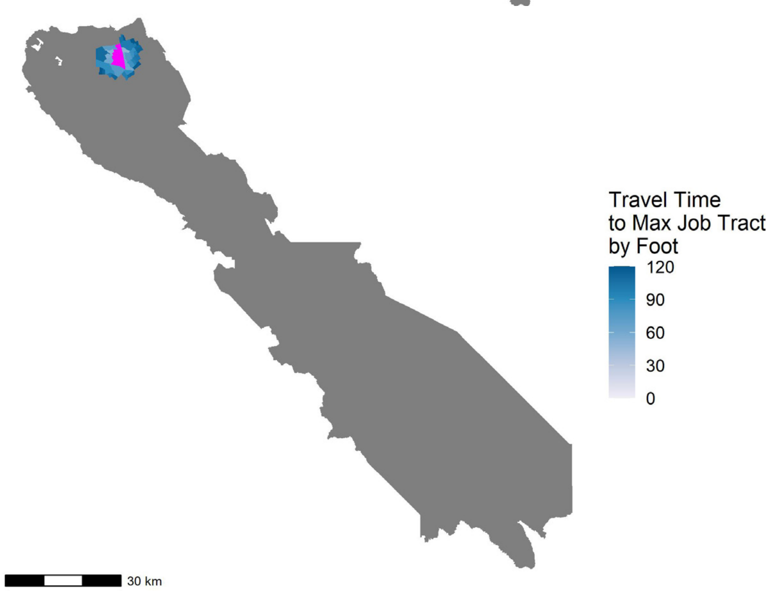


Figure 13 - Pedestrian Travel Time.



Networks

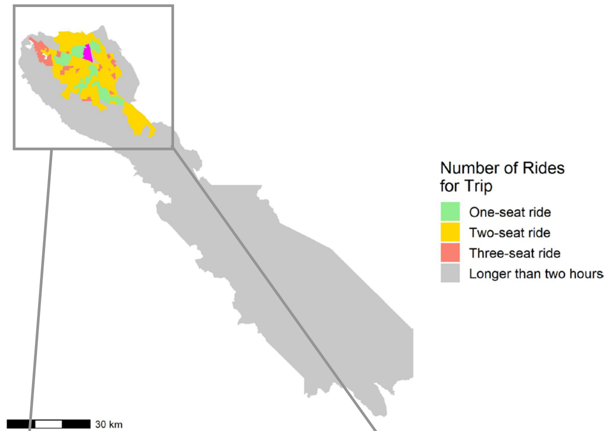


Figure 14 - Necessary Transit Transfers.

Access to the Valley Transportation Authority (VTA) in the MSA is largely concentrated in San Jose. Most of the transit network can be accessed from the major business center within two hours in two- or one-seat rides. The north western area is accessible in under two hours in a three-seat ride. The VTA routes do extend farther south than the San Jose city limits, but it takes longer than two hours to get there on transit. A traveler can only get to the edges of the MSA in under two hours by traveling in a personal vehicle.

Downtown San Jose, as expected, has the densest street network within the MSA. Figure 16 shows the primary, secondary, and tertiary roads.

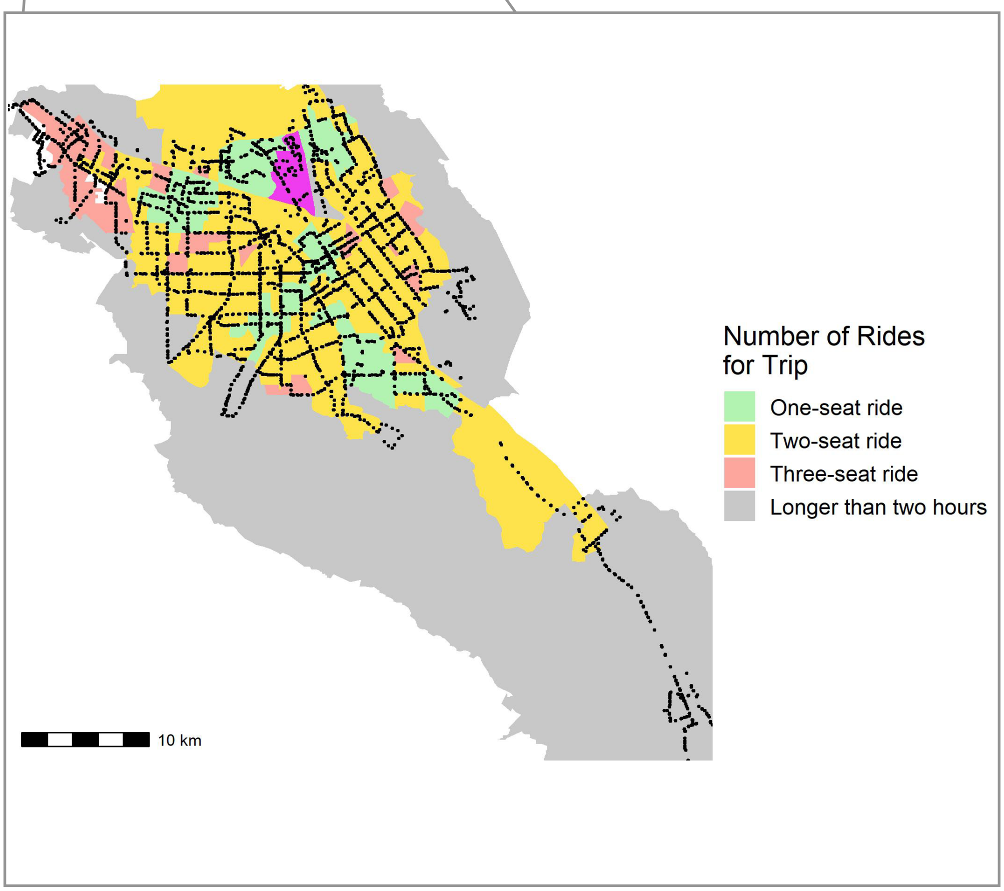


Figure 15 - Existing Transit Stops

Networks

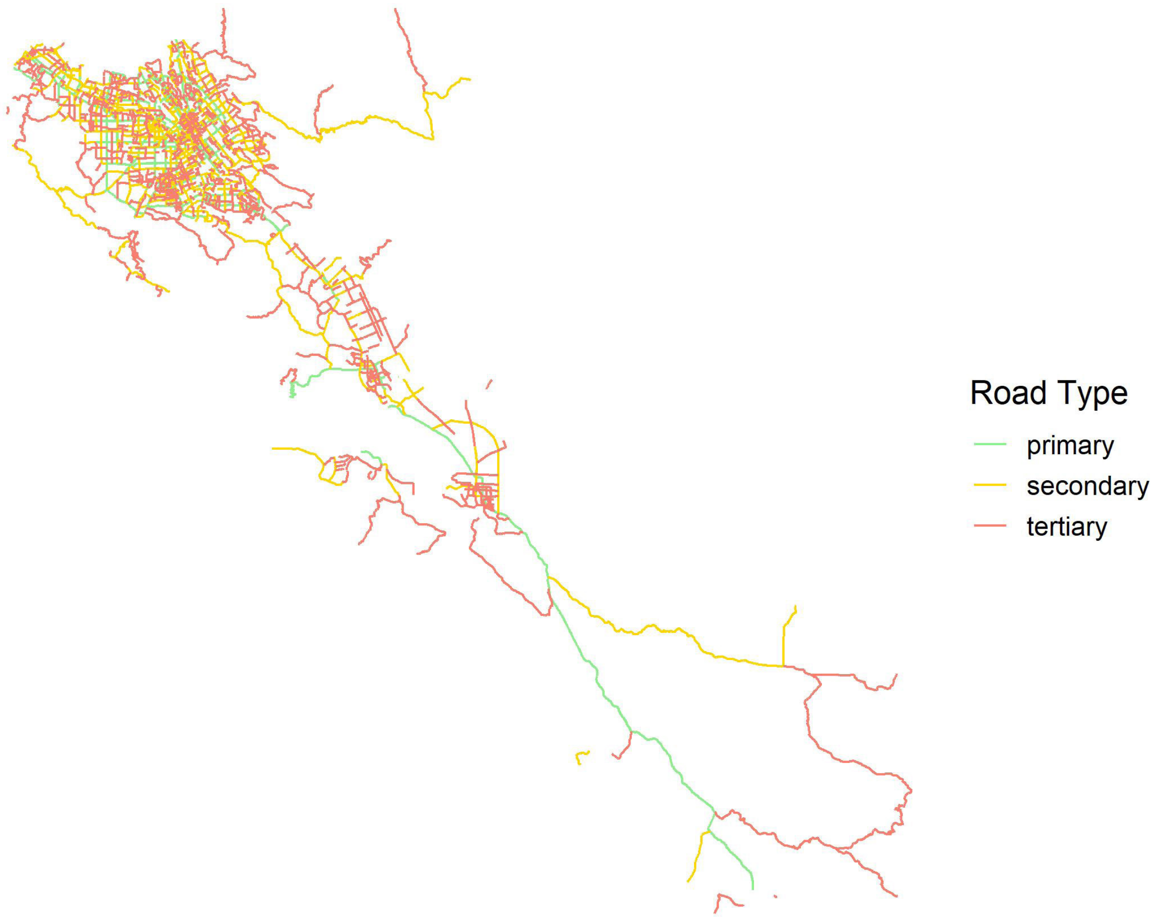


Figure 16 - Road Types.

Accessibility

Background

A broad consensus in the field defines accessibility as the availability of opportunities (proximity, Figure 17) reachable in a specific amount of time (related to mobility, Figures 15 and 16 at the previous page). Consequently, results for accessibility studies at San Jose MSA census tracts will be deeply related to both elements.

Not surprisingly, opportunities, defined as jobs (Figure 17), are concentrated around the downtown, with some minor participation of cities like Morgan Hill. Both transit (Figure 15) and road networks (Figure 16) also show concentration at Downtown San Jose, from which a narrow corridor runs up the valley, until it eventually vanishes in terms of hierarchy.

Conducted Study

The analysis used 30 minute cutoffs for driving and riding transit respectively, taking for the latter an average starting time at 4 p.m. on a weekday, and along a 2-hour window, intending to target evening peak hours' headways. The selected decay function was the logistic one. Reasons for this decision responded to its smoother curve (unlike step or linear), while it maintains an inflection point (unlike exponential). Also, given the relatively small number of tracts, the higher computational capacity it requires could be handled in a decent time. Finally, the study was considered to have no alternative scenario: working from home reduces the number of weekly commutes, but as for accessibility, it is still important for potential workers to be able to get to their offices when needed. Their potential positions are fixed at some specific locations even if remoteness is becoming increasingly often an option.

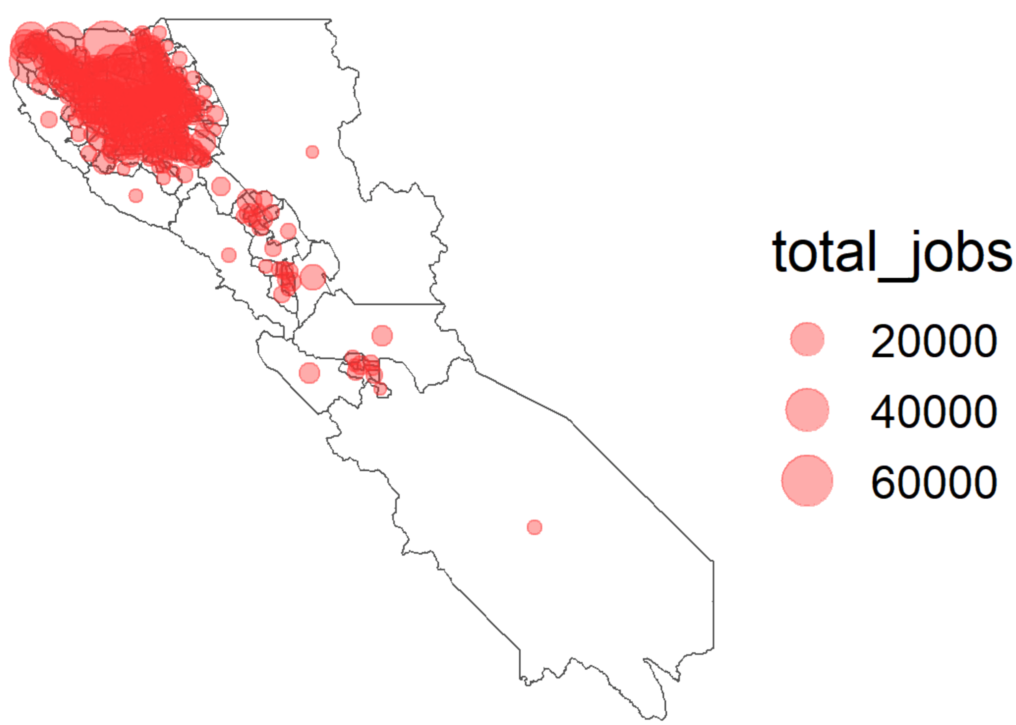


Figure 17 - Centroids of the census tracts showing the number of jobs they offer.

Accessibility

Results

Results are summarized by Figures 18 and 19. As a general fact, having ratios below 10% for almost every tract and below 5% for a vast majority of them (Figure 18) suggest that transit is not nearly as appealing as driving is at this MSA, leading to expected car-oriented preferences (at least with regards to accessibility).

However, in relative terms, there were some counterintuitive findings. Tracts closer to the downtown have worse ratios despite their much better transit supply. The effect that seems to prevail is that the further potential workers can travel, the more tracts they can *conquest*, and consequentially, the more job opportunities they can reach. Some peripheral census tracts, in turn, perform slightly better (or even *perfectly* in some cases) not because transit mobility is equally as good as that derived from driving, but instead because at them, any given commuter can only access the local (tract-level) jobs. This means that in 30 minutes, neither driving nor riding transit could take potential workers from their *hometown centroid* to another one. The southernmost census tract of the MSA is an example of this, with a ratio equal to 1.

An additional anomaly for the study was the case of the *gray* census tract to the northeast (see Figure 19), where the ratio turned out to be infinite. After double checking the outputs, this was not a *0/0* indeterminate form (that although it still would have been a bug, it would have been at least uniform), but truly a division by zero, meaning that the transit rider could reach the jobs at his/her own tract, but drivers could not reach any. The hypothesis in this case is that the centroid probably lies somewhere completely detached from the road network, and while transit options include the ability to walk to stops, driving ones need trips to be feasible 100% on a car.

A final remark is that if these models could account for congestion, transit at central areas would be likely to perform relatively better when compared to driving.

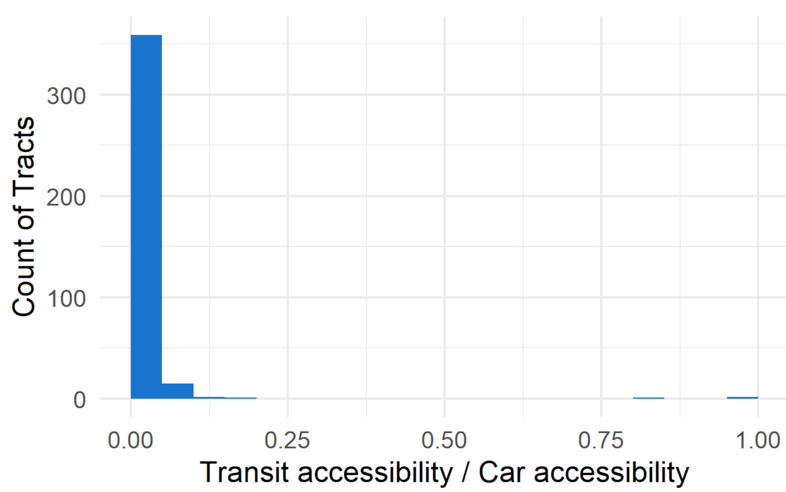


Figure 18 - Histogram showing the count of tracts according to their ratios between transit accessibility and car accessibility. The bins group 5-pp. intervals.

Accessibility

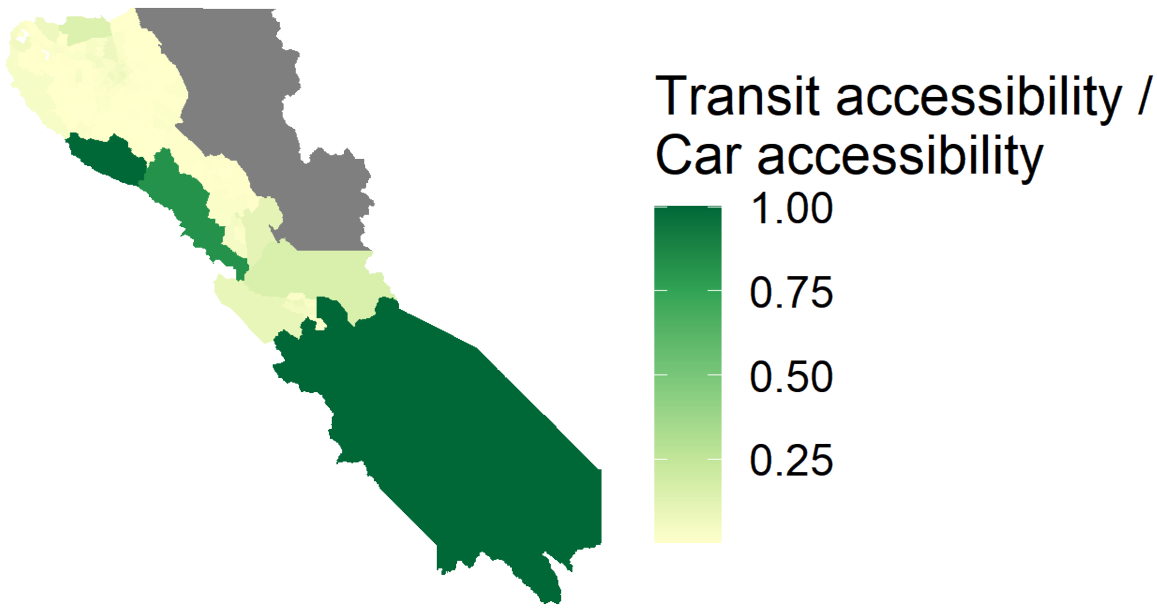


Figure 19 - Choropleth map showing the different ratios of transit accessibility to car accessibility. The southernmost tract counterintuitively shows a *perfect score* due to its remoteness.

Vehicle Access Model

Overview

The regression model was used to predict the number and percent of zero-vehicle households in each zone, based on zone-level household and employment characteristics. Work-from-home changes in employment and transit access were found not to be statistically significant for the alternative scenario. Nevertheless, these variables were included to predict the alternative percent of zero-vehicle households in each tract.

(Intercept)	0.09 ***
	(0.02)
pct_big_hh	-0.10 ***
	(0.01)
pct_lo_inc	0.39 ***
	(0.04)
pct_hi_inc	-0.06 ***
	(0.02)
pct_wfh_pop	0.04
	(0.06)
transit_access_100k	0.02
	(0.02)
N	381
R2	0.56

*** p < 0.001; ** p < 0.01; * p < 0.05.

Figure 20 - Regression results.

no_veh_hhE		no_vehE	
Min.	: 0.00	Min.	:-Inf
1st Qu.	: 29.00	1st Qu.	: 40
Median	: 57.00	Median	: 69
Mean	: 87.25	Mean	:-Inf
3rd Qu.	:108.00	3rd Qu.	: 113
Max.	:860.00	Max.	: 490

Figure 21 - Descriptive statistics of existing (left) and alternative (right) zero-vehicle households per tract.

Regression Model

Using scatter plots, the different variables are visualized while related to the independent variable of zero-vehicle households for the existing data. Correlation with low-income households was explored at Figure 20, showing evident correlation. Conversely, working-from-home population at each tract did not show clear correlation with household vehicle ownership (Figure 21).

Linear regressions were further used to confirm this finding. In the model, the variables that were statistically significant at the 0.1% level were the percentage of big households, the percentage of low-income households, and the percentage of high-income households. Working-from-home changes in employment and transit access were not statistically significant for our alternative scenario (Figure 22).

No simplified model was built by removing non-statistically significant variables, given that the scope of the report is on working-from-home populations.

By applying the coefficients to the alternative scenario, the alternative percentage of zero-vehicle households was obtained.

Model Prediction on Vehicle Ownership

The model showed that fewer tracts had no zero-vehicle households in the predicted vehicle ownership distribution (Figures 23 and 24). This might be because of the positive linear correlation between WFH population and transit access with zero-vehicle households. The median also increased from 57 zero-vehicle household to 69. Nevertheless, the maximum zero-vehicle households for a tract decreased significantly for the predicted alternative from 860 to 490 (Figure 25).

Vehicle Access Model

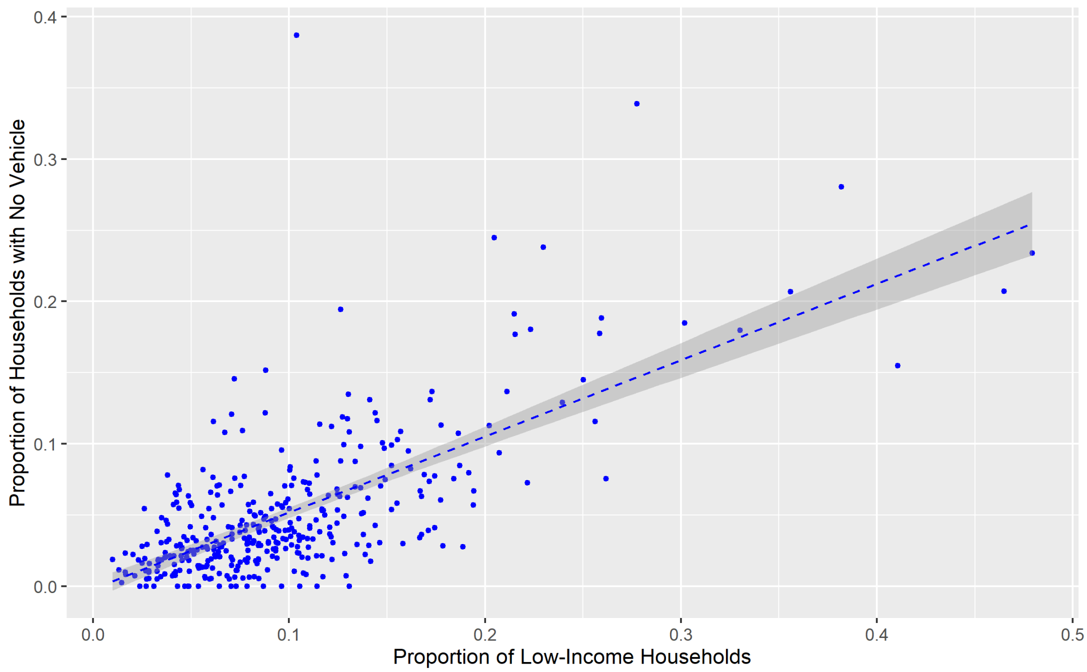


Figure 22 - Scatter plot showing the proportion of zero-vehicle households versus the proportion of low-income households.

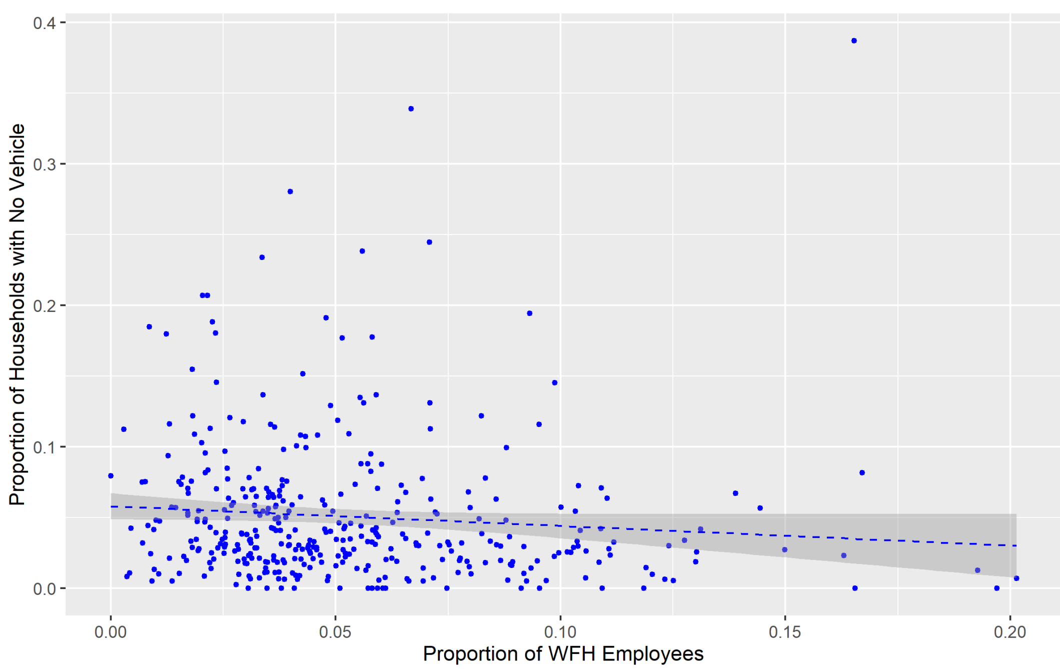


Figure 23 - Scatter plot showing the proportion of zero-vehicle households versus the proportion of working-from-home population.

Vehicle Access Model

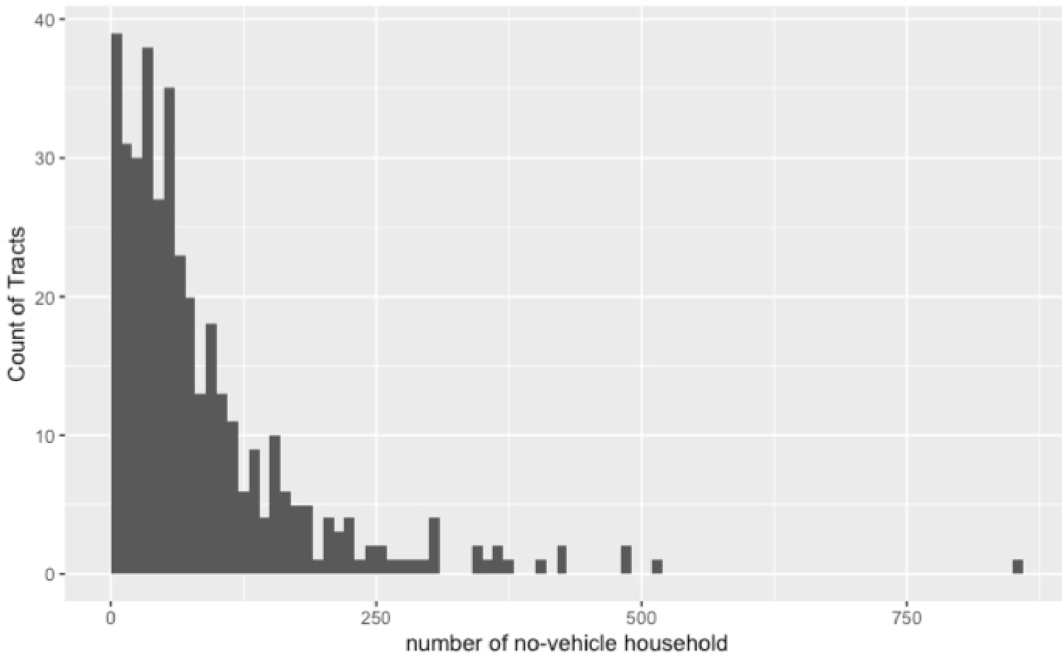


Figure 24 - Histogram of the existing vehicle ownership.

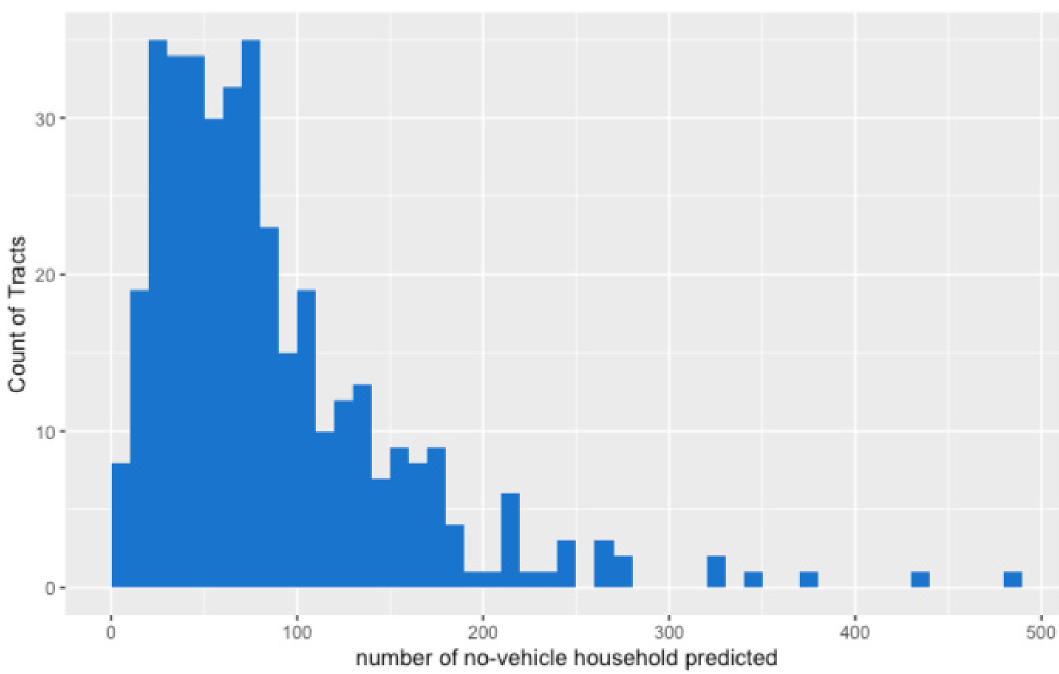


Figure 25 - Histogram of the predicted, alternative vehicle ownership.

Trip Generation Models

Overview

This chapter details the findings of the trip generation analysis and how trips generated differed between the existing and alternative scenarios. NHTS data were used to estimate three regression models that were in turn used to predict the number of home-based work trips, home-based other trips, and non-home-based trips per household in the San Jose MSA. These models estimate all person trips, including both motorized and non-motorized trips.

For the three trip types, the explanatory variables that had a statistically significant effect at the 95 percent confidence level on the number of trip productions included household size and ratio of workers who worked from home. Zero-vehicle households and household income were initially included but were not found to be statistically significant and did not substantially change the R2 value so were ultimately excluded.

Home-Based Other Trips

Home-based other (HBO) trips refer to trips that either originate at home to go to a location other than a person's place of work, or end at home coming from a location other than a person's place of work. The regression model used to estimate the trips produced in each zone in the San Jose MSA is included below as Figure 26. The regression model suggests that the larger the household, the more average daily HBO trips are made, holding all else equal. Households with one person make almost six fewer HBO trips on average than households with four or more people. Additionally, the model suggests that the average household in zones with a high WFH ratio will make almost one additional HBO trip per day than zones with a low WFH ratio. This finding seems logical because individuals need to run errands and perform other various activities that other people who do not work from home may perform with a trip originating at the office, for example stopping at the grocery store on the way home from work.

After applying the regression model to the analogous household-level variables in each of the zones, HBO trip productions and subsequently the HBO trip attractions were estimated for each zone in the San Jose MSA. Estimating the trip attractions also required balancing them so the regional total of attractions matched the total number of trip productions estimated by the regression model. The zones with the highest amount of productions and attractions are, as would be expected, in line with the zones with the highest populations. Figure 27 below shows the HBO trip productions and attractions in each zone for the existing conditions, where

	Full model		Reduced model	
(Intercept)	8.01 ***	(p = 0.00)	7.67 ***	(p = 0.00)
zero_veh_TRUE	-0.83	(p = 0.13)		
size_one	-5.67 ***	(p = 0.00)	-5.84 ***	(p = 0.00)
size_three	-2.33 ***	(p = 0.00)	-2.44 ***	(p = 0.00)
size_two	-4.45 ***	(p = 0.00)	-4.49 ***	(p = 0.00)
inc_quint_2nd	-0.17	(p = 0.85)		
inc_quint_3rd	-1.01	(p = 0.16)		
inc_quint_4th	-1.06	(p = 0.13)		
inc_quint_5th	0.13	(p = 0.83)		
wfh_int_high	0.60	(p = 0.13)	0.89 *	(p = 0.02)
wfh_int_mid	-0.46	(p = 0.45)	-0.23	(p = 0.69)
N	906		939	
R2	0.27		0.25	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Figure 26 - Regression Model for HBO Trips.

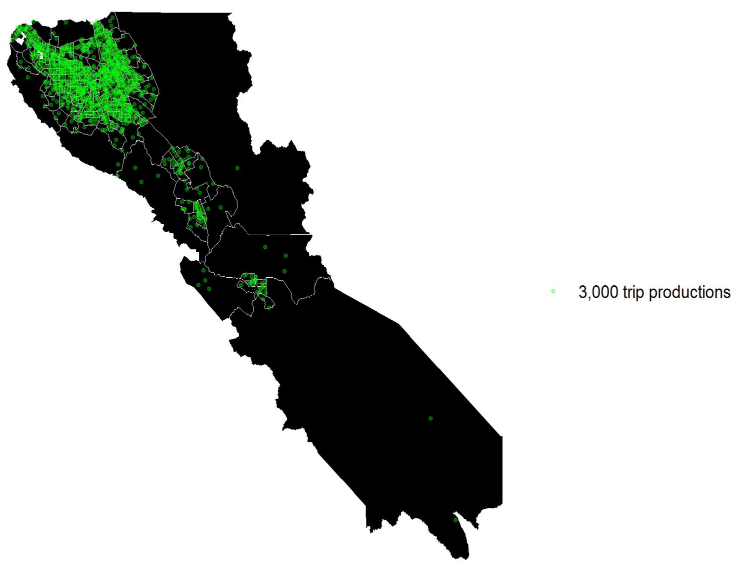
Trip Generation Models

each dot represents 3,000 trip productions and attractions, respectively.

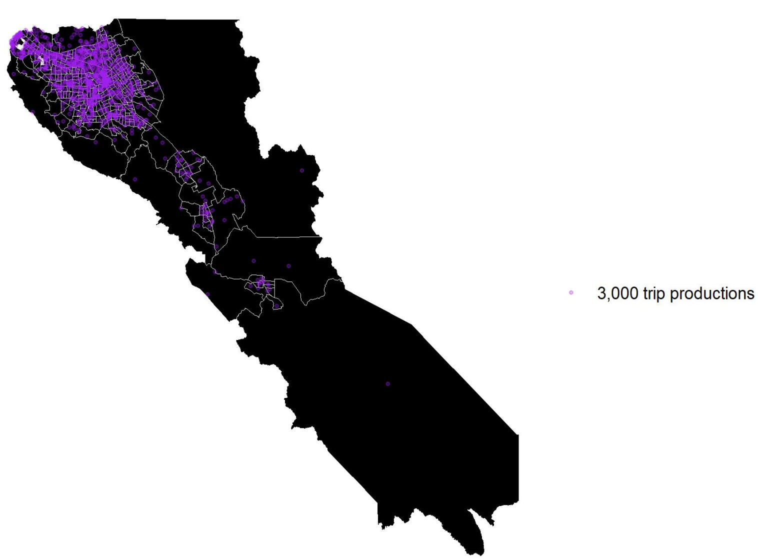
The HBO productions and attractions by zone are in line with expectations, but more interesting is the potential change in attractions and productions from the existing scenario to the alternative scenario. Figure 28 below shows the percent change by zone for HBO trips. All of the zones increased their WFH ratio in the alternative scenario, so naturally all of the HBO trips increased, as suggested by the regression model. However, the variation in percent increases had a much wider range for trip attractions than for trip productions, indicating that in the alternative scenario, people have fewer reasons to travel to the downtown zones for HBO trips.

Figure 27 - HBO Trip Productions and Attractions.

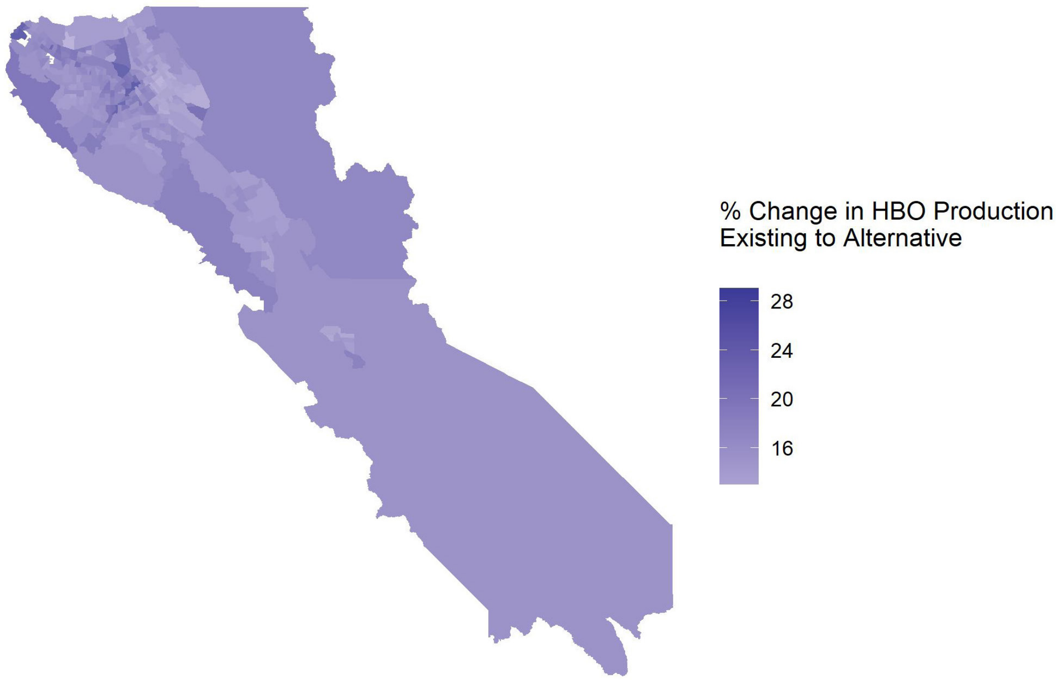
Existing HBO Production



Existing HBO Attraction



Trip Generation Models



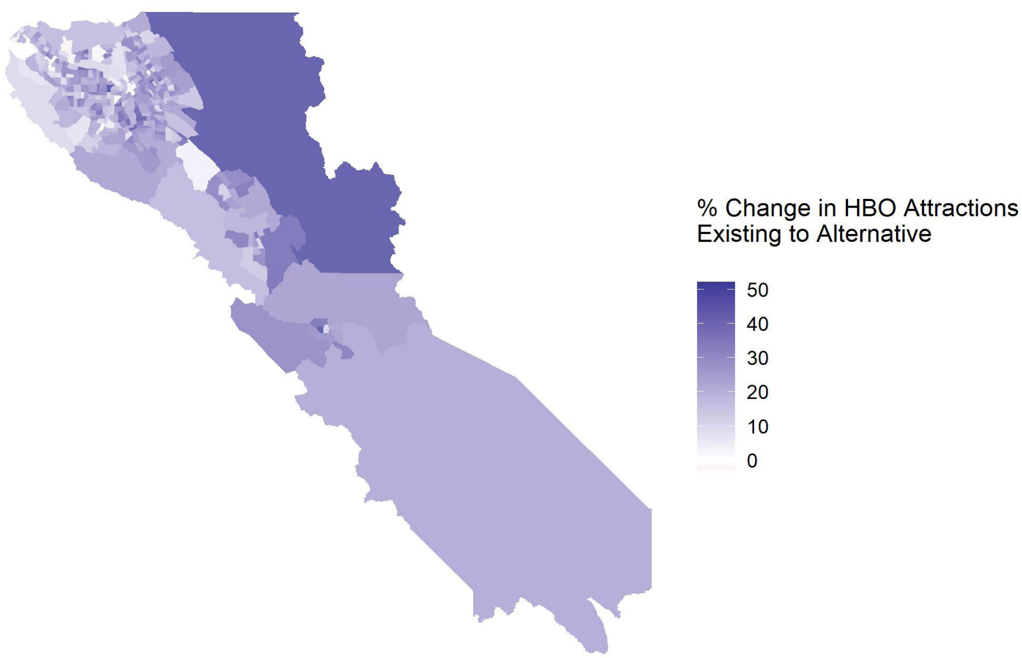


Figure 28 - Percent Change of HBO Trips from Existing to Alternative Conditions.

Trip Generation Models

Home-Based Work Trips

Home-based work (HBW) trips refer to those that originate at home to go to a person's place of work, or vice versa. The associated regression model is included below as Figure 29. The significant variable in this model is again the household size: the smaller the household, the fewer daily HBW trips, all else being equal. The WFH ratio is not a statistically significant variable in explaining variations in HBW trips. The process for estimating the HBW trip productions and attractions by zone was identical to the HBO process. The findings are shown below in Figure 30, which again tracks logically with population.

The HBW productions decreased in every zone in the alternative scenario, which is in line with the main condition in the alternative scenario which decreases the amount of jobs that require commuting. However, the HBW attractions also decreased in most zones but did increase in a few zones as well. This is perhaps an area for further examination, as it implies that there are more jobs that require commuting in those zones in the alternative scenario than in the existing scenario. These findings are shown below in Figure 31.

Non-Home Based Trips

Non-home based (NHB) trips are trips that neither originate or end at home. The regression model used to estimate the NHB trip productions by zone is included as Figure 32 below. In terms of significant variables, the regression model suggests that in the San Jose MSA, a household with one person will make 2.15 fewer NHB daily trips per household compared to households with four or more people, all else being equal. Additionally, the average household in zones with a high WFH ratio will make almost one additional NHB trip per day than zones with a low WFH ratio. This finding is perhaps counterintuitive, as one might

	Full model		Reduced model	
(Intercept)	1.65 ***	(p = 0.00)	1.49 ***	(p = 0.00)
zero_veh_TRUE	0.13	(p = 0.68)		
size_one	-1.08 ***	(p = 0.00)	-1.01 ***	(p = 0.00)
size_three	0.02	(p = 0.92)	0.07	(p = 0.75)
size_two	-0.41 *	(p = 0.02)	-0.40 *	(p = 0.02)
inc_quint_2nd	-0.09	(p = 0.81)		
inc_quint_3rd	-0.15	(p = 0.71)		
inc_quint_4th	-0.22	(p = 0.58)		
inc_quint_5th	-0.12	(p = 0.75)		
wfh_int_high	-0.14	(p = 0.37)	-0.13	(p = 0.37)
wfh_int_mid	0.18	(p = 0.37)	0.22	(p = 0.26)
N	906		939	
R2	0.09		0.09	

*** p < 0.001; ** p < 0.01; * p < 0.05.

Figure 29 - Regression Model for HBW Trips.

	Full model		Reduced model	
(Intercept)	2.70 ***	(p = 0.00)	3.33 ***	(p = 0.00)
zero_veh_TRUE	0.09	(p = 0.89)		
size_one	-2.12 ***	(p = 0.00)	-2.15 ***	(p = 0.00)
size_three	-0.12	(p = 0.80)	-0.17	(p = 0.73)
size_two	-0.75	(p = 0.08)	-0.72	(p = 0.09)
inc_quint_2nd	1.33	(p = 0.08)		
inc_quint_3rd	0.25	(p = 0.66)		
inc_quint_4th	0.79	(p = 0.24)		
inc_quint_5th	0.74	(p = 0.14)		
wfh_int_high	0.80 *	(p = 0.05)	0.94 *	(p = 0.02)
wfh_int_mid	0.27	(p = 0.58)	0.26	(p = 0.57)
N	906		939	
R2	0.07		0.06	

*** p < 0.001; ** p < 0.01; * p < 0.05.

Figure 30 - Regression Model for NHB Trips.

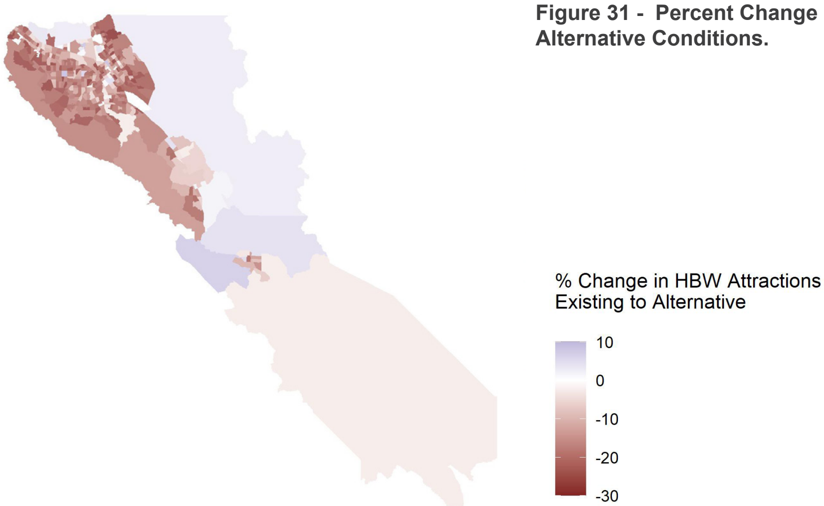
Trip Generation Models

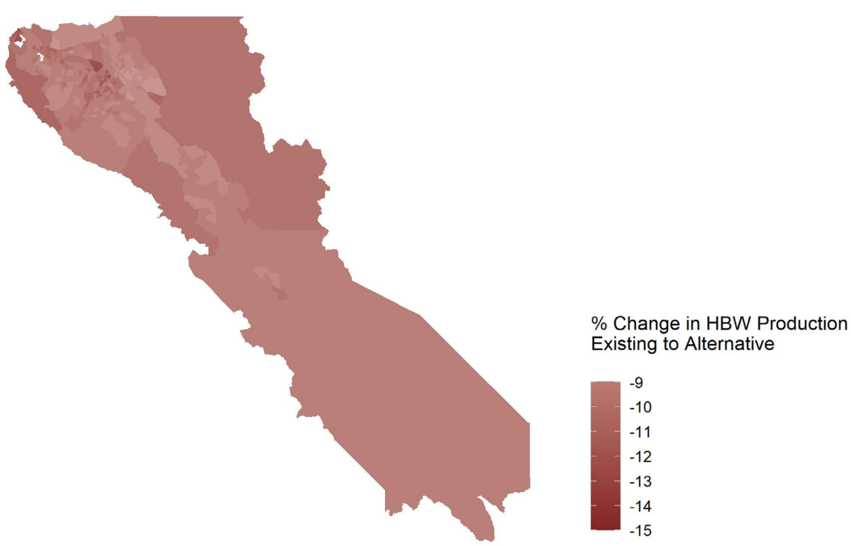
expect NHB trips to be higher for individuals who leave their homes regularly to commute to work and thus have more opportunities to make trips neither originating nor ending at home. It is possible that there is a link between working from home and trip-chaining, although this would need further exploration.

The process for estimating the NHB trip productions and attractions by zone was identical to both processes described for the HBO and HBW trips. The findings are shown above in Figure 33, which again tracks logically with population.

The changes in trip productions and attractions from the existing to alternative scenarios by zone for NHB trips are similar to the changes observed for HBO trips, as seen in Figure 34. The trips increase in every zone for both trip types, but the range of increases for trip productions across zones is much more narrow than the range for trip attractions, suggesting an increase in flexibility allowed by the new WFH scenario.

Figure 31 - Percent Change of HBW Trips from Existing to Alternative Conditions.





Trip Generation Models

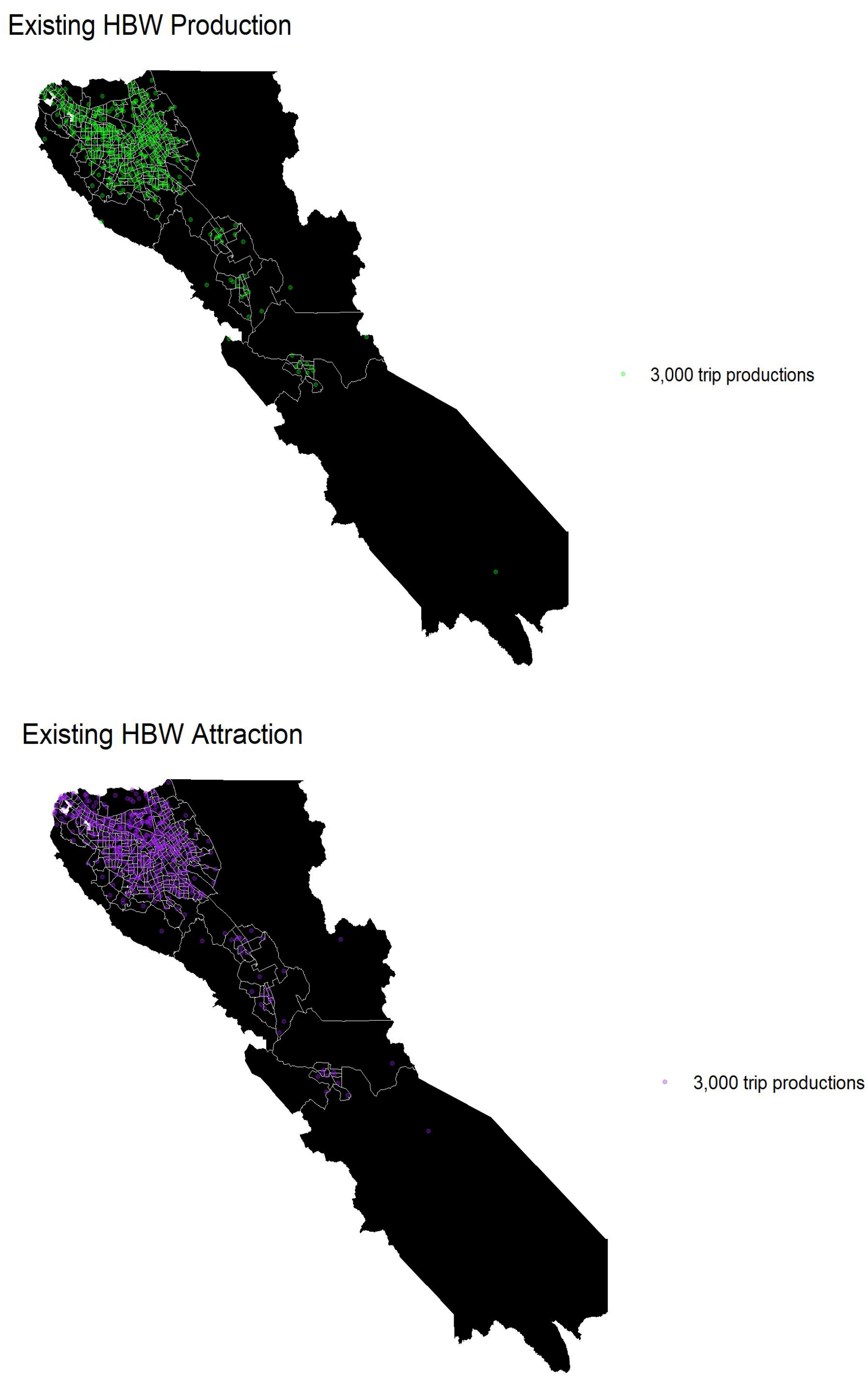


Figure 32 - HBW Trip Productions and Attractions.

Trip Generation Models

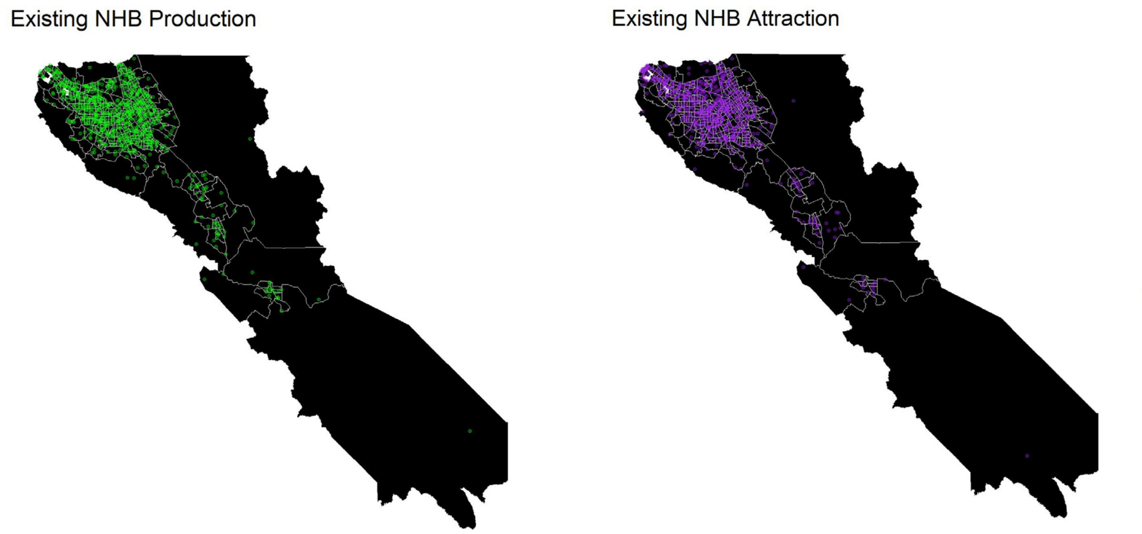


Figure 33 - NHB Trip Productions and Attractions.

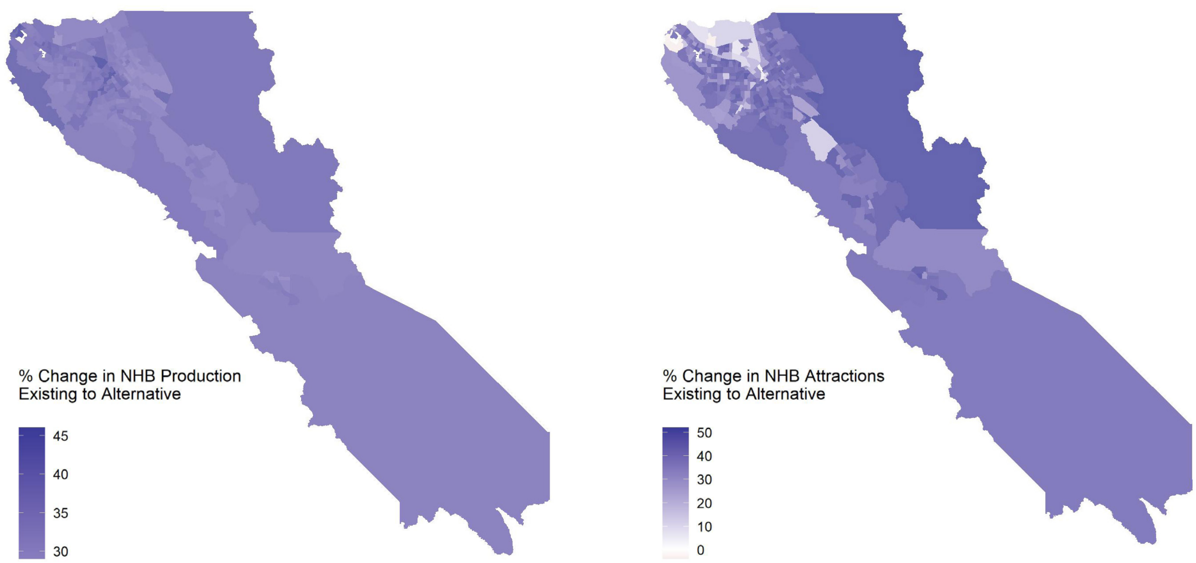


Figure 34 - Percent Change of HBW Trips from Existing to Alternative Conditions.

Trip Distribution

Background and Methodology

This chapter illustrates the distribution of the trips according to the power gravity model. The modeled home-based other (HBO), non-home based (NHB), and home-based work (HBW) trips were allocated among the different census tracts. Additionally, the alternative scenario would adapt these findings according to the previously estimated increases in HBO and NHB trips, and the mostly (but surprisingly not always) decrease in HBW trips.

Using the NHTS data, the average trip lengths by purpose were calculated, as well as the minimum travel time across modes. At first, the selected friction factors followed a Gamma function, using in turn the parameters derived from the *Large MPO 1* row at Table 4.5 of NCHRP 716. In the end, a Power function was adopted instead, so as to improve the fit between the generated distribution and that of the NHTS data, using the usual *-2* power derived from the gravity model. Iterations resulted in the final set of travel flows, both for the existing conditions and the alternative scenario.

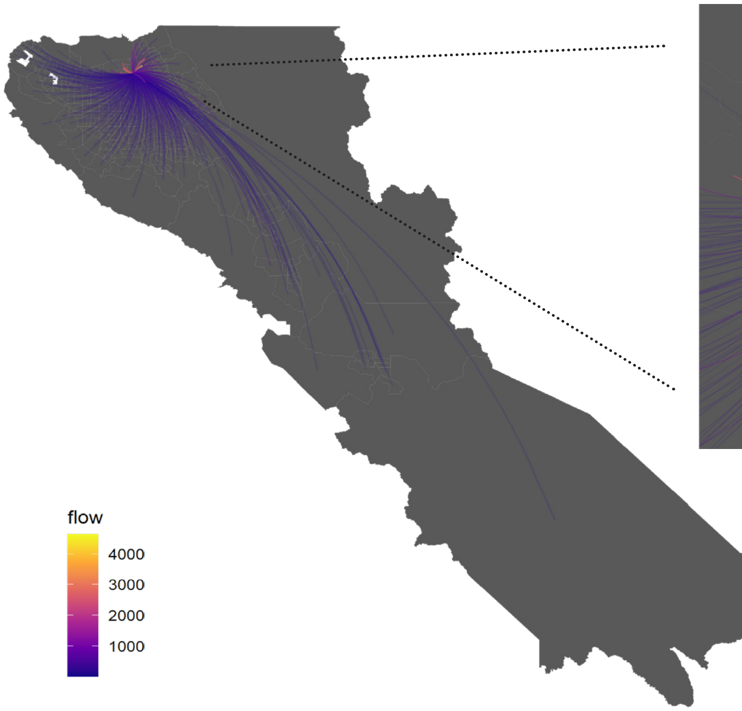


Figure 35 - Desire lines visualizing origin-destination data of the existing conditions for Home-Based Other (HBO) trips. The zone with the highest number of attractions is used as reference.

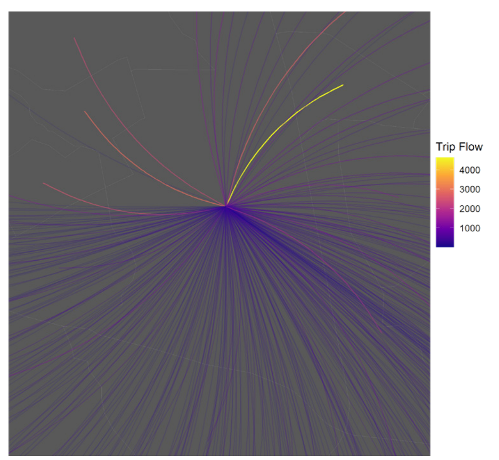


Figure 36 - Closer perspective of desire lines belonging to existing HBO trips, and having the zone with the greatest number of attractions as a destination.

Trip Distribution

Results

Desire lines for each trip purpose and for both scenarios showed in general a concentration at closer distances to any referenced zone. Regarding trip distribution itself, results were similar across all three types of travel: although HBO, NHB, and HBW represent different shares of the modeled total trips at the MSA, all of them prove to be monotonously greater or smaller versions of each other (i.e. total counts of trips vary, but the relative importance of a given zone to other zones is maintained). This is probably associated with the extrapolation for trip generation, which had its origin in the same demographic data and set of variables.

For the aforementioned reasons, Figure 35 only represents HBO trips, the most robust type (theoretically and empirically) found at the previous chapter, by showing its zone with the highest number of attractions. Figure 36, in turn, zooms in on this zone to show the flow in a clearer way: intuitively, nearby zones have a stronger connection with it (a greater flow).

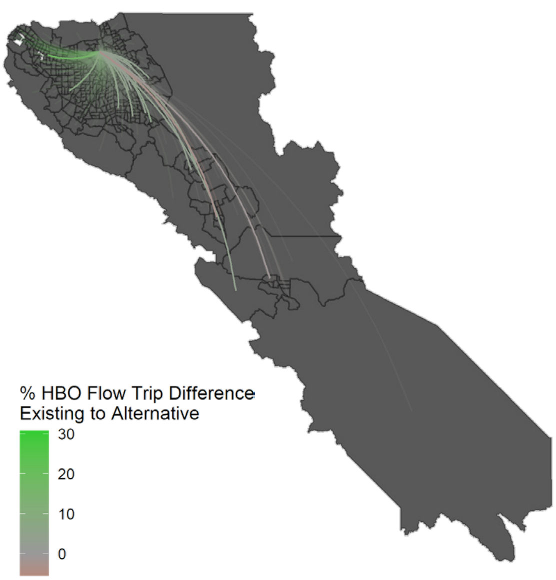


Figure 37 - Increase in HBO trips (alternative scenario versus existing conditions), stronger at the central zones and weaker at the peripheral ones.

As for changes between existing and alternative conditions, effects were not uniform, in line with the uneven impact that would be derived from increased working from home along the region. All types share however a similar pattern: peripheral census tracts are the ones that would face the most meager increments (for HBO and NHB trips) and the steepest falls (in the case of HBW). This is not trivial, since although these zones were expected to have weaker flows (after being located further away - greater frictions), that did not necessarily mean higher elasticities (i.e. stronger impact over their *first and second derivatives*). Interpretations for each type could be the following:

- HBO trips (Figure 37): while working from home, additional possibilities to travel to downtown arise (spare time because of no commuting, flexible schedule), but this is especially practical for nearby zones and less intense with distance.
- HBW trips (Figure 38): the stronger reduction of trips at the periphery could have a twofold explanation. In the first place, employees who are eligible to work from home may live, as suspected, up the Santa Clara Valley (e.g., Morgan Hill). Secondly, if one is able to choose whether to go to the office or not, it is more likely to do so if the related trip is convenient and short. Consequently, further zones would experience the greatest reduction in HBW.
- NHB trips (Figure 39): the whole increase in NHB trips has been analyzed with caution from the beginning. Although it could be due to noise or spurious correlations, and further analysis is needed, working from home could by definition only increase NHB trips through trip chaining where intermediate stops were unrelated to work. Be-

Trip Distribution

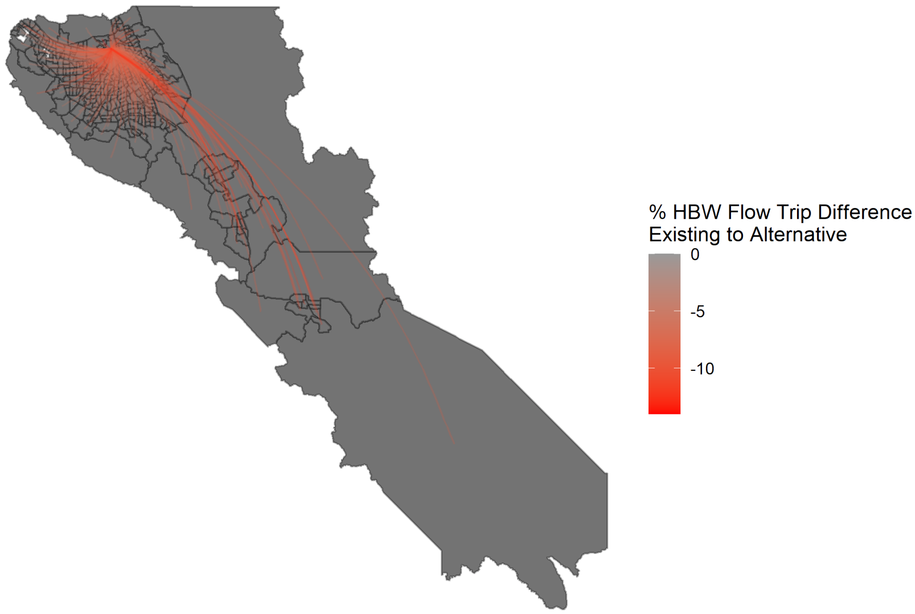


Figure 38 - Decrease in HBW trips (alternative scenario versus existing conditions), stronger at the peripheral zones and weaker at the central ones.

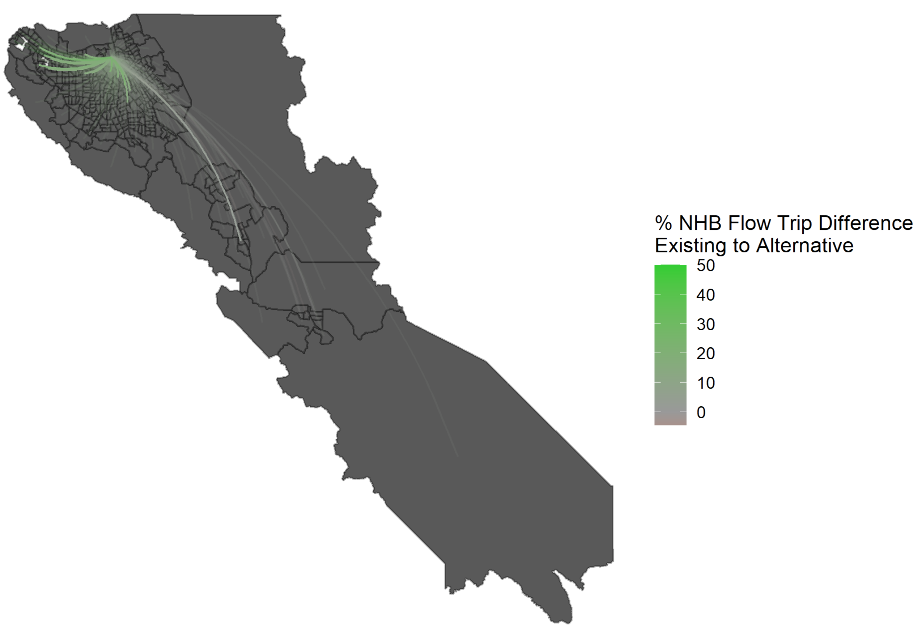


Figure 39 - Increase in NHB trips (alternative scenario versus existing conditions), stronger at the central zones and weaker at the peripheral ones.

Mode Choice

Overview

This chapter presents the estimated regional mode share for home-based other (HBO), home-based work (HBW), and non-home based (NHB) trips and how those mode shares differ between the existing and alternative conditions.

Findings

The alternative scenario does not have a substantial effect on mode choice in the San Jose MSA. The proposed alternative reduces the number of days a subset of workers will have to travel to work, but does not in any way attempt an intervention that would encourage transit over personal vehicle, for example.

Mode choice is most affected by the trip type. Figures 40 and 41 below show the proportion of trips by trip type estimated for each mode. For each trip type in both the existing and alternative scenarios, personal vehicles have by far the highest share. However, the likelihood that a trip is made in a single-occupancy (SOV) vehicle as opposed to a high-occupancy vehicle (HOV) is almost double for HBW trips

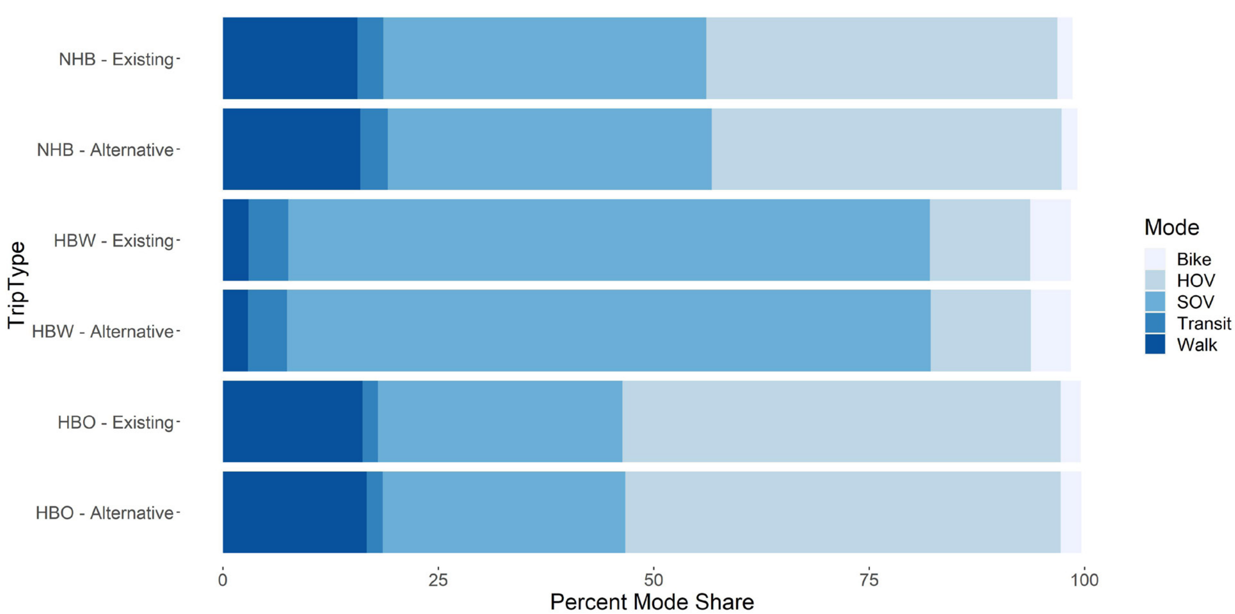


Figure 40 - Mode Share by Trip Type - Bar Chart

Trip Type	Percent Bike	Percent SOV	Percent HOV	Percent Transit	Percent Walk
HBO_model 2	2.3	28.3	50.9	1.8	16.2
HBW_model 2	4.7	74.4	11.7	4.6	3.0
NHB_model 2	1.7	37.5	40.8	3.0	15.6
HBO_model 2 alt	2.4	28.2	50.5	1.8	16.7
HBW_model 2 alt	4.6	74.7	11.6	4.5	2.9
NHB_model 2 alt	1.8	37.6	40.6	3.2	16.0

Figure 41 - Mode Share by Trip Type - Table

Mode Choice

compared to HBO or NHB trips. This is likely observed because people do not tend to travel with their family to the office, as they might on a HBO or NHB trip. Similarly, the proportion of trips done on foot is much higher for both HBO and NHB trips than for HBW, but the bike share is higher for HBW than for the other two trip types.

While the proportion of each mode did not change noticeably when comparing the existing to alternative scenario (Figure 43), there are changes seen across the mode share of different magnitudes. Figure 42 below shows these modeled changes. The biggest modeled effect that the alternative scenario has on mode share is an increase in transit and bike use as a proportion of NHB trips. The absolute value of these changes is small, as these two modes constitute such a small portion of overall trips, but each are modeled to increase by over five percent. Conversely, HBW trips are expected to be made increasingly using SOVs, with all other types of mode decreasing in share. HOV trips are expected to decrease for all trip types in the alternative scenario.

The finding that mode share for all modes except SOV may decrease in the alternative scenario suggests that many of the jobs that will allow remote work in this model are jobs where the employees live close enough that these alternative modes are currently an option. Workers in jobs that cannot be performed remotely may tend to live farther away and need to drive, meaning that they would constitute a higher proportion of HBW trips in the alternative scenario.

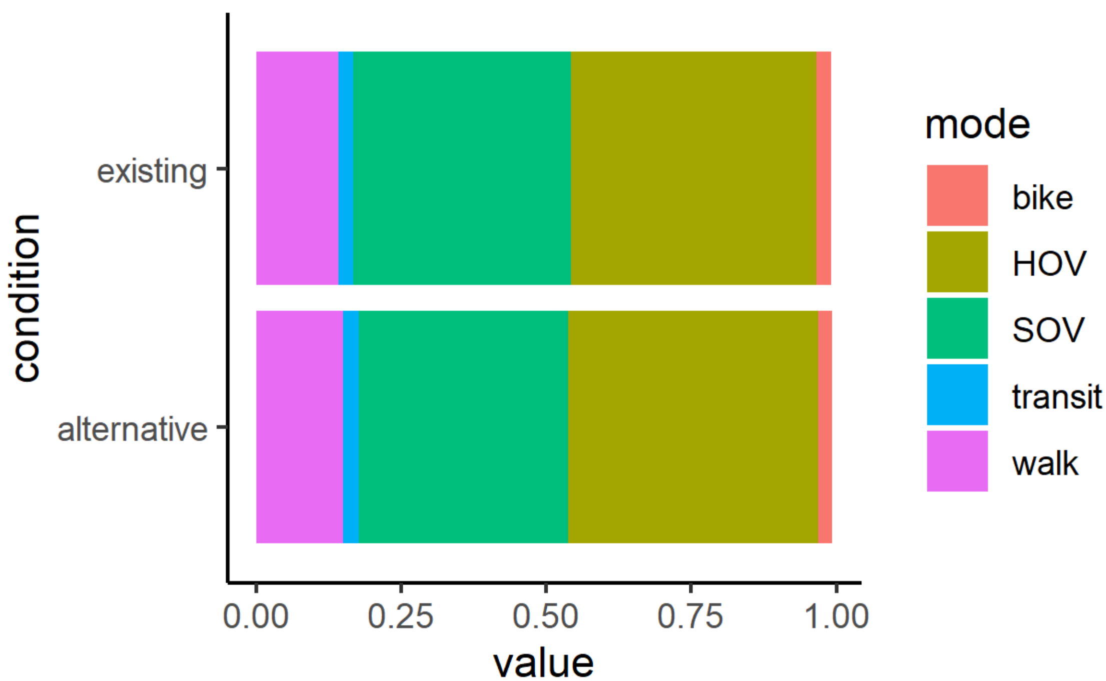


Figure 42 - Comparison of overall mode share at the existing and alternative scenarios.

Mode Choice

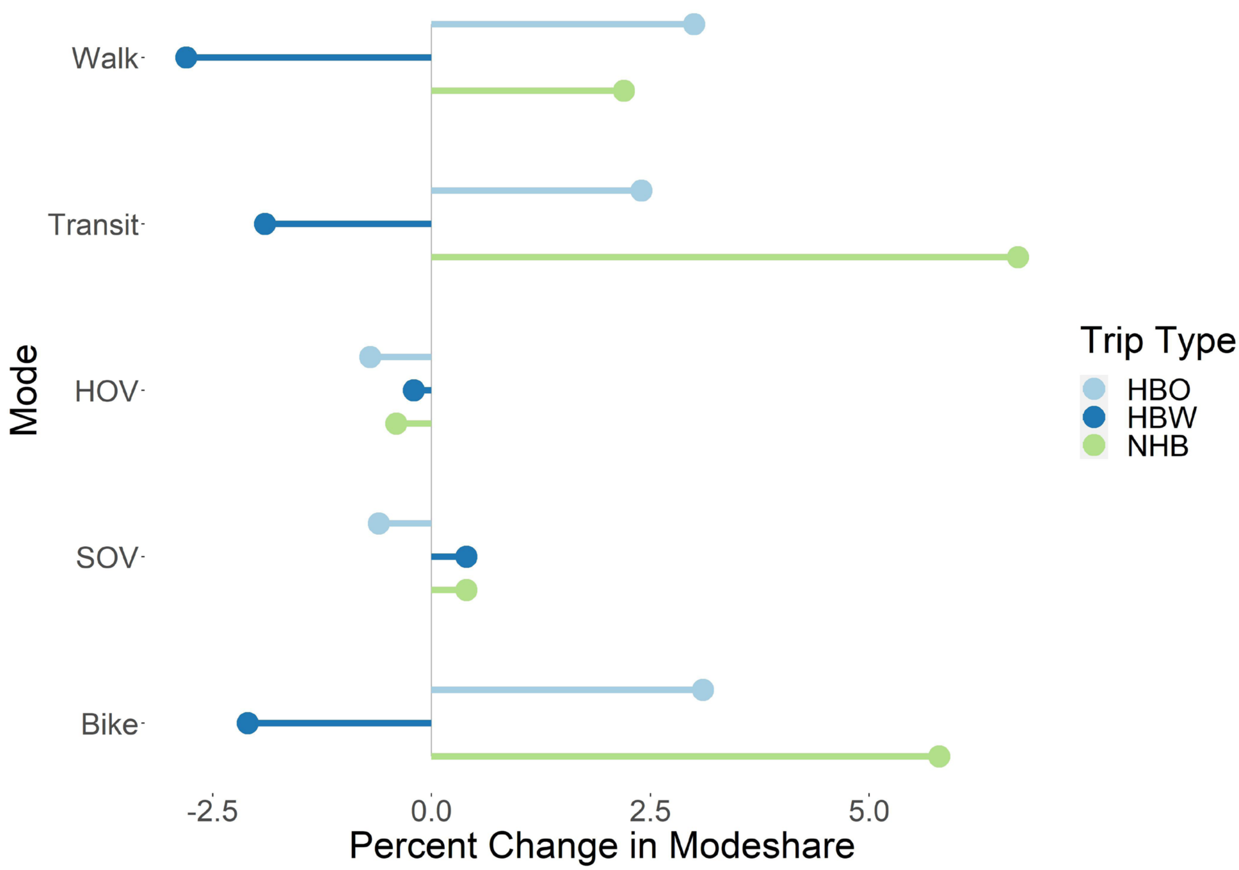


Figure 43 - Percent change in mode share, existing to alternative scenarios

Transit Assignment

Background and Methodology

Production-Attraction matrices were converted into Origin-Destination ones, to account for round trips. Based on these new matrices, transit routes connecting zones were identified according to the lines that passengers would need to ride in order to travel between their desired nodes. The first outcome was the ridership for each transit line.

Additionally, trip distances were calculated for all other modes (drive, walk, bike), leading to the estimated Personal Miles Traveled (PMT), and Vehicle Miles Traveled (VMT, calculated after using average vehicle occupancy at the aggregate level from NCHRP 716, Table 4-16).

Transit Ridership - Results

Transit lines were then grouped according to their ridership, showing their corresponding distribution, both by purpose and overall. Figures 44 and 46 show stacked histograms by purpose, counting the number of lines within each bin of trip counts. The distribution is skewed to the right, showing a large number of lines with low ridership, something that resonates with the public good and accessibility goals transit pursues. Besides this finding, HBW-trips show a narrower range, and from a threshold level of ridership of around 3,000 and onwards, they remain negligible as compared to the other purposes. For the alternative conditions, the picture is similar, but that threshold becomes even smaller, less than 3,000. Likewise, NHB-trips expand their range, reaching a greater number of lines with high ridership. This is part of the curious expansion NHB-trips experimented, arguably counterintuitive given that the non-home component of NHB-trips is generally the workplace, being precisely what the alternative undermines.

The most prominent lines in terms of ridership, both by purpose and condition, are shown at Figure 45. Those with the highest ridership appear to be consistently 522, 89, and 22. While clearly defined by purpose, they remained unchanged for the alternative scenario. Regarding overall ridership, the leading values

purpose <chr>	existing <chr>	alternative <chr>
HBO	522	522
HBW	89	89
NHB	22	22
Total	89	89

Figure 45 - Table showing the transit lines with the highest ridership for each purpose, comparing existing and alternative conditions.

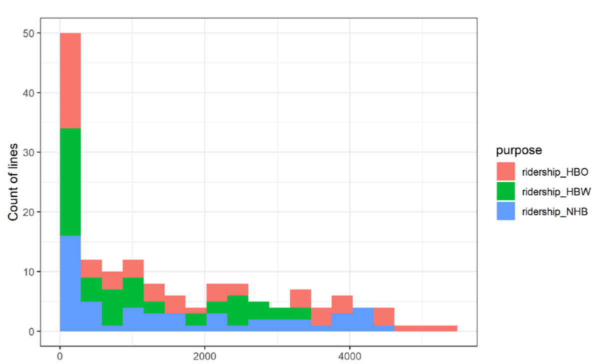


Figure 44 - Stacked histogram showing the existing distribution of transit ridership across lines for each purpose.

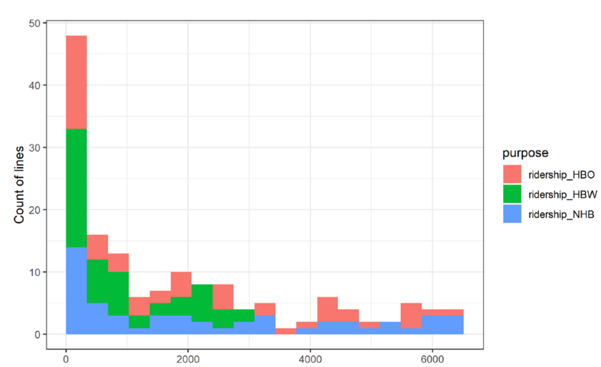


Figure 46 - Stacked histogram showing the alternative distribution of transit ridership across lines for each purpose.

Transit Assignment

belonged to line 522, followed by line 22, and although it did not lead any individual purpose category, VTA's Blue line came third. This *podium* was also maintained at the alternative scenario.

Vehicle Miles Traveled - Results

The difference in VMT between the existing and the alternative conditions is shown at Figure 47. In previous chapters, an increased or diminished number of trips suggested possible interpretations, but having the PMT and VMT indicators sheds additional light on this matter. Signs are consistent, featuring an expected reduction of HBW trips at the alternative scenario, and some growth of HBO ones (presumably due to the additional flexibility at work). So does NHB, but again, under less clear hypotheses.

What is particularly interesting is that the growth of HBO and NHB miles would seem to outnumber the reduction in those for HBW. Although a slight decrease in HBW could still outnumber large growths for HBO and NHB under certain combinations of total trips per purpose, this is not the case, and the situation of the expected total VMT is of concern: current conditions estimate 20,814,117 VMT, whereas the alternative ones predict 24,328,220. This 17% increment, if accurate, would raise a flag about the real convenience of working-from-home trends when it comes to their impact on congestion and environmental concerns like carbon emissions.

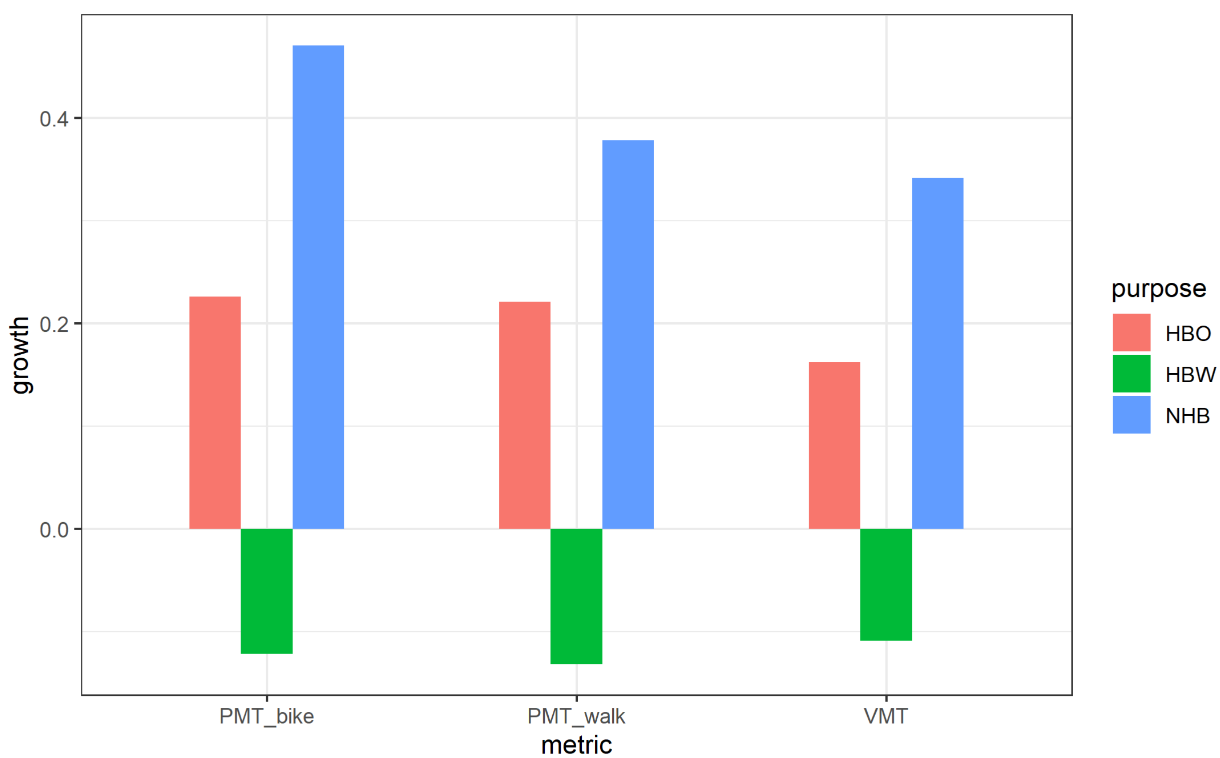


Figure 47 - Bar chart showing the difference in PMT (for biking and walking) and VMT (for driving) between the existing conditions and the alternative ones. Values express net growth, which results from *alternative value / existing value - 1*.