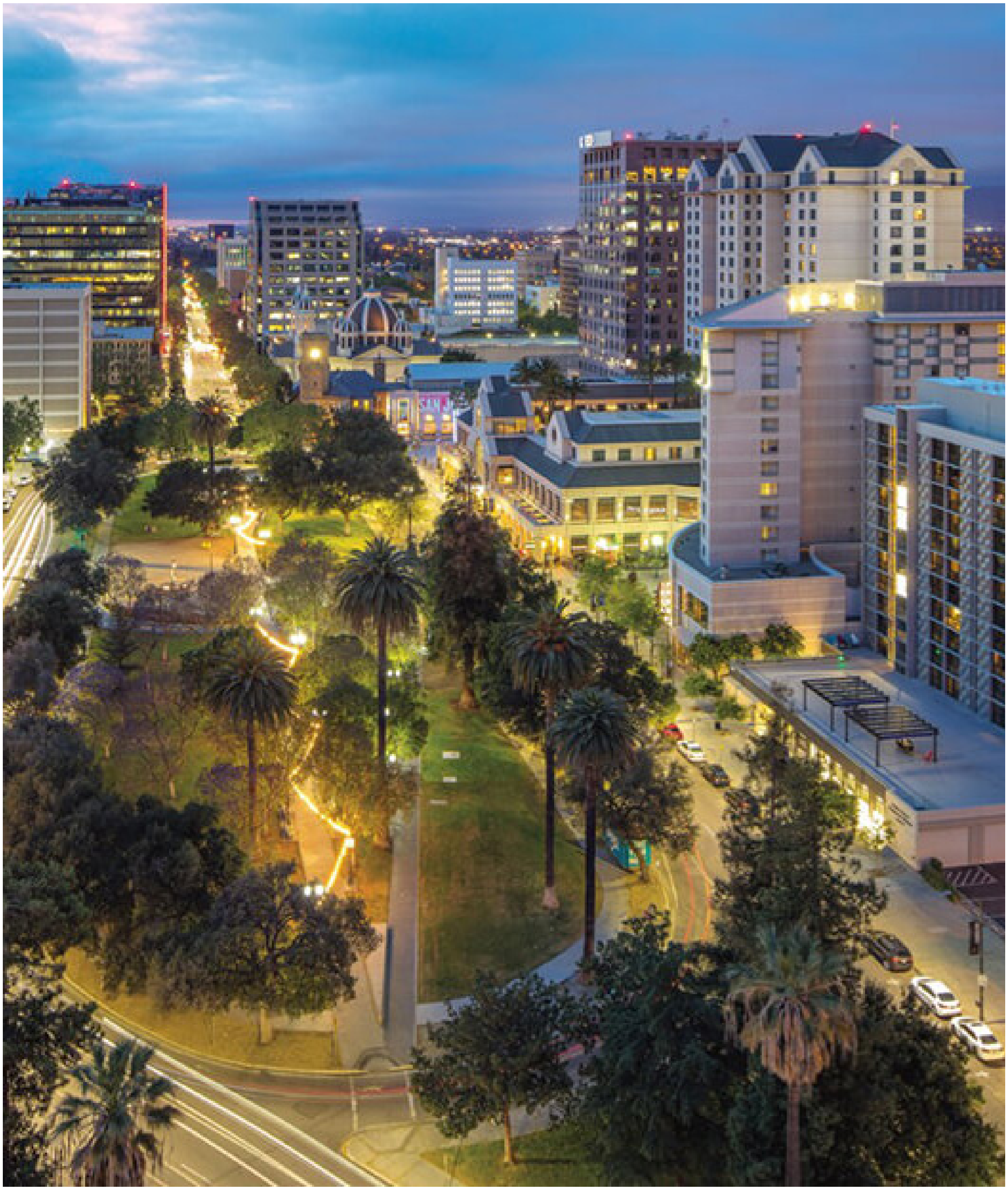

San Jose
Travel Forecasting Report

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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, the city 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 (labor supply) and jobs (labor demand) were considered according to broad categories of industries: 'basic jobs', 'service jobs', and 'retail jobs'. Employees and jobs 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 jobs 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. 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, jobs and employees 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 their expected impact would be uneven both spatially and across industries, which in turn would correlate to income groups and other socioeconomic dimensions.

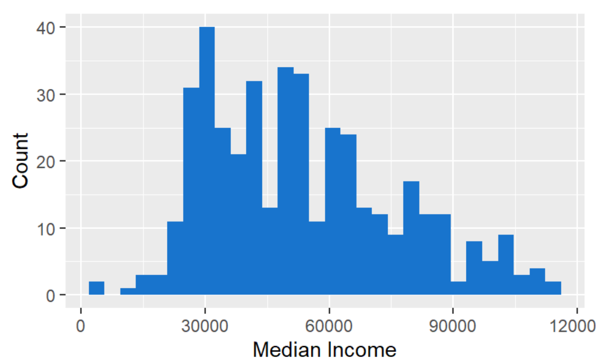


Figure 1 - Distribution of the median income across tracts.

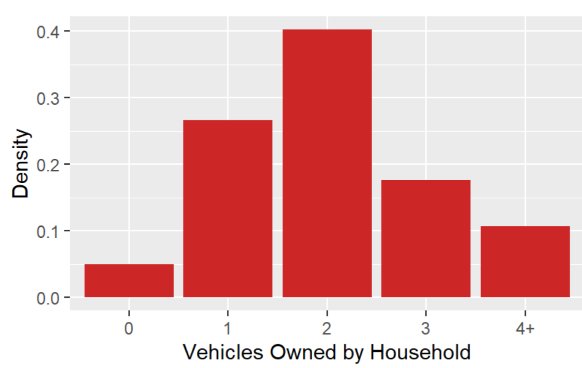


Figure 2 - Distribution of vehicle ownership across tracts.

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 distributed according to these vulnerability indicators in a more precise way are also provided (Figure 4).

LEHD variables

As for labor-related variables, census block-level data was collapsed into census tract-level data, which was in turn joined to its ACS counterpart. A dual approach of labor supply (employees at each location and from each

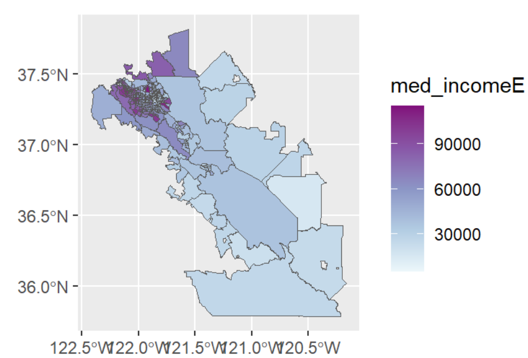


Figure 3 - Spatial distribution of median income by tract.

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.

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. At the other end, if the overlap had been perfect (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 (the only workers who do not travel to other defined zones).

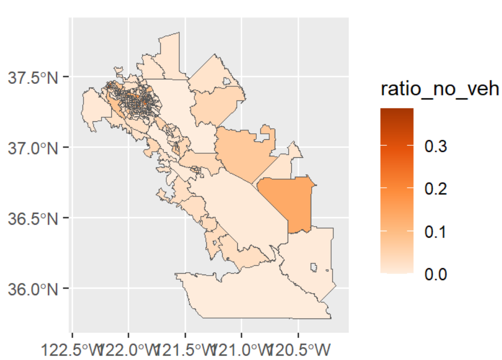


Figure 5 - Share of households not owning any vehicles. One outer census tract draws some attention, but the ratio seems to be higher near Downtown San Jose.

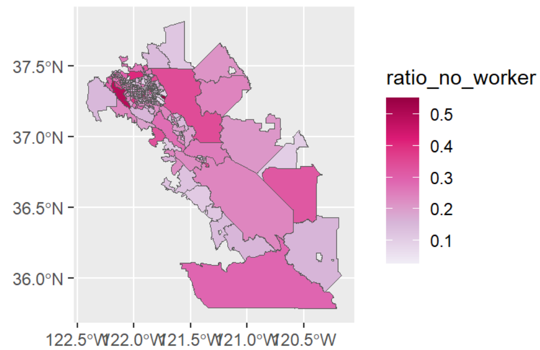


Figure 6 - Share of households not having any workers. Spatial correlation is not that clear, and senior households could offer an explanation for high values while not necessarily being problematic.

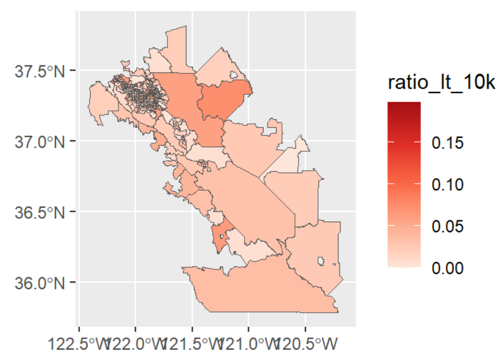


Figure 7 - Share of households with an annual income under USD 10k. Some centric and peripheral tracts show the highest values, whereas the furthest outskirts are not particularly poorer from this perspective.

WFH assumptions

Among the employees and jobs available at the LEHD database, industries suitable to working from home practices were defined. These were: Information, Finance and Insurance, Professional, Scientific, and Technical Services, Management of Companies and Enterprises, Other Services [except Public Administration], and Public Administration. Reasons for this selection were intuitive, based on stereotypical positions and tasks performed by each sector.

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 deducted before applying this subtraction.

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 (who were removed), and 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 8) 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 *WFM* 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.

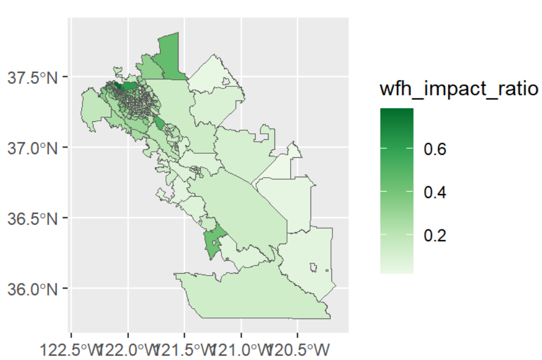


Figure 8 - Ratio of jobs that would be suitable for working from home according to this paper's definition. Recall Figure 3 and how similar their highlighted census tracts are. Additionally, Downtown San Jose concentrates most of the jobs suitable for the analyzed regime.

Figure 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 cannot 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.

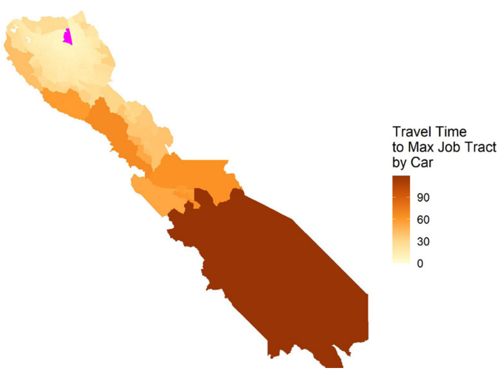


Figure 10 - Car Travel Time.

Figure 11 - Transit Travel Time.

Figure 12 - Bike Travel Time.

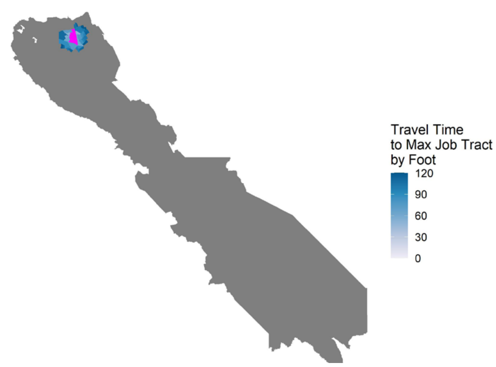


Figure 13 - Pedestrian Travel Time.

Networks

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 11 shows the primary, secondary, and tertiary roads.

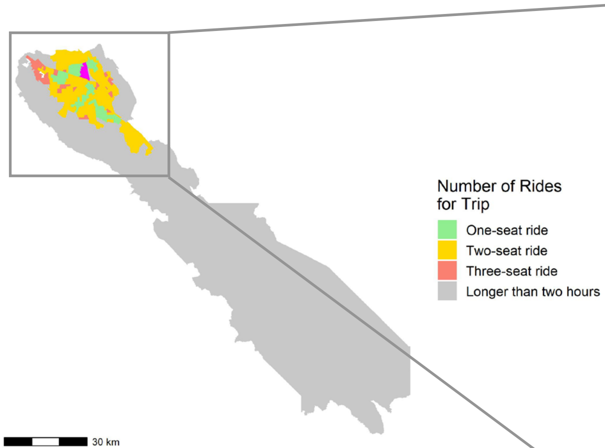


Figure 14 - Necessary Transit Transfers.

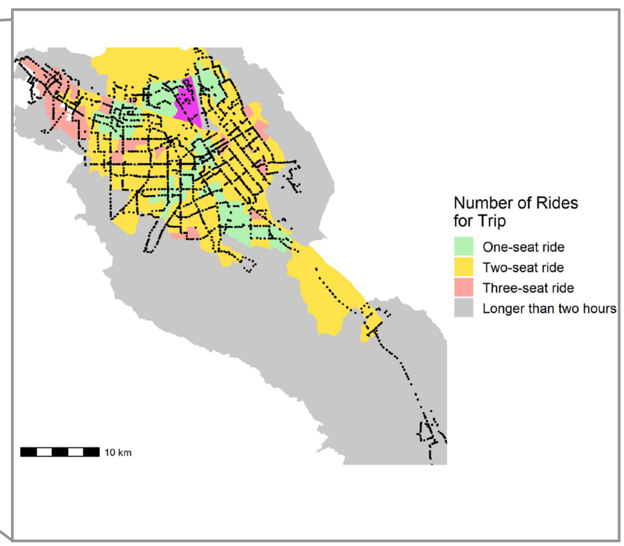


Figure 15 - Existing Transit Stops

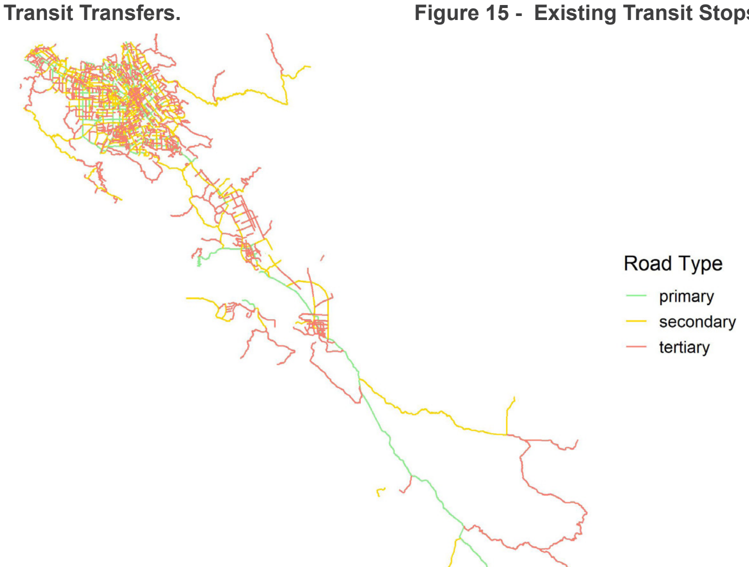


Figure 16 - Road Types.

Accessibility

Background

A broad consensus in the field defines accessibility as the availability of opportunities (proximity, Figure 1) reachable in a specific amount of time (related to mobility, Figures 2 and 3, generated and shown for Assignment 4). 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 1), are concentrated around the downtown, with some minor participation of cities like Morgan Hill. Both transit (Figure 2) and road networks (Figure 3) 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.

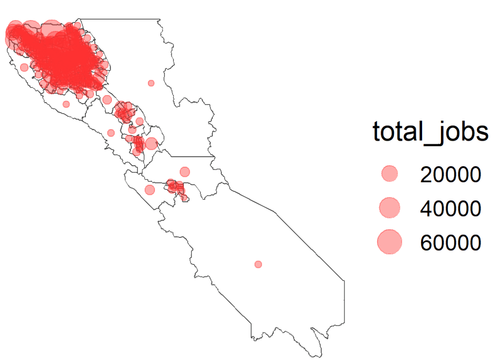


Figure 17 - Centroids of the census tracts showing the number of jobs they offer.

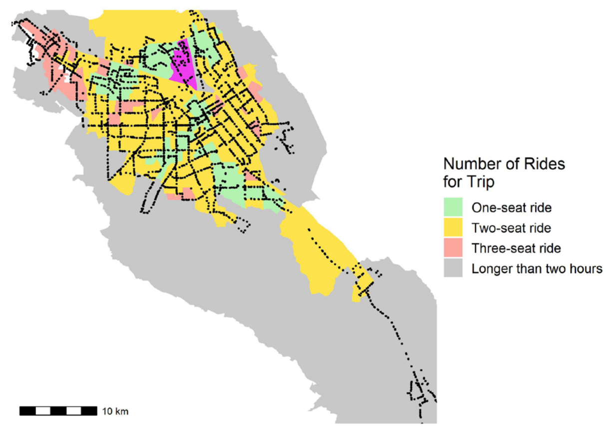


Figure 18 - VTA transit stops and number of rides for a trip to the tract with the highest number of jobs.

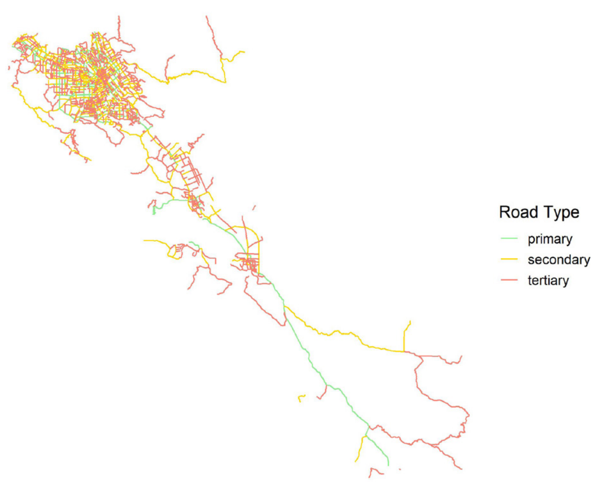


Figure 19 - Road network highlighting primary, secondary, and tertiaryroads only, according to OSM.

Accessibility

Results

Results are summarized by Figures 4 and 5. As a general fact, having ratios below 10% for almost every tract and below 5% for a vast majority of them (Figure 4) suggests 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 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 5), 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 of walking 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.

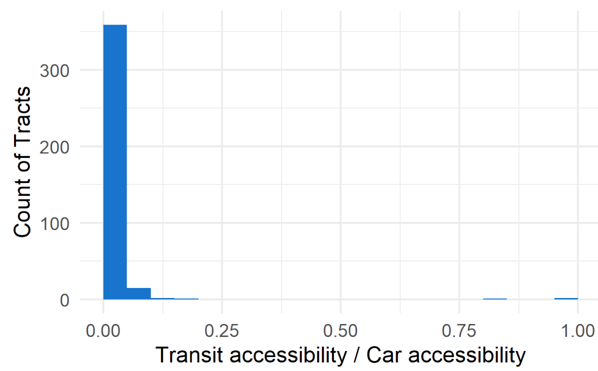


Figure 20 - Histogram showing the count of tracts according to their ratios between transit accessibility and car accessibility. The bins group 5 pp. intervals.

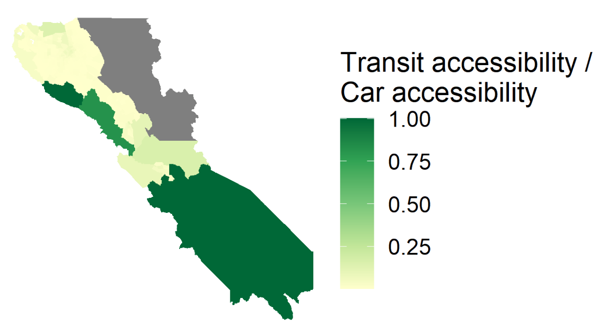


Figure 21 - Choropleth map showing the different ratios of transit accessibility to car accessibility. The southernmost tract counterintuitively shows a *perfect score* due to its remoteness.

Vehicle Access Model

Overview

We used the regression model to predict the number and percent of zero-vehicle households in each zones based on zone-level household and employment characteristics. We found that the work-from-home changes in employment and transit access are not statistically significant for our alternative scenario. Nevertheless, we included these variables to predict the alternative percent of zero-vehicle households in each tract.

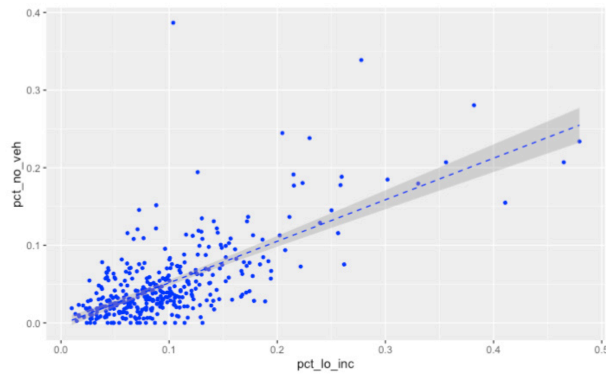


Fig. 1 scatter plot of percentage of zero-vehicle households vs percentage of low-income households

Regression Model

Using scatter plots, we visualized how different variables are related to our independent variable of zero-vehicle household for our existing data. Below shows some examples. We could already see that work-from-home population does not show clear correlation with household vehicle ownership (fig.1 &2).

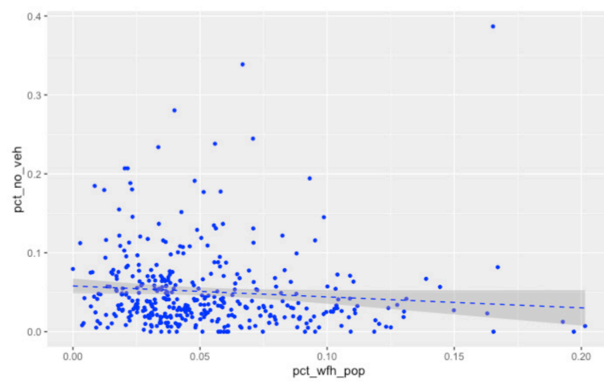


Fig. 2 scatter plot of percentage of zero-vehicle households vs percentage of work-from-home populations

We further used linear regression to confirm this finding. In the model, the variables that are statistically significant at 0.1% level are percentage of big households, percentage of low-income households, and percentage of high-income households. Work-from-home changes in employment and transit access are not statistically significant for our alternative scenario (fig.3).

We did not use alternative model that has only the statistically significant variables as our alternative is on work-from-home populations.

Applying the relationships to our alternative scenarios, we arrived at the alternative percentage of zero-vehicle households.

(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.

Fig.3 Regression results

Vehicle Access Model

Model Prediction on Vehicle Ownership

Our model shows that the fewer tracts have no zero-vehicle households in the predicted vehicle ownership distribution (Fig. 3&4). 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.

```
  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
```

Fig. 5 Descriptive statistics of existing zero-vehicle households (left) and predicted (right).

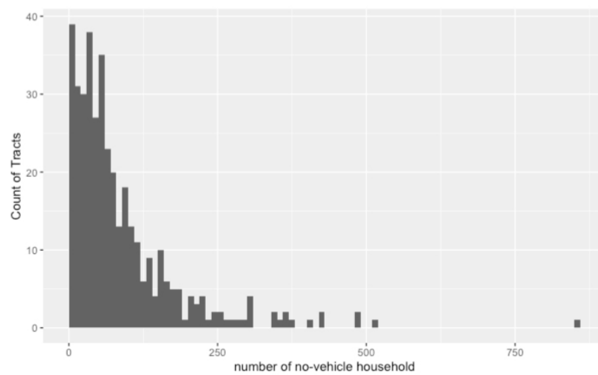


Fig. 3 Existing vehicle ownership histogram

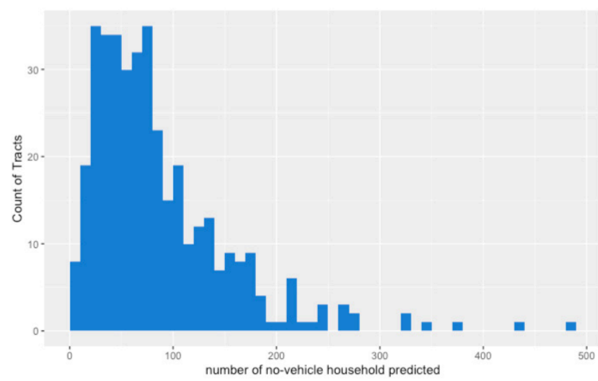


Fig. 4 Predicted vehicle ownership histogram

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. We used NHTS data to estimate three regression models that were then 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 Fig. 1. 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.

Figure 22 - Regression Model for HBO Trips.

	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	

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

After applying the regression model to the analogous household-level variables in each of the zones, we estimated the HBO trip productions and subsequently the HBO trip attractions 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 2 below shows the HBO trip productions and attractions in each zone for the existing conditions, where each dot represents 3,000 trip productions and attractions, respectively.

Trip Generation Models

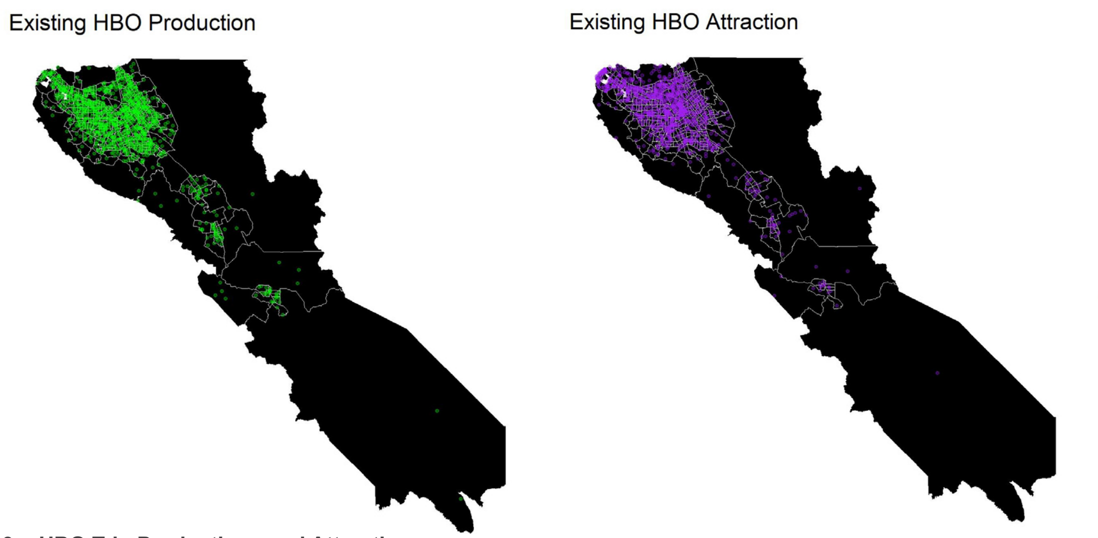


Figure 23 - HBO Trip Productions and Attractions.

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 3 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

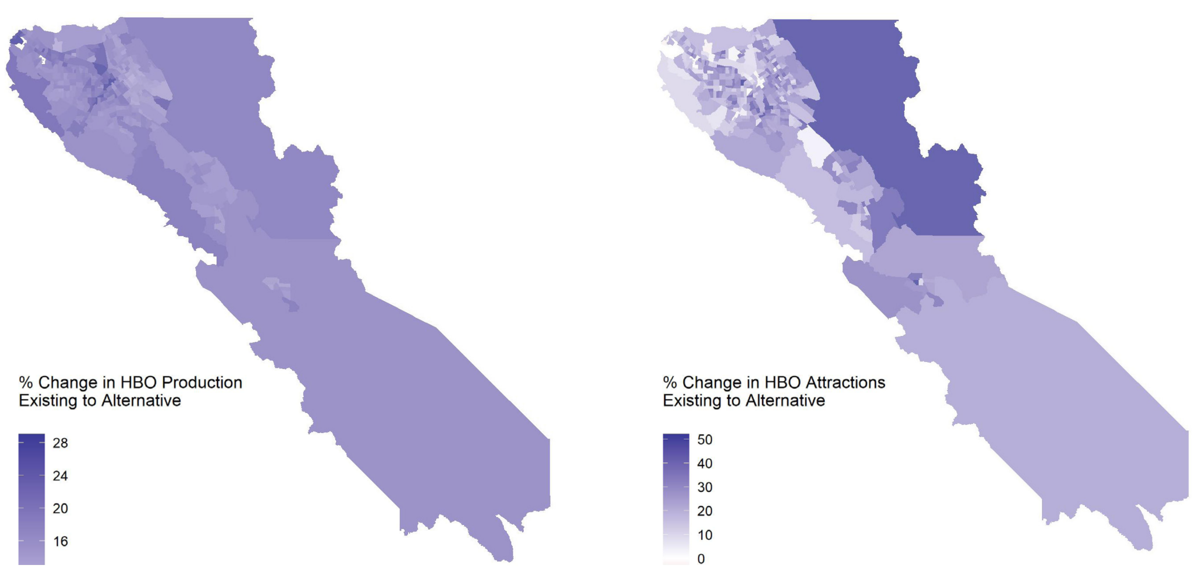


Figure 24 - Percent Change of HBO Trips from Existing to Alternative Conditions.

Trip Generation Models

to the downtown zones for HBO trips.

Home-Based Work Trips

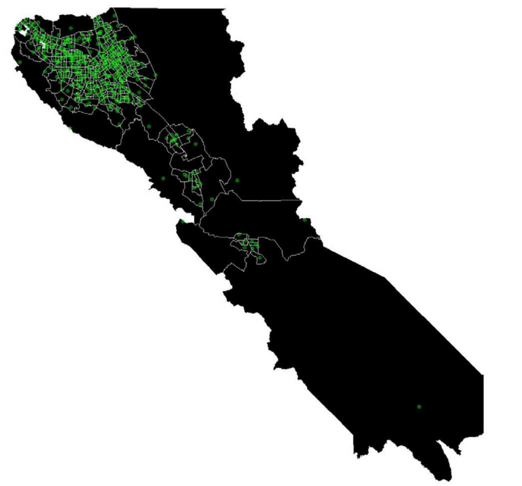
Home-based work (HBW) trips refer to those that originate at home to go to a person's place of work, or vice versa. The associated regression model is included below as Fig. 4. The significant variable in this model is again household size: the smaller the household, the fewer daily HBW trips, all else being equal. The WFH ratio is not a statistically significant variable in explaining variations in HBW trips.

Figure 25 - Regression Model for HBW Trips.

	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.

Existing HBW Production



Existing HBW Attraction

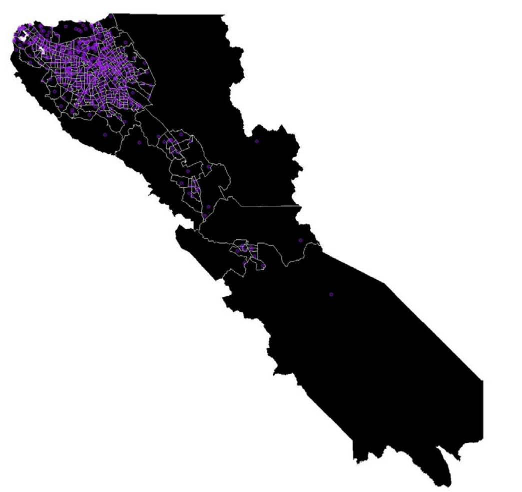


Figure 26 - HBW Trip Productions and Attractions.

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 5, 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

Trip Generation Models

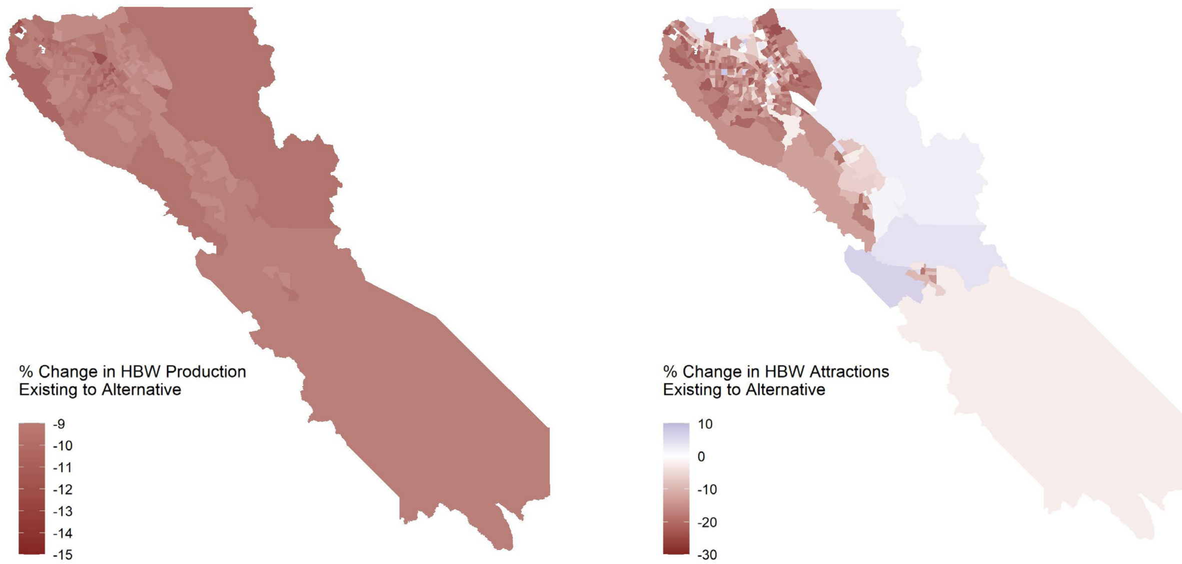


Figure 27 - Percent Change of HBW Trips from Existing to Alternative Conditions.

findings are shown below in Figure 6.

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 7 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 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.

Figure 28 - Regression Model for NHB 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	

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

Trip Generation Models

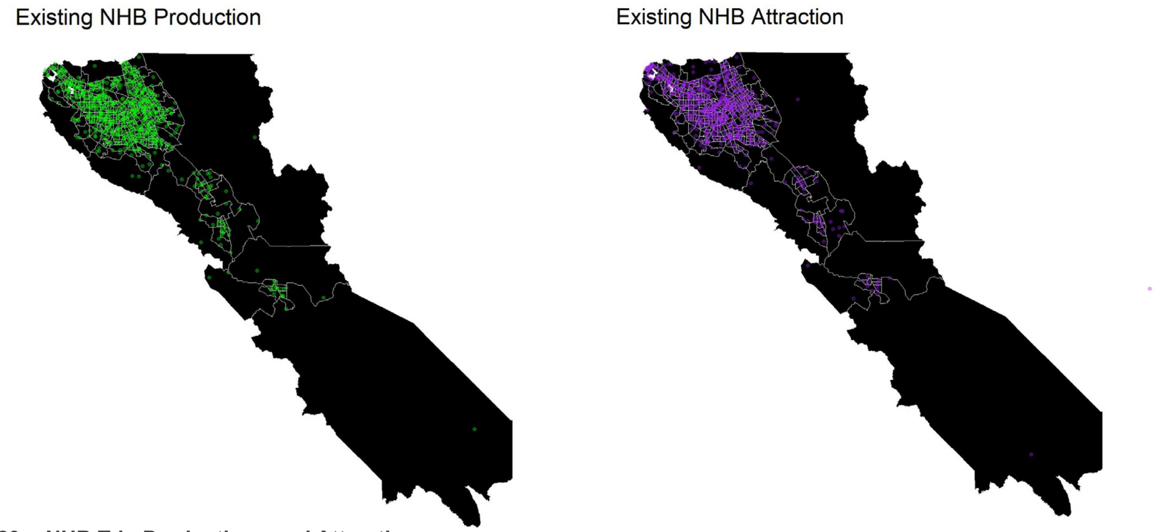


Figure 29 - NHB Trip Productions and Attractions.

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 8, 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 9. 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.

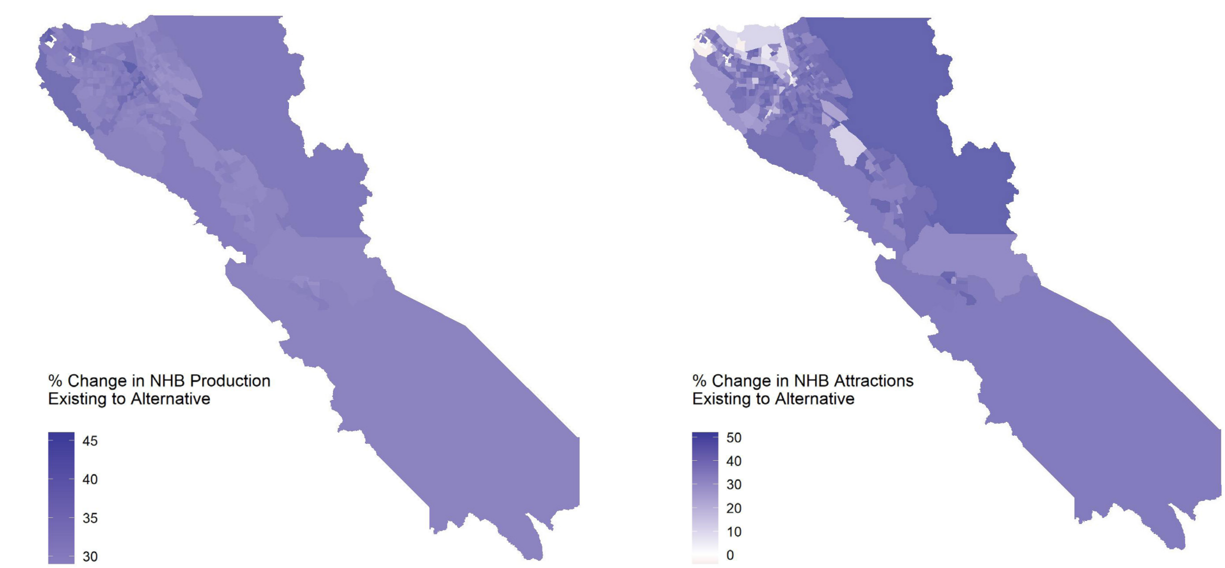


Figure 30 - Percent Change of HBW Trips from Existing to Alternative Conditions.

Estimate 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 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.

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). The latter is probably associated with the extrapolation for trip generation, which had an origin in the same demographic data and set of variables.

For the aforementioned reasons, Figure 26 only represents HBO trips, the most robust type (theoretically and empirically) found at the previous chapter, by using its zone with the highest number of attractions. Figure 27, 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).

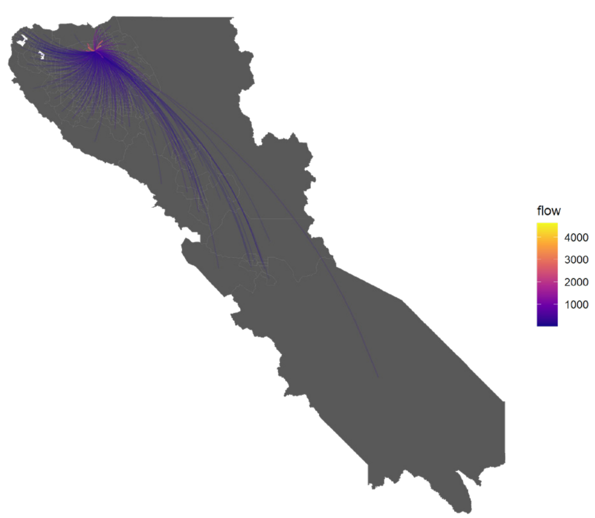


Figure 31 - Desire lines visualizing origin-destination data of the existing conditions for Home-Based Other (HBO) trips. The zone with the highest number of attractions is used as reference.

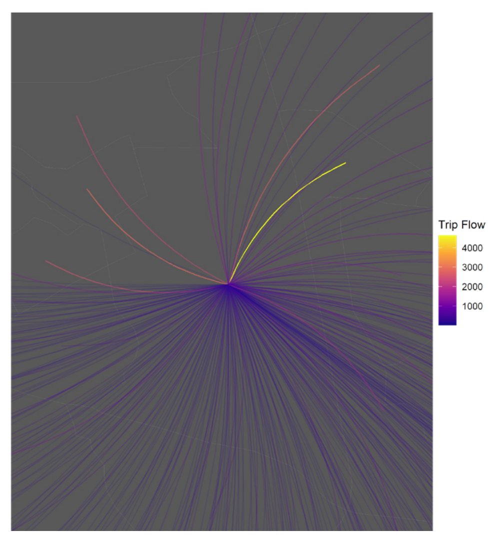


Figure 32 - Closer perspective of desire lines belonging to existing HBO trips, and having the zone with the greatest number of attractions as a destination.

Estimate Trip Distribution

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 these zones were expected to have weaker flows (after being located further away - greater frictions), but 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 28): 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 29): 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 previously suggested, 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 30): 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. Because of the availability of opportunities, the latter are more likely to take place at central zones as well.

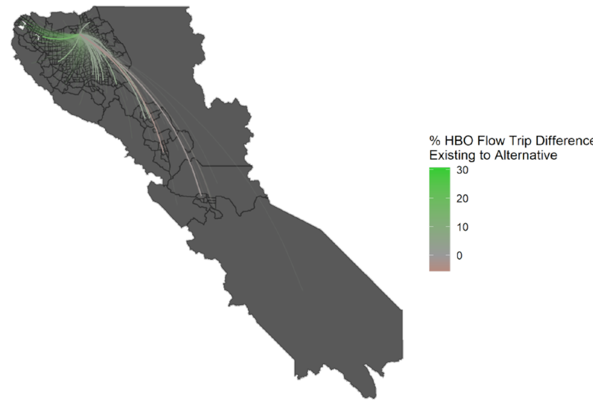


Figure 33 - Increase in HBO trips (alternative scenario versus existing conditions), stronger at the central zones and weaker at the peripheral ones.

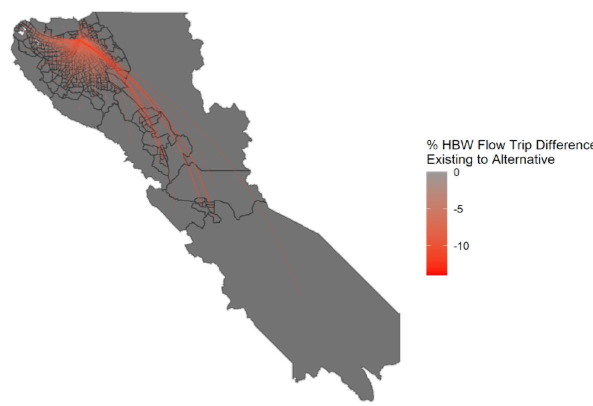


Figure 34 - Decrease in HBW trips (alternative scenario versus existing conditions), stronger at the peripheral zones and weaker at the central ones.

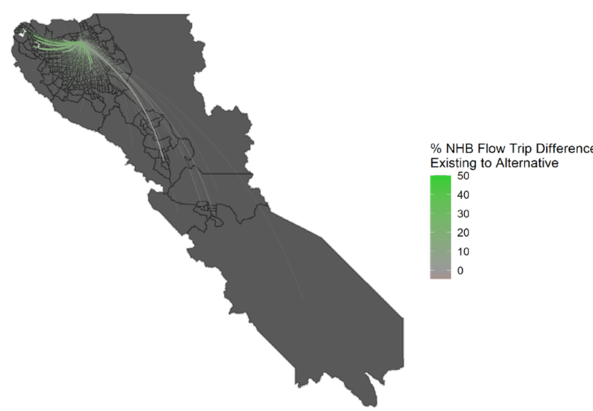


Figure 35 - Increase in NHB trips (alternative scenario versus existing conditions), stronger at the central zones and weaker at the peripheral ones.

Transit Ridership

Highway Analysis