11 Sensitivity Testing

11.1 Introduction

Testing and documentation of travel demand model sensitivity is not new, but has garnered more interest in recent years due to passage of Senate Bill 375 (SB375), subsequent discussions of travel demand modeling at the Regional Targets Advisory Committee meeting, and the workshops and public meetings leading up to the California Transportation Commission's (CTC) 2017 update of the "Regional Transportation Plan (RTP) Guidelines". In combination, these initiatives resulted in expansion of documentation and testing of regional travel demand models.

This chapter reports results of testing SACSIM's sensitivity to several key policy input variables and other, exogenous inputs. The testing falls into four categories:

- **Traditional "experimental" testing**, where one input factor is systematically varied, holding all other factors constant, and comparing the variations in the input factor to variations in key outputs. Variables tested in this manner are:
    - Auto-operating costs,
    - Off-street parking price,
    - Household income,
    - Transit fares, and
    - Highway capacity.

- **Cross-sectional testing**, where variations in multiple input variables for a single model run are statistically analyzed for correlations to variations in key outputs. Because of the disaggregate nature of SACSIM output for household-generated travel, the options for performing statistical testing of cross-sectional (i.e., single model run) results are more straightforward than for an aggregate "four-step" travel demand model. Variables tested in this manner are land use/transportation interaction variables, also known as "the Ds":
    - Regional accessibility (or "destinations"),
    - Mix of use (or "diversity"),
    - Proximity to transit (or "distance"),
    - Street pattern (or "design"), and
    - Residential density.

- **Testing of random variation** in the microsimulation of demand for household-generated travel, where the random "seed" for the simulation is varied. A seed variable is common to most simulation models like the DAYSIM submodel of SACSIM. The seed determines the order of simulation of events within the model run. In DAYSIM, it determines the order of simulation of person-level activities. Even with identical input files, the results of the simulation can vary based on the order in which person-level activities are modeled. This testing is not different than the traditional "experimental" testing described above, but the test variable (the random seed) is unique to simulation models and is not a policy variable or exogenous input. The purpose of this testing is to quantify the potential random variation in the simulation results themselves.

11.2 Experimental Testing of Key Exogenous Input Factors

For experimental sensitivity tests, each factor was varied by fixed amounts in six test runs, using the model inputs from year 2008 and the DAYSIM submodel of SACSIM19. We used 2008 data because 2016 data were not available at the time and 2012 was a low point of the Great Recession and its elasticities may not be reflective of "normal" conditions. The following input factors were tested:

- Auto operating costs (a function of gasoline price and average fleet efficiency), in cents per mile, using year 2000 dollars. The model program only allows for costs to be stated in whole cents;
- Off-street parking price;
- Household income, in year 2000 dollars;
- Transit fares (average discounted transit fares, in year 2000 dollars); and
  highway capacity, stated in vehicles per lane per hour, and used in the SACSIM vehicle assignment scripts.

Sensitivity to changes were tested in each of these inputs by performing three increases (+10%, +25%, +50%) and three decreases on their base input values (-10%, -25%, -50%), except for highway capacity, whose base input value was only tested for changes of -10%, -5%, +5%, and +10%.

We further explored parking price sensitivity through focused tests for trips heading specifically to the downtown core, as well as how parking price sensitivity differed for workers who must pay to park at their usual workplace.

Tests were made with full runs of SACSIM, so secondary effects of the changes on choice of destination are included in the test results. Sensitivities for the following outputs were checked, based on household-generated activity for people living within the SACOG region:

- total person trips,
- total vehicle trips,
- total vehicle miles traveled (VMT),
- congested vehicle miles traveled (CVMT),
- total transit person trips, and
- total bike and walk person trips

11.2.1 Elasticity

Reasonable sensitivity is judged by comparing the model sensitivity to the consistent range of observed sensitivity to the test factors in published literature. The most common measure of sensitivity is *elasticity*, which is defined as the ratio of percent change in a dependent factor (e.g., numbers of trips or vehicle miles traveled) to percent change in a test factor (auto costs, income, transit fares, or highway capacity). If a consistent range of elasticities for the exact factors tested is available, the changes of test variables in the predicted direction based on travel behavior theory will be the reasonableness criteria.

The elasticity formulation, known as arc elasticity, used for most SACSIM sensitivity calculations was:

Elasticity = [log (Output_1) - log (Output_0)] /[log (TestFactor_1) - log (TestFactor_0)]

Where "_0" variables are the base run, and "_1" variables are the test runs with one variable changed.

Due to the difficulty of getting exact test factor values for it, highway capacity elasticity was calculated with the following alternative elasticity formula:

Elasticity = [percent change in output] / [percent change in test factor]

11.2.2 Auto Operating Cost

Reported sensitivities to auto operating costs vary widely in research literature. The values discussed below were used as a range of reasonable sensitivity. The model sensitivities shown are "end-to-end" elasticities, or the elasticity based on comparing the highest and lowest test values. Elasticity typically varies as you change the value of the test factor (e.g., the effect of increasing the auto operating cost from 12 cents to 15 cents on VMT will be different than increasing it from 15 cents to 18 cents), and the end-to-end elasticity helps give a rough average elasticity we can use for comparing with observed data.

- **VMT**: Studies summarized in Litman (2017) show short term elasticity of VMT with respect to auto cost as low as -0.03 (i.e., a 10 percent increase in auto cost results in a 0.3 percent decrease in VMT), and as high as -0.38 in the long term[19]. A separate study by Small and Van Dender (2007), which attempted to account for the "rebound" effect (i.e., people switching to more efficient vehicles, changing driving habits, and changing other trip-making behavior) estimated the long run VMT/auto cost elasticity as between -0.11 and -0.15[20].
    - Reasonable range of elasticity = -0.03 and -0.38
    - Model results = -0.135
    - The model was somewhat less sensitive to reductions from base auto costs than to increases, likely because there are diminishing returns to additional vehicle travel, and once auto travel becomes cheap enough, it ceases to matter and further reductions generate little to no additional travel.

- **CVMT**: No research was found linking auto operating cost to congested vehicle miles traveled (CVMT), though we expect the elasticity to be negative and somewhat greater than VMT elasticity because reducing even a small proportion of vehicle trips can disproportionately reduce congestion.
    - Reasonable range of elasticity: somewhat greater magnitude and same direction as VMT
    - Model results = -0.442

- **Transit person trips**: Less research has been conducted on the relationship between auto operating costs and transit trips. A 2008 study conducted for small urban and rural areas

[19] Litman, Todd, "Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior", Victoria Transport Policy Institute, 2017, pp. 34-36, 46-47.

[20] Small, Kenneth A. and Van Dender, Kurt, "Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect," *Energy Journal,* vol. 28, no. 1 (2007), pp. 25–51.

found an elasticity of transit ridership with respect to fuel price, a reasonable proxy for auto operating cost, ranging from +0.08 to +0.16[21]. An additional study of continental European cities from 1999 and summarized in Litman (2017) indicated a cross elasticity of transit trips with respect to fuel price of +0.13[19]. However, a study from Chicago from 2013 suggested that the elasticity of transit demand with respect to fuel price varies with the fuel price, and that elasticities for fuel prices below $3.00/gallon can be less than +0.05[22].

  - Reasonable range of elasticity = +0.05 to +0.16
  - Model results = +0.121
  - As with VMT, the changes transit trips in response to decreases in auto operating costs were smaller than changes in response to increases.

- **Bike and walk person trips**: The only research found on the relationship between auto operating cost and bike/walk trips is a 1999 study summarized in Litman (2017), which found a cross-elasticity of bike/walk trips with respect to fuel price to be +0.13 in continental European cities[19]. European cities generally have a more pedestrian-friendly urban form and land use context than the SACOG region, making walking a more attractive substitute to driving relative to the SACOG region, which has large areas in which walking is a relatively unattractive option compared to driving.

  We also predict that the magnitude of the relationship would be less than the VMT/auto cost elasticity, given that a significant share of the VMT change results from shortening vehicle trips (e.g., choosing destinations closer to place of residence) rather than changing modes, and the transit elasticity shows that some of the mode shift goes to transit rather than non-motorized modes.

  - Reasonable range of elasticity = less than +0.13, lower magnitude than auto cost-VMT elasticity
  - Model results = +0.119

- **Person trips**: We did not find any recent research could be found on the relationship between total person trips and auto operating costs. We predicted the elasticity of person trips with respect to auto operating cost to be slightly negative, assuming an increase in auto cost would may slightly reduce overall travel, but in many cases people would either make shorter trips or shift modes.

  However, as shown below, trip elasticity was slightly positive, indicating that increasing auto operating cost slightly increased the number of trips. One explanation for this finding is that as auto operating cost increases, people shift to other modes like transit that do not allow combining trips in the way that auto travel does. To test this explanation, we measured the elasticity of tours with respect to auto operating cost and found that there was a slight negative elasticity, indicating that a higher auto operating cost will slightly increase the number of trips people make, but those trips will be consolidated into a smaller number of tours.

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[21] Jeremy Mattson, "Effects of Rising Gas Prices on Bus Ridership for Small Urban and Rural Transit Systems", Upper Great Plains Transportation Institute (www.ugpti.org), North Dakota State University; 2008. www.ugpti.org/pubs/pdf/DP201.pdf

[22] Nowak, William and Savage, Ian, "The cross elasticity between gasoline prices and transit use: Evidence from Chicago", Northwestern University, 2013

- Reasonable range of elasticity = very small, negative
- Model results, person trips = +0.010
- Model results, person tours = -0.002

- **Vehicle trips**: Litman (2017) summarized a 2001 European study of elasticity of vehicle trips with respect to fuel price, which is a reasonable proxy for auto operating cost. Observed elasticities in this study ranged from -0.06 to -0.22 in the short term and -0.07 to -0.4 in the long term[19], depending on trip purpose. As with the walk/bike cross elasticity, we expect this relationship to be somewhat less elastic in the SACOG region given that European cities generally provide more attractive alternatives to driving (e.g., older, more walkable urban areas, more extensive transit systems, etc.), making walking a more attractive option relative to driving.
    - Reasonable range of elasticity = very small, negative in sign
    - Model results = -0.008

Table 11-1 presents results of sensitivity testing of auto operating costs. The base cost used was 17 cents per mile, in year 2000 dollars. Tests added or subtracted two, five, and nine cents from the average auto operating costs.

Table 11-1 Sensitivity to Auto Operating Cost, All Incomes

AO Cost (Cents per Mile)	8	12	15	17	19	22	26	**End-to-End Changes**
Change From Base	-9	-5	-2	0	2	5	9	
% Change from Base	*-52.94%*	*-29.41%*	*-11.76%*	*0*	*11.76%*	*29.41%*	*52.94%*	
Response Variable								
Person Trips	7,949,371	7,986,235	8,008,099	8,020,393	8,032,540	8,046,464	8,056,731	n/a
Change From Base	-71,022	-34,158	-12,294	0	12,147	26,071	36,338	107,360
% Change from Base	*-0.89%*	*-0.43%*	*-0.15%*	0	*0.15%*	*0.33%*	*0.45%*	1.34%
Computed Elasticity	*0.012*	*0.012*	*0.012*	0	*0.014*	*0.013*	*0.011*	*0.011*
Vehicle Trips	5,183,097	5,177,483	5,171,133	5,166,547	5,162,398	5,151,431	5,131,435	n/a
Change From Base	16,550	10,936	4,586	0	-4,149	-15,116	-35,112	51,662
% Change from Base	*0.32%*	*0.21%*	*0.09%*	0	*-0.08%*	*-0.29%*	*-0.68%*	1.00%
Computed Elasticity	*-0.004*	*-0.006*	*-0.007*	0	*-0.007*	*-0.011*	*-0.016*	*-0.008*
VMT	41,374,141	39,785,756	38,692,778	37,986,521	37,388,773	36,440,782	35,296,600	n/a
Change From Base	3,387,620	1,799,235	706,257	0	-597,748	-1,545,739	-2,689,921	6,077,541
% Change from Base	*8.92%*	*4.74%*	*1.86%*	0	*-1.57%*	*-4.07%*	*-7.08%*	16.00%
Computed Elasticity	*-0.113*	*-0.133*	*-0.147*	0	*-0.143*	*-0.161*	*-0.173*	*-0.135*
CVMT	3,185,413	2,810,910	2,564,859	2,410,182	2,302,205	2,131,799	1,892,268	n/a
Change From Base	775,231	400,728	154,677	0	-107,978	-278,383	-517,914	1,293,145
% Change from Base	*32.16%*	*16.63%*	*6.42%*	0	*-4.48%*	*-11.55%*	*-21.49%*	53.65%
Computed Elasticity	*-0.370*	*-0.442*	*-0.497*	0	*-0.412*	*-0.476*	*-0.569*	*-0.442*
Transit Person Trips	96,568	99,205	102,457	104,015	105,669	107,879	111,410	n/a
Mode Share	*1.21%*	*1.24%*	*1.28%*	*1.30%*	*1.32%*	*1.34%*	*1.38%*	0.17%
Change From Base	-7,447	-4,810	-1,558	0	1,654	3,864	7,395	14,842
% Change from Base	*-7.16%*	*-4.62%*	*-1.50%*	0	*1.59%*	*3.71%*	*7.11%*	14.27%
Computed Elasticity	*0.099*	*0.136*	*0.121*	0	*0.142*	*0.141*	*0.162*	*0.121*
Bike+Walk Person Trips	458,770	475,749	487,101	494,825	501,559	513,273	527,780	n/a
Mode Share	*5.77%*	*5.96%*	*6.08%*	*6.17%*	*6.24%*	*6.38%*	*6.55%*	0.78%
Change From Base	-36,055	-19,076	-7,724	0	6,734	18,448	32,955	69,010
% Change from Base	*-7.29%*	*-3.86%*	*-1.56%*	0	*1.36%*	*3.73%*	*6.66%*	13.95%
Computed Elasticity	*0.100*	*0.113*	*0.126*	0	*0.122*	*0.142*	*0.152*	*0.119*

Source: SACOG 2020.

11.2.3 Off-Street Parking Price

SACSIM19 incorporates parking pricing with data on the parking supply at the parcel level and data on how many people pay to park at their usual work places. Parcel-level parking data include:

- Count of daily and hourly parking spaces on the parcel.
- Daily and hourly price for spaces on the parcel.
- Count of daily and hourly spaces off the parcel but within quarter and half mile buffers around the parcel. Daily and hourly prices for spaces off the parcel but within quarter and half mile buffers around the parcel.

SACSIM19 only considers off-street parking available to the general public, and does not factor in any free parking supply or private parking (e.g., employees only, customers only, etc.).

Price Adjustment at the Parcel Level

For each sensitivity test, we modified the parking prices associated with each parcel, specifically we modified the following for each parcel:

- The price of parking on the parcel
- Prices for parking on parcels within ¼ mile of the parcel
- Prices for parking on parcels within ½ mile of the parcel

Aggregating to Calculate Elasticity

We used the regional median parking price as the regional cost of parking that we would adjust to check sensitivity to the parking price. The regional median price incorporated the parking prices of on-parcel spaces for all parcels with a parking price greater than zero.

To account for the fact that only a small portion of parcels in the region have paid parking, making the "regional average" parking price is essentially free, we experimented using a regional average parking price that included parcels without any paid parking, as well as a regional average price weighted by the number of spaces. These two experiments gave elasticities that were identical to the median-based elasticities, which makes sense considering that elasticities are based on percentage changes in prices, rather than absolute changes in prices. So even if the absolute value of the regional average price differed significantly from the regional median price, the proportional changes in parking cost were the same, therefore resulting in the same elasticity value.

11.2.3.1 Limitations of Literature Comparison

While there is an ample body of literature on parking price elasticities, it is hard to perform an "apples to apples" comparison with elasticities found in literature with those we found through SACSIM19 testing. The literature we reviewed generally measured the effect of parking prices within a limited geographic area such as a central business district (Litman 2017, Farber et al 2009, NAS 2005) or a college campus (Farber et al 2009) where a relatively high share of drivers must pay to park, meaning that a price change will affect a greater share of travelers. In contrast, SACSIM19 looks at the entire SACOG region, which is primarily rural or suburban and has mostly free parking outside of limited areas like downtown Sacramento and select college campuses. In addition, we only adjusted parking prices on parcels that had paid parking in the base scenario and did not add or remove any paid parking in our initial tests, so parking price increases only would have potentially affected travelers with destinations in the limited areas that had paid parking.

11.2.3.2 Region-Level Parking Price Elasticities

We initially calculated the elasticities of the response variables (VMT, vehicle trips, total person trips, transit trips, CVMT, and walk/bike trips) with respect to parking price for all trip types at the regional level. For the reasons discussed above, we expected these elasticities to be of lower magnitude but in the same direction as observed elasticities. Because most trips within the SACOG region are made to destinations that have free parking, increasing parking prices only applied to a relatively small portion of the regional population (about eight percent of the model's input population pays to park at their workplace).

Bearing in mind the above limitations, Table 11-2 summarizes the cross-elasticities for parking estimated through SACSIM19 runs, and below is a summary comparing observed elasticities with those found in SACSIM19 for all trips at the regional level.

- **VMT**: A 1999 study cited in Litman (2017)[19], based on observations in European cities, found an elasticity of VKT (vehicle kilometers traveled) with respect to parking price to be about -0.07. Another study summarized in Litman (2017), conducted in Seattle in 2011, found an elasticity to be about -0.04[23], based on a model developed from a 2006 regional household travel survey. We expect these elasticities to be higher than those in the SACOG model, because the 1999 study looks at European cities, which generally have less free parking and more alternatives to driving. The 2011 Seattle study should also show different elasticities, given that it looks at the effect of VMT at an individual level rather than at a region level.
    - Reasonable range of elasticity = less than -0.04, negative in sign
    - Model results (entire region) = -0.005
- **Transit person trips**: Litman (2017) reviewed an ample body of literature on parking pricing. He references a 1999 study he references, for "auto oriented urban areas," indicated an elasticity of +0.02[19]. Another study in Litman (2017), based on U.S. central business districts, found elasticities ranging from +0.023 to +0.291, the latter applying to "preferred [central business district] locations." [19] We would expect elasticities to be at the lower end of this range when referring to the SACOG region, given that our transit sensitivity considers transit trips made to all parts of the region, with mostly free parking, and not just downtown Sacramento (the region's equivalent of a central business district and limited free parking).
    - Reasonable range of elasticity = +0.02 to +0.29, closer to +0.02
    - Model results (entire region) = +0.08
- **Bike and walk person trips**: While there are scarce data on the cross elasticity between parking price and a shift to bike/walk modes, data from 1999 provided in Litman (2017) indicate an average cross elasticity of approximately +0.03[19] to +0.05, depending on trip purpose. This is an expected elasticity assuming that a higher parking price will incentivize some travelers to switch from driving to biking or walking.
    - Reasonable range of elasticity: +0.03 to +0.05
    - Model results (entire region) = +0.037

[23] Frank et al "An Assessment of Urban Form and Pedestrian and Transit Improvements as an Integrated GHG Reduction Strategy", Seattle DOT, 2011

- **Person trips**: Our literature review did not find provide any information on how parking pricing influences the total number of person trips. We assume elasticity to be zero to slightly negative given that a parking price increase will either result in a mode switch (meaning no change in total trips) or cause some travelers to forego a trip altogether (resulting in a decrease in total trips).
    - Reasonable range of elasticity = small, negative in sign
    - Model results (entire region) = -0.001
- **Vehicle trips**: There are several studies looking at how parking price affects vehicle trips. A 1999 study of European cities, summarized in Litman (2017) indicated an elasticity of -0.08 to -0.3, depending on trip purpose, with business trips being the least elastic. Several studies, including Farber and Weld (2013)[24] and Shoup and Pierce (2013)[25] found parking price elasticities ranging from -0.1 to -0.4.

    None of these studies provides an ideal "apples to apples" comparison with SACSIM19 outputs. Farber and Weld focused their study on a university campus, while Shoup and Pierce observed behavior in downtown San Francisco. Both locations have little free parking to "dilute" the effects of increasing the prices of paid parking. In addition, the dependent variable in these studies was parking occupancy, rather than vehicle trips. Bearing these weaknesses in mind, we expect SACSIM19 elasticities to be the same direction as those in the literature, though of lesser magnitude because any effects in parking price changes on the small portion of parcels that have parking pricing will be significantly reduced by the presence of free parking on most other parcels.

    - Reasonable range of elasticity = -0.08 to -0.4, SACOG region should be toward lower end if not below low end.
    - Model results (entire region) = -0.007

[24] Farber, Weld "Econometric Analysis of Public Parking Price Elasticity in Eugene, Oregon", University of Oregon, 2013
[25] Shoup and Pierce "SFPark: Pricing Parking by Demand", University of California, 2013

Table 11-2 Sensitivity to Parking Cost, Entire Region

Median Day Park Price	$ 4.60	$ 6.90	$ 8.28	$ 9.20	$ 10.12	$ 11.50	$ 13.80	**End-to-End**
% Change from Base	*-50%*	*-25%*	*-10%*	*0%*	*10%*	*25%*	*50%*	**Changes**
Response Variable								
Person Trips	8,022,335	8,020,511	8,021,376	8,020,393	8,017,518	8,016,678	8,016,669	n/a
Change From Base	1,942	118	983	n/a	-2,875	-3,715	-3,724	5,666
% Change from Base	0.02%	0.00%	0.01%	n/a	-0.04%	-0.05%	-0.05%	0.07%
Computed Elasticity	*0.000*	*0.000*	*-0.001*	n/a	*-0.004*	*-0.002*	*-0.001*	*-0.001*
Vehicle Trips	5,188,309	5,176,737	5,171,582	5,166,547	5,161,257	5,155,468	5,146,365	n/a
Change From Base	21,762	10,190	5,035	n/a	-5,290	-11,079	-20,182	41,944
% Change from Base	0.42%	0.20%	0.10%	n/a	-0.10%	-0.21%	-0.39%	0.81%
Computed Elasticity	*-0.006*	*-0.007*	*-0.009*	n/a	*-0.011*	*-0.010*	*-0.010*	*-0.007*
VMT	38,310,753	38,251,676	38,223,861	38,202,941	38,176,399	38,137,827	38,111,117	n/a
Change From Base	107,812	48,735	20,920	n/a	-26,542	-65,114	-91,823	199,635
% Change from Base	0.28%	0.13%	0.05%	n/a	-0.07%	-0.17%	-0.24%	0.52%
Computed Elasticity	*-0.004*	*-0.004*	*-0.005*	n/a	*-0.007*	*-0.008*	*-0.006*	*-0.005*
CVMT	2,420,233	2,410,674	2,399,875	2,384,933	2,392,870	2,378,733	2,346,677	n/a
Change From Base	35,301	25,742	14,943	n/a	7,937	-6,200	-38,255	73,556
% Change from Base	1.48%	1.08%	0.63%	n/a	0.33%	-0.26%	-1.60%	3.08%
Computed Elasticity	*-0.021*	*-0.037*	*-0.059*	n/a	*0.035*	*-0.012*	*-0.040*	*-0.028*
Bike+Walk Person Trips	99,645	101,937	103,112	104,015	105,412	106,782	108,853	n/a
Change From Base	-4,370	-2,078	-903	n/a	1,397	2,767	4,838	9,208
% Change from Base	-4.20%	-2.00%	-0.87%	n/a	1.34%	2.66%	4.65%	8.85%
Computed Elasticity	*0.062*	*0.070*	*0.083*	n/a	*0.140*	*0.118*	*0.112*	*0.080*
Transit Person Trips	484,578	488,864	492,197	494,825	496,317	499,377	504,541	n/a
Change From Base	-10,247	-5,961	-2,628	n/a	1,492	4,552	9,716	19,963
% Change from Base	-2.07%	-1.20%	-0.53%	n/a	0.30%	0.92%	1.96%	4.03%
Computed Elasticity	*0.030*	*0.042*	*0.051*	n/a	*0.032*	*0.041*	*0.048*	*0.037*

Source: SACOG 2020.

11.2.3.3 Downtown Parking Elasticities

To attempt a more "apples to apples" comparison between the model and the literature review environments, we compared elasticities for trips at the region level to trips made only to the downtown RAD, which contains most of the region's parcels with paid parking and the highest percentage of employees that pay for parking. While we anticipate higher parking elasticities in the downtown RAD due to fewer free parking substitutions, we expect these elasticities to still be lower than those shown in the literature since even the downtown RAD, as represented in the model, has a relatively small share of paid parking when compared to the examples in literature.

As Table 11-3 shows, parking price elasticities are significantly higher for trips made to the downtown RAD and generally in line with the observed elasticity ranges. Bike and walk trip elasticity for downtown trips, however, appears to be somewhat higher than indicated by the range found in literature. However, the literature, from 1999 is an average based on a survey of several European cities.

Table 11-3 Comparison Of Observed Elasticities, Regional Elasticities, And Downtown Elasticities For Parking Price - All Trips

Response Variable	Observed Elasticities		Region	Downtown Sacramento
	Low	High		
Person Trips	No data, expect weak negative		-0.001	-0.072
Vehicle Trips	-0.05	-0.3	-0.007	-0.134
VMT	-0.04	-0.07	-0.005	-0.097
CVMT	No data, expect weak negative		-0.028	-0.095
Transit Person Trips	0.01	0.3	0.080	0.159
Bike+Walk Person Trips	0.03	0.03	0.037	0.180

Source: SACOG, March 2020, based on 2020 MTP/SCS forecasts and modeling

11.2.3.4 Elasticity by "Pay to Park" Status for Work Tours

As described above, we predicted that region-wide parking elasticities would have a lower magnitude than those found in literature because while most observed elasticity data is from areas where a large share of motorists must pay to park, most of the parking in the SACOG region is free.

To approximate a more apples-to-apples comparison, we performed a separate sensitivity check in which we compared two trip groups: trips belonging to work tours for people who had to pay to park at work and trips belonging to work tours for all travelers[26]. For this test we only considered work tours because the "pay to park at work" status only applies to work trips.

We predicted that people who need to pay to park at work would be more sensitive to parking price changes because they were less likely to have a free parking alternative and therefore more likely to respond to the price change by switching modes. As Table 11-4 shows, all elasticity magnitudes are greater for people who pay to park at their workplaces and more closely in line with observed parking price elasticities. Some SACSIM19 elasticities, especially for bike and walk trips and vehicle trips, have a

[26] The SACSIM19 person table indicates whether a person needs to pay to park at work by assigning a value of 1 or 0 to the "PPAIDPRK" column.

higher magnitude than those found in the literature. This difference is not particularly surprising given that even though the literature focuses on areas where most parking is paid parking, it did not focus exclusively on travelers who must pay to park.

Table 11-4 Comparison of Observed Elasticities, Regional Elasticities, And Downtown Elasticities For Parking Price - Work Trips

Response Variable	Observed Elasticities		Region		Downtown Sacramento	
	Low	High	People who Paid to Park at Work	All Travelers' Work Trips	People who Paid to Park at Work	All Travelers' Work Trips
Person Trips	No data, expect weak negative		-0.014	-0.002	-0.064	-0.04
Vehicle Trips	-0.05	-0.3	-0.033	-0.007	-0.174	-0.08
VMT	-0.04	-0.07	-0.026	-0.004	-0.128	-0.062
CVMT	No data, expect weak negative		-0.05	-0.027	-0.136	-0.072
Transit Person Trips	0.01	0.3	0.25	0.097	0.297	0.137
Bike+Walk Person Trips	0.03	0.03	0.126	0.055	0.228	0.145

Source: SACOG 2020.

11.2.4 Household Income

Reported sensitivities of travel demand quantities to household income are thinly reported in research literature. The model sensitivities shown are “end-to-end” elasticities, or the elasticity based on comparing the highest and lowest test values, giving a rough average elasticity to compare with observed data.

- **VMT**: A 2011 Study of the Portland, OR region a near-term elasticity of VMT with respect to income of +0.05, and a long-run elasticity of +0.24[27], while a 1992 study for the U.S. overall found elasticities of +0.18 in the short run and as high as +1.0 for the long-run[28].
  - Reasonable range of elasticity = +0.05 to +0.18 in near term
  - Model results = +0.12
- **Transit person trips**: One study relating transit trips to household income, from 2015 and based on data from 198 U.S. transit systems, found near-term transit trip elasticity with respect to household income to be -0.36 for large urban areas (population > 1M) and -0.26 for small urban areas (population <1M). While the SACOG region as a whole is a “large” area with more than 2M residents, this population is broken up into several smaller urban areas within the region, with

[27] B. Starr McMullen, Nathan Eckstein, “The Relationship Between VMT and Economic Activity” OSU TREC, 2011

[28] Sterner, T., Dahl, C. and Franzén, M., “Gasoline Tax Policy, Carbon Emissions and the Global Environment”, Journal of Transport Economics and Policy, 1992

large sections being rural. Therefore, we would consider it reasonable for modeled elasticity of transit trips with respect to household income to tend closer to the "small" UZA estimate. Also important to consider is that while the 2015 study uses transit systems as the unit of analysis, the modeled elasticity for transit trips is based on the entire region, which has large areas with little or no transit service. Changes to household income in these areas will have little to no effect on transit ridership and therefore we would expect it to somewhat lower the magnitude of elasticity.

  - Reasonable range of elasticity = -0.26 to -0.36, SACOG may be somewhat lower
  - Model results = -0.239

- **Bike and walk person trips**: No recent research was found which analyzed the relationship between non-motorized travel and household income. However, it is presumed here to be *negative* (i.e., increases in household income would tend to decrease non-motorized travel) and that the magnitude of the relationship would be relatively small.
  - Reasonable range of elasticity = small, negative in sign
  - Model results = -0.126
- **Person trips**: No recent research was found which analyzed the relationship between total person trips and household income. However, it is presumed here to be *positive* (i.e., that increases in household income would tend to increase the number of person and vehicle trips) and that the magnitude of the relationship would be relatively small.
  - Reasonable range of elasticity = small, positive in sign
  - Model results = +0.068
- **Vehicle trips**: No recent research was found which analyzed the relationship between vehicle trips and household income. However, it is presumed here to be *positive* (i.e., that increases in household income would tend to increase the number of person and vehicle trips) and that the magnitude of the relationship would be higher than that for person trips, given that with income increases comes some shift from transit and other modes to vehicle modes.
  - Reasonable range of elasticity = higher than person trip elasticity, positive in sign
  - Model results = +0.109

Table 11-5 presents results of sensitivity testing of household income. The base income was the 2005 household income distribution. Tests added or subtracted five, ten, and fifty percent of household income for each household.

Table 11-5 Sensitivity to Household Income

Median HH Income *% Change from Base*	$ 23,466 *-50%*	$ 42,238 *-10%*	$ 44,585 *-5%*	$ 46,932 *0%*	$ 49,278 *5%*	$ 51,625 *10%*	$ 70,398 *50%*	**End-to-End Changes**
Response Variable								
Person Trips	7,634,087	7,959,207	7,990,083	8,020,393	8,041,905	8,067,082	8,221,872	n/a
Change From Base	-386,306	-61,186	-30,310	n/a	21,512	46,689	201,479	587,785
% Change from Base	-4.82%	-0.76%	-0.38%	n/a	0.27%	0.58%	2.51%	7.33%
Computed Elasticity	*0.071*	*0.073*	*0.074*	n/a	*0.055*	*0.061*	*0.061*	*0.068*
Vehicle Trips	4,761,483	5,105,994	5,136,411	5,166,547	5,189,186	5,214,750	5,365,448	n/a
Change From Base	-405,064	-60,553	-30,137	n/a	22,639	48,202	198,901	603,964
% Change from Base	-7.84%	-1.17%	-0.58%	n/a	0.44%	0.93%	3.85%	11.69%
Computed Elasticity	*0.118*	*0.112*	*0.114*	n/a	*0.090*	*0.097*	*0.093*	*0.109*
VMT	34,838,042	37,737,616	37,991,946	38,202,941	38,398,670	38,583,108	39,759,080	n/a
Change From Base	-3,364,899	-465,325	-210,995	n/a	195,729	380,167	1,556,139	4,921,038
% Change from Base	-8.81%	-1.22%	-0.55%	n/a	0.51%	1.00%	4.07%	12.88%
Computed Elasticity	*0.133*	*0.116*	*0.108*	n/a	*0.105*	*0.104*	*0.098*	*0.120*
CVMT	1,642,128	2,281,920	2,324,286	2,384,933	2,445,595	2,504,470	2,789,536	n/a
Change From Base	-742,805	-103,013	-60,647	n/a	60,663	119,537	404,603	1,147,408
% Change from Base	-31.15%	-4.32%	-2.54%	n/a	2.54%	5.01%	16.96%	48.11%
Computed Elasticity	*0.538*	*0.419*	*0.502*	n/a	*0.515*	*0.513*	*0.386*	*0.482*
Bike+Walk Person Trips	545,914	500,851	497,880	494,825	491,909	489,243	475,528	n/a
Change From Base	51,089	6,026	3,055	n/a	-2,916	-5,582	-19,297	70,386
% Change from Base	10.32%	1.22%	0.62%	n/a	-0.59%	-1.13%	-3.90%	14.22%
Computed Elasticity	*-0.142*	*-0.115*	*-0.120*	n/a	*-0.121*	*-0.119*	*-0.098*	*-0.126*
Transit Person Trips	124,834	106,699	105,987	104,015	103,214	102,163	95,962	n/a
Change From Base	20,819	2,684	1,972	n/a	-801	-1,852	-8,053	28,872
% Change from Base	20.02%	2.58%	1.90%	n/a	-0.77%	-1.78%	-7.74%	27.76%
Computed Elasticity	*-0.263*	*-0.242*	*-0.366*	n/a	*-0.158*	*-0.189*	*-0.199*	*-0.239*

Source: SACOG 2020.

11.2.5 Transit Fares

Except for changes in transit ridership, we found few reported sensitivities of transit demand with respect to transit fares in research literature. As with the other tests, sensitivities shown are "end-to-end" elasticities, or the elasticity based on comparing the highest and lowest test values, giving a rough average elasticity to compare with observed data.

- **VMT**: None of the studies we reviewed explicitly quantified the relationship between transit fare levels and VMT. Two studies cited in Litman (2017) described an elasticity of "car use" with respect to transit fare to range between +0.01 to +0.19[19], though it was unclear whether "car use" referred to VMT or vehicle trips. We expect the elasticity to be small and positive, given that even a proportionally large increase in transit ridership due to lower fares would be a proportionally small decrease in VMT.
    - Reasonable range of elasticity = small, positive in sign
    - Model results = +0.001
- **Transit person trips**: A wide range of studies have analyzed the changes in transit ridership (usually measured as passenger boardings) after changes in fares. Changes in fares have included changes in cost, level or distribution of discounts, fare media, and other aspects of fare. The SACSIM model is limited to representing average transit fare, so the evaluation focused on percentage changes to average fares by operator for all operators. Studies summarized in Litman (2017) found transit ridership changes with respect to overall transit fare range from -0.2 to -0.3 in the short run and -0.4 to -1.0 in the long run[19].
    - Range of observed elasticities = -0.2 to -1.0
    - Model results = -0.098
- **Bike and walk person trips**: No recent research was found which analyzed the relationship between non-motorized travel and transit fares. However, it is presumed here to be *positive* (i.e., that increases in fares would tend to increase non-motorized travel) and that the magnitude of the relationship would be small.
    - Reasonable range of elasticity = small, positive in sign
    - Model results = +0.000
- **Person trips**: No recent research was found which analyzed the relationship between total person trips and transit fares. However, it is presumed here to be *negative* (i.e., that increases in fares would tend to decrease the number of person and vehicle trips) and that the magnitude of the relationship would be small.
    - Reasonable range of elasticity = small, negative in sign
    - Model results = -0.000
- **Vehicle trips**: Like the relationship between VMT and transit fares, none of the studies we reviewed explicitly quantified the relationship between transit fare levels and vehicle trips. Two studies cited in Litman (2017) described an elasticity of "car use" with respect to transit fare to range between +0.01 to +0.19[19],though it was unclear whether "car use" referred to VMT or vehicle trips. We expect the elasticity to be small and positive, given that even a proportionally large increase in transit ridership due to lower fares would be a proportionally small decrease in vehicle trips.
    - Reasonable range of elasticity = small, positive in sign
    - Model results = +0.001

Table 11-6 presents results of sensitivity testing of transit fares. Tests added or subtracted five, ten, and fifty percent of fares for each operator.

Table 11-6 Sensitivity to Transit Fare, All Incomes

Regional Avg Transit Fare	0.82	1.47	1.56	1.64	1.72	1.8	2.46	**End-to-End Changes**
Change From Base	-0.82	-0.17	-0.08	n/a	0.08	0.16	0.82	
% Change from Base	*-50%*	*-10%*	*-5%*	*0%*	*5%*	*10%*	*50%*	
Response Variable								
Person Trips	8,020,162	8,018,744	8,014,028	8,020,393	8,020,909	8,019,385	8,016,944	n/a
Change From Base	-231	-1,649	-6,365	0	516	-1,008	-3,449	3,218
% Change from Base	*0.00%*	*-0.02%*	*-0.08%*	0	*0.01%*	*-0.01%*	*-0.04%*	0.04%
Computed Elasticity	*0.000*	*0.002*	*0.016*	*0*	*0.001*	*-0.001*	*-0.001*	*0.000*
Vehicle Trips	5,162,864	5,164,734	5,159,516	5,166,547	5,167,673	5,167,863	5,168,531	n/a
Change From Base	-3,684	-1,813	-7,031	0	1,126	1,315	1,984	5,668
% Change from Base	*-0.07%*	*-0.04%*	*-0.14%*	0	*0.02%*	*0.03%*	*0.04%*	0.11%
Computed Elasticity	*0.001*	*0.003*	*0.027*	*0*	*0.005*	*0.003*	*0.001*	*0.001*
VMT	38,171,355	38,193,424	38,136,913	38,202,941	38,220,631	38,216,735	38,216,640	n/a
Change From Base	-31,586	-9,517	-66,028	0	17,690	13,794	13,699	45,285
% Change from Base	*-0.08%*	*-0.02%*	*-0.17%*	0	*0.05%*	*0.04%*	*0.04%*	0.12%
Computed Elasticity	*0.001*	*0.002*	*0.035*	*0*	*0.010*	*0.004*	*0.001*	*0.001*
CVMT	2,383,238	2,412,445	2,412,035	2,384,933	2,381,873	2,406,136	2,416,036	n/a
Change From Base	-1,694	27,513	27,102	0	-3,060	21,203	31,104	32,798
% Change from Base	*-0.07%*	*1.15%*	*1.14%*	0	*-0.13%*	*0.89%*	*1.30%*	1.38%
Computed Elasticity	*0.001*	*-0.105*	*-0.226*	*0*	*-0.027*	*0.095*	*0.032*	*0.012*
Transit Person Trips	110,190	105,136	104,921	104,015	103,433	103,472	98,936	n/a
Mode Share	*1.37%*	*1.31%*	*1.31%*	*1.30%*	*1.29%*	*1.29%*	*1.23%*	0.14%
Change From Base	6,175	1,121	906	0	-582	-543	-5,079	11,254
% Change from Base	*5.94%*	*1.08%*	*0.87%*	0	*-0.56%*	*-0.52%*	*-4.88%*	10.82%
Computed Elasticity	*-0.083*	*-0.098*	*-0.173*	*0*	*-0.118*	*-0.056*	*-0.123*	*-0.098*
Bike+Walk Person Trips	494,322	494,597	495,088	494,825	495,170	493,866	494,532	n/a
Mode Share	*6.16%*	*6.17%*	*6.18%*	*6.17%*	*6.17%*	*6.16%*	*6.17%*	0.01%
Change From Base	-503	-228	263	0	345	-959	-293	210
% Change from Base	*-0.10%*	*-0.05%*	*0.05%*	0	*0.07%*	*-0.19%*	*-0.06%*	0.04%
Computed Elasticity	*0.001*	*0.004*	*-0.011*	*0*	*0.015*	*-0.021*	*-0.001*	*0.000*

Source: SACOG 2020.

11.2.5.1 Effect of Household Income on Transit Fare Sensitivity

The sensitivities shown in Table 11-6 reflect trips made by people of all income levels. We also tested how a traveler's household income affects his/her sensitivity to transit fares by comparing sensitivity for households in the highest and lowest income quartiles. Among our key findings:

- Travelers in the lowest income quartile are more sensitive to transit fare increases than the general population. Specifically, as transit fares increase, lower-income travelers are more likely to shift away from transit to either using a private vehicle, walking, or biking. This finding makes sense given that lower-income populations are generally more sensitive to price increases since a given cost will represent a larger share of their total income.
- As expected, higher income travelers are significantly less sensitive to transit fare increases than the general population. Following the logic for why lower-income travelers are more sensitive to fare increases, higher-income riders are less sensitive to fare increases because the cost of a fare represents a smaller share of their total income compared to a lower-income rider.

11.2.6 Roadway Capacity

The primary research literature analyzing the effect of roadway capacity on travel demand may be grouped into a category called "induced travel". The induced travel hypothesis is that adding roadway capacity itself generates or "induces" travel demand, even after accounting for growth in population and employment. Induced travel is at best a loosely defined term, potentially including many levels of short-term and long-term transportation and land use interactions.

The simplest effects of induced demand are based purely on traditional travel demand theory: by alleviating congestion or providing additional roadway routes, travel by auto becomes faster and shorter in time, although potentially longer in distance. The short-term **traveler response** is in shifts in travel mode, routes, and time of day, and possibly more trips accounting for latent demand. The long-term **land use response** is that people, jobs and land development relocate to take advantage of the increased accessibility along an expanded roadway corridor, eroding the speed and accessibility benefits of the expanded capacity. Over time much of the improvement in accessibility from the expansion tends to be transitory—the congestion relief provided by new or widened roadways is eroded by growth in overall demand and VMT.

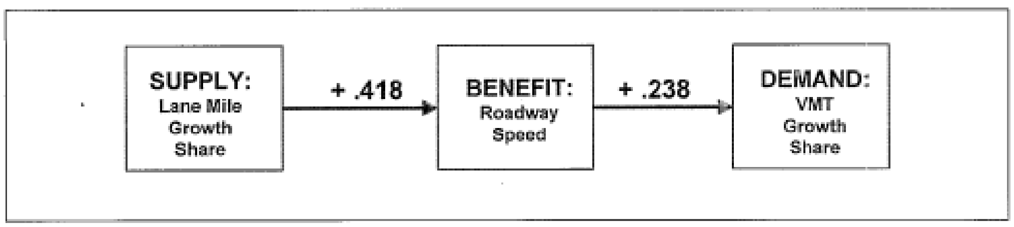
Research conclusions on induced travel have been largely agnostic as to its underlying causes, but in relative concord as to the existence of an effect which connects adding roadway capacity to increasing VMT. Most research defaulted to a definition of induced travel as a statistically significant, positive relationship between provision of additional lane mileage of roadway and VMT, after accounting in aggregate form for the most obvious other factors normally related to VMT growth (e.g., population growth, changes to income, demographic factors, changes in the cost of fuel, geographic spread of the land use pattern).

One study by Robert Cervero sorted out the near-term and long-term effects, and estimated elasticities segmented by road improvements and other variables[29]. The short term or "traveler

[29] Cervero, Robert, "Road Expansion, Urban Growth, and Induced Travel: A Path Analysis", *APA Journal*, Spring 2003 Vol.69, No. 2.

response" induced travel effects are split into two components: the effect of added capacity on average speed of roadway travel; and the effect of speed on VMT. The Cervero study estimated elasticities for each of these short-term effects: the elasticity of speed with respect to added capacity was estimated to be +0.42 (i.e., a 10 percent increase in capacity results in a 4.2 percent increase in travel speed). The elasticity of VMT with respect to speed was estimated to be +0.24 (i.e., a 10 percent increase in speed results in a 2.4 percent increase in VMT). The "combined" effect of capacity and speed on VMT is calculated by multiplying the individual effects (0.42 x 0.24 = +0.10). The combined elasticity of +0.10 is used as a benchmark for reasonable sensitivity of the short term, "traveler response" effects of induced travel.

Figure 11-1 Short Term or Traveler Response Induced Travel Effects



Source: Cervero, Robert, "Road Expansion, Urban Growth, and Induced Travel: A Path Analysis", *APA Journal*, Spring 2003 Vol.69, No. 2.

We measured VMT sensitivity to changes in capacity by modifying highway capacity and tallying changes in VMT predicted for each change. This approach captures only the short-term traveler response to changes in auto travel speed and resulting shorter travel times as a result of increased road capacity. None of the longer-term effects of increased capacity on land use are measured in this test. The next section "Cross Sectional Testing of Sensitivity to Land Use / Transportation Factors", partly addresses these questions by analyzing the relationship between modeled travel behavior and transportation/land use factors.

Table 11-7 estimates the combined short-term effects of capacity on speed, and speed on VMT. Table 11-7 shows each effect separately, and the combined effect. The range of SACSIM sensitivity of speed with respect to capacity ranged from +0.06 to +0.08, lower than the +0.42 estimated in the Cervero study. The range of SACSIM sensitivity of VMT with respect to speed was +2.33 to +2.65, compared to +0.24 estimated from Cervero study. In combination, SACSIM elasticity of VMT with respect to capacity was +0.06 to +0.08, with an "end-to-end" average elasticity of +0.07. The range of elasticities falls slightly below the target of +0.10, and the end-to-end SACSIM elasticity is somewhat below the target. In other words, SACSIM speeds are significantly less sensitive to capacity changes than observed data show, but its predicted VMT is significantly more sensitive to speed than observed. Taking the capacity-speed and speed-VMT elasticities together, SACSIM's VMT is only somewhat less sensitive to changes in capacity than observed data show.

We expect some difference between our sensitivity test results and observed sensitivities because the nature of how we changed capacity (doing a systemwide flat percent change on all roadways) differs significantly from how Cervero et al measured capacity changes (on specific corridors).

However, we do expect the direction of sensitivity for both observed and modeled data to be the same, i.e., an increase in capacity should lead to an increase in VMT, even if the magnitude of the sensitivity is different.

Table 11-7 SACSIM19 Model Testing Results of Short Term, Traveler Response Induced Travel Effects

	Capacity Change from Base					End-to-End
Test Variables	-10%	-5%	**Base**	5%	10%	**Change**
Weekday VMT	59,648,242	59,897,121	60,120,818	60,297,761	60,474,822	826,580
System Average Speed (mph)	40.27	40.33	40.39	40.44	40.48	0.22
% Changes from Base						
VMT	-0.79%	-0.37%	n/a	0.29%	0.59%	1.37%
Speed	-0.30%	-0.14%	n/a	0.13%	0.24%	0.54%
Elasticities						
Speed w.r.t. Capacity	0.03	0.03	n/a	0.03	0.02	0.03
VMT w.r.t. Speed	2.62	2.65	n/a	2.33	2.48	2.56
Combined (VMT w.r.t. Capacity)	0.08	0.07	n/a	0.06	0.06	0.07

Source: SACOG 2020.

11.3 Cross Section Testing of Land Use/Transportation Factors

11.3.1 Background and Definition

"Land use/transportation" factors (also known as "the Ds") combine an area's land use and transportation characteristics to explain variation in travel behavior of its residents. LU/T factors are very well-studied in research literature, using household travel surveys and disaggregated land use data as the basis of analysis. For evaluating SACSIM19, our primary reference was a 2010 meta-analysis (a review and compilation of studies) by Ewing and Cervero[30]. Although several years old, a more recent (July 2017) article by Litman[31] summarizing research done on the land use-transportation relationship indicated that the 2010 Ewing-Cervero meta-analysis is the most recent of its kind, therefore we consider it reasonable to continue using its findings in our evaluation of SACSIM19. The meta-analysis examined the following land use/transportation factors, with results summarized in Table 11-8:

- **Regional accessibility**, which quantifies how connected a given area is to existing development, and is usually stated as the number of jobs within an average auto commute time. Regional accessibility is usually higher in areas within the existing urbanized area, and tends to be lower in outlying areas or areas on the urban edge. This factor has the strongest potential effect on VMT—a 10 percent increase in an area's accessibility results in a roughly two percent decrease in VMT for residents of that area.
- **Street pattern/urban design**, or how walkable a given area is based on characteristics of its street pattern and is usually measured as intersection density. A higher intersection density typically means smaller blocks and more potential walking connections there are in that area. Although other factors affect walkability and walk mode share (e.g., presence/absence of sidewalks, pedestrian amenities on the street, traffic volumes on streets, presence/absence of crosswalks, treatment of pedestrians at signalized intersections), intersection density has been used in research as a proxy for walkability, in part because it is relatively easy to assemble data. In terms of VMT reduction, street pattern is the second strongest factor with a 10 percent increase in intersection density resulting in a roughly one percent decrease in VMT.
- **Mix of use** refers to the inclusion in an area of a range of complementary land uses, which allows for more activities (i.e., working, shopping, school) to be contained within that area. Good land use mix allows for reductions in VMT through shortening of vehicle trips or shifting to other non-vehicle modes of travel such as walking. The most common measures of mix of use combine the relative proportions of residential, overall jobs, retail and other residential-supporting land uses into an "entropy" formula, which translates the balance of land use mix into a 0 to 100 scale[32].

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[30] Ewing, R. and Cervero, R., "Travel and the Built Environment: A Meta-Analysis," *Journal of the American Planning Association*, Vol. 76, No. 3, Summer 2010.
[31] Litman T., "Land Use Impacts on Transport: How Land Use Factors Affect Travel Behavior" Victoria Transport Policy Institute, July 2017
[32] Hossack, Gary, "Measuring and Visualizing the Diversity of Land Use and Its Relationship with Travel Behavior", TRB 2008 Annual Meeting, Paper #08-2742, Session 337.

- **Proximity to transit** refers to the distance from a residence to the nearest transit station or stop, with VMT declining, and both walking and transit use increasing, as distance to the nearest transit decreases.
- Residential density refers to the number of persons or dwellings within a given area. Conceptually, density is quite easy to understand—the number of persons or housing units within a given area. However, different definitions of area (e.g., net acreage, gross acreage, total area) and the fact that higher densities often co-exist with other land use/transportation factors such as high regional accessibility, walkable street patterns, and more transit service, the effects of density are often over- or under-stated. The Ewing/Cervero meta-analysis controlled for differences in definition of density across the studies they reviewed.

Table 11-8 provides a summary of the results of the Ewing/Cervero meta-analysis of LU/T factors and travel outcomes, stated as an elasticity of the travel outcomes for each land use/transportation factor. These elasticities will be used as a basis for evaluating whether SACSIM19's sensitivity to LU/T factors is reasonable.

Table 11-8 Land Use/Transportation Factors and Travel Outcomes

	Travel Outcome		
Land Use /Transportation Factor	*VMT**	Walk	Transit
Reported Elasticities[33,34,35]			
Regional Accessibility	-0.20 [*-0.13 to -0.25*]	+0.15	n/a
Street Pattern/Urban Design	-0.12 [*-0.03 to -0.19*]	+0.39	+0.23
Mix of Use	-0.09 [*-0.02 to -0.11*]	+0.15	+0.12
Proximity to Transit	-0.05 [*uncertain*]	+0.15	+0.29
Residential Density	-0.04[*-0.04 to -0.19*]	+0.07	+0.07

*Ranges were reported for VMT but not for other travel outcomes because the amount of research done on the land use/transportation effects on VMT is more robust.

11.3.2 Challenges of Testing Land Use-Transportation Sensitivities

Although it is tempting to assume that the relationships shown in Table 11-8 are discrete dials that can be adjusted to achieve pre-defined results, there are many factors that confound attempts to isolate individual effects. Self-selection bias is a major confounding factor, which is poorly accounted for in most of the research. Self-selection bias refers to fact that personal preference affects where someone chooses to live and the travel choices they make. E.g., people who like walking may

[33] Elasticities are stated as the proportional change in the travel outcome with respect to a change in the land use/transportation factor.

[34] Unbracketed elasticities from Ewing, R. and Cervero, R., "Travel and the Built Environment: A Meta-Analysis," *Journal of the American Planning Association*, Vol. 76, No. 3, Summer 2010.

[35] Bracketed elasticities are the range of elasticities reported by in research syntheses by, as well as by Boarnet, M. and Handy, S. and posted on the CARB website: http://arb.ca.gov/cc/sb375/policies/policies.htm

gravitate to walkable environments in their place of residence or place of work, and some of the land use-transportation relationships which are shown in research based on travel surveys may simply be measuring personal preferences rather than the environment's effects on behavior. Replicating in new areas the high walk share observed in existing well-mixed, walkable neighborhoods may be impossible, simply because the existing areas may have attracted a unique population of individuals who prefer walking.

Further, interactions among the land use-transportation factors themselves are difficult to control, and many factors are highly correlated. For example, many areas with denser street patterns (i.e., more intersections per unit of area) also have higher development densities, simply because their block and lot sizes are also smaller. Research has also recognized that the combined effects of many factors is not always equal to adding up the individual effects of each factor—there may be ceilings on some of the combined results. On the other side, some of the combined effects may be greater than the sum of the individual effects. For example, evidence from transit-oriented developments suggests that the combined effects of density, proximity to transit, and street pattern around rail stations with frequent service may far exceed the reductions in VMT and increases in walking and transit travel suggested by Table 11-8.[36] Although some factors are known to have greater potential influence (e.g., regional accessibility), significantly changing those factors may be difficult.

11.3.3 Land Use-Transportation Sensitivity Testing with SACSIM

The approach used to evaluate the sensitivity of SACSIM to LU/T factors focused on the household-generated travel and DAYSIM submodel outputs. SACSIM has several advantages in doing this sort of evaluation:

- Land use data in SACSIM is maintained at parcel/point level (see Chapter 1), which allows for much more nuanced and accurate representations of the land use context for a given area. Land use context is defined at parcel/point level, with surrounding land uses based on one-quarter and one-half mile "buffers" around each parcel/point. This provides more accurate land use context than the zone or fixed subarea systems typically used in travel demand modeling. SACSIM19's buffering system further increases the accuracy by basing its buffers on a "circuity factor," which instead of assuming a circle-shaped, or radial buffer, modifies the buffer's shape to consider street network characteristics that affect what is actually within a quarter or half mile. For example, two destinations may be 500 feet apart "as the crow flies", but due to some obstacle like a freeway or river would require a much longer trip to travel between using the street network.
- Demographics is a disaggregate, representative population file rather than a zone-aggregated summary or cross-classification of households. The population file includes characteristics such as an individual's age , worker or student status, and income of the household he/she lives in. The file also includes variables related to household structure (e.g., presence/absence of school age children) which are highly influential in determining travel behavior. Realistically zeroing in on the LU/T effects *requires controlling for key*

[36] Arrington, G.B., and Cervero, Robert, "Effects of TOD on Housing, Parking, and Travel", Transit Cooperative Research Program No. 128, Transportation Reseach Board, 2008.

demographic factors. Often these controls are not implemented, and LU/T factors are consequently over-attributed with effects on travel behavior.

- The activity/tour based modeling approach used for household-generated travel allows for a more complete accounting of travel by residents of the region. Tours are series of trips made from home to an activity (e.g., work), and back home. All trips on the tour are counted and "tracked" by DAYSIM as part of a given person's travel. This allows for all travel to be attributed to a given person or household, and be correlated with the LU/T characteristics of that person's place of residence or work. This contrasts with a traditional, trip-based travel demand model in which approximately one-third of all trips are "non-home-based" and the characteristics of the traveler and the traveler's place of residence or place of work are unknown and unaccounted for.

Given the disaggregate nature of the DAYSIM travel outputs, the units of analysis for LU/T sensitivity testing are individual people. For this test, all VMT and person trips by mode of travel are tallied by person and attributed to the person's place of residence. LU/T characteristics of the place of residence are tallied for each person in the population (2.2 million in this case). Key demographic characteristics (e.g., age, income, worker status, student status) as well as household structure characteristics (e.g., household size) are used as continuous (in the case of income or age) or categorical (in the case of worker or student status) variables.

The analysis performed is *cross-sectional*—that is, it examines a single set of data for one point in time, and evaluates variations in independent (in this case, a combination of demographic and LU/T factors) and dependent (household-generated VMT per person, transit trips per person, and walk trips per person) variables across the dataset, then evaluates the correlations between these variables. This is distinct from the experimental approach, which tests variables through direct manipulation of independent or input variables, and measures variations in output variables. Because LU/T factors by definition combine several different factors, this sort of experimental approach is difficult or impossible. For example, varying density means, of course, adding population or jobs to a given area—but that variation also affects mix of use and regional accessibility. The cross-sectional approach relies on statistical analysis to sort out and quantify the major LU/T effects.

Table 11-9 provides a comparison of the LU/T effects, converted from regression coefficients to elasticities, to the elasticities reported in the Ewing/Cervero meta-analysis[30] referred to above. Two values for SACSIM-estimated elasticities are provided; one is an "all variables" value, in which the elasticity was drawn from regression coefficients from a regression with all LU/T factors and all demographic factors in the model. The second is a "single variable" elasticity, in which the elasticity was drawn from regression coefficient from a regression with only a single LU/T variable and all demographic factors.

We determined how reasonable SACSIM's sensitivity to Land Use factors was by comparing its land use-transportation elasticities to those in Ewing and Cervero meta-analysis[30]. If the elasticity found in the meta-analysis fell within SACSIM's all-variable and single-variable elasticities, the LU/T factor is considered to be reasonably sensitive. This general test of reasonable sensitivity is not a "hard and fast" rule, nor do Ewing and Cervero recommend rigidly applying the values published in the meta-analysis.

In part, this flexible approach to comparing to the meta-analysis elasticities is consistent with the level of certainty around the research and limitations of "borrowing" research results from a range of geographic areas and a range of studies. The flexibility recognizes that many of the studies combined in the meta-analysis include some, but not all, of the LU/T factors, and some, but not all, of the demographic control variables.

Many of the LU/T variables themselves correlate with one another. An example is residential density and street pattern, which in the SACOG region show partial correlation of 0.52. Other LU/T factors which are highly correlated area residential density and transit accessibility to jobs (0.40), and street pattern and level of land use mix (0.36). By combining all variables within one statistical regression, some of the strength of variables may be shared, which may in turn account for the "all variables" elasticities falling somewhat below the published meta-analysis elasticities.

Finally, some of the research studies in the Ewing/Cervero meta-analysis[30] treated households as units of analysis while some treated persons as units of analysis. The effects of differences in units of analysis were not controlled in the meta-analysis[37]. Because households in areas with higher density and access to good transit service (i.e., areas which have "good" LU/T context) also tend to be smaller in size, results of person-level analysis, which was used for the SACSIM testing, may result in slightly lower LU/T elasticity effects.

As shown in Table 11-9, all but two SACSIM LU/T elasticities bound the meta-analysis elasticities (i.e., the meta-analysis elasticity fell within the range bound by the all-variable and single-variable SACSIM elasticities). The exceptions were:

- SACSIM's range of elasticity of VMT with respect to mix of use is somewhat higher than the meta-analysis elasticity, indicating that SACSIM is slightly more sensitive to mix of use than the literature suggests.
- SACSIM's range of elasticity of transit trips with respect to residential density is significantly higher than the meta-analysis elasticity, indicating that SACSIM is more sensitive to residential density than the literature suggests.

Because the elasticities computed from the regression results matched the published Ewing/Cervero elasticities as to sign, and closely matched the elasticities as to magnitude of effect, SACSIM is reasonably sensitive to land use/transportation factors.

[37] Personal communication from Reid Ewing, December 2011.

Table 11-9 Land Use/Transportation Elasticity Comparison

Land Use/Transportation Factor	Variable	Elasticities: From Literature[38]	Elasticities: Estimated From SACSIM19 (all variables)	Elasticities: Estimated From SACSIM19 (single variable)
VMT Per Person				
Regl Auto Accessibility	Jobs w/in 30-Min Drive†	-0.2	-0.217	-0.38
Regl Transit Accessibility	Jobs w/in 30-Min Transit Trip*	-0.05	-0.006	-0.04
Mix of Use	SACOG Mix Index (0-1 scale)†	-0.09	-0.167	-0.31
Street Pattern	3- and 4-way Intersections within 0.25mi of residence	-0.12	-0.093	-0.31
Proximity to Transit	Distance to Nearest Transit Stop (miles)**	-0.05	-0.001	-0.32
Residential Density	Households within 0.25 miles of residence†	-0.04	-0.100	-0.27
Transit Trips Per Person				
Regl Transit Accessibility	Jobs w/in 30-Min Transit Trip	na	0.128	0.22
Mix of Use	SACOG Mix Index (0-1 scale)†	0.12	0.235	0.57
Street Pattern	3- and 4-way Intersections within 0.25mi of residence	0.23	-0.164††	0.66
Proximity to Transit	Distance to Nearest Transit Stop (miles)**	0.29	0.000	0.39
Residential Density	Households within 0.25 miles of residence†	0.39	0.520	0.87
Walk Trips Per Person				
Destination Accessibility	Jobs within 0.25mi of parcel*	0.15	0.030	0.09
Mix of Use	SACOG Mix Index (0-1 scale)†	0.15	0.253	0.41
Street Pattern	3- and 4-way Intersections within 0.25mi of residence	0.39	0.172	0.54
Proximity to Transit	Distance to Nearest Transit Stop (miles)**	0.15	0.001	0.23
Residential Density	Households within 0.25 miles of residence†	0.07	0.307	0.53

* Range of SACSIM elasticity magnitudes below meta-analysis elasticity magnitude.

† Range of SACSIM elasticity magnitudes greater than meta-analysis elasticity magnitude.

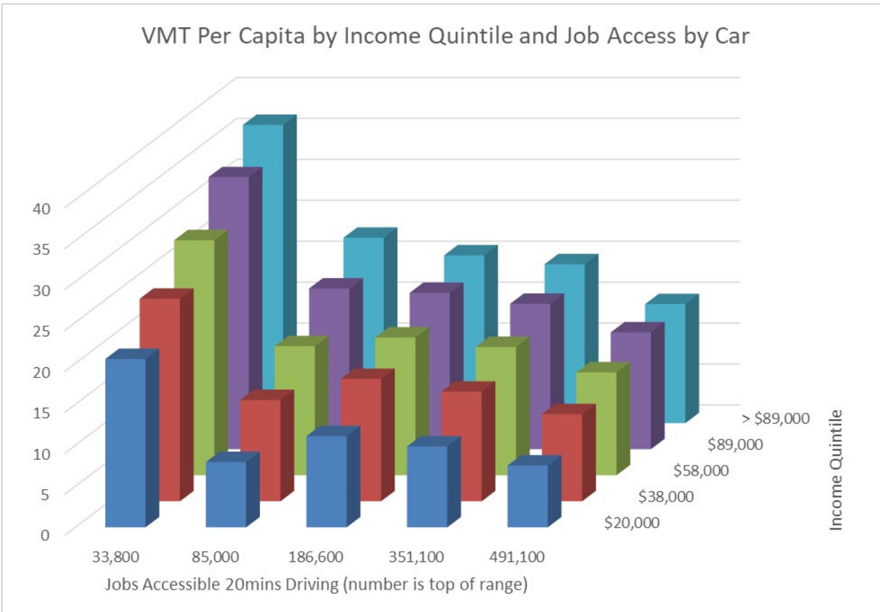
** Persons living more than 30 miles from a transit stop in the model were tagged as having a distance of 999 miles to transit. We included these cases for the all-variables regressions, but excluded them from the single-variable regressions for distance to nearest transit stop due to the skewing effect of having most cases being between 0-30 miles from transit, then have all other cases be "999" miles from transit.

†† Street pattern has high collinearity with housing density (0.52), job driving access (0.39), job transit access (0.39), and mix index (0.39), which likely explains the unexpected negative relationship between street pattern density and transit trips per person when all other land use factors are considered. As a single-variable regression, however, street pattern density shows an expected strong positive relationship with transit trips.

[38] Ewing, R. and Cervero, R., "Travel and the Built Environment: A Meta-Analysis", Journal of the American Planning Association, Vol. 76, No. 3, Summer 2010.

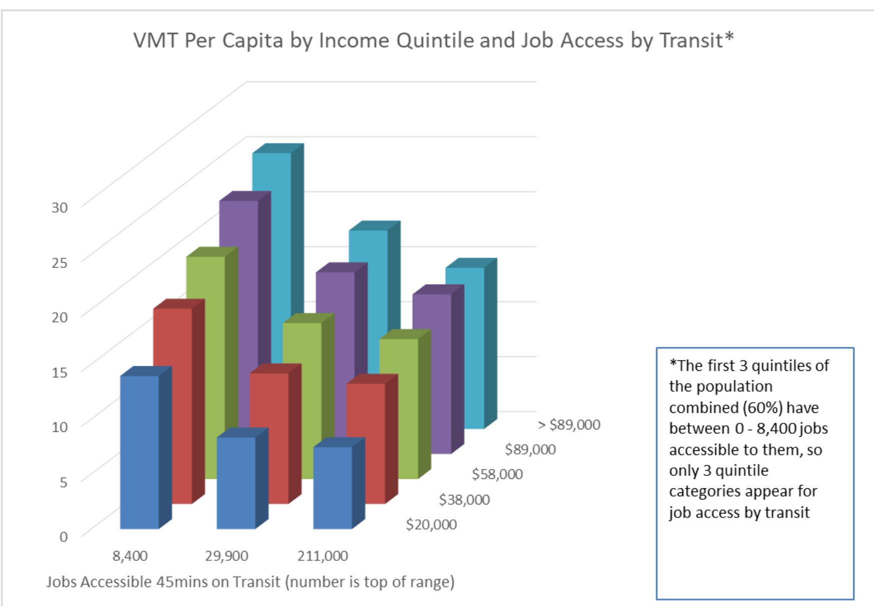
The charts in Figure 11-2 through Figure 11-5Figure 11-2 help illustrate the relationships between demographic factors, LU/T factors, and VMT per capita:

Figure 11-2 Modeled VMT Per Capita by Income and Job Accessibility by Car



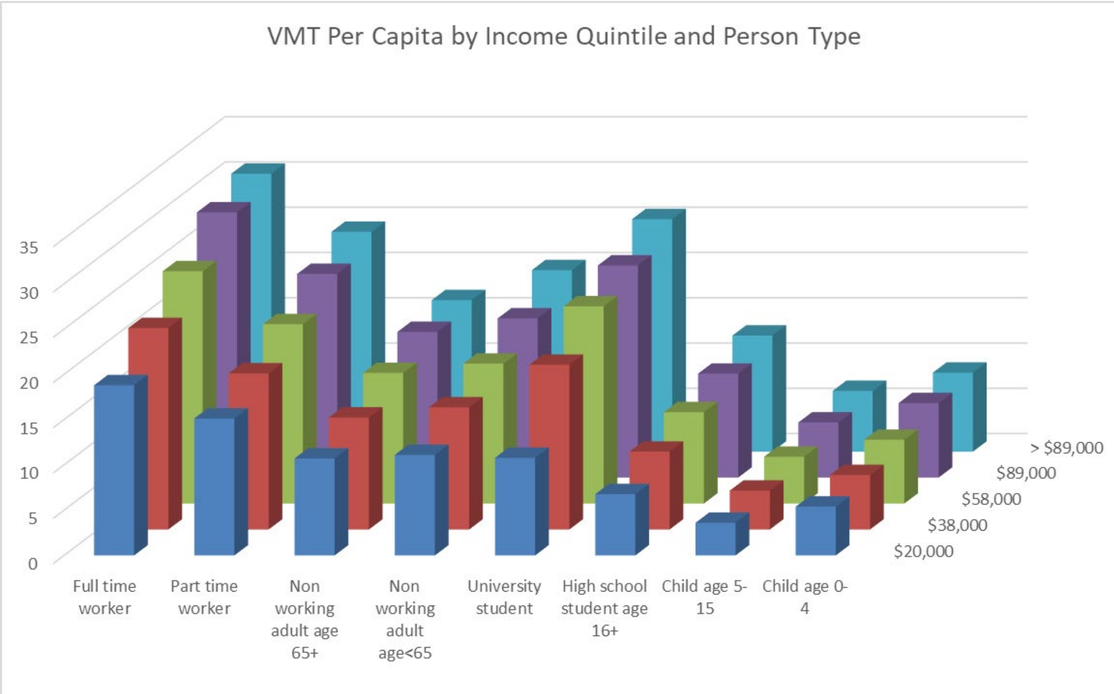
Source: SACOG 2020.

Figure 11-3 Modeled VMT Per Capita by Income and Job Accessibility by Transit



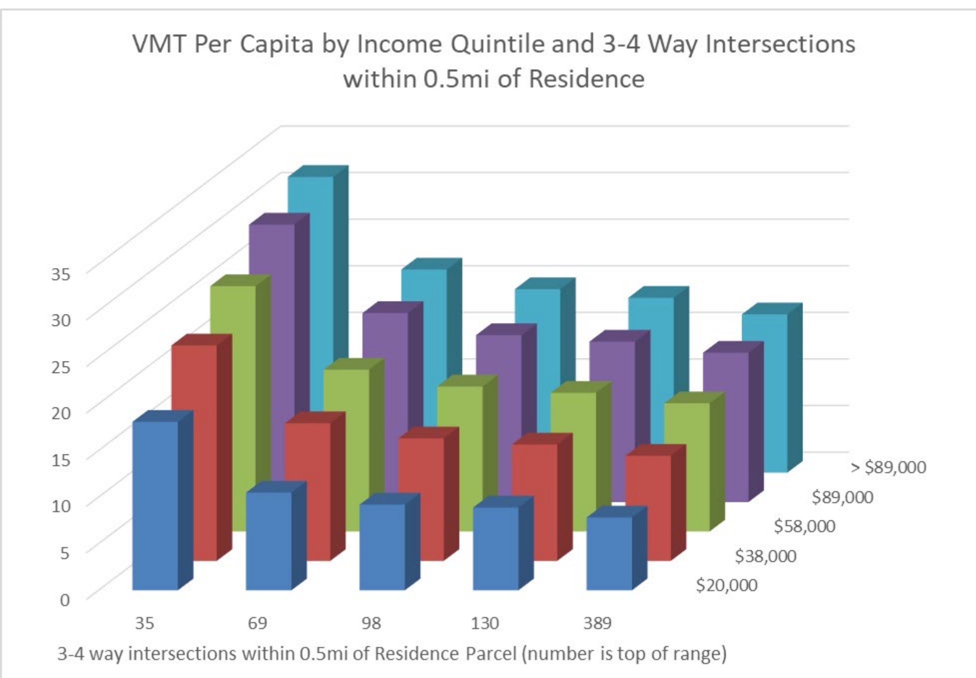
Source: SACOG 2020.

Figure 11-4 Modeled VMT Per Capita by Income and Person Type



Source: SACOG 2020.

Figure 11-5 Modeled VMT Per Capita by Income and Street Intersection Density Near Residence



Source: SACOG 2020.

11.4 **Testing of Random Variation in Model**

Testing of random variation is performed to assess the potential “noise” in the DAYSIM simulation of household-generated travel. Because DAYSIM is a person-level simulation of demand, travel patterns of each person in the representative population file is computed in a randomized order. The order of this simulation is varied using a numeric seed value. Changing this seed value generates a different order of stepping through the simulation, and of applying choice probabilities to each person-day activities and travel. This randomization means that the results of one model run may vary somewhat from the results of another run, assuming the “seed” value is varied from one run to the next.

We ran a series of 10 model runs using different seed values using SACSIM19 to estimate random variation of key travel outputs. To measure variation, we compared individual model run output values for vehicles, work tours, other tours, person trips, vehicle trips, transit trips, and VMT against the 10-run average values of these outputs. Specifically, we compared the model runs whose outputs were most different from the 10-run average. We performed this comparison at the region level, for the largest-population RAD, median-population RAD, and smallest-population RAD to observer how the amount of variation changed at different granularity levels. Results are summarized in Table 11-10.

As Table 11-10 shows, random variation increases as the scale of the output decreases. E.g., a “large scale” output like VMT at the region level had a maximum difference from the 10-run average of only -0.06 percent. In contrast, transit trips in the smallest-population RAD had a maximum difference from the 10-run average of about -60 percent while transit trips in the median-population RAD had a maximum difference of about -75 percent.

These large percentage differences, however, are due to the very small absolute number of transit trips taken in these RADs, with an average of 12 transit trips taken in the smallest RAD and 45 transit trips taken in the largest RAD. Therefore, even a small numeric variation in model outputs equates to a large percentage variation. Furthermore, our findings are generally in line with Bradley et al.’s 2003 findings from a random-seed test they performed on San Francisco’s microsimulation model, which utilized 100 model runs[39]. Similar to our SACSIM19 results, they found overall very low random variation at the city level, with greater levels of variation at the TAZ level and when looking at more specific outputs (e.g., estimated tours between two specific neighborhoods as opposed to total tours in the entire city).

[39] Mark Bradley, Joe Castiglione, Joel Freedman, “Systematic Investigation of Variability due to Random Simulation Error in an Activity-Based Microsimulation Forecasting Model”, Transportation Research Record 1831, 2003

Table 11-10 Random Variation of DAYSIM Submodel

Variable	10-Run Average Value	Max % Difference from Average	
		High	Low
Regional Totals			
Vehicles	1,538,828	0.04%	-0.04%
Work Tours	766,727	0.11%	-0.07%
Other Tours	2,260,177	0.08%	-0.04%
Person Trips	8,023,709	0.06%	-0.05%
Vehicle Trips	5,169,100	0.07%	-0.07%
Transit Trips	103,943	0.68%	-0.89%
VMT	38,201,565	0.05%	-0.06%
Largest-Population RAD			
Vehicles	96,277	0.18%	-0.27%
Work Tours	46,909	0.45%	-0.48%
Other Tours	173,890	0.48%	-0.27%
Person Trips	577,242	0.19%	-0.17%
Vehicle Trips	348,582	0.18%	-0.30%
Transit Trips	8,892	3.37%	-2.97%
VMT	2,037,169	0.30%	-0.34%
Median-Population RAD			
Vehicles	13,247	0.54%	-0.51%
Work Tours	5,404	0.74%	-0.87%
Other Tours	16,402	1.00%	-0.77%
Person Trips	58,709	0.75%	-0.79%
Vehicle Trips	40,778	1.03%	-0.76%
Transit Trips	45	30.65%	-76.73%
VMT	368,112	0.98%	-1.03%
Smallest-Population RAD			
Vehicles	4,206	0.97%	-0.93%
Work Tours	1,036	4.17%	-4.32%
Other Tours	4,357	2.18%	-2.32%
Person Trips	14,965	1.52%	-1.20%
Vehicle Trips	9,697	1.89%	-1.36%
Transit Trips	14	56.20%	-60.58%
VMT	174,439	1.88%	-2.01%

Source: SACOG 2020.

Borrowing methodology from Bradley et al's test of San Francisco's microsimulation model, we also charted running averages for each output to see how quickly those outputs converged toward the 10-run average. This test enables model users to better estimate how many times the model needs to be run in order to give a reasonably stable "average" output value.

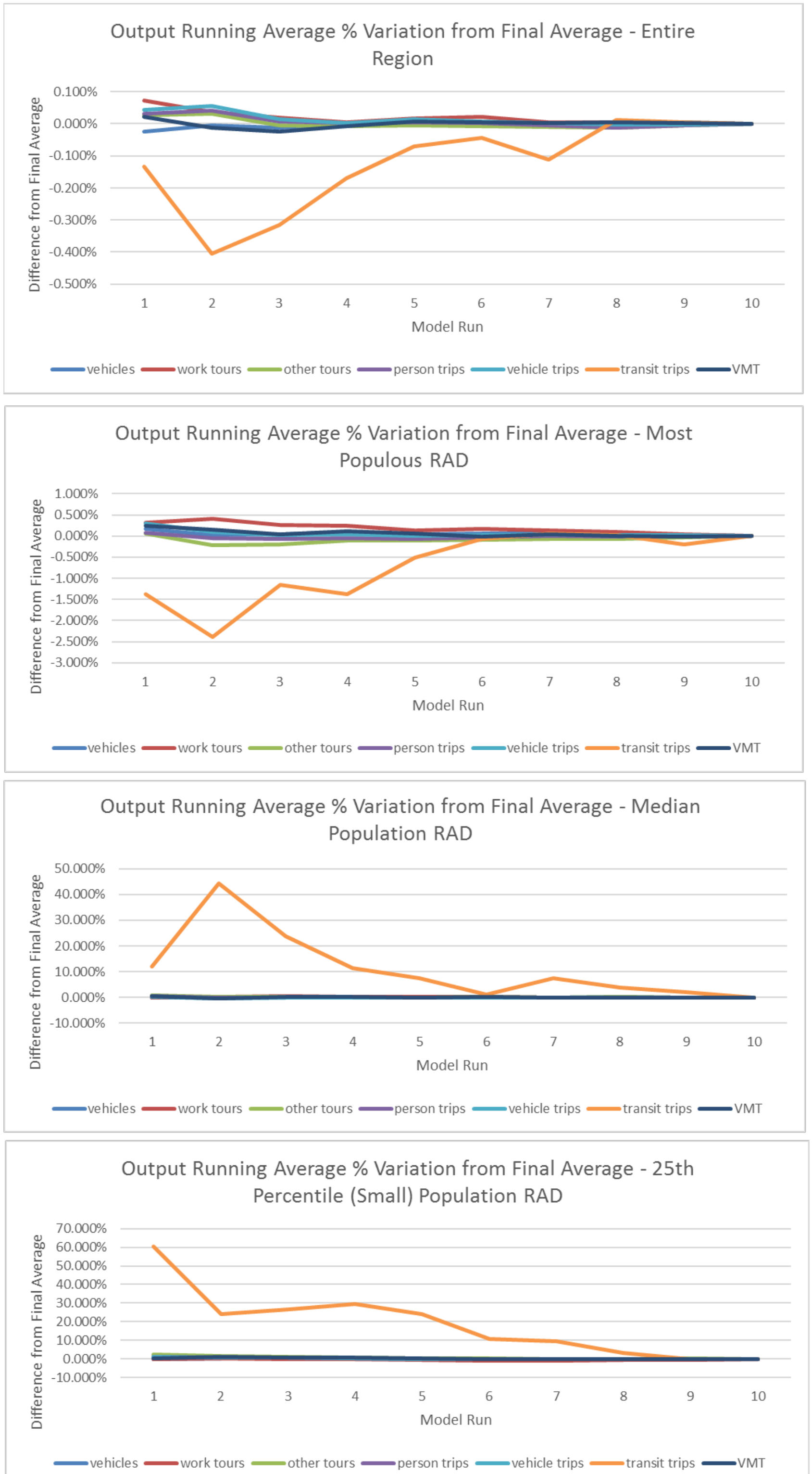
As the charts in Figure 11-6 show, variation is lower and convergence is faster at larger scales. At the region level, the maximum variation from the 10-run average for most outputs is less than +/- 0.1 percent even on the first run, and by the third run is effectively identical to the 10-run average. At the RAD levels, and particularly the smallest RAD level, variation is somewhat higher and convergence somewhat lower because the absolute values of the outputs are smaller and a smaller numeric change equates to a larger percentage change.

Transit variation is higher and takes longer to converge at all levels (region, large-population RAD, medium-population RAD, and small-population RAD), largely due to transit having very small absolute numbers of riders, leading even small output changes to appear as larger percentage changes.

As a general takeaway, the effect of random seed variation on SACSIM19's is generally very small, especially at larger scales. In practice, for region-level estimates a single model run will be sufficient, though seeking estimates at smaller scales (e.g., for modes with fewer trips like transit, looking at trips between a specific pair of RADs or TAZs, etc.) may require taking the average output values from multiple model runs to account for variation. Based on findings from SACSIM19, most values stabilize within five model runs, that is, after five model runs, the running average output values are negligibly different from the 10-run average output values.

When reviewing each figure, it is important to note the vertical scale bar, which is different for each geographic level.

Figure 11-6 Results of Testing Sensitivity to Random Variation



Source: SACOG 2020.

11.5 Facility-Based and Pay-as-You-Go Pricing Testing

Pricing corridors and a VMT user fee are strategies implemented to meet 2020 MTP/SCS key performance targets. Express lanes along major corridors are included to improve traffic management and reliability throughout the region. A mileage-based or Pay-As-You-Go (PAYGo) fee charge is implemented as a sustainable replacement to the gas tax and manage transportation network efficiently and equitably.

Both corridor pricing and user fee are a new feature to SACSIM19. Around the country, implementation of travel modeling software to capture express lanes is recognized as a very complex challenge, so testing of these features is critical. Testing of these new features included sensitivity testing and reasonableness checking, based on guidelines provided by state and federal agencies[26]. In addition to SACOG's testing, the beta-test group and early release of the draft SACSIM19 software and data files, described above in the "Public Access to the Model and Data" section, provided significant additional critical review of these new features. Testing focused on the high-occupancy/toll (HOT) and express lanes facility pricing, because those facilities are the major priced facilities included in the proposed MTP/SCS. HOT lanes, for purposes of this document, are conventional, one-lane HOV lanes, which allow priced access to drive alone vehicles or trucks. Express lanes, for purposes of this document, are generally multi-lane facilities that may allow HOV2 or HOV3+ vehicles access at reduced (or no) price, but allows priced access to drive alone vehicles and trucks. SACSIM19 has the capability to model "all-tolled" roadway facilities, however—given that no all-tolled facilities are included in the propose MTP/SCS, testing mainly focused around HOT and express lanes.

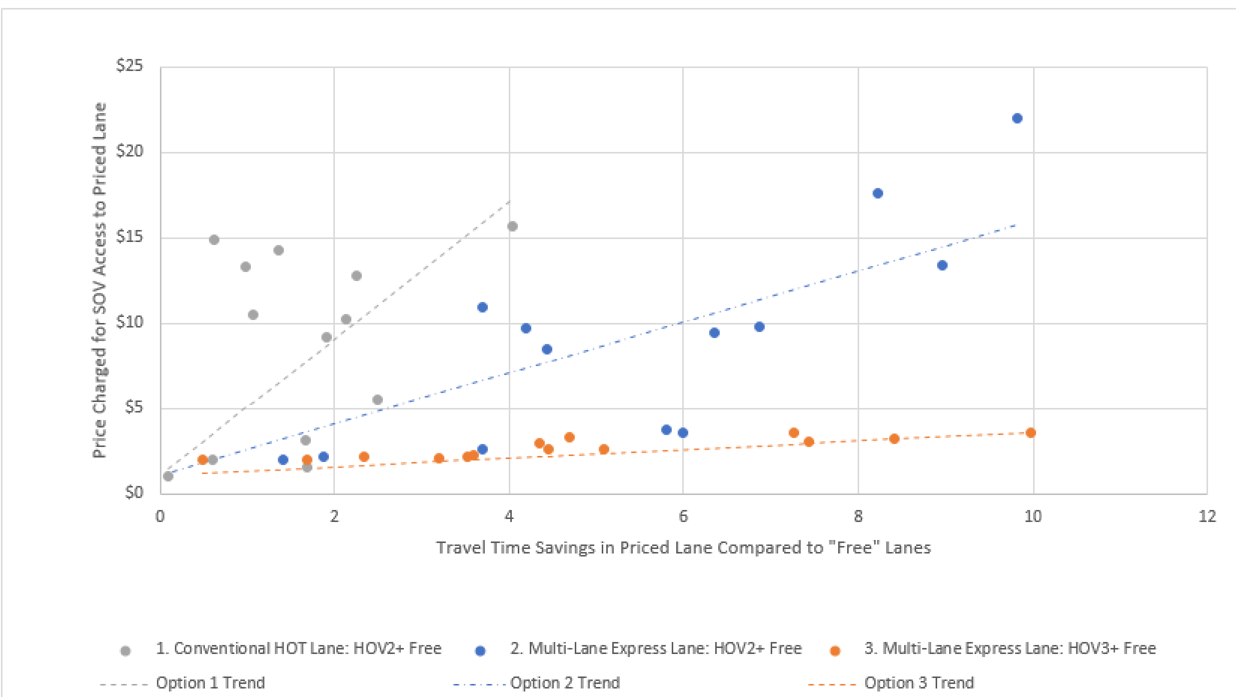
For HOT or express lanes facilities, SACSIM19 pricing software was developed to represent different rules on free versus paid access to HOT or express lanes. The general framework of the software is to iteratively identify a balance point between price of access, based on the rules for access for a given project, that ensures some level of travel time savings for the HOT or express lane, relative to the "free" parallel lanes. Testing focused on two dimensions: sensitivity of price-setting to time savings; and variations on the relationship between price and time savings, based on the rules governing access to the priced facility. Testing results summarized for three options:

- A conventional single-lane HOT lane, with HOV2 and HOV3+ vehicles allowed access for free, and drive alone vehicles and trucks accessing for a price. Available capacity for priced access to the HOT lane is the smallest for this option, because in the highest demand corridors, HOV2 and HOV3+ vehicle nearly fill up the lane. In order to limit the number of drive alone vehicles and trucks that can access the facility, the prices may have a drastic increase surge.
- A conventional 2-lane express facility, with HOV2 and HOV3+ vehicles accessing the facility free, and drive alone vehicles and trucks accessing the facility for a price. Because the facility has two lanes per direction, rather than one, there is generally more capacity to offer for priced access, and prices tend to be somewhat lower than the HOT lane option.
- An express lane option that allows free access to HOV3+ vehicles only, and priced access to HOV2 and drive alone vehicles, and trucks. This option prices off many HOV2s, so the

amount of capacity available for priced access is the highest of the three options, and the prices tend to be the lowest of the three.

Figure 11-7 graphically illustrates the results of the of the three test options, across 14 test corridors. Shown in the figure is the comparison of corridor time savings (defined as the number minutes saved in the priced lane, compared to the parallel free lane) and average price charged to access the priced lane (or lanes). For all three options, the expected relationship showing price increasing with time savings offered by the priced facility is evident. The three options differed very widely, and in expected ways, on the magnitude of price and its volatility across the corridors within each option. Option 1, the conventional HOT lane, showed the highest prices (average just under $10) relative to time saved, largely because in the highest priced corridors, very little-to-no capacity was available to priced access, and virtually all potential users had to be priced off. Table 11-11 Managed Lane / Pricing Tests provides option-level tallies, and shows that of users of the HOT lane, only 2 percent paid their way into the lane—98 percent had access for free. At the other end of the spectrum is option 3, the express lane, which allowed free access only to HOV3+ vehicles. This option offered priced access to the largest number of users, and the prices charged were the lowest at under $3 average, and 50 percent of the users paying. Option 2 (express lane with free access to HOV2 and HOV3+ vehicles) splits the difference between Options 1 and 3.

Figure 11-7 Price Versus Time Savings for Three Managed Lane Options



Source: SACOG 2020.

Table 11-11 Managed Lane / Pricing Tests

	Facility Pricing Scenario	Drivers Accessing Time Savings for Free	Drivers Accessing Time Savings with Toll	Travel Time Savings in Priced Lane (minutes)	Average Toll Rate per Mile	Average SOV Toll Facility Price	VMT Accessing Travel Time Savings (thousands)	Percent VMT Accessing Travel Time Savings	Percent VMT Accessing Travel Time Savings and Paying Toll
1	Conventional HOT Lane	HOV2+	SOV, Truck	-1.5	$0.89	$9.71	974	21%	2%
2	Multi-Lane Express Lane	HOV2+	SOV, Truck	-5.1	$0.58	$9.68	1,170	27%	11%
3	Multi-Lane Express Lane	**HOV3+**	**HOV2, SOV, Truck**	-4.7	$0.36	$2.89	877	21%	50%

Source: SACOG 2020.

Suggested by one of the beta-testers of the new SACSIM19 pricing features was testing around extreme pricing values. The specific suggestion was to test a range of pricing for access to a facility up to $100, which is recognized as an unreasonably high price for an actual project. Testing around extreme values is informative for software testing, and not as a potential actual project proposal. A test of this nature was conducted based on change in travel decisions comparing a range in pricing, time of day, and demand of a particular route. Table 11-12 shows testing along Interstate 80 over the Causeway between Davis and Sacramento. Three scenarios of an all-lane tolled facility are compared at different pricing rates: $5, $25, and $100 dollars. It is important to note that ALL of these pricing rates were set purely for testing purposes, and that actual rates for a proposed express lane project will be the subject of extensive project development work, public input, and policy debate. It is also important to note that the test scenario was based on all-lanes tolling, as opposed to express lanes, where a "free" option always exists. The $5 rate shows a shift of 31 percent of vehicles use alternative routes. At $25, almost 90 percent of traffic avoided the facility. At $100 dollars, the price is so extreme the facility is effectively closed down, and all traffic avoids it. This test shows SACSIM19 highway assignment is sensitive to the level of pricing added to a facility as different persons have a range of valuation of time with respect to their preferred routing choices.

Table 11-12 All Lane Pricing Sensitivity to Extreme Value Test

SACSIM19	**DAILY**					
	Causeway EB			**Causeway WB**		
2035	**Quantity**	**Change**	**% Change**	**Quantity**	**Change**	**% Change**
2035 Base	95,242	0	0.00%	95,974	0	0.00%
$5 Toll, All Time Periods, Mainline & HOV	64,162	-31,080	-32.60%	65,496	-30,478	-31.80%
$25 Toll, All Time Periods, Mainline & HOV	10,334	-84,908	-89.10%	11,825	-84,149	-87.70%
$100 Toll, All Time Periods, Mainline & HOV	19	-95,223	-100.00%	16	-95,958	-100.00%

Source: SACOG 2020.

In addition to corridor pricing, a mileage-based user fee was also tested. Table 11-13 shows sensitivity testing on different mileage based user fee rates based on time of day and location. A discounted fee was applied for rural areas and off peak hours with less congestion. When the user fee increase, the household VMT and Congested VMT decrease. The orders of magnitude of decrease changes based on the rate showing the model is sensitive to different user fee rates.

Table 11-13 User Fee Sensitivity Testing

Scenario	HH VMT % Change from Base	HH Congested VMT % Change from Base
No user fee – Baseline	0.0%	0.0%
1/2 cent peak/off peak rural/urban user fee	-0.3%	-1.9%
2/4 cent peak/off peak rural/urban user fee	-1.5%	-8.2%

Source: SACOG 2020.

NOTE – These scenarios were run for sensitivity testing only and do not reflect the 2020 MTP/SCS preferred scenario.