Plan Bay Area 2040: Final Travel Modeling Report

July 2017

METROPOLITAN
TRANSPORTATION
COMMISSION

Association of
Bay Area Governments

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Executive Summary

This supplementary report presents selected technical results from the analysis of alternatives performed in support of the Metropolitan Transportation Commission's (MTC's) and the Association of Bay Area Governments' (ABAG's) Plan Bay Area 2040 environmental impact report (EIR). A brief overview of the technical methods used in the analysis, as well as a brief description of the key assumptions made for each alternative, precede the presentation of results.

Chapter 1: Analytical Tools

MTC uses an analytical tool known as a travel model (also known as a travel demand model or travel forecasting model) to first describe the reaction of travelers to transportation projects and policies and then to quantify the impact of cumulative individual decisions on the Bay Area's transportation networks and environment. MTC's travel model is briefly described below, along with two supporting tools: a population synthesizer and a vehicle emissions model.

Population Synthesizer

MTC's travel model is an agent-based simulation. The "agents" in our case are individual households, further described by the people who form each household. In this way, the travel model attempts to simulate the behavior of the individuals and the households who carry out their daily activities in a setting described by the input land development patterns and input transportation projects and policies. In order to use this type of simulation, each agent must be characterized in a fair amount of detail.

Software programs that create lists of households and persons for travel model simulations are known as population synthesizers. MTC's population synthesizer attempts to locate households described in the 2000 Decennial Census Public Micro-sample (PUMS) data (i.e., those who responded to the old "long forms" used by the Census Bureau to collect detailed household information) in such a way that when looking at the population along specific dimensions spatially (at a level of detail below which the PUMS data is reported), the aggregate sums more or less match those predicted by other Census summary tables (when synthesizing historical populations) or the land use projections made by our land use modeling tools/procedures (when forecasting populations). For example, if our land use tools project that 60 households containing 100 workers and 45 children will live in spatial unit X in the year 2035, the population synthesizer will locate 60 PUMS households in spatial unit X and will select households in such a way that, when summing across households, the number of workers is close to 100 and the number of children is close to 45.

MTC's population synthesizer "controls" (i.e., minimizes the discrepancy between the synthetic population results and the historical Census results or the land use forecasts) along the following dimensions:

1. Household "type", i.e. individual household unit or non-institutionalized group quarters (e.g., college dorm);
2. Household income category;
3. Age of the head of household;
4. Number of people in the household;
5. Number of children under age 17 in the household;
6. Number of employees in the household; and,
7. Number of units in the household's physical dwelling (one or more than one, as in an apartment building).

Travel Model

Travel models are frequently updated. As such, a bit of detail as to which version of a given travel model is used for a given analysis is useful. The current analysis uses MTC's *Travel Model One* (version 0.6),

released in July 2016, calibrated to year 2000 conditions and validated against year 2000, 2005, 2010 and 2015 conditions[1].

Travel Model One is of the so-called "activity-based" archetype. The model is a partial agent-based simulation in which the agents are the households and people who reside in the Bay Area. The simulation is partial because it does not include the simulation of individual behavior of passenger, commercial, and transit vehicles on roadways and transit facilities (though the model system does simulate the behavior of aggregations of vehicles and transit riders). In regional planning work, the travel model is used to simulate a typical weekday – when school is in session, the weather is pleasant, and no major accidents or incidents disrupt the transportation system.

The model system operates on a synthetic population that includes households and people representing each actual household and person in the nine-county Bay Area – in both historical and prospective years. Travelers move through a space segmented into "travel analysis zones"[2] and, in so doing, use the transportation system. The model system simulates a series of travel-related choices for each household and for each person within each household. These choices[3] are as follows (organized sequentially):

1. Usual workplace and school location – Each worker, student, and working student in the synthetic population selects a travel analysis zone in which to work or attend school (or, for working students, one zone to work and another in which to attend school).
2. Household automobile ownership – Each household, given its location and socio-demographics, as well as each member's work and/or school locations (i.e., given the preceding simulation results), decides how many vehicles to own.
3. Daily activity pattern – Each household chooses the daily activity pattern of each household member, the choices being (a) go to work or school, (b) leave the house, but not for work or school, or (c) stay at home.
4. Work/school tour[4] frequency and scheduling – Each worker, student, and working student decides how many round-trips they will make to work and/or school and then schedules a time to leave for, as well as return home from, work and/or school.
5. Joint non-mandatory[5] tour frequency, party size, participation, destination, and scheduling – Each household selects the number and type (e.g., to eat, to visit friends) of "joint" (defined as two or more members of the same household traveling together for the duration of the tour) non-mandatory (for purposes other than work or school) round trips in which to engage, then

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[1] Additional information is available here: http://analytics.mtc.ca.gov/foswiki/Main/Development.
[2] An interactive map of these geographies is available here: http://analytics.mtc.ca.gov/foswiki/Main/TravelModelOneGeographies.
[3] These "choices", which often are not really choices at all (the term is part of travel model jargon), are simulated in a random utility framework – background information is available here: https://en.wikipedia.org/wiki/Choice_modelling.
[4] A "tour" is defined as a round trip from and back to either home or the workplace.
[5] Travel modeling practice use the term "mandatory" to describe work and school travel and "non-mandatory" to refer to other types of travel (e.g., to the grocery store); we use this jargon as well to communicate efficiently with others in our space. We neither assume nor believe that all non-work/school-related travel is non-mandatory or optional.

determines which members of the household will participate, where, and at what time the tour (i.e., the time leaving and the time returning home) will occur.

6. Non-mandatory tour frequency, destination, and scheduling – Each person determines the number and type of non-mandatory (e.g., to eat, to shop) round trips to engage in during the model day, where to engage in these tours, and at what time to leave and return home.

7. Tour travel mode – The tour-level travel mode choice (e.g., drive alone, walk, take transit) decision is simulated separately for each tour and represents the best mode of travel for the round trip.

8. Stop frequency and location – Each traveler or group of travelers (for joint travel) decide whether to make a stop on an outbound (from home) or inbound (to home) leg of a travel tour, and if a stop is to be made, where the stop is made, all given the round trip tour mode choice decision.

9. Trip travel model – A trip is a portion of a tour, either from the tour origin to the tour destination, the tour origin to a stop, a stop to another stop, or a stop to a tour destination. A separate mode choice decision is simulated for each trip; this decision is made with awareness of the prior tour mode choice decision.

10. Assignment – Vehicle trips for each synthetic traveler are aggregated into time-of-day-specific matrices (i.e., tables of trips segmented by origin and destination) that are assigned via the standard static user equilibrium procedures to the highway network. Transit trips are assigned to time-of-day-specific transit networks.

The *Travel Model One* system inherits without significant modification the representation of interregional and commercial vehicle travel from MTC's previous travel model system (commonly referred to as BAYCAST or BAYCAST-90). Specifically, commercial vehicle demand is represented using methods developed for Caltrans and Alameda County as part of the Interstate 880 Intermodal Corridor Study conducted in 1982 and the Quick Response Freight Manual developed by the United States Department of Transportation in 1996. When combined, these methods estimate four classes of commercial travel, specifically: "very small" trucks, which are two-axle/four-tire vehicles; "small" trucks, which are two-axle/six-tire vehicles; "medium" trucks, which are three-axle vehicles; and, "combination" trucks, which are truck/trailer combinations with four or more axles.

Reconciling travel demand with available transportation supply is particularly difficult near the boundaries of planning regions because little is assumed to be known (in deference to efficiency – the model must have boundaries) about the land development patterns – the primary driver of demand – or supply details beyond these boundaries. The typical approach to representing this interregional travel is to first estimate the demand at each location where a major transportation facility intersects the boundary and to then distribute this demand to locations either within the planning region (which results in so-called "internal/external" travel) or to other boundary locations ("external/external" travel). MTC uses this typical approach and informs the process with Census journey-to-work flows (from the 2000 Decennial Census, specifically), which are allocated via simple method to represent flows to and from MTC's travel analysis zones and 21 boundary locations, as well as the flows between boundary locations.

The travel of air passengers to and from the Bay Area's airports is represented with static (across alternatives), year-specific vehicle trip tables. These trip tables are based on air passenger survey data

collected in 2006 and planning information developed as part of MTC's Regional Airport Planning Study[6]. Similarly, the travel of high speed rail passengers to and from the Bay Area's expected high speed rail stations is represented with static (across alternatives), year-specific vehicle trip tables. The high speed rail demand estimates are derived from the California High Speed Rail Authority's 2016 Business Plan[7].

Vehicle Emissions Model

The MTC travel model generates spatially- and temporally-specific estimates of vehicle usage and speed for a typical weekday. This information is then input into an emissions model to estimate emitted criteria pollutants as well as emitted carbon dioxide (used as a proxy for all greenhouse gases). For the current analysis, MTC used the EMFAC 2014 version of the California Air Resources Board emissions factor software[8].

Chapter 2: Input Assumptions

In total, 12 scenarios were simulated. Selected results are presented and discussed in the remainder of the document. Four *categories* of scenarios are included, as follows: historical, no action, planned action, and alternative actions. Historical scenarios are labeled by their year and include Year 2005 and Year 2015. The no action alternative is referred to as "No Project"; No Project simulations were performed for a 2040 forecast year. The planned action is referred to as the "Proposed Plan" (often abbreviated as "Plan") alternative; Proposed Plan Simulations were performed for 2020, 2030, 2035, and 2040. Three separate alternative scenarios are included, and are labeled "Main Streets", "Big Cities", and "Environment, Equity, and Jobs" ("EEJ"). Year 2040 simulations were conducted for each of these alternatives. The various simulation years serve different purposes: historical years demonstrate the model's ability to adequately replicate reality[9] and provide the reader data for a familiar scenario; the California Air Resources Board established greenhouse gas targets for 2020 and 2035; the transportation plan, as guided by federal regulations, extends to 2040; and, air quality regulations require a 2030 simulation.

The above scenarios differ across four dimensions, namely: land use, roadway supply, transit supply, and prices. By land use, we mean the locations of households and jobs (of different types). Roadway supply is the physical network upon which automobiles, trucks, transit vehicles, bicycles, and pedestrians travel. Transit supply refers to the facilities upon which public transit vehicles travel (the roadway, along rail lines, ferry routes, and other dedicated infrastructure), as well as the stop locations, routes, and frequency of transit service. Prices include the monetary fees users are charged to board transit vehicles, cross bridges, operate and park private vehicles, and use express (also known as high occupancy toll) lanes.

In the remainder of this chapter, each of the six scenarios (the rows in Table 1) are discussed, organized by the above four dimensions; additional notes on "other assumptions" concludes the section. This organization should allow the reader to compare the input assumptions across scenarios.

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[6] Additional information is available here: http://mtc.ca.gov/our-work/plans-projects/economic-vitality/regional-airport-plan.

[7] Additional information is available here: http://hsr.ca.gov/docs/about/business_plans/2016_BusinessPlan.pdf.

[8] Additional information is available here: http://www.arb.ca.gov/msei/msei.htm.

[9] Details of this "validation" process are available here: http://analytics.mtc.ca.gov/foswiki/Main/Development.

Table 1: Simulations by Year and Alternative

Alternative	Simulation Year					
	2005	*2015*	*2020*	*2030*	*2035*	*2040*
Historical	✓	✓				
No Project			✓		✓	✓
Proposed Plan			✓	✓	✓	✓
Main Streets			✓		✓	✓
Big Cities			✓		✓	✓
Environment, Equity, and Jobs			✓		✓	✓

Land Use

Additional information regarding the land development patterns is available in the companion supplementary report, *Summary of Predicted Land Use Responses*. Here, we provide a handful of details regarding the transformation of these land use inputs into the information needed by the travel model.

Prior to executing the travel model, the land development inputs provided by ABAG (control totals) and the UrbanSim model (distribution details) are run through the MTC population synthesizer as described above. The journey from control totals through UrbanSim and through the population synthesizer introduces very minor inconsistencies between the ABAG-estimated regional control totals, which are carried through UrbanSim, and the totals implied by the synthetic population. These inconsistencies are presented in Table 2.

Table 2: Demographic Statistics of Control and Simulated Populations

Alternative	Year	ABAG Results		Synthetic Population	Percent Difference[†]	ABAG Results	Synthetic Population	Percent Difference
		Households	*Group Quarters*					
Historical	2015	2,760,000	133,000	2,875,000	-0.6%	7,571,000	7,571,000	0.0%
No Project	2040	3,427,000	176,000	3,579,000	-0.7%	9,628,000	9,567,000	-0.6%
Proposed Plan	2040	3,427,000	176,000	3,579,000	-0.7%	9,628,000	9,561,000	-0.7%
Main Streets	2040	3,427,000	176,000	3,579,000	-0.7%	9,628,000	9,563,000	-0.7%
Big Cities	2040	3,427,000	176,000	3,579,000	-0.7%	9,628,000	9,554,000	-0.8%
EEJ	2040	3,427,000	176,000	3,579,000	-0.7%	9,628,000	9,559,000	-0.7%

The table header has spanning groups: **Households** spans the first four data columns (ABAG Results: Households, Group Quarters; Synthetic Population; Percent Difference[†]) and **Population** spans the last three (ABAG Results; Synthetic Population; Percent Difference).

† – Individuals living in group quarters are considered individual households in the synthetic population and, subsequently, the travel model.

A key function of the population synthesizer is to identify each member of the representative populous with one of eight "person type" labels. Each person in the synthetic population is identified as a full-time worker, part-time worker, college student, non-working adult, retired person, driving-age student, non-driving-age student, or child too young for school. The travel model relies on these person type classifications, along with myriad other variables, to predict behavior.

Figure 1 shows the distribution of person types for the historical scenarios and the Proposed Plan alternative, from years 2005 to 2040. Interesting aspects of these distributions, which are driven by assumptions embedded in ABAG's regional forecast, are as follows:

- The share of full-time workers peaks in 2015;
- The share of retired workers steadily increases from 2005 to 2040; and,
- The person type shares are effectively identical.

Figure 2 shows the distribution of person types across the five forecast year alternatives for year 2040.
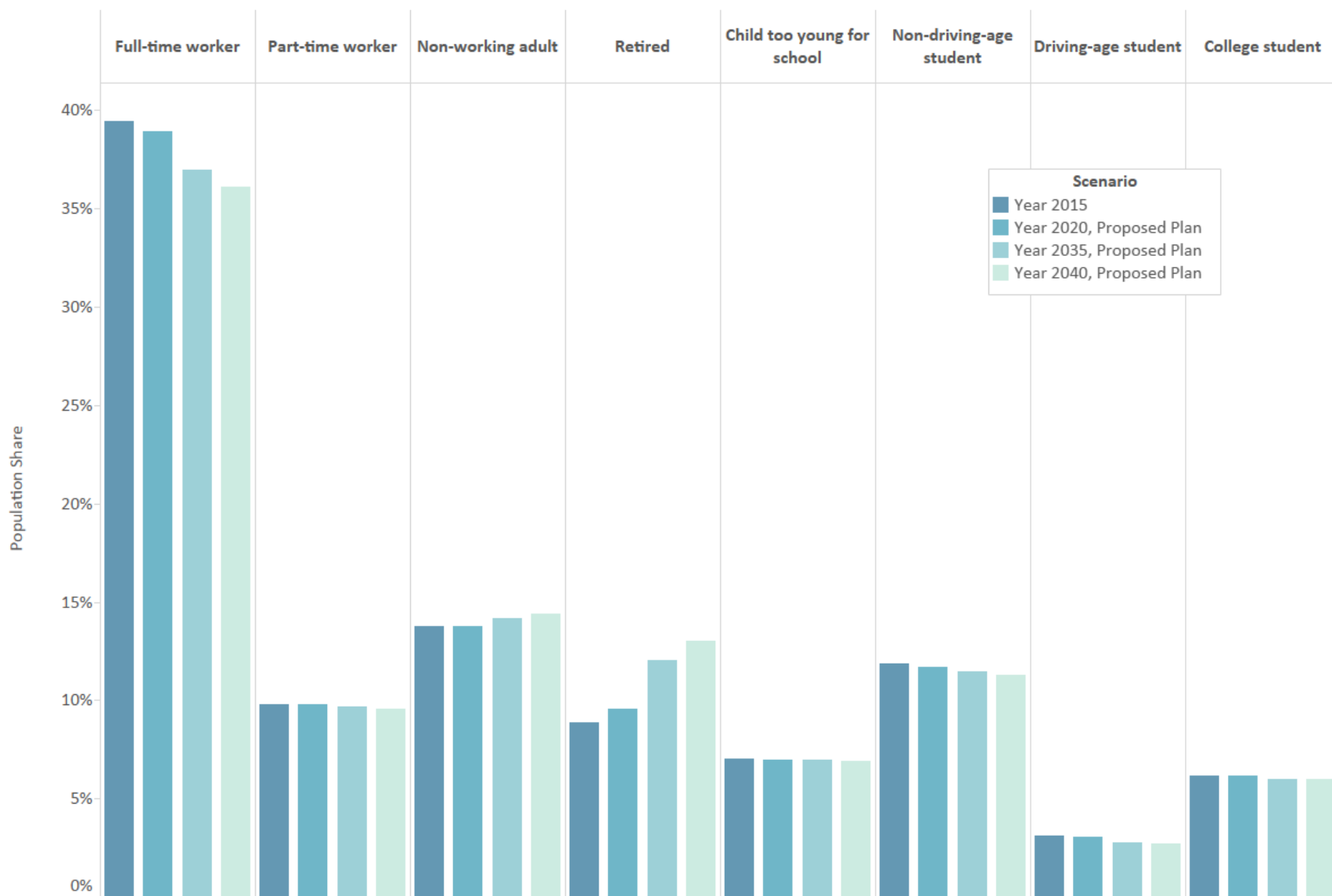
Figure 1: Historical and Forecasted Person Type Distributions for Proposed Plan Alternative
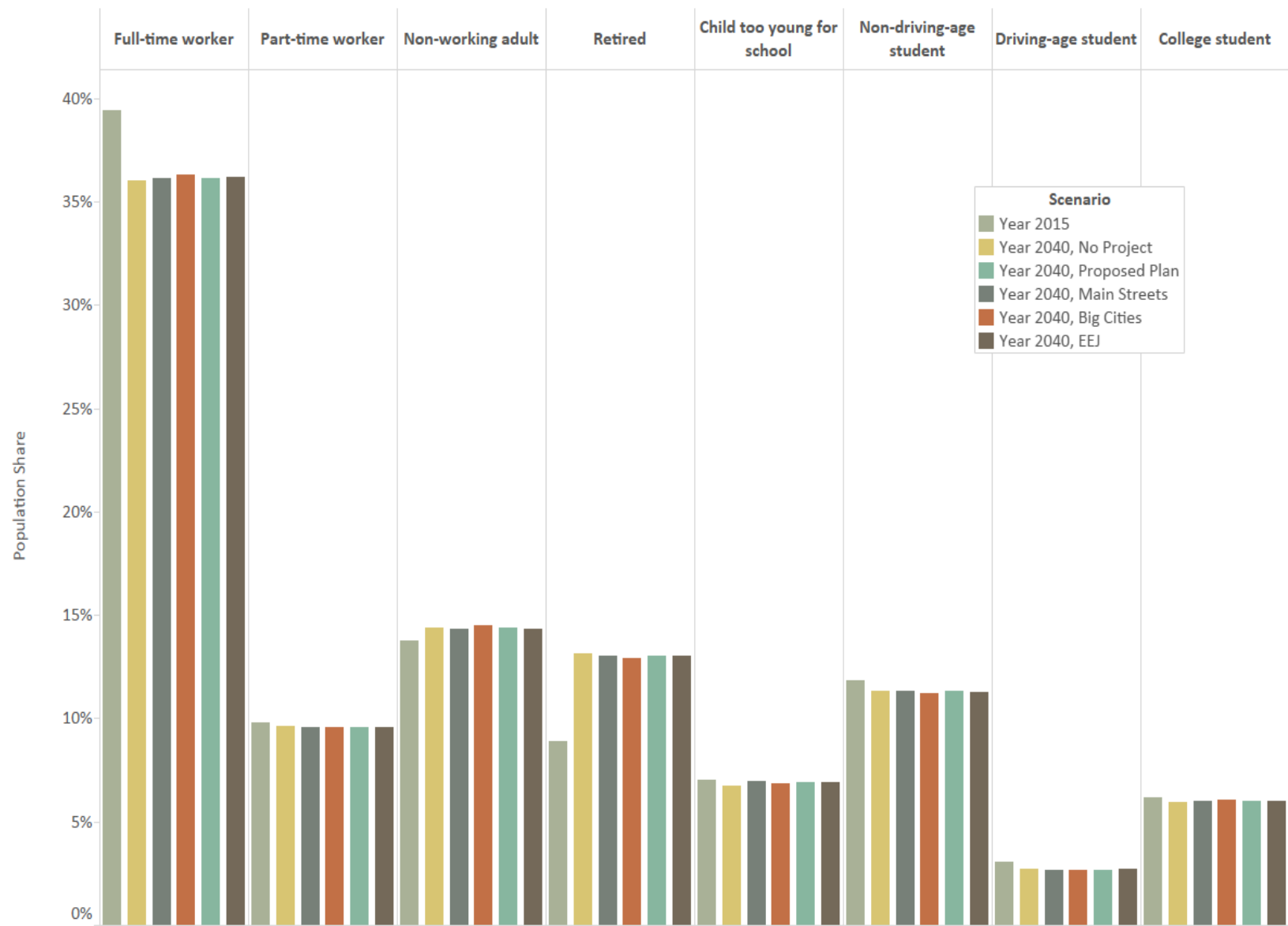
Figure 2: Year 2040 Person Type Distributions

Roadway Supply

The historical scenarios for 2005 and 2015 have a representation of roadways that reflect infrastructure that was in place in 2005 and 2015.

The No Project alternative includes projects that are either in place in 2016 or are "committed" per MTC policy. The Proposed Plan alternative includes the roadway projects included in the transportation investment strategy, which is discussed in detail elsewhere.

The Main Streets and Big Cities alternative roadway projects were detailed to MTC's Planning Committee in May 2016[10].

The Environment, Equity, and Jobs alternative starts with the No Project alternative roadway network and then adds the Proposed Plan alternative's bus rapid transit (BRT) infrastructure and the Columbus Day Initiative intelligent transportation systems scheme. No other uncommitted roadway projects are included in the EEJ alternative.

A graphical depiction of the changes in the roadway network is presented in Figure 3 below. The chart shows the change in lane-miles (e.g., a one-mile segment of a four-lane road is four lane-miles) available to automobiles in year 2040 relative to year 2015. San Francisco County shows a decrease in lane-miles, s some roadway segments are converted to dedicated bus ways. Figure 4 shows the change in lane-miles over time for the Proposed Plan alternative.

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[10] For additional details, please see https://mtc.legistar.com/View.ashx?M=F&ID=4446887&GUID=31890CF7-8A5A-4A54-BA45-4466DEF7831B.
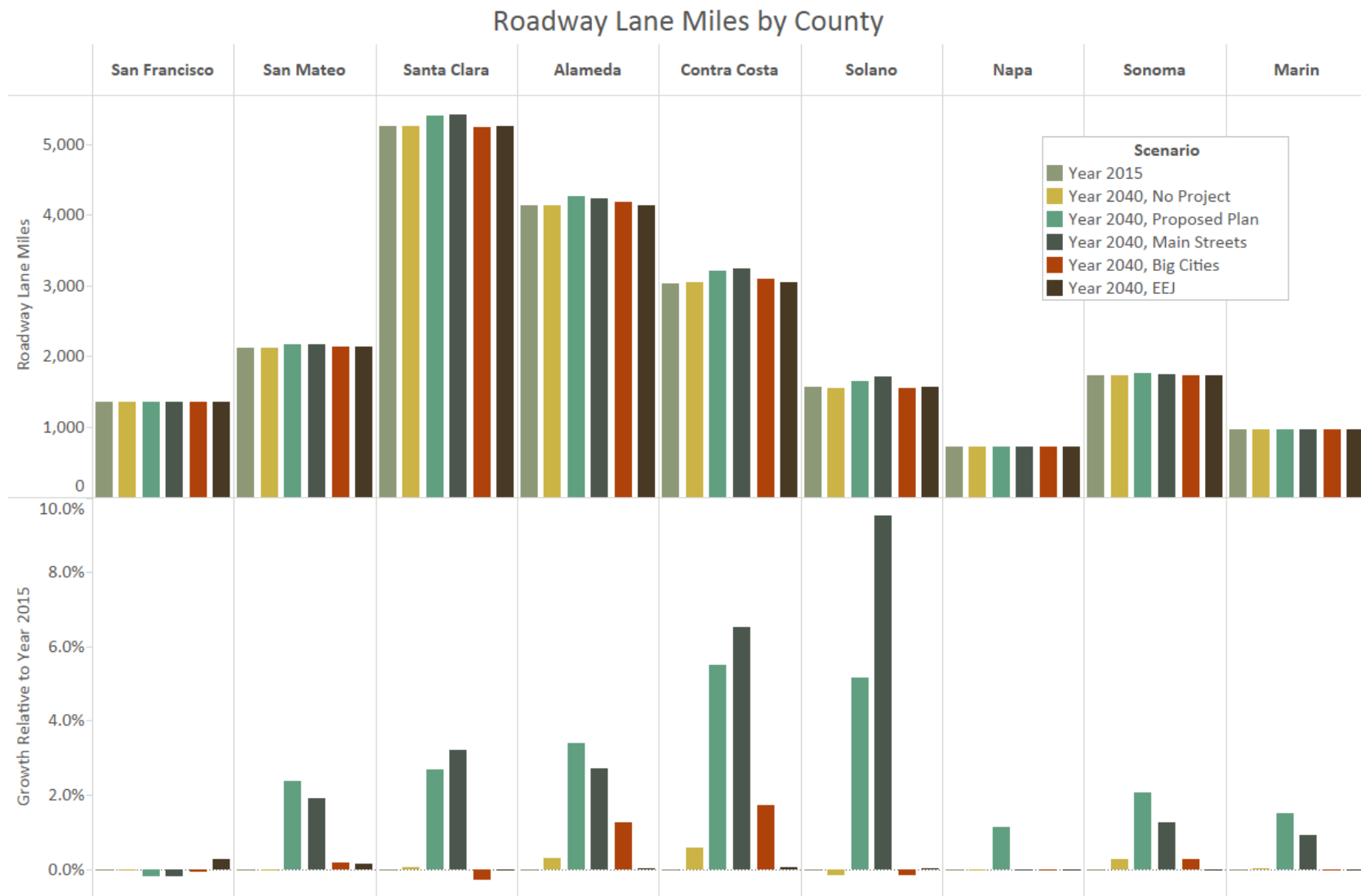
Figure 3: Year 2040 Growth in Roadway Lane Miles Available to Automobiles Relative to 2015
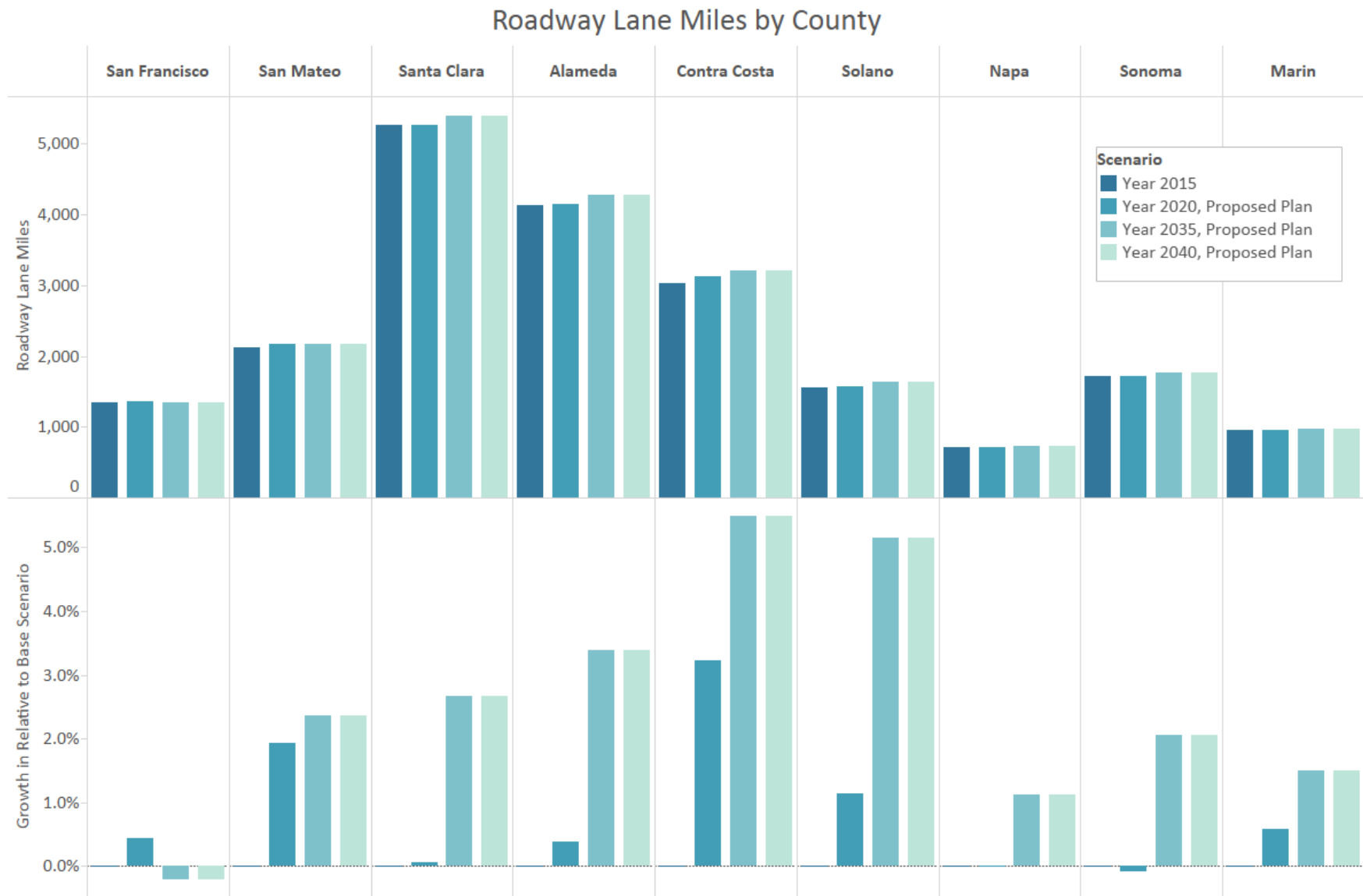
Figure 4: Growth in Roadway Lane Miles Available to Automobiles for Proposed Plan Alternative

Transit Supply

The historical scenarios for 2005 and 2015 reflect service in these years.

The No Project alternative begins with 2015 service levels and adds projects that are committed per MTC policy. The Proposed Plan alternative begins with 2015 service levels and adds both the committed projects as well as those included in the transportation investment strategy.

The Main Streets and Big Cities alternative transit projects were detailed to MTC's Planning Committee in May 2016[11].

The Environment, Equity and Jobs alternative begins with the Proposed Plan transit network and increases transit service frequency in some suburban areas.

A graphical depiction of these changes in transit service is presented in Figure 5 below. The chart shows the change in seat-miles (e.g., a one-mile segment of a bus with 40 seats is 40 seat-miles) in year 2040 compared to year 2015 across alternatives. Figure 6 shows the change in seat-miles over time for the Proposed Plan Alternative.

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[11] Ibid.
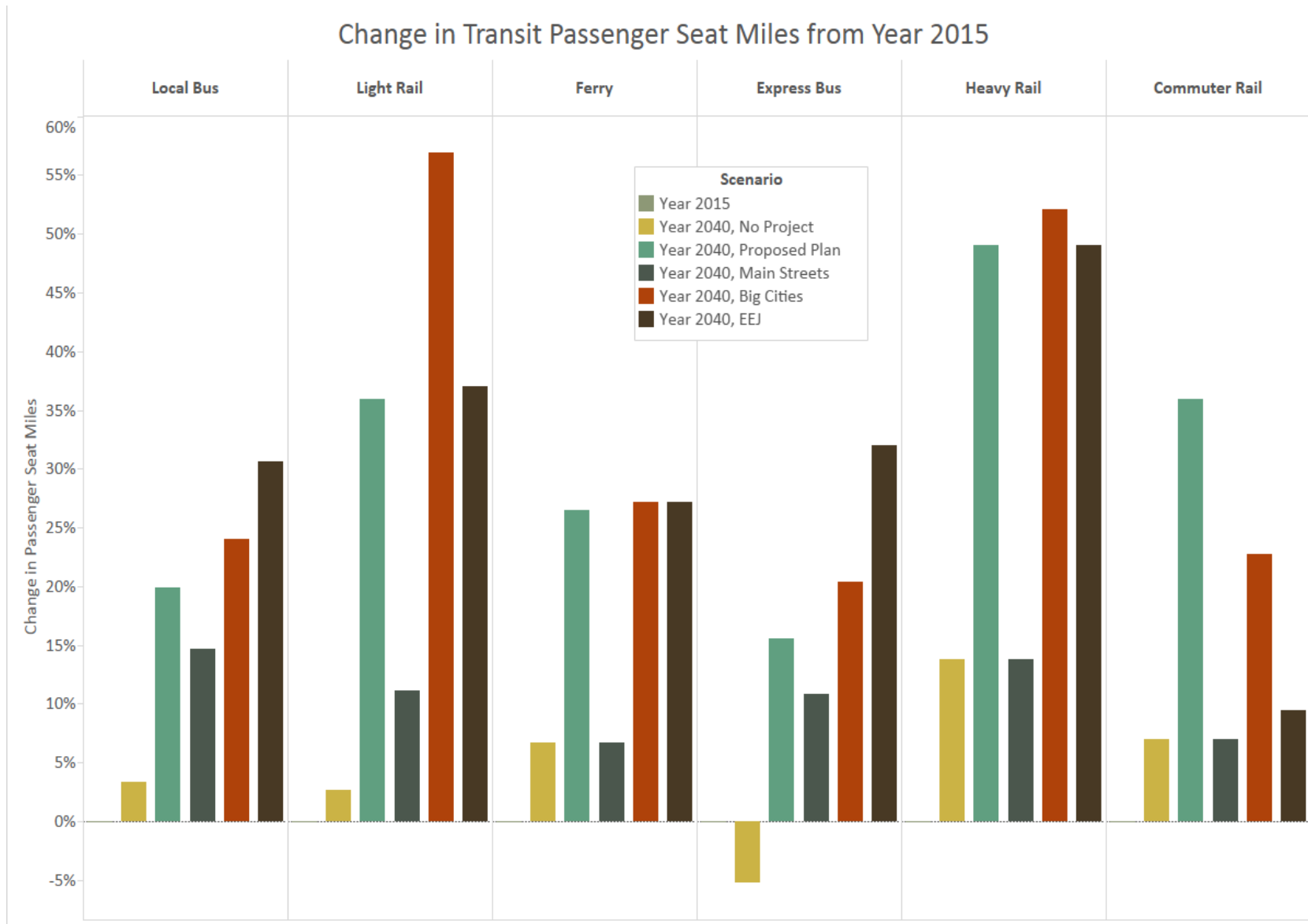
Figure 5: Year 2040 Growth in Transit Passenger Seat Miles from 2015

Change in Transit Passenger Seat Miles from Year 2015

| Local Bus | Light Rail | Ferry | Express Bus | Heavy Rail | Commuter Rail |

Scenario
- Year 2015
- Year 2020, Proposed Plan
- Year 2035, Proposed Plan
- Year 2040, Proposed Plan

Change in Passenger Seat Miles

Figure 6: Year 2040 Growth in Transit Passenger Seat Miles from 2015 for Proposed Plan

Prices

The travel model system includes probabilistic models in which travelers select the best travel mode (e.g., automobile, transit, bicycle, etc.) for each of their daily tours (round trips) and trips. One consideration of this choice is the trade-off between saving time and saving money. For example, a traveler may have two realistic options for traveling to work: (i) driving, which would take 40 minutes (round trip) and cost $10 for parking; or, (ii) taking transit, which would take 90 minutes (round trip) and cost $4 in bus fare ($2 each way). The mode choice model structure, as estimated in the early 2000s, includes coefficients that dictate how different travelers in different contexts make decisions 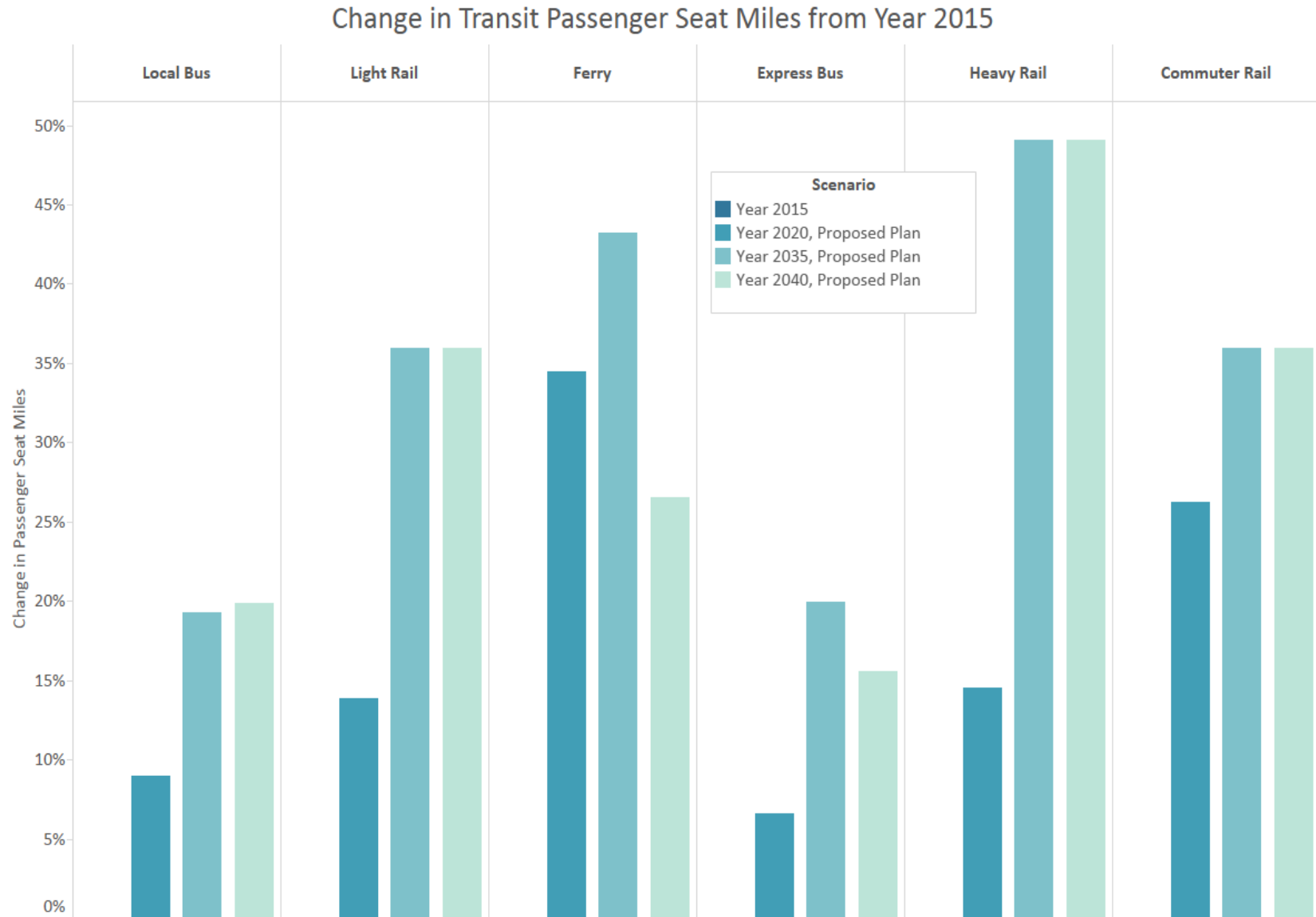regarding saving time versus saving money. These model coefficients value time in units consistent with year 2000 dollars, i.e. the model itself – not an exogenous input to the model – values time relative to costs in year 2000 dollars. Because re-estimating model coefficients is "expensive" (in terms of staff time and/or consultant resources), it is done infrequently, which, in effect, "locks in" the dollar year in which prices are input to the travel model. To use the model's coefficients properly, all prices must be input in year 2000 dollars. In the remainder of this document, prices are presented both in (close to) current year dollars, to give the reader an intuitive sense as to the scale of the input prices, as well as year 2000 dollars, which are the units required by the model coefficients.

Six different types of prices are explicitly represented in the travel model: (i) bridge tolls; (ii) express lane tolls; (iii) transit fares; (iv) parking fees; (v) perceived automobile operating cost and gas taxes; and (vi) cordon tolls. A brief discussion on how the model determines each synthetic traveler's value of time is presented next, after which the input assumptions across each of these price categories are presented.

Value of Time

The model coefficients that link the value of time with the other components of decision utilities remain constant between the baseline and forecast years, with the one exception of the coefficients on travel cost. These coefficients are a function of each synthetic individual's value of time, a number drawn, in both the historical and forecast year simulations, from one of four log-normal distributions (see Figure 7). The means of these distributions are a function of each traveler's household income. The value of time for children in a household is equal to two-thirds that of an adult. The means and shapes of these distributions remain constant across forecast years and scenarios.
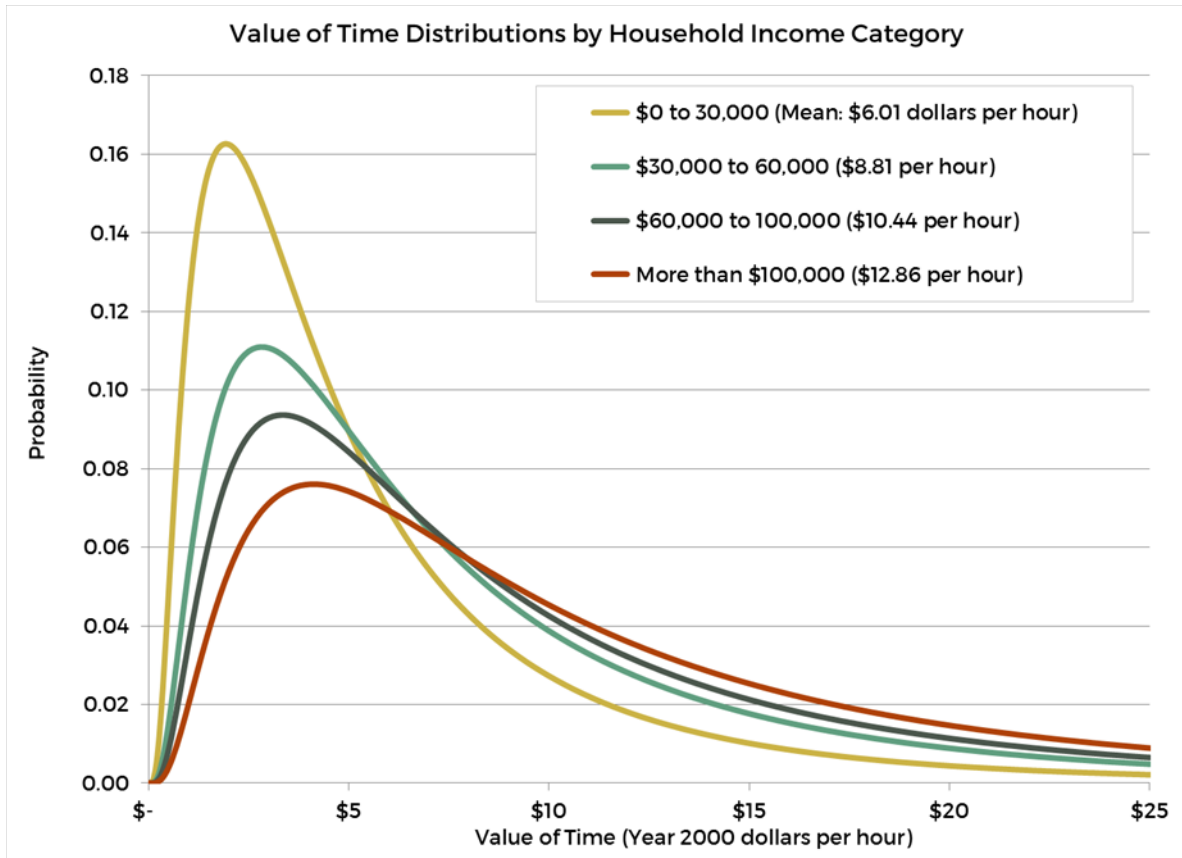
Figure 7: Value of Time Distribution by Household Income

Bridge Tolls

The bridge tolls assumed in the year 2015 baseline scenario are shown below in Table 3. Please note that Table 3 includes the price of tolls in year 2015 expressed in both year 2000 and year 2015 dollars.

The No Project alternative assumes the toll schedule in place as of July 1, 2012[12]. This schedule is consistent with the year 2015 tolls presented in Table 3.

The bridge tolls assumed in the Proposed Plan, Main Streets, Big Cities and Equity, Environment, and Jobs alternatives are summarized in Table 4. Again, the price of tolls in year 2040 are expressed in year 2000 and year 2015 dollars.

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[12] Complete details are available here: http://bata.mtc.ca.gov/getting-around#/.

Table 3: Year 2015 Common Peak Period Bridge Tolls[†]

Bridge	2-axle, single occupant toll		2-axle, carpool[*] toll	
	$2000	$2015	$2000	$2015
San Francisco/Oakland Bay Bridge	$4.82	$6.00	$2.01	$2.50
Antioch Bridge	$4.02	$5.00	$2.01	$2.50
Benicia/Martinez Bridge	$4.02	$5.00	$2.01	$2.50
Carquinez Bridge	$4.02	$5.00	$2.01	$2.50
Dumbarton Bridge	$4.02	$5.00	$2.01	$2.50
Richmond/San Rafael Bridge	$4.02	$5.00	$2.01	$2.50
San Mateo Bridge	$4.02	$5.00	$2.01	$2.50
Golden Gate Bridge	$4.02	$5.00	$2.41	$3.00

† – The full toll schedule includes off-peak tolls and tolls for 3- or more axle vehicles.
* – Carpools are defined as either two-or-more- or three-or-more-occupant vehicles, depending on the bridge, and only receive a discount during the morning and evening commute periods (source: bata.mtc.ca.gov; goldengatebridge.org).

Table 4: Common Peak Period Bridge Tolls for Proposed Plan, Main Streets, Big Cities, and EEJ Alternatives[†]

Bridge	2-axle, single occupant toll		2-axle, carpool[*] toll	
	$2000	$2015	$2000	$2015
San Francisco/Oakland Bay Bridge	$5.72	$8.00	$2.86	$4.00
Antioch Bridge	$5.01	$7.00	$2.50	$3.50
Benicia/Martinez Bridge	$5.01	$7.00	$2.50	$3.50
Carquinez Bridge	$5.01	$7.00	$2.50	$3.50
Dumbarton Bridge	$5.01	$7.00	$2.50	$3.50
Richmond/San Rafael Bridge	$5.01	$7.00	$2.50	$3.50
San Mateo Bridge	$5.01	$7.00	$2.50	$3.50
Golden Gate Bridge	$4.47	$6.25	$3.04	$4.25

† – The full toll schedule includes off-peak tolls and tolls for 3- or more axle vehicles.
* – Carpools are defined as either two-or-more- or three-or-more-occupant vehicles, depending on the bridge, and only receive a discount during the morning and evening commute periods (source: bata.mtc.ca.gov; goldengatebridge.org).

Express Lane Tolls

MTC's travel model explicitly represents the choice of travelers to pay a toll to use an express lane (i.e., a high-occupancy toll lane) in exchange for the time savings offered by the facility relative to the parallel free lanes. To exploit this functionality, the analyst must assign a travel price by time of day and vehicle class on each express lane link in the network. To efficiently and transparently simulate the impacts of the express lanes on behavior, we segment the express lane network in the scenarios into logical segments, with each segment receiving a time-of-day-specific per mile fee. To illustrate the detail involved in this coding, Figure 8, Figure 9, Figure 10, and Figure 11 (abstractly) present the morning commute period price for the year 2040 simulations. Please note that the simulated prices are not perfectly optimal – meaning, MTC did not analyze each corridor iteratively to find the price that maximized a pre-defined operational goal. Rather, the prices are adjusted a handful of times in an attempt to keep congestion low and utilization high. Importantly, the prices are held constant over four-hour morning (6 to 10 am) and evening (4 to 7 pm) commute periods. MTC's travel model assumes that congestion is uniform over the entire four-hour commute periods. We know this is not true, but make this assumption as a simplification. The peak one-hour within the four-hour commute period would require a higher toll than those simulated in the model.
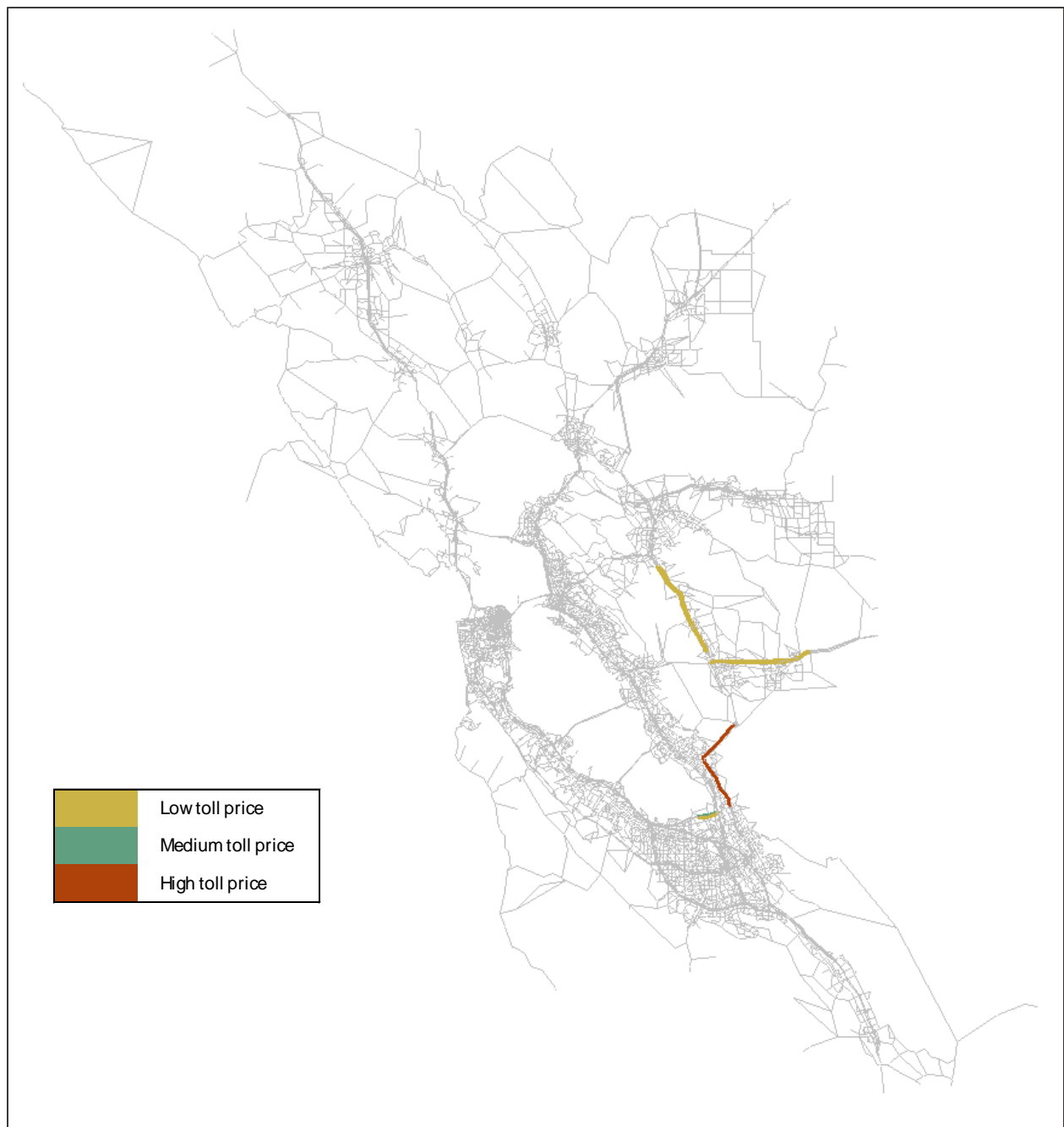
Figure 8: Morning Commute Express Lane Prices for No Project
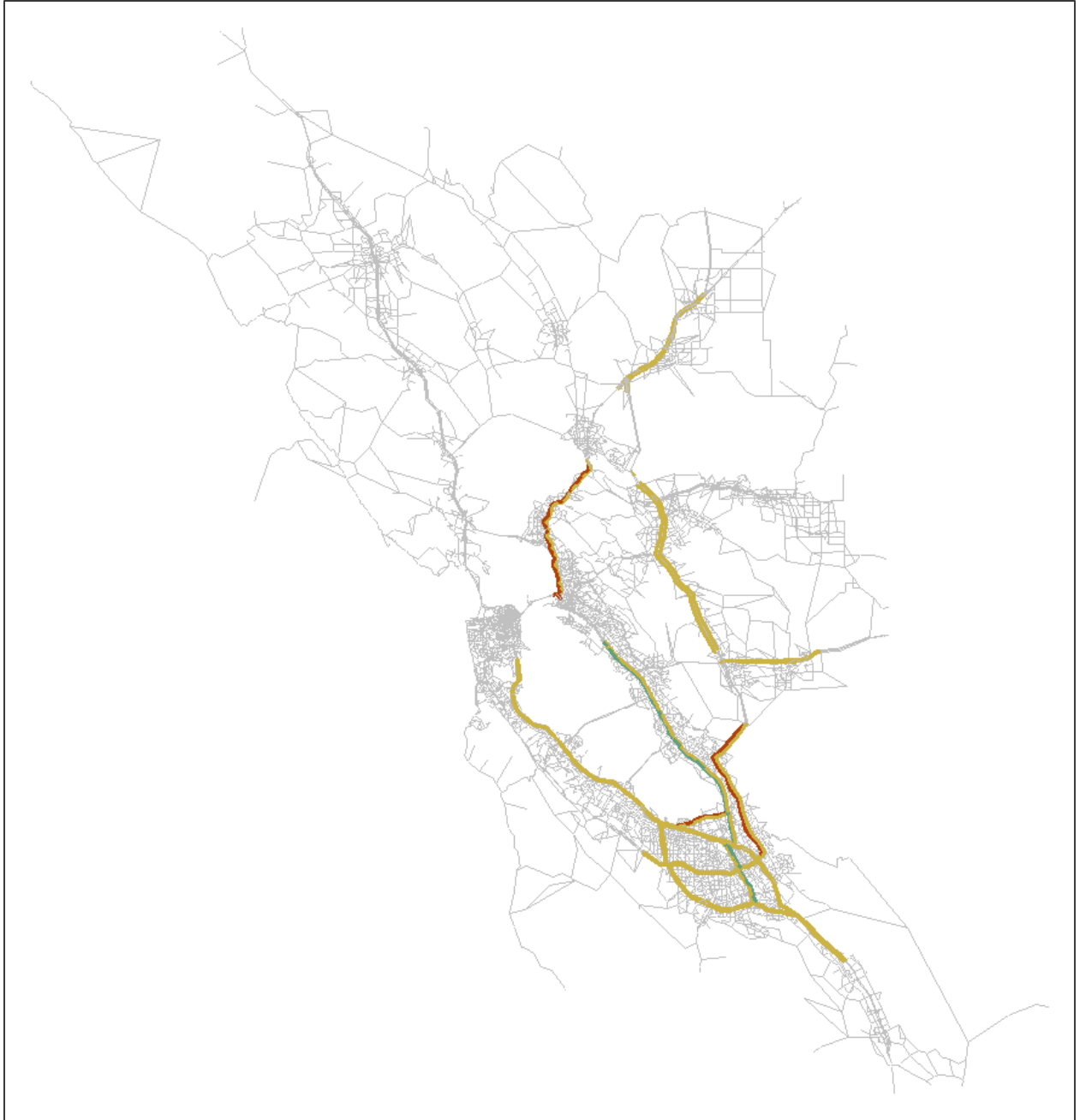
Figure 9: Morning Commute Express Lane Prices for Proposed Plan Alternative
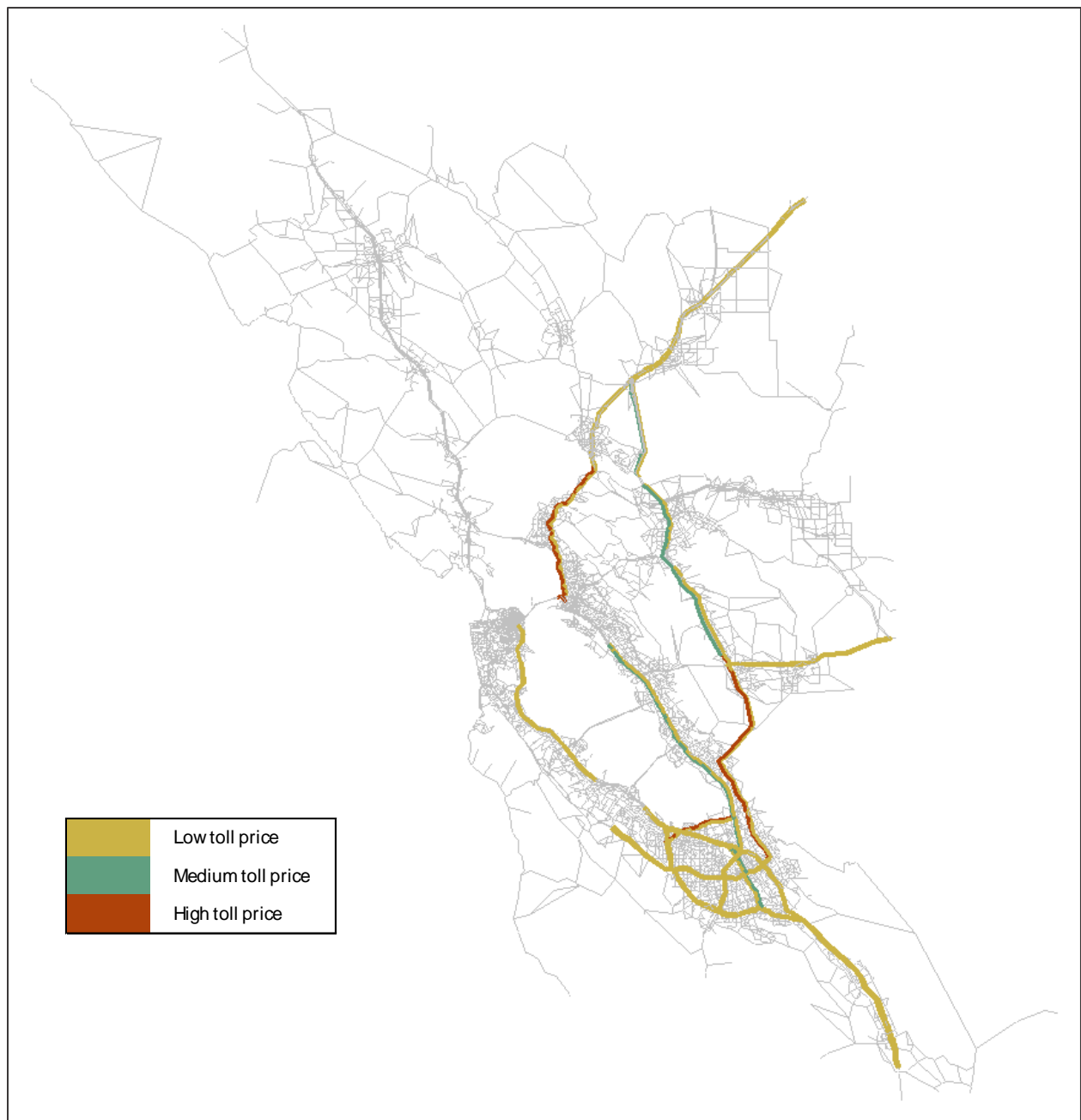
Figure 10: Morning Commute Express Lane Prices for Main Streets Alternative

Figure 11: Morning Commute Express Lane Prices for Big Cities and EEJ Alternatives

Transit Fares

The forecast year transit networks pivot off a year 2015 baseline network, i.e. the alternatives begin with 2015 conditions and add/remove service to represent the various alternatives. The transit fares in 2015 are assumed to remain constant (in real terms) in all of the forecast years. We are therefore explicitly assuming that transit fares will keep pace with inflation and that transit fares will be as expensive in the forecast year as they are today, relative to parking prices, bridge tolls, etc. As a simplification, we assume travelers pay the cash fare to ride each transit service. Table 5 includes fare prices in year 2015 expressed in both year 2000 and year 2015 dollars (i.e., the table does not include information about the cost of taking transit in the year 2000).

Table 5: Year 2015 Common Transit Fares

	Base fare	
Operator	*$2000*	*$2015*
San Francisco Municipal Transportation Agency (Muni)	$1.57	$2.25
Alameda/Contra Costa Transit (AC Transit) – Local buses	$1.47	$2.10
Santa Clara Valley Transportation Authority (VTA) – Local buses	$1.40	$2.00
Santa Clara Valley Transportation Authority (VTA) – Express buses	$2.80	$4.00
San Mateo County Transit (SamTrans) – Local buses	$1.40	$2.00
Golden Gate Transit – Marin County to San Francisco Service	$3.67	$5.25
County Connection (CCCTA)	$1.40	$2.00
Tri-Delta Transit	$1.40	$2.00
Livermore Amador Valley Transit Authority (Wheels, LAVTA)	$1.40	$2.00

Note: this is a sample, rather than an exhaustive list, of Bay Area transit providers and fares.

Parking Prices

The travel model segments space into travel analysis zones (TAZs). Simulated travelers move between TAZs and, in so doing, burden the transportation network. Parking costs are applied at the TAZ-level: travelers going to zone X in an automobile must pay the parking cost assumed for zone X.

The travel model uses hourly parking rates for daily/long-term (those going to work or school) and hourly/short-term parkers. The long-term hourly rate for daily parkers represents the advertised monthly parking rate, averaged for all lots in a given TAZ, scaled by 22 days per month, then scaled by 8

hours per day; the short-term hourly rate is the advertised hourly rate – generally higher than the rate daily parkers pay – averaged for all lots in a given TAZ. Priced parking in the Bay Area generally occurs in greater downtown San Francisco, downtown Oakland, Berkeley, downtown San Jose, and Palo Alto.

When forecasting, we assume that parking prices change over time per a simple model: parking cost increases linearly with employment density. Across the scenarios, therefore, the parking charges vary with employment density.

Perceived Automobile Operating Cost and Gas Tax

When deciding between traveling in a private automobile or on a transit vehicle (or by walking, bicycling, etc.), MTC assumes travelers consider the cost of operating and maintaining, but not owning and insuring, their automobiles. The following three inputs are used to determine the perceived automobile operating cost: average fuel price, average fleet-wide fuel economy, and non-fuel related operating and maintenance costs.

In an effort to improve consistency among regional planning efforts across the state, the Regional Targets Advisory Committee (formed per Senate Bill 375) recommended that California's metropolitan planning organizations (MPOs) use consistent assumptions for fuel price and for the computation of automobile operating cost in long range planning. Using forecasts generated by the United States Department of Energy (DOE) in the summer of 2013 (and expressed in year 2010 dollars), the MPOs agreed[13] to procedures to consistently estimate forecast year fuel and non-fuel-related prices. The average fleet-wide fuel economy implied by the EMFAC 2014 software is used to represent the average fleet-wide fuel economy. A summary of our assumptions are presented below in Table 6. Note that the prices in Table 6 are presented in year 2015 (i.e., current year) dollars, year 2010 dollars (the units used in the above referenced documentation), and year 2000 dollars (units of the travel model).

In all of the year 2040 scenarios save the No Project, a regional gas tax of 10 cents per gallon ($2015 dollars) is assumed.

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[13] Please see the memorandum titled "Automobile Operating Cost for the Second Round of Sustainable Communities Strategies" dated October 13, 2014.

Table 6: Perceived Automobile Operating Cost Calculations

	Analysis Year	
Measure	*2010*	*2040*
Average fuel price (Year 2000 dollars per gallon)	$2.51	$4.21
Average fuel price (Year 2010 dollars per gallon)	$3.17	$5.26
Average fuel price (Year 2015 dollars per gallon)	$3.61	$6.06
EMFAC-implied fuel economy (miles per gallon)	20.10	42.36
Non-fuel-related operating cost ($2000 per mile)	$0.04	$0.07
Non-fuel-related operating cost ($2010 per mile)	$0.05	$0.09
Non-fuel-related operating cost ($2015 per mile)	$0.06	$0.10
Perceived automobile operating cost ($2000 per mile) †	$0.17	$0.17
Perceived automobile operating cost ($2010 per mile) †	$0.21	$0.22
Perceived automobile operating cost ($2015 per mile) †	$0.24	$0.24

† – Sum of the fuel-related operating cost (fuel price divided by fuel economy) and non-fuel-related operating cost.

Cordon Tolls

The Proposed Plan, Big Cities and EEJ scenarios include a cordon toll in San Francisco. The scheme requires all vehicles to pay a $6 (in 2015 dollars) fee to enter or leave the greater downtown San Francisco area during the evening commute period. The cordoned area is bounded by Laguna Street to the west, 18th Street to the south, and the San Francisco Bay to the north and east.

Other Key Assumptions

Technology currently allows large numbers of Bay Area residents to work at home. In the forecast years, MTC assumes the trend of workers working at home revealed in Census data from 1980 through 2014 will continue through 2040. Figure 12 presents the historical data, the trend, and the MTC forecasts. These telecommuting assumptions are the same across all year 2040 scenarios, including the No Project.
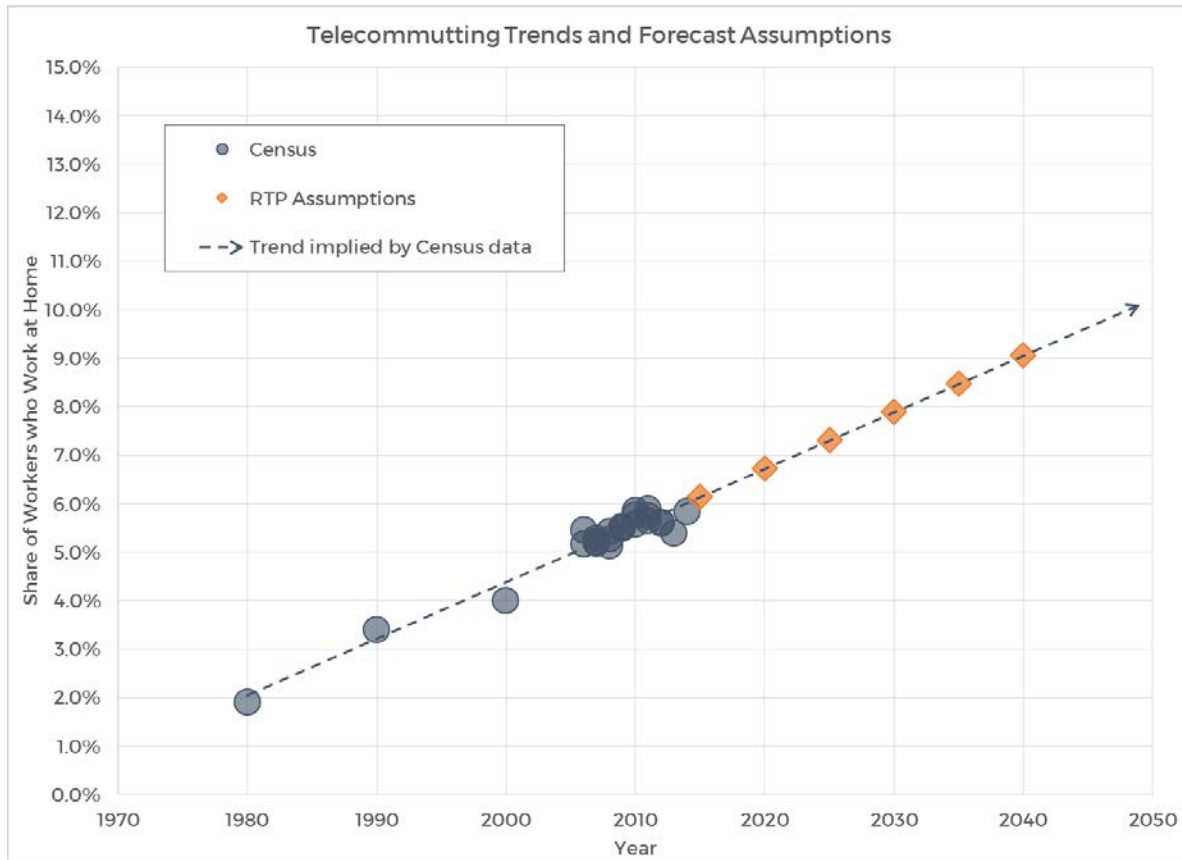
Figure 12: Work at Home Observations, Trends and Forecasts

Chapter 3: Key Results

Selected travel model results across a variety of dimensions are summarized and discussed here. The presented results are not exhaustive and are intended only to give the reader a general sense of the expected behavioral changes in response to differing input assumptions across scenarios.

Performance Targets and Equity Analysis

The purpose of this document is to describe the response of travelers to the projects and policies implemented in the scenarios described in the previous section. Information from the travel model is also used to help assess the performance of each of the scenarios per agency-adopted targets. This information is described in MTC's May 2016 Planning Committee memorandum[14].

Information from the travel model also is used to analyze how different populations are impacted by the investments and policies included in each alternative. This information is described in MTC's May 2016 Planning Committee memorandum[15].

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[14] Available here: http://mtc.legistar.com/gateway.aspx?M=F&ID=a78d1547-7db3-4dd2-afdb-2d14fe3aec71.pdf
[15] Ibid.

Automobile Ownership

Figure 13 presents the automobile ownership rates across the four scenarios in the year 2040 simulations as well as year 2015. The differences across scenarios are not dramatic. A key finding is the general increase in zero automobile households in the Proposed Plan, Big Cities and EEJ scenarios.
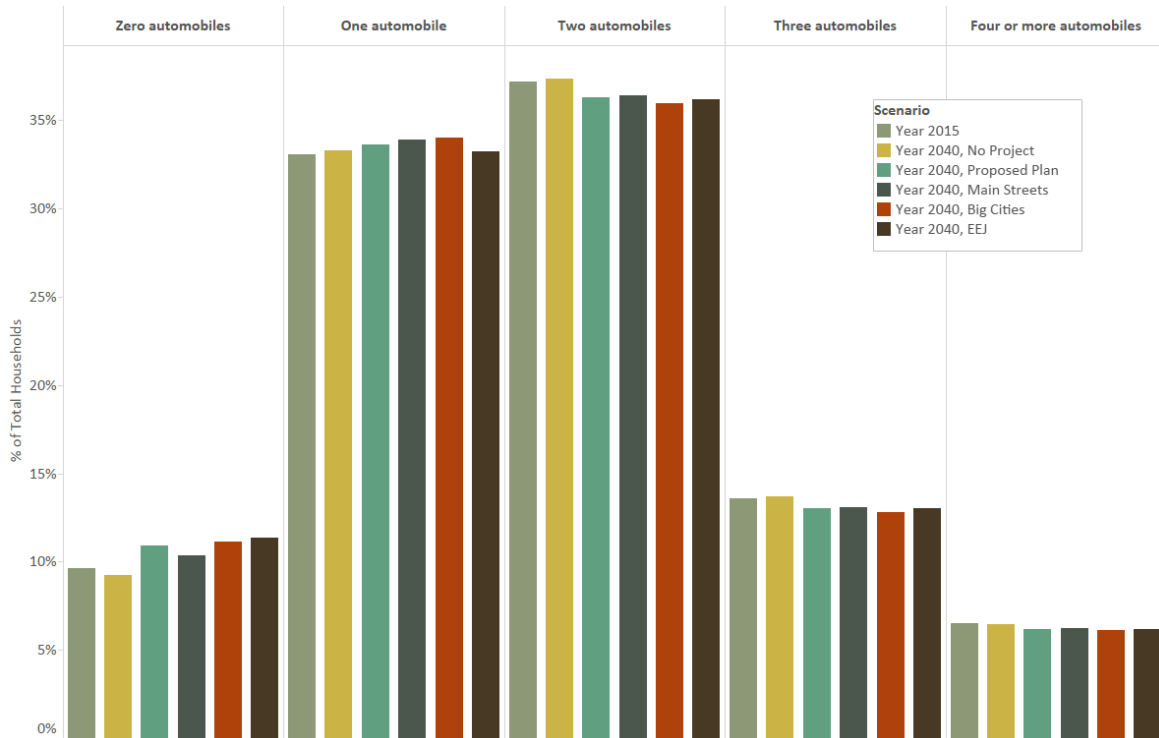
Figure 13: Year 2040 Automobile Ownership Results

Activity Location Decisions

Figure 14 and Figure 15 present the average trip distance by travel mode for all travel and for trips on work tours, respectively. The key finding here is that the Big Cities scenario brings activities slightly closer together, when compared to the 2015 baseline.
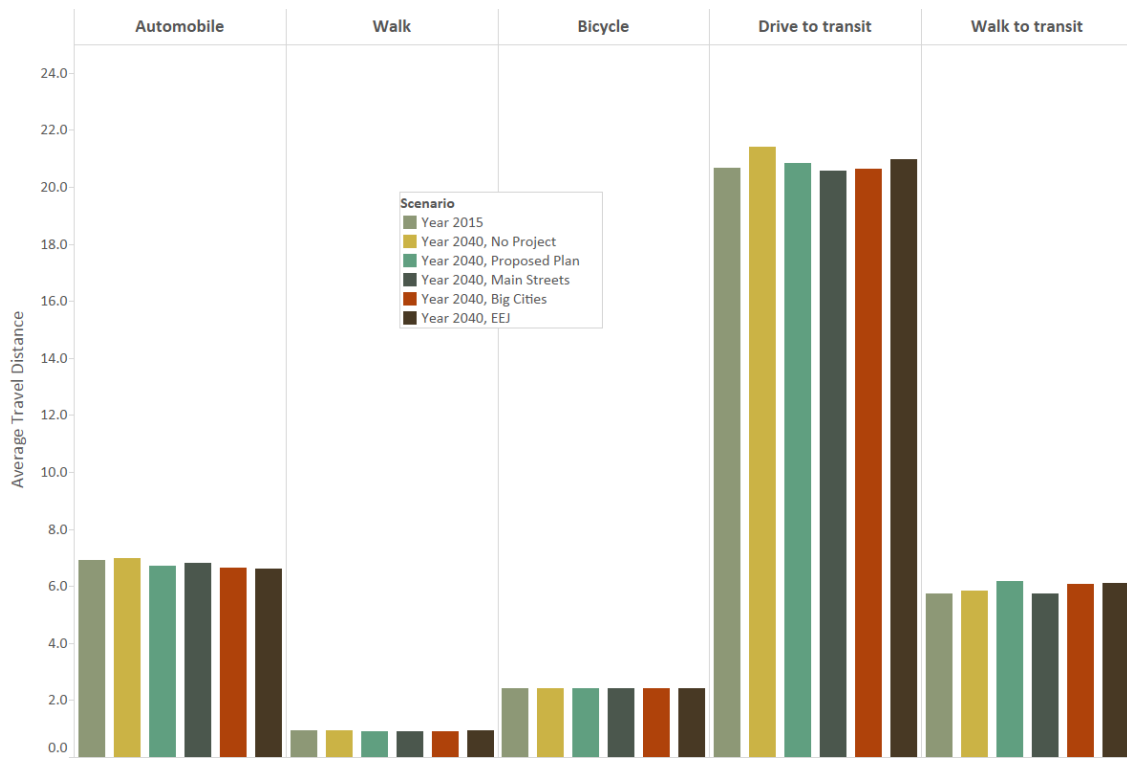
Figure 14: Year 2040 Average Trip Distance
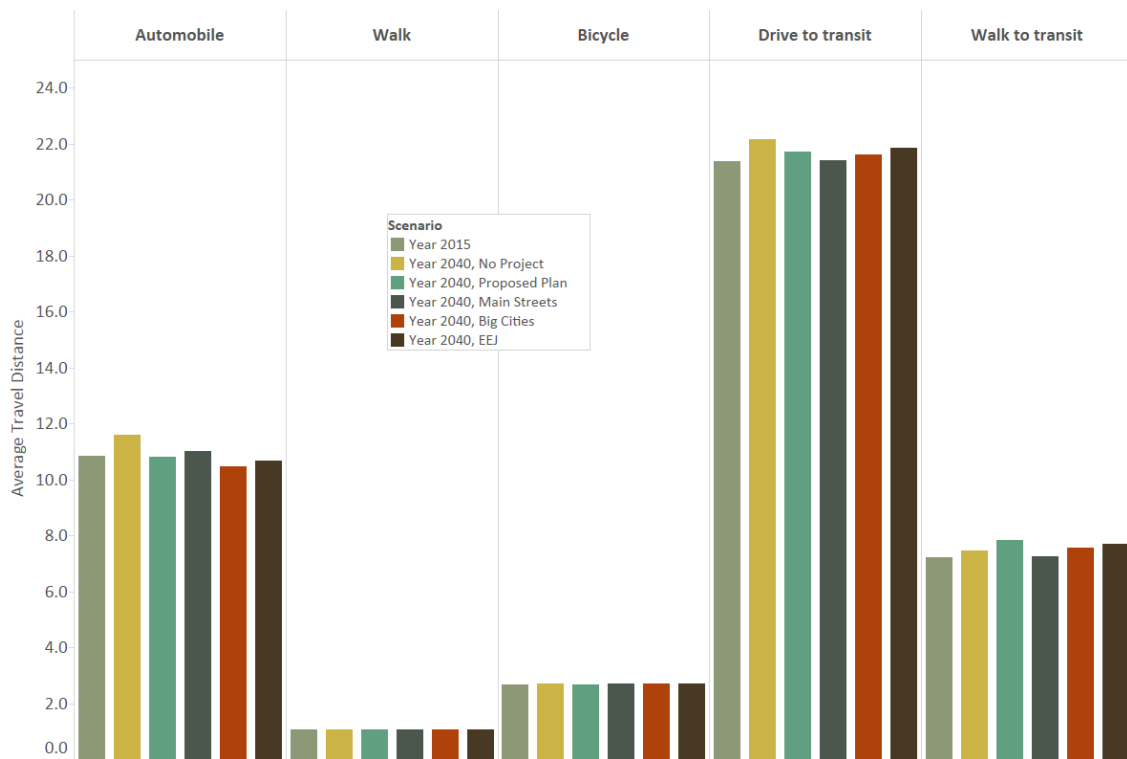
Figure 15: Year 2040 Average Trip Distance for Travel on Work Tours

Travel Mode Choice Decisions

The means by which a traveler gets from point A to point B is referred to as the travel mode. Within MTC's representation of travel behavior, five automobile-based modal options are considered, specifically:

- traveling alone in a private automobile and opting not to pay to use an express lane ("single occupant, no HOT"), an option only available to those in households who own at least one automobile;
- traveling alone in a private automobile and opting to pay to use an express lane ("single occupant, pay to use HOT"), an option only available to those who both own a car and whose journey would benefit from using the express lane facility (e.g., this option is not available to those driving through a residential neighborhood to drop a child at school);
- traveling with one passenger in a private automobile and opting not to pay to use an express lane ("two occupants, no HOT) (these travelers can use carpool lanes for which they are eligible), an option available to all households;
- traveling with one passenger in a private automobile and opting to pay to use an express lane ("two occupants, pay to use HOT"), an option available to all households provided they would benefit from using an express lane (if the express lane facility which benefits travelers allows two-occupant vehicles to travel for free, than these travelers are categorized as "two occupants, no HOT"); and,
- traveling with two or more passengers in a private automobile ("three-or-more occupants") – these travelers are allowed to travel for free on express lane facilities across all the scenarios (as well as carpool facilities).

The travel model explicitly considers numerous non-automobile options which are collapsed in these summaries into the following four options: transit, getting to and from by foot ("walk to transit"); transit, getting to or from in an automobile ("drive to transit"); walk; and, bicycle.

Figure 16 and Figure 17 present the share of trips made by various travel modes. Figure 16 shows shares of travel in automobiles by occupancy category as well as by willingness to pay to use an express lane. Overall, mode shares shift slightly towards transit in the four project scenarios compared with a slight shift towards auto travel in the No Project scenario. Figure 17 presents companion results for non-automobile travel modes, including public transit, walking, and bicycling. Here, we see a slight increase in walk-to-transit in the Big Cities and EEJ scenarios, which reflects the scenarios' increase in transit service and increasingly efficient land development patterns.
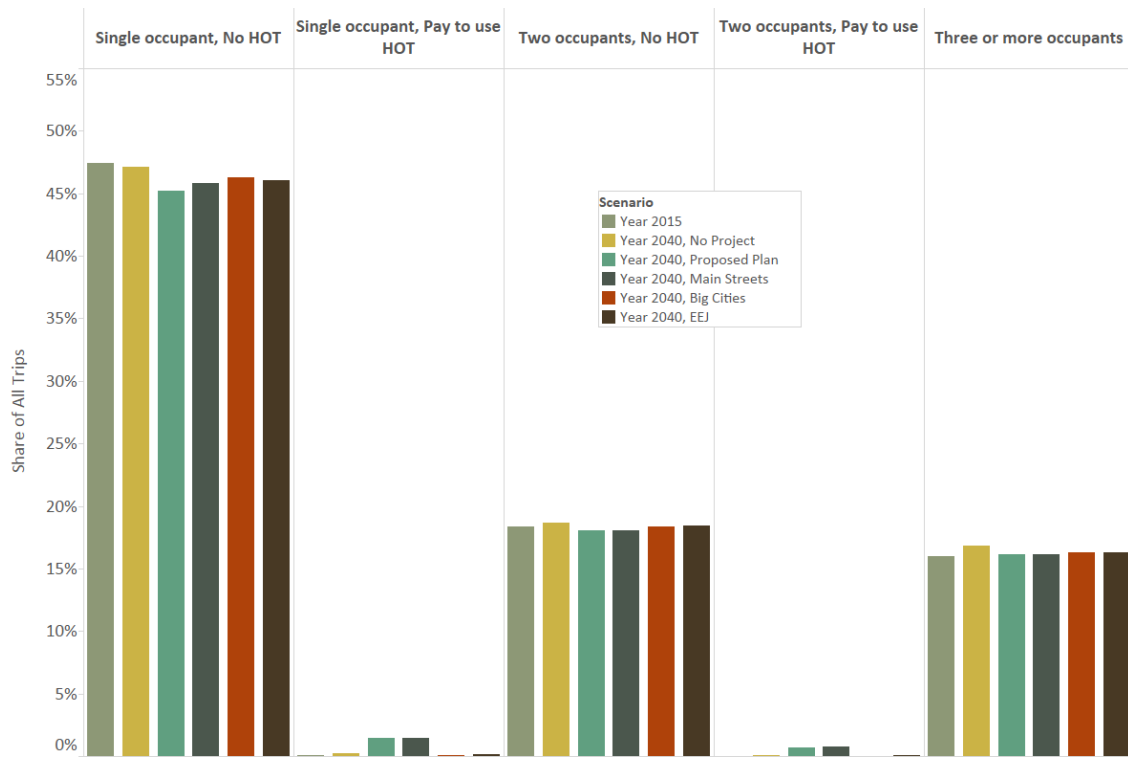
Figure 16: Year 2040 Automobile Mode Shares for All Travel
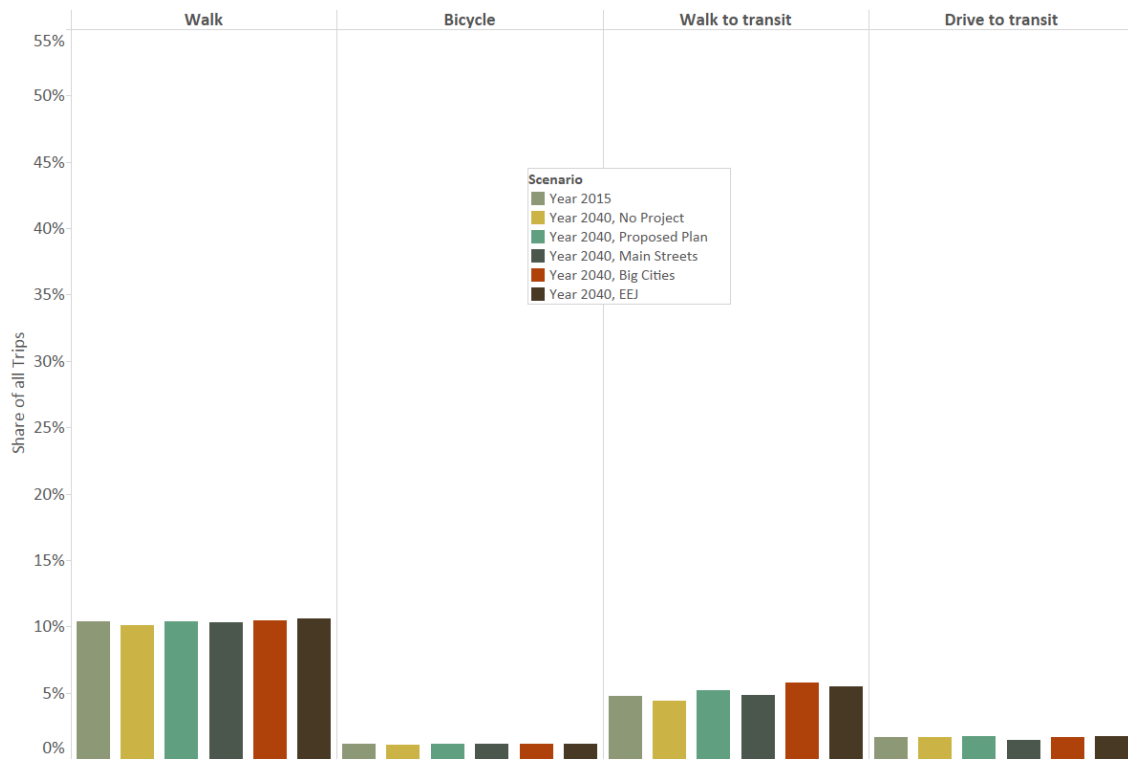
Figure 17: Year 2040 Non-Automobile Mode Shares for All Travel

Aggregate Transit Demand Estimates

Bay Area residents choosing to travel by transit are explicitly assigned to a specific transit route. As a means of organizing the modeling results, MTC groups transit lines into the following technology-specific categories:

- **Local bus**: standard, fixed-route bus service, of the kind a traveler may take to and from a neighborhood grocery store or to work, as well as so-called "bus rapid transit" service.
- **Express bus**: longer distance service typically provided in over-the-road coaches. Golden Gate Transit, for example, provides express bus service between Marin County and Downtown San Francisco.
- **Light rail**: represented in the Bay Area by San Francisco's Muni Metro and streetcar services (F-Market and E-Caltrain), as well as Santa Clara Valley Transportation Authority's light rail service.
- **Heavy rail**: another name for the Bay Area Rapid Transit (BART) service.
- **Commuter rail**: longer distance rail service typically operating in dedicated right-of-way, including Caltrain, Sonoma-Marin Area Rail Transit (SMART), Amtrak's Capitol Corridor, and Altamont Commuter Express.

Figure 18 presents the estimates of transit boardings by these categories on the typical weekday simulated by the travel model. Ridership increases from about 2.3 million daily boardings in 2015 to over 3 million daily boardings in all project scenarios, and over 3.4 million boardings in the 2040 Big Cities scenario.
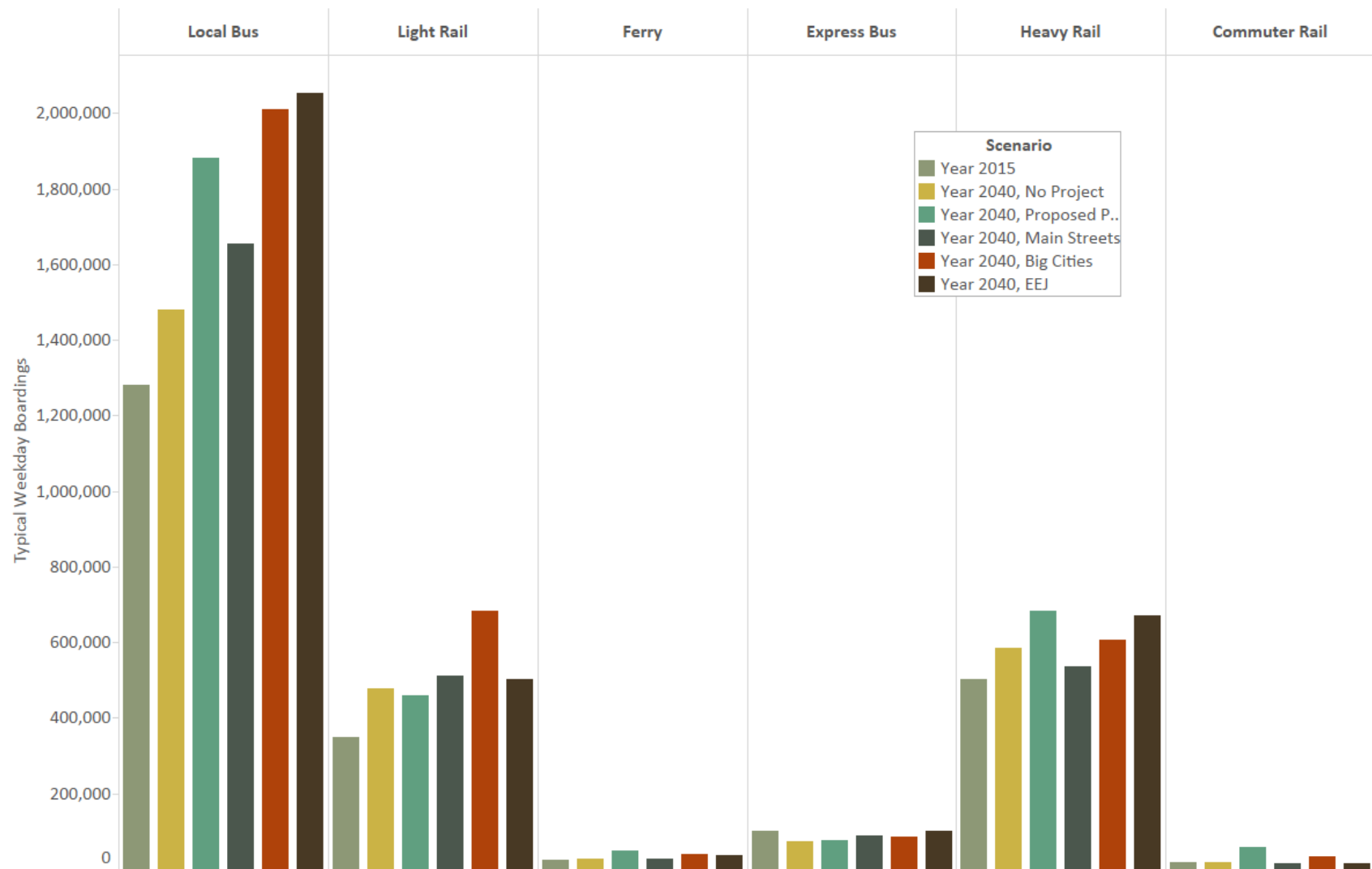
Figure 18: Year 2040 Typical Weekday Transit Boardings by Technology

Roadway Utilization and Congestion Estimates

Trips made by automobile are first aggregated into matrices identifying each trip's origin and destination, and then "assigned" to a representation of the Bay Area's roadway network. The assignment process iteratively determines the shortest path between each origin-destination pair, shifting some number of trips to each iteration's shortest path, until the network reaches a certain level of equilibrium – defined as a state in which travelers cannot change to a lower "cost" route (where cost includes monetary and non-monetary (time) expenditures). Several measures of interest are generated by the assignment process, including vehicle miles traveled, delay, and average travel speed.

Please note that MTC maintains three separate estimates of the quantity of vehicle miles traveled (VMT), as follows:

(1) the quantity assigned directly to the highway network;
(2) the quantity (1) plus so-called "intra-zonal" VMT (i.e., travel that occurs at a geographic scale finer than the travel model's network representation), which is computed off-line; and,
(3) the quantity (2) adjusted to match the VMT the California Air Resources Board (CARB) believes takes place in the Bay Area (a number slightly higher than MTC's estimate).

In this document, the VMT identified as (1) in the above list is presented.

Figure 19 first segments VMT into five time periods and then scales the VMT by the number of hours in each time period. The result is the intensity of VMT by time of day as well as the increase in VMT from 2015 to 2040. Overall, VMT varies only slightly across the year 2040 alternatives, with the Big Cities and EEJ scenarios having the lowest VMT.

Figure 20 presents the average freeway speed across scenarios. Looking at the speeds during the morning and evening commute periods, we see a reduction in speed (or, said another way, an increase in congestion) from the year 2015 scenario to the year 2040 No Project scenario. Each of the alternatives improves freeway speeds.
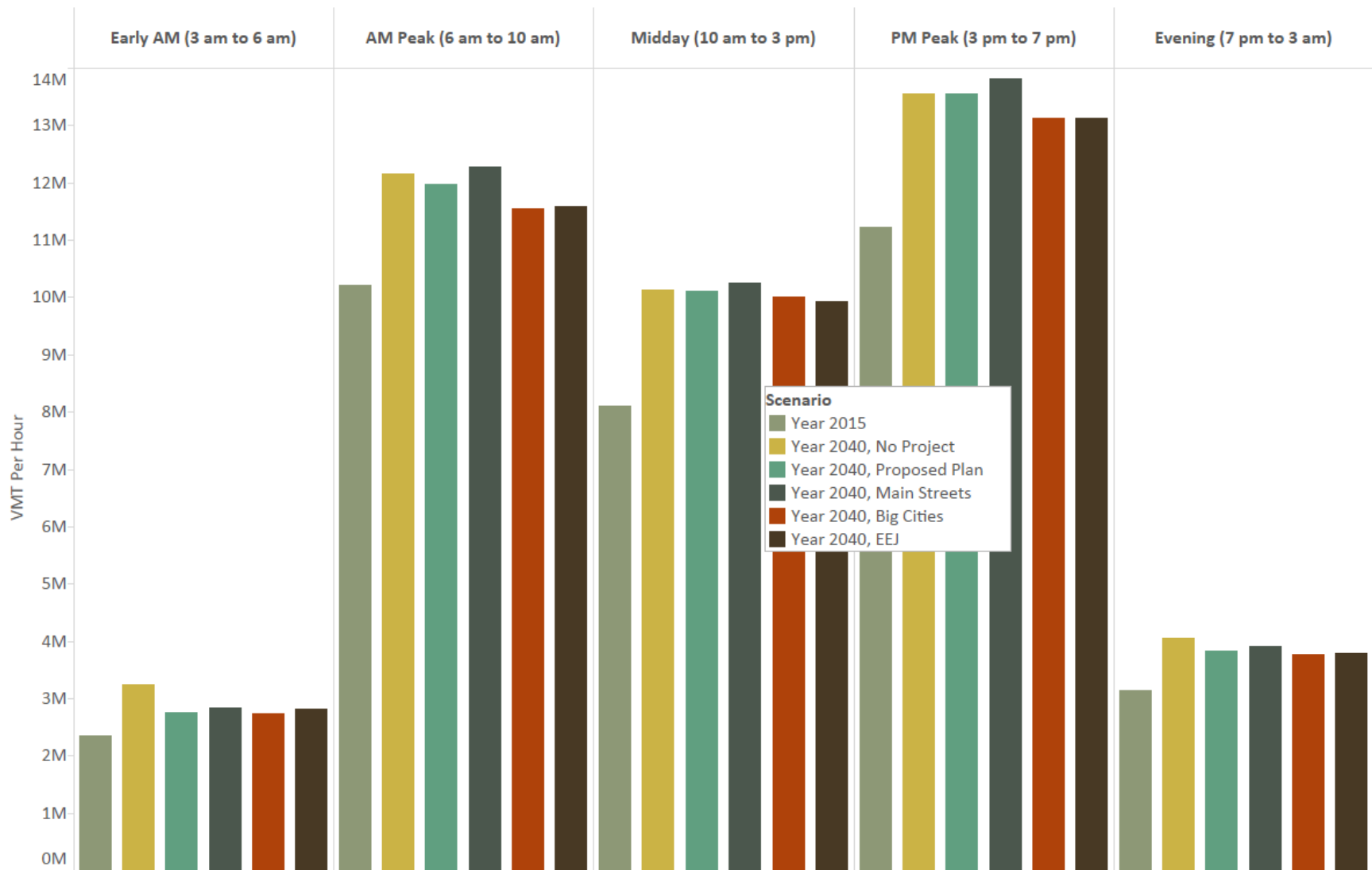
Figure 19: Year 2040 Vehicle Miles Traveled per Hour by Time Period
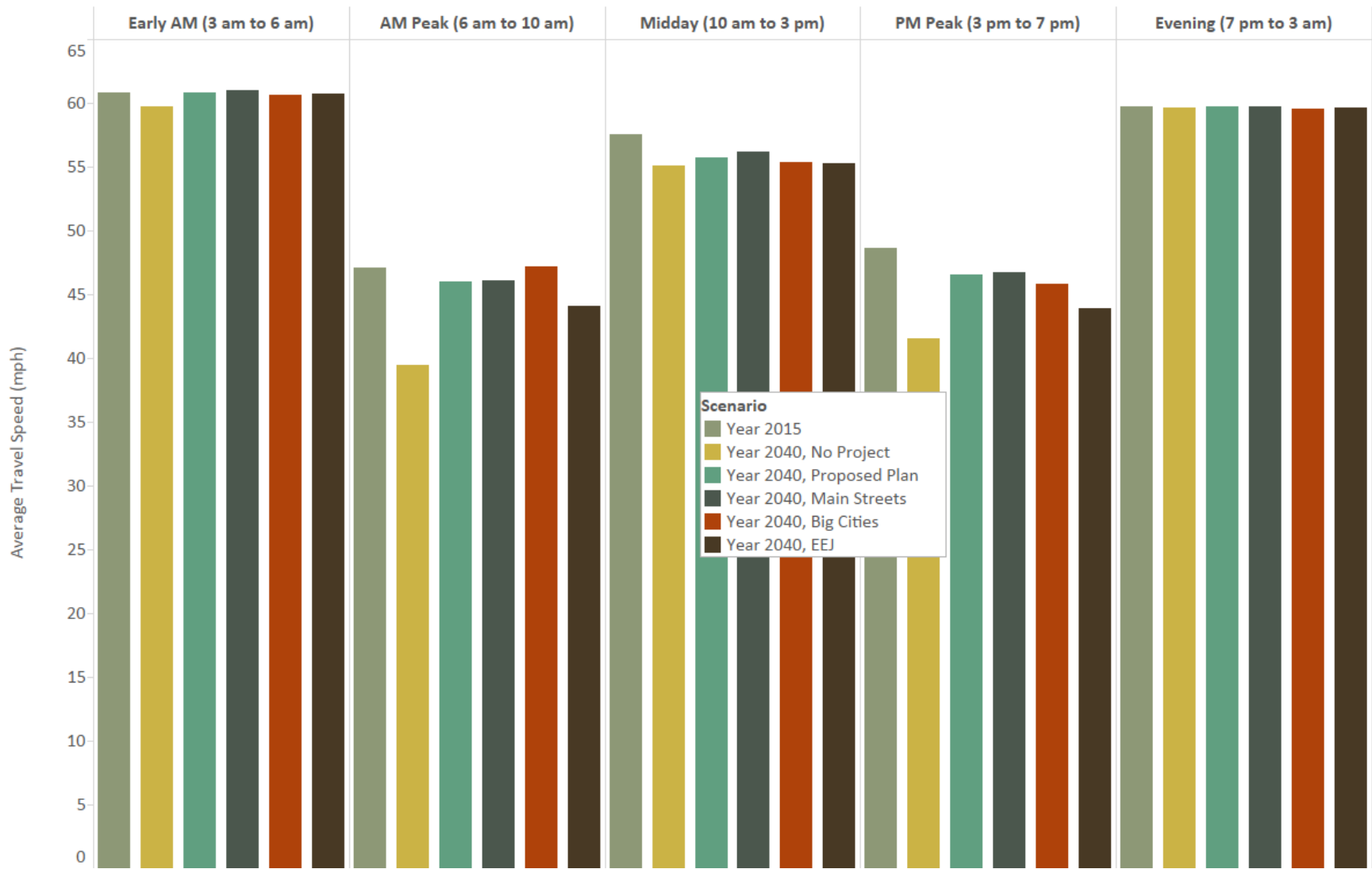
Figure 20: Year 2040 Average Vehicle Speeds on Freeways

Appendix A: Off-Model Emission Reduction Estimates

Off-Model Emission Reduction Estimates

MTC, with consultant assistance, prepared off-model analyses of various strategies, referred to as climate initiatives, anticipated to produce measurable per-capita greenhouse gas (GHG) emission reductions. Investments are made in programs that will accelerate the adoption of clean vehicle technologies and promote the use of sustainable travel modes.

The 2013 Plan Bay Area included an analysis of a variety of off-model strategies. In 2015, MTC reassessed the current strategies and explored new ones for inclusion in the update to Plan, Plan Bay Area 2040. This assessment took into account findings from the implemented strategies and review of new and emerging strategies not included in Plan Bay Area.

Based on the ICF assessment, MTC plans to include many of the climate strategies that were included in Plan Bay Area, namely:
- Commuter Benefits Ordinance;
- Car Sharing;
- Vanpools and Employer Shuttles;
- Regional Electric Vehicle Charger Network;
- Vehicle Buyback and PEV Incentive;
- Clean Vehicles Feebate Program; and
- Smart Driving.

Strategies not currently captured by MTC's travel model were added to the Plan update:
- Targeted Transportation Alternatives;
- Trip Caps;
- Bike Share; and
- Bicycle Infrastructure.

Each Climate Policy Initiative is summarized in the following pages, including a description of the project objective, contextual background, assumptions and methodology, analytic steps and results.

Emission Rates

To calculate the carbon dioxide (CO_2) emissions reductions from the Climate Policy Initiatives, the California Emissions Model (EMFAC) trip end emission rates and exhaust per mile emission rates for light and medium duty vehicles were used. The regional average rates for annual CO_2 emissions from light and medium duty vehicles are applied to the calculated trip reductions and VMT reductions, which are summarized in the individual policy descriptions below.

In order to compare results with SB 375's regional GHG emissions targets derived using EMFAC2007, EMFAC2014 GHG emissions outputs have been converted to EMFAC2007 equivalents by applying an adjustment methodology in accordance with ARB staff's guidance and consultation for the off-model analysis in order to derive the CO_2 emission factors used in the 2020 and 2035 CO_2 reduction estimates. Unadjusted EMFAC2014 outputs were used to create emission factors for 2040 CO_2 reduction

estimates. Table 1 summarizes the CO_2 emission factors used for passenger vehicles. Except where otherwise noted, we use these factors throughout our analysis.

Table 1: CO_2 emission factors

	2020 (based on EMFAC2007 equivalents)	**2035** (based on EMFAC2007 equivalents)	**2040** (based on EMFAC2014 outputs)
CO_2 Exhaust Emission Rate (grams per mile)	386.45	389.19	386.75
CO_2 Trip End Emission Rate (grams per trip)	80.75	79.09	85.80

Commuter Benefits Ordinance

In fall 2012, Senate Bill (SB) 1339 authorized the Bay Area Air Quality Management District (Air District) and MTC to adopt and implement a regional commuter benefits ordinance in the San Francisco Bay Area on a pilot basis through December 31, 2016. The goal of the pilot was to promote the use of transit and other sustainable commute modes in order to reduce single-occupant vehicle commute trips, traffic congestion, GHG and other pollutants. After completion of the pilot, MTC and the Air District achieved bi-partisan support in the State Legislature, and SB 1128 was signed by Governor Brown on September 22, 2016. SB 1128 extends the provisions of the Commuter Benefits Ordinance (CBO), establishing the pilot program permanently. MTC and the Air District continue to jointly administer the program and implement the law.

The CBO requires employers with 50 or more full-time employees in the Bay Area to offer their employees incentives to commute to work by modes other than driving alone. Employers can choose to offer one of the following options in order to make sustainable commute modes more attractive to their employees:
- Pre-Tax Benefit - allows employees to exclude their transit or vanpooling expenses from taxable income (IRS Code Section 132 (f));
- Employer-Provided Subsidy - provides a subsidy to reduce or cover employees' monthly transit or vanpool costs;
- Employer-Provided Transit - provides a free or low-cost transit service for employees, such as a bus, shuttle or vanpool service; or
- Alternative Commuter Benefit - provides an alternative commuter benefit that is as effective in reducing single-occupancy commute trips as Options 1, 2 or 3.

Off-model analysis is necessary to capture CO_2 reductions from the CBO because MTC's last household travel survey, which informs its model, was conducted in 2010, and does not capture the impacts of new strategies that change travel behavior such as this one. The CBO might be captured by a future model once it has been implemented to the extent that the options offered through the ordinance influence people's behavior in a way that can be captured by the travel surveys, and once the model framework has been altered to include inputs that are reflective of the CBO.

Assumptions and methodology

In Plan Bay Area, CO_2 reductions due to the CBO were projected based on research and evidence from similar efforts, particularly San Francisco's CBO, which has been in effect in since 2009. In 2015, MTC completed an evaluation of the CBO based on a random sample survey of over 1,400 Bay Area employees.[1] In the update to the Plan, Plan Bay Area 2040, the same methodology is applied to estimate CO_2 reductions as in the previous Plan, but the assumptions are based on MTC's evaluation.

CBOs encourage employees to shift from driving alone to taking transit, carpooling, bicycling or walking by offering incentives to cover the costs of using these modes or by providing shuttle/vanpool service. In order to quantify the benefits, the number of employees covered by the CBO and the corresponding VMT reduction are estimated.

Additionally, the number of employees at businesses that begin to offer benefits due to the CBO are estimated for each of the 34 superdistricts in MTC's travel model. The total number of employees in each superdistrict for each scenario-year was also collected and compared to the current Dun and Bradstreet size of business data to identify the percentage of employees in each superdistrict that work at businesses with 50 or more employees subject to the CBO. Region-wide, slightly over 50 percent of employees work at establishments with 50 or more employees, though the percentages range from 31% to 68 percent for individual superdistricts. Since some employers already offer the types of benefits described in the legislation, the methodology estimated the percentage of employees who do not already receive the benefits, which includes all new employees (i.e., employees added between 2015 and the scenario year) and a percentage of current (2015) employees. In 2009, the City and County of San Francisco enacted a CBO and found that 46 percent of employers already offered one of the required benefits prior to implementation of the city's ordinance.[2] Accordingly, 54 percent of current employees in the Bay Area are assumed to be receiving new benefits as a result of the CBO. This is a conservative estimate when applied to areas outside of San Francisco which is well-served by transit and other options to driving alone, and has many progressive employers who are more likely to offer their workers benefits to take advantage of these options independent of a CBO. The results were summed across all superdistricts within each of the nine Bay Area counties to estimate the total number of employees that receive benefits due to the CBO at the county level.

From MTC's evaluation of the CBO, which included a survey of employees, the county-level estimates of the percentage of employees who are aware that their employer offers a CBO program and the percentage of employees who reduce at least one SOV trip due to the CBO were determined. The methodology assumes that as time passes, all employers will comply with the CBO and all employees will be aware of the benefits available to them. These findings were applied to the average regional reduction in vehicle trips and VMT for employees who respond to the CBO to estimate VMT reductions. Table 2 summarizes the evaluation results used in the analysis.

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[1] Bay Area Air Quality Management District, Metropolitan Transportation Commission. Bay Area Commuter Benefits Program, Report to the California Legislature. February 2016. http://www.baaqmd.gov/~/media/files/planning-and-research/commuter-benefits-program/reports/commuter-benefits-report.pdf

[2] Data supplied by the San Francisco Department of Environment.

County	% of eligible employees who reduce SOV trips due to CBO	% of eligible employees who are aware of CBO benefits	% of eligible employees who reduce SOV trips due to CBO (adjusted)	Average yearly trip reductions for employees who reduce SOV trips	Average yearly VMT reductions for employees who reduce SOV trips
Alameda	4.5%	51.5%	8.7%	36.0	697.5
Contra Costa	7.6%	43.8%	17.4%	36.0	697.5
Marin	7.0%	32.0%	21.9%	36.0	697.5
Napa	8.8%	42.4%	20.8%	36.0	697.5
San Francisco	7.1%	75.0%	9.5%	36.0	697.5
San Mateo	8.8%	53.8%	16.4%	36.0	697.5
Santa Clara	6.4%	56.2%	11.4%	36.0	697.5
Solano	0.0%	28.0%	0.0%	36.0	697.5
Sonoma	0.0%	21.8%	0.0%	36.0	697.5

Analysis steps

To calculate CO_2 reductions due to the CBO, the methodology:

1. Identified the current and future number of employees for each MTC superdistrict.
2. Subtracted current from future employees to calculate the number of new employees for each MTC superdistrict.
3. Multiplied the number of current employees by the estimated percentage of employees who do not currently receive commuter benefits (54%) and added the result to the number of new employees to calculate the total number of employees who do not currently receive commuter benefits.
4. Multiplied the result by the percentage of employees in each superdistrict that are currently employed at businesses with over 50 employees to estimate the total number of employees who are newly eligible for CBO benefits in each superdistrict.
5. Summed results across all superdistricts within each county.
6. Multiplied the result by the adjusted percentage of eligible employees in each county who reduce drive-alone trips due to the CBO (see Table 2) and summed results across all counties to estimate the total number of employees who change behavior due to the CBO.
7. Multiplied the result by the average annual reduction in vehicle trips and VMT per affected employee (see Table 2) to estimate total annual reduction in vehicle trips and VMT.
8. Summed the product of trip-end emission rates and daily vehicle trip reductions and the product of exhaust emission rates and daily VMT reductions to calculate total CO_2 emission reductions.

Results

Table 3 and Table 4 summarize the CO_2 reductions due to the CBO.

Table 3: Daily CO_2 emissions reductions due to CBO (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	296	328	340

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[3] MTC Climate Initiatives Program Evaluation: Commuter Benefits Ordinance, Prepared for MTC by True North Consulting, 2015. A summary of findings is available at http://mtccms01.prod.acquia-sites.com/sites/default/files/CIP%20Evaluation%20Summary%20Report_7-13-15_FINAL.pdf.

Main Streets	297	329	343
Big Cities	297	327	339
EEJ	297	327	340

Table 4: Per capita CO_2 emissions reductions from 2005 baseline due to CBO (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-0.36%	-0.35%	-0.34%
Main Streets	-0.36%	-0.35%	-0.35%
Big Cities	-0.36%	-0.35%	-0.34%
EEJ	-0.36%	-0.35%	-0.34%

Car Sharing

Car sharing allows individuals to rent vehicles by the minute or by the hour, thus giving them access to an automobile without the costs and responsibilities of individual ownership. Car sharing is growing rapidly in the Bay Area through traditional for-profit/non-profit services (City CarShare/Carma, Zipcar, UHaul Car Share, Enterprise CarShare), peer-to-peer car sharing (Getaround, RelayRides) and one-way car share services (Scoot, some preliminary offerings from Zipcar).

Traditional car sharing businesses operate on a membership basis. Users pay an annual fee in addition to hourly and sometimes per-mile rates. Gas, maintenance, parking, insurance and 24-hour access are included in the membership and usage rates. The pricing scheme is set up to encourage the use of the vehicles for errands, airport pickups and other short trips. For trips longer than one day, it is usually less expensive to rent a vehicle through a car rental agency. Traditional car sharing models are most effective for households in neighborhoods that are served by high-quality transit where vehicles are only infrequently needed. After joining a car sharing program, households in these neighborhoods can sometimes shed one or more vehicles due to the variety of modes accessible to them and the occasional use of a car sharing vehicle. In less dense neighborhoods, car sharing may allow a two- or three-car family to shed one car by making a vehicle accessible for the rare instances that multiple vehicles are needed at the same time. Car sharing can also help to enable and expand the trend of younger generations putting off obtaining licenses at age 16 and purchasing vehicles. In general, car sharing members are required to have a clean driving record and be over the age of 18 in order to join. Businesses can also sign up for business memberships to avoid maintaining or reduce the size of a company fleet of vehicles.

Peer-to-peer car sharing (also known as P2P) allows an individual to rent out his/her private vehicle when not in use. Participation in this car sharing model generates income for the owner and provides a wide range of vehicle types and prices to the renter. Peer-to-peer is similar to the traditional car sharing model insofar as vehicles need to be returned to the starting location, but differ in that they are more likely to succeed than traditional car sharing in less dense, suburban neighborhoods.[4] This is because the service is providing additional income to the vehicle owner, and the usage does not need to be high

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[4] Hampshire, R. and C. Gaites, Peer-to-peer Carsharing: Market Analysis and Potential Growth, *Transportation Research Record* 2217, 2011.

enough to completely offset the vehicle ownership costs. One peer-to-peer company, Getaround, was launched in 2011 and has built a rapidly growing network of vehicles, including in the Bay Area cities of San Francisco, Berkeley and Oakland.

One-way car sharing allows a driver to pick up a vehicle in one location and drop it off at another—in some cases a dedicated pod; in others, wherever is convenient within a set geographic area. This model could allow an individual who takes transit to work to then pick up a vehicle and run errands on her way home. This model also allows vehicles to turn over more frequently since users can drive to an event, park the car, let someone else rent it and then pick up a different vehicle nearby for their return trip, which can lead to higher utilization of vehicles. Some of the more widespread one-way car sharing services include Car2Go, operated by Mercedes-Benz, and ZipCar's one-way service, both of which currently operate in seven cities. Scoot, a one-way scooter sharing system, currently operates in San Francisco.

Car sharing has positioned itself to cause a major shift in the market, but it is not captured in MTC's travel model, and accordingly is accounted for off-model. Car sharing reduces emissions in two primary ways: by lowering the average VMT of members and by allowing trips to be taken with more fuel-efficient vehicles than would have been used without car sharing. While shared transportation modes are becoming ever more popular and car sharing may continue to increase absent any intervention by MTC, MTC will be helping to accelerate expansion through this program. MTC could offer grants to fund a variety of efforts to encourage car sharing, potentially including opening new traditional car sharing offices or pods in underserved communities, developing parking codes that remove barriers to one-way car sharing and marketing and outreach programs.

Assumptions and methodology

CO_2 reductions due to car sharing are based on the number of Bay Area residents who are in the age groups likely to adopt car sharing and who live in communities that are compact enough to promote shared use. Research shows that adults between the ages of 20 and 64 are most likely to adopt car sharing, and estimates that between 10 percent[5] and 13 percent[6] of the eligible population in more compact areas when car sharing is available. With the introduction of one-way and peer-to-peer car sharing, as well as the implementation of regional strategies to support car sharing, adoption rates are assumed to reach 14 percent of the eligible population in dense urban areas (i.e., areas with at least ten people per residential acre) by 2035, while three percent of the eligible population could adopt car sharing by 2035 in suburban areas. Table 5 below summarizes the assumptions with respect to adoption rates.

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[5] Zipcar. http://www.zipcar.com/is-it#greenbenefits. Accessed March 20, 2017.
[6] Zhou, B., Kockelman, K, and Gao, R. "Opportunities for and Impacts of Carsharing: A Survey of the Austin, Texas Market", TRB, 2009.

Table 5: Car sharing adoption rates

Scenario year	Adoption rates in urban areas (>10 people/res acre)	Adoption rates in suburban areas (<10 people/res acre)
2020	12%	0%
2035	14%	3%
2040	14%	3%

Research by Robert Cervero[7] indicates that on average traditional car share members drive seven fewer miles per day than non-members. This is mostly due to the members who shed a vehicle after joining car sharing. Their daily VMT drops substantially and outweighs the increase in VMT from car share members that previously did not have access to a vehicle. In addition to this reduction in VMT, when members drive in car share vehicles, their per-mile emissions are lower because car share vehicles are more fuel efficient than the average vehicle. Research by Martin and Shaheen[8] shows that the car share fleet uses 29 percent less fuel per mile than the passenger vehicle fleet in general, a difference assumed to persist through 2040. The same paper also shows that on average, members of traditional car sharing programs drive an average of 1,200 miles in car sharing vehicles per year. Also assumed is annual car share mileage will remain constant over time.

Although there are currently no one-way car sharing programs in the Bay Area, it is expected that this model will emerge over the coming years. Recent research suggest that while one-way car sharing still reduces CO_2 emissions, but not as much as traditional car sharing. For this analysis, it is assumed that one-way car sharing is not yet widespread in the Bay Area in 2020. However, by 2035, it is assumed that 20 percent of Bay Area car sharing members will be participating in a one-way car sharing program rather than a traditional program, and by 2040 this figure will increase to 25 percent. Table 6 summarizes these assumptions.

Table 6: One-way car sharing participation rates

	2020	2035	2040
Percent of car share members that participate in one-way car sharing (rather than traditional programs)	0%	20%	25%

New research by Martin and Shaheen[9] indicates that on average one-way car share members drive 1.07 fewer miles per day than non-members. Additionally, the one-way car sharing fleet uses 45 percent less fuel per mile, a difference assumed to persist through 2040. The same paper also shows that on average, members of traditional car sharing programs drive an average of 104 miles in car sharing vehicles per year. This mileage is also assumed to remain constant over time.

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[7] Cervero, Golub, and Nee, "City CarShare: Longer-Term Travel-Demand and Car Ownership Impacts", July 2006, TRB 2007 Annual Meeting paper.

[8] Martin, Elliot, and Susan Shaheen, "Greenhouse Gas Emission Impacts of Carshaing in North America," 2010, Mineta Transportation Institute. MTI Report 09-11.

[9] Martin, Elliot, and Susan Shaheen, "Impacts of Car2Go on Vehicle Ownership, Modal Shift, Vehicle Miles Traveled, and Greenhouse Gas Emissions", July 2016, Working Paper.

Analysis steps

To calculate the CO_2 emission reductions due to car sharing, the methodology:

1. Calculated the residential density of every TAZ (transportation analysis zone) during the scenario year by dividing the total population by the residential acres.
2. Summed the total car sharing eligible population (between the ages of 20 and 64) for urban areas (TAZs with a population density greater than 10 residents per residential acre) and for suburban areas (TAZs with a population density greater than 10 residents per residential acre).
3. Calculated total future car share membership population by multiplying the factors in Table 5 by the total car sharing eligible population in urban and suburban areas, respectively.
4. Applied the percentages in Table 6 above to determine the number of members in both traditional and one-way car sharing services.
5. Calculated the daily VMT reduction by multiplying the miles shed per day per member (7 miles in traditional car sharing programs, and 1.07 miles in one-way car sharing programs) to the number of members of each service type and summed the result across both service types.
6. Multiplied daily VMT reductions by exhaust emission rates to calculate CO_2 emission reductions due to car share members driving less.
7. Calculated the total annual miles driven in car share vehicles in the Bay Area by multiplying the car sharing member estimates for traditional and one-way car sharing by 1,200 annual miles, and 104 annual miles respectively. This was divided by the assumed number of travel days/year (250) to determine daily VMT for vehicles in each car share service type.
8. Multiplied daily VMT for vehicles in each car share service type by the vehicle efficiency gains for each service type (29% for traditional services and 45% for one-way services) and by exhaust emission rates to estimate CO_2 reductions due to car share members driving more efficient vehicles.
9. Summed CO_2 emission reductions due to car share members driving less (Step 6) and CO_2 reductions due to car share members driving more efficient vehicles (Step 8) to estimate total CO_2 reductions due to car sharing.

Results

Table 7 and Table 8 summarize the CO_2 reductions due to car sharing.

Table 7: Daily CO_2 emissions reductions due to car sharing (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	-1,713	-1,935	-1,900
Main Streets	-1,709	-1,936	-1,900
Big Cities	-1,694	-1,925	-1,895
EEJ	-1,713	-1,936	-1,901

Table 8: Per capita CO_2 emissions reductions from 2005 baseline due to car sharing (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-2.09%	-2.06%	-1.92%
Main Streets	-2.09%	-2.06%	-1.92%
Big Cities	-2.07%	-2.05%	-1.91%
EEJ	-2.09%	-2.06%	-1.92%

Vanpools and Employer Shuttles

Vanpool

MTC has coordinated a vanpool program since 1981 to encourage alternative commutes and reduce congestion and emissions. To date, MTC's 511 vanpool program recruitment has consisted of online passenger and driver matching, employer outreach, up to $500 for startup fees, empty seat subsidies to encourage continued participation when a passenger is lost, free bridge tolls, and various other incentives. With these basic incentives there is an operational vanpool fleet in the Bay Area of over 515 vans. Since vanpools are not represented in MTC's travel model, the travel model cannot be used to assess the impacts of expanding the vanpool program, and therefore is captured off-model.

Employer shuttles

In addition to these traditional vanpools, there has been explosive growth in the number of employer-provided shuttles in the Bay Area. These shuttles are used as a recruiting tool and they allow for increased worker productivity due to the onboard wireless internet, thus turning commute time into productive time. Rough estimates indicate that the technology company shuttles that operate between San Francisco and Silicon Valley transport close to 17,500 people per workday.[10] The Google shuttle alone carried over 9,000 employees to work on peak days in 2015.[11] Google's shuttle system began as a vanpool in 2006 and rapidly grew into the current system. Prior to the SB 375 CO_2 emissions baseline year (2005) there were very few employer provided shuttles in the region. For purposes of this analysis there are assumed to have been no shuttles prior to 2005.

There are private shuttles running through all parts of the Bay Area including some that connect the East Bay and San Mateo County to Silicon Valley, some that operate just within San Francisco and San José, and others from BART and Caltrain stations to corporate campuses. These shuttles are not represented in MTC's travel model, and the 2010 travel survey that informs the model does not reflect the rapid growth in employer shuttles in recent years nor its impact on travel patterns, and therefore shuttles are accounted for off-model. To be conservative, the 17,500 daily employer operated shuttle riders from

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[10] Based on Stamen's estimate that San Francisco shuttles carry approximately equal to 35% of Caltrain ridership levels (https://hi.stamen.com/the-city-from-the-valley-57e835ee3dc6#.4ic9o338l). Obtaining shuttle ridership levels is extremely difficult due to the confidential nature of the information since businesses use these shuttles as a recruiting tool. In the month prior to Stamen releasing their work, Caltrain reported ridership levels of 50,000 passengers per weekday.

[11] Google. 2016. Environmental Report, https://environment.google/projects/environmental-report-2016/. Accessed March 20, 2017

San Francisco to the Silicon Valley are assumed to account for all employer operated shuttle riders in the Bay Area.

Figure 1: Employer-operated shuttles running from San Francisco to Silicon Valley[12]
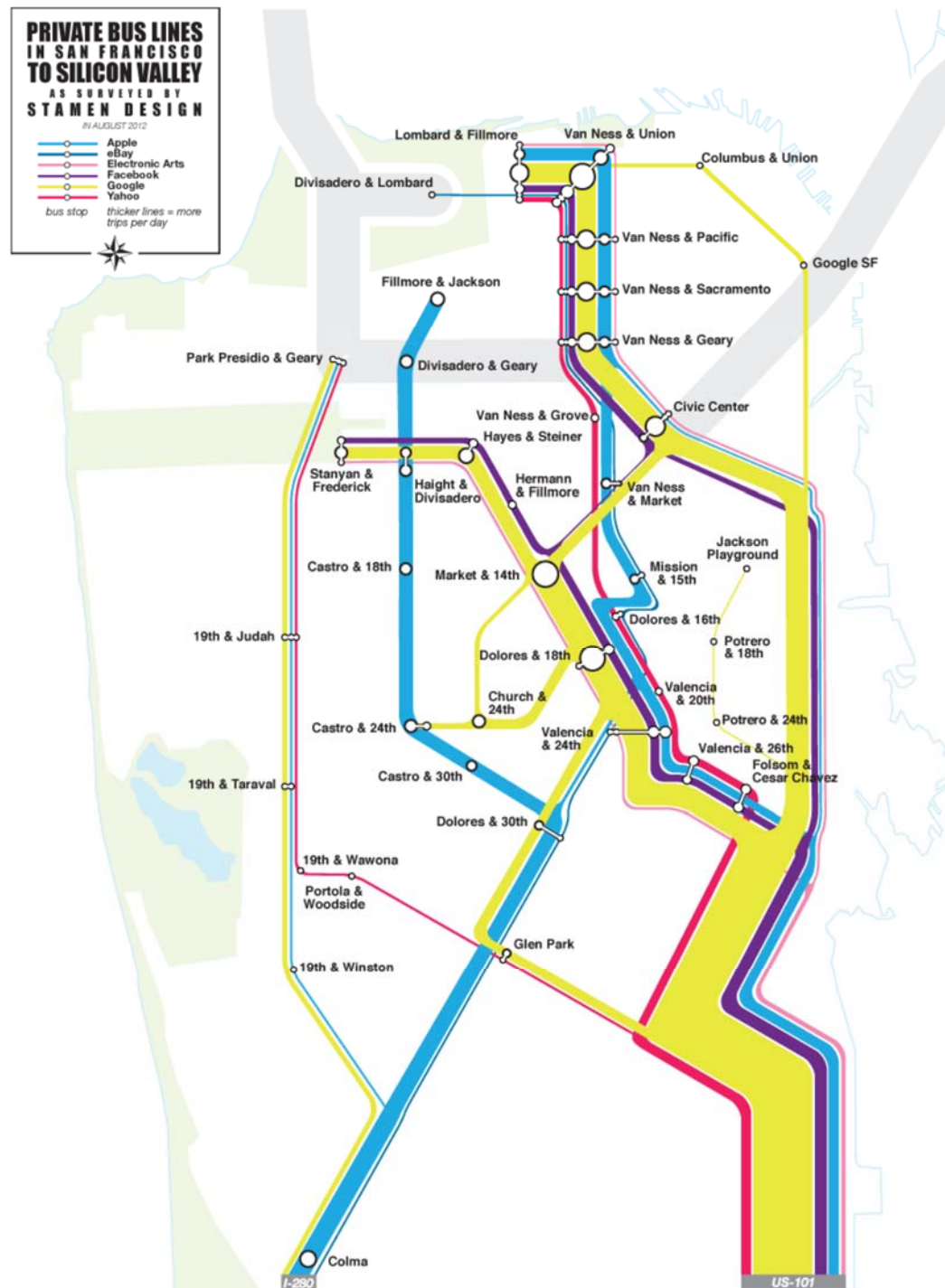
[12] *Source:* Stamen Design. The City from the Valley. 2012. https://hi.stamen.com/the-city-from-the-valley-57e835ee3dc6#.ifn458frg

Assumptions and Methodology

Vanpools

MTC plans to implement a vanpool program similar to programs already in operation in San Diego, Los Angeles, Denver, Arizona and elsewhere. San Diego's program began in 2001 and saw five to ten percent growth in the vanpool fleet every year through fiscal year 2013. LA Metro began its program in 2007 and the vanpool fleet has grown about 14 percent per year. MTC assumes the incentives these program provided will increase the Bay Area's vanpool fleet, increasing the number of vans in 2020 to 700 and doubling the 2013 fleet by 2035 (this equates to 1,030 vanpools), after which the number of vanpools would stabilize. The sustained fleet of 1,030 vans is slightly more than the 1996 peak of 900 vans. Accordingly, MTC plans to reevaluate the incentive package to reduce monthly operating costs.

Over time, the vanpool incentive is expected to become self-funding. This is accomplished by reporting the ridership mileage to the National Transit Database (NTD) which returns funding to the region for transit. Cities such as San Diego, Los Angeles, Denver and Arizona have found that NTD reporting of vanpool data returns more money to a jurisdiction than the amount spent to offset vanpool costs. For example, the Northern Virginia Transportation Commission found that failure to report vanpool data in the Washington, D.C. metropolitan area resulted in a $6-$8 million loss per year, and that each $1 invested would have returned more than $2 in transit funds.[13] Los Angeles spends $7 million annually to off-set vanpool costs and brings back $20 million in additional transit funding.[14] While the amount returned varies depending on the number of passenger miles travelled; vanpools that log more miles and carry more passengers have higher returns. MTC estimates that for every $1 spent on vanpools, it could expect a return of about $1.40 in transit funds.

Along with the increased subsidy, the methodology assumes that vanpools have an average of 10.8 passengers and roundtrip distance of 110 miles, both of which are expected to remain constant over time. In order to account for the emissions from the vanpool van itself, the calculations only account for 9.8 passengers in the van. Reducing the vanpool size is a simplified proxy for the emissions from the shared van.

The population that shifts to vanpools is expected to be consistent with the general population's commute mode share. Emissions reduced from a commuter switching from a single occupancy vehicle (SOV) are assumed to be 100 percent. Emissions reduced from a commuter switching from a two person carpool are assumed to be 50 percent. Emissions reduced from a commuter switching from a 3+ person carpool are assumed to be 33 percent. Shifts from other modes (walking, biking, or transit modes) are not assumed to reduce CO_2 emissions, because these modes emit fewer CO_2 emissions per mile than vanpools. In reality, it is unlikely that anyone would shift from walking or biking, which are typically short-distance modes, to a long-distance vanpool trip, and MTC focuses on providing vanpools for routes that are not currently well-served by transit. However, assuming consistency with the general commute mode share produces a conservative estimate of CO_2 reductions.

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[13] Northern Virginia Transportation Commission; FTA Section 5307 Earnings Potential from Vanpools in DC Metropolitan Region; Revised: August 7, 2009.

[14] MTC October 2014 interview with LA Metro program manager, Jamie Carrington.

Since the baseline year for the SB 375 CO_2 emissions reduction target is 2005, the current vanpool fleet of 515 vans is not included in the analysis; only growth above and beyond 515 vans is included in the calculations.

Employer shuttles

Increases in the shuttle fleet from 2013 forward is assumed to be caused by companies meeting the requirements of the Commuter Benefit Ordinance (CBO). However, the benefits of existing shuttles are analyzed as the CBO program evaluation found that 46 percent of employers were already offering a benefit prior to the ordinance. The CBO therefore does not estimate the CO_2 reductions associated with these travelers. Some of these commuters take transit, which is captured in MTC's travel model. However, those who take shuttles are not captured in the model, and for this reason, the benefits of the existing shuttles are analyzed. To be conservative, the 17,500 daily employer operated shuttle riders from San Francisco to the Silicon Valley are assumed to account for all employer operated shuttle riders in the Bay Area.

The shuttles are assumed to carry an average of 30 passengers[15] and that the average round trip commute on a shuttle is 40 miles.[16] The assumption is if shuttle service was unavailable, the passenger commute mode split would mirror that of the general population. This is a conservative estimate given that some sources suggest shuttle riders would be likely to otherwise drive. For example, San Francisco County's survey of shuttle riders, which indicated that 63 percent of shuttle riders would have otherwise driven alone to work,[17] while the countywide drive-alone mode share is closer to 43 percent.[18]

Also accounted for are emissions from shuttle vehicles, assuming that they emit CO_2 at the same rate as urban buses. This likely overestimates emissions from shuttles since the shuttle fleet incorporates a range of vehicle sizes and the employers who have taken a proactive approach to sustainable transportation often strive to use the cleanest vehicles and fuels available. The exhaust emission rate extracted from EMFAC and used for 2020 shuttles is 2,265 grams/mile. The 2035 exhaust emission rate is 2,112 grams/mile, and the 2040 rate is 1,988 grams/mile.

Analysis steps

Vanpool

To calculate the CO_2 emission reductions due to vanpools, the methodology:

1. Multiplied the projected increase in vanpools by the number of passengers (minus the driver) to obtain number of vanpool participants.
2. Estimated the number of vehicle round trips reduced by vanpools, accounting for the previous mode selection of the vanpool participants by multiplying the number of vanpool participants by

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[15] SFCTA Strategic Analysis Report (SAR) 08/09-2. The Role of Shuttle Services in San Francisco's Transportation System. http://www.sfcta.org/sites/default/files/content/Planning/Shuttles/Final_SAR_08-09_2_Shuttles_062811.pdf Most shuttles have a capacity of 25 passengers but the large employers operated shuttles that seat 50 to 70 passengers. An average capacity of 30 passengers per shuttle seems reasonable.
[16] Many shuttles operate from BART or Caltrain to employers offices. For this analysis the average round trip commute length includes a passenger's travel on transit since that is part of their low emission commute.
[17] SFCTA Strategic Analysis Report (SAR) 08/09-2. The Role of Shuttle Services in San Francisco's Transportation System. http://www.sfcta.org/sites/default/files/content/Planning/Shuttles/Final_SAR_08-09_2_Shuttles_062811.pdf
[18] See https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk.

each of the vehicle mode shares and an adjustment factor that accounts for the number of passengers and summed the results (i.e., vanpool participants * drive alone mode share * 1 + vanpool participants * 2 person carpool mode share * 0.5 + vanpool participants * 3 person carpool mode share * 0.33).

3. Multiplied the number of vehicle round trips reduced by 2 to estimate the daily one-way vehicle trips reduced.
4. Multiplied the number of vehicle round trips reduced by the round trip vanpool mileage to obtain daily VMT reduced.
5. Summed the product of trip-end emission rates and daily vehicle trip reductions and the product of exhaust emission rates and daily VMT reductions to calculate total CO_2 emission reductions.

Employer Shuttles

To calculate the CO_2 emission reductions due to employer shuttles, the methodology:

1. Estimated the number of vehicle round trips reduced by employee shuttles, accounting for the previous mode selection of the shuttle riders by multiplying the number of shuttle riders by each of the vehicle mode shares and an adjustment factor that accounts for the number of passengers and summed the results (i.e., shuttle riders * drive alone mode share * 1 + shuttle riders * 2 person carpool mode share * 0.5 + shuttle riders * 3 person carpool mode share * 0.33).
2. Multiplied the number of vehicle round trips reduced by 2 to estimate the daily one-way vehicle trips reduced.
3. Multiplied the number of vehicle round trips reduced by the average round trip shuttle mileage to obtain daily VMT reduced.
4. Summed the product of trip-end emission rates and daily vehicle trip reductions and the product of exhaust emission rates and daily VMT reductions to calculate total CO_2 emission reductions due to shuttle riders.
5. Calculated the minimum number of shuttle trips required to transport the shuttle riders by dividing the number of shuttle passengers by the average shuttle capacity.
6. Multiplied the number of shuttle trips by the round trip mileage of the shuttles to calculate the minimum shuttle VMT needed to serve the passengers.
7. Multiplied the shuttle VMT by the EMFAC emission rates for urban buses to obtain the shuttle vehicle emissions.
8. Subtracted the shuttle vehicle emissions (step 7) from the emissions reductions due to shuttle riders (step 4) to obtain the net emissions reduced.

Results

Table 9 and Table 10 summarize the combined CO_2 reductions due to vanpools and employer shuttles.

Table 9: Daily CO_2 emissions reductions due to vanpooling and employer shuttles (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	-220	-328	-332
Main Streets	-221	-347	-354
Big Cities	-222	-321	-327
EEJ	-218	-322	-323

Table 10: Per capita CO_2 emissions reductions from 2005 baseline due to vanpooling and employer shuttles (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-0.27%	-0.35%	-0.33%
Main Streets	-0.27%	-0.37%	-0.36%
Big Cities	-0.27%	-0.34%	-0.33%
EEJ	-0.27%	-0.34%	-0.33%

Regional Electric Vehicle Charger Program

Plug-in electric vehicles (PEVs) have the potential to significantly reduce CO_2 emissions from motor vehicles. Today, the Bay Area is the leading market for PEV sales, including both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). PHEVs have a hybridized powertrain which is fueled by chemical energy from a battery or by gasoline/diesel. BEVs are powered exclusively by the chemical energy from a battery. The focus of this strategy is on expanding the charging opportunities for PHEVs by establishing a regional public network of electric vehicle charging stations.

The costs of installing charging infrastructure can be high, and there are other barriers (e.g., on-site electrical capacity) that may also limit the potential for deploying charging infrastructure at workplaces. This program will be designed to help overcome some of those barriers by providing financial assistance to interested employers, retailers, parking management companies and others that qualify. PG&E received approval to install up to 7,500 charging stations in its service territory with a minimum of 15 percent in disadvantaged communities; this parallel process will support this program's goal of expanding charging opportunities for PHEV drivers. A regional network of charging infrastructure will provide drivers an opportunity to plug in while at work, which is where most vehicles spend most of their time parked when not at home. This will mean that PHEVs are able to travel more miles using electricity and fewer using gasoline, reducing CO_2 emissions.

MTC's travel model does not account for the mix of passenger vehicle and fuel types (e.g., conventional vehicles, PHEVs, BEVs, hybrids, etc.) in the Bay Area. Instead, the mix of vehicles, as well as the amount of miles that PHEVs travel using gasoline versus electricity, is accounted for in the emissions rates that MTC draws from EMFAC. This means that CO_2 reductions due to strategies that increase the miles that vehicles travel using electricity, like this one, must be captured off-model, by adjusting the assumptions contained within EMFAC. The assumptions from EMFAC, which fully accounts for the impact of state policies to reduce vehicle emissions, were used as a basis for analyzing this strategy.

Assumptions and methodology

The Plan Bay Area analysis was revised to account for improved fuel economy estimates, updated vehicle populations, and new vehicle sales in the Bay Area based on data included in EMFAC. PG&E's expected investment to deploy 7,500 chargers in the Bay Area was also incorporated along with the assumption that MTC would fund additional chargers after PG&E's initial investment. The analysis assumes a total of 76,000 chargers deployed, roughly one charger for every five PHEVs, which would enable all of these PHEVs to be able to plug in at work if multiple vehicles are able to plug into a single charger over the course of a day).

In the baseline, it was assumed that 40 percent of miles traveled by PHEVs would be in charge-depleting mode, i.e., electric miles instead of gasoline-powered miles. This comes from EMFAC, which indicates that:

> [CARB] staff modeled PHEVs as having a 25-mile all-electric range, which equates to a utility factor of 0.40. For the average commute, this would mean that 40 percent of the VMT could be from all-electric, and 60 percent would be from gasoline operations.[19]

This percentage is assumed to increase to 80 percent due to the Regional Charger Program. PHEVs have what is referred to as an all-electric range of between ten and fifty miles. For instance, the Ford C-MAX Energi has an all-electric range of 21 miles; the first-generation Chevrolet Volt has an all-electric range of 38 miles; and the second-generation Volt has a range of 53 miles. Data from The EV Project[20] and a paper from GM engineers[21] indicate that drivers of the Chevrolet Volt, a proxy for a PHEV with a 40-mile range (PHEV-40), are able to drive about 74 percent of their total miles in EV-mode without support from the internal combustion engine. Data from Ford Motor Company[22] indicate that vehicles in their Energi line, including the C-Max and Fusion, both of which are proxies for a PHEV with a 20-mile range (PHEV-20), travel about 33 percent of miles using electricity. ICF estimates that the current market is about 50/50 for PHEV-20/PHEV-40 today. Note that these values represent driver behavior during the early stages of charging infrastructure deployment, during which there has been no substantial dedicated effort to maximize eVMT. In other words, absent any concerted effort to deploy charging infrastructure to maximize electric miles, the average PHEV is likely traveling about 54 percent of its miles using electricity.

A network of regional charging infrastructure will further increase the percentage of miles that PHEVs travel in electric mode and the methodology assumes:

- Each charger deployed through the Regional Charger Network serves multiple vehicles each day over the course of a four-hour charging shift
- The chargers deployed are Level 2 chargers that deliver electricity with a rating of 5 kW; and
- The average electric vehicle consumes 0.35 kWh/mi.

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[19] California Air Resources Board, EMFAC2014 Volume III – Technical Documentation v1.0.7, May 2015. Available online at http://www.arb.ca.gov/msei/downloads/emfac2014/emfac2014-vol3-technical-documentation-052015.pdf.
[20] EV Project, Quarterly Reports e.g., http://www.theevproject.com/cms-assets/documents/127233-901153.q2-2013-rpt.pdf.
[21] Duhon, A., Sevel, K., Tarnowsky, S., and Savagian, P., "Chevrolet Volt Electric Utilization," SAE Int. J. Alt. Power. 4(2):269-276, 2015.
[22] Proceedings EVS29, Montreal.

A ratio of approximately one charger for every five vehicles over the program years is assumed, consistent with charger-to-vehicle ratios estimated by Electric Power Research Institute (EPRI) for workplace and public charging opportunities and research conducted by ICF regarding charging optimization.[23]

These assumptions mean that these chargers would provide enough electricity to power 57 electric miles per day. Given that there are expected to be 420,000 PHEVs in the Bay Area in 2035 and 76,000 chargers funded through this program, this is equivalent to ten electric miles per PHEV per day. According to EMFAC, the average vehicle travels an average of 31 miles per day, so this additional electricity amounts to 32 percent of miles traveled. Given that the charger program is designed to fill gaps in charging opportunities, this is added to the baseline of 54 percent eVMT, which equals 86 percent. Even though there is the potential for improvements in the parameters that form the basis for the assumptions used to derive the additional eVMT potential of the regional charger network—battery sizing, vehicle efficiency, charger utilization, power delivered—over the next several decades, a conservative 80 percent eVMT assumption is used.

It is conceivable that the increased availability of chargers could increase the sales of BEVs in addition to increasing the percentage of electric miles for PHEVs, but this effect is not included in the calculations to be conservative.

Analysis steps

To determine the CO_2 emission reductions from charging infrastructure deployment throughout the region, the methodology:

1. Modified the percentage of miles traveled in charge depleting mode from the baseline 40% to 80%.
2. Determined the CO_2 emissions reduction.
   a. The CO_2 emissions attributable to PHEVs are based on how many miles each vehicle spends in each mode (charge depleting or gas/diesel).
   b. The CO_2 emission reductions are determined as the difference between the emissions attributable to the PHEV versus the emission that would have otherwise occurred using an average conventional gasoline vehicle.
3. Made no changes to the VMT.

Results

Table 11 and Table 12 summarize the CO_2 reductions due to the Regional Charger Program.

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[23] D. Bowermaster, EPRI. *How Much Electric Vehicle Charging is Needed?* California Plug-in Electric Vehicle Collaborative Meeting, August 2012.

Table 11: Daily CO$_2$ emissions reductions due to the Regional Charger Program (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	-252	-1,188	-1,287
Main Streets	-252	-1,188	-1,287
Big Cities	-252	-1,188	-1,287
EEJ	-252	-1,188	-1,287

Table 12: Per capita CO$_2$ emissions reductions from 2005 baseline due to the Regional Charger Program (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-0.35%	-1.42%	-1.46%
Main Streets	-0.35%	-1.42%	-1.46%
Big Cities	-0.35%	-1.42%	-1.46%
EEJ	-0.35%	-1.42%	-1.46%

Emission reductions are consistent across all EIR alternatives since the analysis does not rely on inputs from MTC's travel model.

Vehicle Buyback & PEV Incentive

Plug-in electric vehicles (PEVs) are being adopted at significant levels today in the Bay Area, and the Zero Emission Vehicle (ZEV) Program and the Low-Carbon Fuel Standard in California are regulatory drivers for advanced vehicle technologies and alternative fuels. However, despite the near-term success of PEVs in the Bay Area, PEV sales are still relatively small, representing just 3.5 percent of total new light-duty vehicle sales. There is also some uncertainty regarding the medium- to long-term availability of PEV purchase incentives; for example, California's Clean Vehicle Rebate Program changed in 2016 to adjust incentives based on household income, and the federal tax credit could change in future tax reform. Furthermore, one of the main drivers today for PEV sales, particularly for PHEVs, is HOV lane access: PHEVs are eligible for the green sticker and BEVs are eligible for the white sticker and qualify for HOV lane access through January 1, 2019. Although the California Air Resources Board (CARB) has continued to expand the number of HOV stickers for PEVs, it is likely that they will be limited and eventually discontinued, as they were for non-plug-in hybrid vehicles.

This program can provide a combination of an incentive of up to $2,500 to purchase a PEV along with the buyback of older, less efficient vehicles. This is intended to extend the market for PEVs into a broader range of income classes. Most analysts agree that the first adopters of PEVs are generally higher income individuals who own their homes, and in many cases, own or have owned a hybrid electric vehicle (e.g., a Toyota Prius). The higher purchase price of PEVs makes it difficult for middle and low income consumers to purchase them. Older and wealthier individuals tend to buy more new vehicles than other cross-sections of the population. This demographic also tends to buy newer cars more frequently. Furthermore, research from IHS Markit has shown that owners of both new and used vehicles are holding on to their vehicles longer, the scrappage rate has flattened, and the average age of vehicles has increased; the researchers forecast that the population of oldest vehicles (16 or more years)

will grow the fastest, increasing by 30% by 2021.[24] Additionally, CARB estimates that half of cars live to be 15 years old and one quarter live to be 20 years old. Interestingly, if a vehicle does survive to 20, there is a 40 percent chance it will be on the road for another ten years after that.[25] This will impact the turnover of the fleet significantly and may slow the purchase of new vehicles, including plug-in electric vehicles.

The vehicle buyback program seeks to accelerate fleet turnover while also incentivizing the purchase of advanced vehicle technology. The program will be designed to target older vehicles meeting a certain fuel economy threshold (as measured via miles per gallon, MPG) for scrapping, and will be coordinated with the Air District's Vehicle BuyBack Program. The consumer is only eligible for the program if the new vehicle being purchased is a PHEV or BEV. The incentive amount will vary with the fuel economy of the vehicle being traded in (measured in MPG) as well as the vehicle type being purchased (e.g., PHEV or BEV). Depending on the fuel economy threshold set by the program, the combination vehicle buyback and incentive program is intended to induce demand in middle and lower income brackets that might otherwise delay car purchasing, purchase a new conventional vehicle or purchase a used vehicle.

MTC's travel model does not account for the mix of passenger vehicle and fuel types (e.g., conventional vehicles, PHEVs, BEVs, hybrids, etc.) in the Bay Area. Instead, the mix of vehicles is accounted for in the emissions rates that MTC draws from EMFAC. This means that CO_2 reductions due to strategies that increase the proportion of clean vehicles in the passenger fleet, like this one, must be captured off-model, by adjusting the assumptions contained within EMFAC. The assumptions from EMFAC, which fully accounts for the impact of state policies to reduce vehicle emissions, were used as a basis for analyzing this strategy.

Assumptions and Methodology

The analysis was updated from Plan Bay Area to account for improved fuel economy estimates, updated vehicle populations, and new vehicle sales in the Bay Area based on data included in EMFAC.

We made the following assumptions in this methodology:

- Implementation of this program will begin in 2020.
- 94,000 additional PEVs will be on the road by 2035. This is a modest annual increase of about 1.5% in new vehicle sales attributable to the buyback incentive program.
- For the initial analysis, the deployed vehicles are evenly split between PHEVs and BEVs.
- The average incentive levels are $1,500 per PHEV and $2,500 per BEV. However, the actual incentive will vary based on the MPG of the vehicle being traded in as well as the technology of the vehicle being purchased.

Analysis steps

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[24] "Vehicles Getting Older: Average Age of Light Cars and Trucks in U.S. Rises Again in 2016 to 11.6 Year, IHS Markit Says." Press release from IHS Markit, November 2016. Available online at: http://news.ihsmarkit.com/press-release/automotive/vehicles-getting-older-average-age-light-cars-and-trucks-us-rises-again-201

[25] Report to the California Legislature, Accelerated Light-Duty Vehicle Retirement Program. http://www.arb.ca.gov/research/apr/reports/l2070.pdf. Accessed March 20, 2013.

To calculate CO_2 reductions due to the introduction of PEVs, the methodology:

1. Determined the difference between the daily CO_2 emissions attributable to the PEV versus the emissions that would have otherwise occurred using an average conventional gasoline vehicle. For PHEVs this depends on the assumed proportion of time spent in charge depleting mode versus gas/diesel mode.
2. Multiplied the result by the number of new PEVs expected to be deployed due to the program.

Results

Table 11 and Table 12 summarize the CO_2 reductions due to the Vehicle Buyback and PEV Incentive Program.

Table 13: Daily CO_2 emissions reductions due to the Vehicle Buyback and PEV Incentive Program (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	0	-363	-234
Main Streets	0	-363	-234
Big Cities	0	-363	-234
EEJ	0	-363	-234

Table 14: Per capita CO_2 emissions reductions from 2005 baseline due to the Vehicle Buyback and PEV Incentive Program (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	0%	-0.44%	-0.27%
Main Streets	0%	-0.44%	-0.27%
Big Cities	0%	-0.44%	-0.27%
EEJ	0%	-0.44%	-0.27%

Emissions reductions will be realized after 2020, which is when program implementation is planned. Emissions reductions are consistent across all EIR alternatives because the analysis does not rely on inputs from the travel model.

Clean Vehicles Feebate Program

Originally coined in the 1990s, feebate programs are envisioned as a revenue-neutral approach to shift buying habits in the transportation and energy sectors. MTC is proposing to use a feebate program to incentivize consumers to scrap older vehicles and purchase higher performing, cleaner vehicles. A feebate program uses a combination of fees and rebates to change consumer behavior. Consumers purchasing a vehicle that emit more carbon dioxide on a gram per mile basis than a defined standard are assessed a fee at the point of purchase. These fees are used to provide rebates to consumers that purchase vehicles that emit less CO_2 on a gram per mile basis than the defined standard.

Feebates have been used with some success in other countries, including Denmark, France, the Netherlands and Norway. The structure of a feebate program for California was studied in considerable

detail for CARB.[26] In fact, California has come close to implementing a statewide feebate program on multiple occasions through legislative efforts – the first time in the early 1990s and more recently in 2008. Feebate programs have been proposed as a legislative initiative (e.g., AB 493 Ruskin in 2007), whereby implementation authority would be delegated to CARB and the State Board of Equalization, and a feebate program is not dissimilar from the fee that was approved by the Legislature via AB 434 (Sher, Chapter 807, Statutes of 1991) establishing the Transportation Fund for Clean Air (TFCA). Moving forward, MTC will engage with CARB and the Air District to determine how the program would be implemented and how to progress legislation prior to the start of the program. The feebate program would require legislation to provide regional agencies with the authority to implement it.

MTC's travel model does not account for the mix of passenger vehicle and fuel types (e.g., conventional vehicles, PHEVs, BEVs, hybrids, etc.) in the Bay Area. Instead, the mix of vehicles is accounted for in the emissions rates that MTC draws from EMFAC. This means that CO_2 reductions due to strategies that increase the proportion of clean vehicles in the passenger fleet, like this one, must be captured off-model, by adjusting the assumptions contained within EMFAC. The assumptions from EMFAC, which fully accounts for the impact of state policies to reduce vehicle emissions, were used as a basis for analyzing this strategy.

Assumptions and methodology

The analysis draws heavily from results reported by Bunche & Greene's feebate analysis for CARB. The lower-end estimate of impact of feebates on average fuel economy (1.6 percent) from their analysis is assumed. The major benefits of the feebate programs are attributable to the first several years of the program. In their report, the authors state, "In later years the level of CO_2 emissions reduction relative to the standard diminishes as the standard becomes more stringent."

It is assumed that the feebate program is introduced in 2020 and that there are not any increases in fuel economy standards at the state or national level after 2025. To maintain consistency with the Bunch & Greene study, this analysis assumes a $20 per g/mi feebate rate in a single benchmark system. Based on a sensitivity analysis performed by Bunch & Greene, an increase to $30 per g/mi feebate rate will yield a 50 percent increase in CO_2 reductions.

Since Plan Bay Area, the analysis was updated to account for improved fuel economy estimates, updated vehicle populations, and new vehicle sales in the Bay Area based on data included in EMFAC.

Analysis steps

To calculate the CO_2 emission reductions due to the Clean Vehicles Feebate Program, the methodology:

1. Estimated the improvement in fuel economy (back-calculated based on grams per mile estimates) of the new vehicle fleet due to the feebate program. Maximum improvement at the outset of the program is about 2.9%; by 2040, the improvement is reduced to 0.1%.
2. Based on vehicle turnover, estimated the modified fuel economy of entire fleet after the change to improved fuel economy of new vehicles as of 2020 due to the feebate program.

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[26] Greene, David L. & Bunch, David S., "Potential design, implementation, and benefits of a feebate program for new passenger vehicles in California", Prepared for the California Air Resources Board, Contract UCD 08-312, February 2011.

3. Calculated the differential in well-to-wheels CO_2 emissions[27] of the modified fleet versus baseline fleet.

Results

Table 15 and Table 16 summarize the CO_2 reductions due to the Clean Vehicles Feebate Program.

Table 15: Daily CO_2 emissions reductions due to the Clean Vehicles Feebate Program (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	0	-682	-446
Main Streets	0	-682	-446
Big Cities	0	-682	-446
EEJ	0	-682	-446

Table 16: Per capita CO_2 emissions reductions from 2005 baseline due to the Clean Vehicles Feebate Program (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	0%	-0.82%	-0.51%
Main Streets	0%	-0.82%	-0.51%
Big Cities	0%	-0.82%	-0.51%
EEJ	0%	-0.82%	-0.51%
No Project	0%	-0.82%	-0.51%

Emission reductions will be realized after 2020, which is when program implementation is planned. Emission reductions are consistent across all EIR alternatives because the analysis does not rely on inputs from the travel model.

Smart Driving

When discussing transportation sector CO_2 reduction strategies, experts often refer to a three-legged stool consisting of vehicle technology, cleaner fuels and driver behavior. California's state agencies are leading the way on the first two legs, and SB 375 focuses on a key approach to changing driver behavior, reducing VMT by investing in alternatives to driving, locating housing closer to jobs and creating complete communities. In addition to changing how *much* someone drives, people can change *how* they drive through training in the techniques of smart driving. Smart driving behaviors are easy-to-implement actions (e.g., change in driving style, vehicle maintenance, etc.) that any driver can do. Research shows that it is possible to affect significant and swift reduction in emissions through behavior change.[28] MTC's

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[27] Well-to-wheels (WTW) analysis refers to lifecycle analysis applied to transportation fuels and their use in vehicles. The analysis includes, for instance, resource extraction, fuel production, delivery of the fuel to vehicle, and end use of fuel in vehicle operations.

[28] See http://assets.511.org/pdf/drivesmart/Smart-Driving-Resource-Guide.pdf for a MTC's review of relevant research.

Smart Driving campaign reduces CO_2 emissions by promoting the driver behaviors that have been shown most effective in improving vehicle efficiency.

This strategy builds on series of previous actions by MTC. From 2013 to 2015, MTC conducted a pilot smart driving campaign that consisted of three core programs, which MTC evaluated to understand which approaches produce the most significant CO_2 reductions:[29]

- Fuel economy meters
- Smart driving lessons
- Smartphone app

In 2015, MTC expanded its smart driving investments into a region-wide program called Drive Smart Bay Area. The program development and implementation included:

- Selecting a smart driving in-vehicle device to distribute to drivers
- Developing a marketing strategy
- Developing a program website and video
- Establishing two device purchasing options
- Implementing the marketing strategy

As part of Plan Bay Area 2040, MTC is assessing the program's evaluation report prior to further implementation of the *Drive Smart Bay Area* program. Off-model analysis is necessary to capture CO_2 reductions due to this strategy because most of the behaviors promoted through *Drive Smart Bay Area* reduce vehicle emission rates, which come from EMFAC, not from MTC's travel model.

Assumptions and methodology

Implementation of the smart driving program is assumed to begin in 2020. Gas prices are currently relatively low, which would mean less consumer interest in the program and fewer CO_2 reductions if it were implemented today. It is assumed that gas prices will rise again by 2020 to the level that they were at when MTC completed its initial evaluations of the strategies discussed below, and remain at least that level thereafter. Therefore the changes to emission rates due to smart driving behaviors are assumed to be constant over time.

Smart driving educational campaign

In February 2011, MTC conducted a Baseline Climate Initiatives Survey that asked Bay Area residents about the ease of adopting various smart driving behaviors.[30] Of the respondents, 55 percent stated that it would be very easy or easy to practice "smooth acceleration and deceleration and staying at or below the speed limit." The U.S. Department of Energy reports that rapid acceleration and deceleration, and speeding can lead to fuel economy reductions from five percent on city streets to 33 percent on

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[29] MTC Climate Initiatives Program Evaluation: Smart Driving, Prepared for MTC by ICF, 2015. A summary of findings is available at: http://mtccms01.prod.acquia-sites.com/sites/default/files/CIP%20Evaluation%20Summary%20Report_7-13-15_FINAL.pdf

[30] MTC conducted a Baseline Climate Initiatives Survey in February 2011. It was a 15 minute random digit dial and cell phone sample of Bay Area driving age residents. It was offered in English, Mandarin, and Spanish and had an overall margin of error of ±3.5%

freeways,[31] but current studies demonstrate a much lower average fuel economy savings of two to four percent[32] for smart driving behaviors.[33] This analysis assumes a conservative fuel efficiency reduction from smooth acceleration and deceleration of three percent.

60 percent of participants stated that it would be very easy or easy to practice "at least once per week, link several trips together, such as going shopping and to the post office, which you would normally make separately." For this analysis, this statement is interpreted to mean the driver will link three shopping trips per week due to the campaign (effectively reducing two trips).

The number of people to adopt smart driving behaviors is based on the survey results listed above and other cost effectiveness assumptions related to marketing investments. Preliminary cost estimates indicate that $1 million in advertising and education can purchase 8,000,000 TV views, 5,000,000 radio listeners and 15,000,000 online hits. Since the public needs to see or hear an advertisement multiple times before recognizing the message and being able to practice the requested behavior change; costs assume twelve views are needed for to internalize the message.[34] In order to reduce CO_2 emissions, potential adopters must also be capable of and motivated to make a change. For trip linking practices, ten percent of potential adopters are assumed to adopt the behavior. For smooth acceleration and deceleration, a more conservative assumption of five percent is used to avoid double counting the benefits of the fuel economy meter distribution program (see below for more details).

Fuel economy meters

Under this program, MTC would offer a rebate to consumers who purchase an on-board diagnostics (OBD)-connected after-market device similar to those made by Automatic and provided by MTC under Drive Smart Bay Area and the ones tested in the initial smart driving pilots. Recent studies have demonstrated an average fuel economy savings of two to four percent from smart driving education and devices. The MTC-funded smart driving pilot found that the installation of OBD-connected smart driving devices resulted in a 1.6 percent improvement in fuel economy; however the results are not statistically significant because they fall within the background fluctuation in fuel economy that was observed among the participating vehicles.[35] MTC also funded a study at UC Davis to test a smart driving app with different types of feedback. The most effective feedback mechanism (presenting the journey fuel

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[31] US Department of Energy, Office of Energy Efficiency and Renewable Energy, US Environmental Protection Agency, Model Year 2005 Fuel Efficiency Guide, DOE/EE-0302

[32] While recent studies have found a range in the potential fuel efficiency improvements from smart driving techniques from zero to 18%, the substantial range in results is likely due to shortcomings in the studies including: insufficient sample sizes, short study periods, variations in the testing environment (simulations or tracks versus real-world driving conditions), and the lack of statistically significant findings. The 2-4% range is seen in studies that overcome these issues.

[33] Kurani, K., Stillwater, T., and Jones, M., 2013. Ecodrive I-80: A Large Sample Fuel Economy Feedback Field Test: Final Report. Institute of Transportation Studies Report: ITS-RR-13-15. Available at http://www.fueleconomy.gov/feg/pdfs/EcoDrive%20I-80.pdf

[34] The estimated number of views needed for the target audience to engage with the message varies dramatically by the medium and quality of the creative, but 12 views is seen as relatively standard conversion rate by marketing firms such as RHDG and Wit Media.

[35] ICF. 2015. *Climate Initiatives Program: Evaluation Summary Report*. Available at: http://mtccms01.prod.acquia-sites.com/sites/default/files/CIP%20Evaluation%20Summary%20Report_7-13-15_FINAL.pdf

economy in the center of the screen) had a statistically discernable effect of a 15.5 percent reduction in fuel consumption; however, the sample size was small with approximately 18 people viewing that version of feedback.[36] Given these varied findings, a three percent fuel economy savings from OBD-connected devices is used.

The analysis assumes that MTC will distribute 900,000 OBD-connected devices by 2035, covering roughly 30 percent of all Bay Area registered vehicles. This assumptions does not account for the fact that an increasing number of vehicles, particularly hybrids, come with displays that show information such as real-time fuel efficiency, five-minute-average fuel efficiency, overall trip fuel efficiency, or simple diagrams that indicate relative fuel efficiency.[37] This may help to further accelerate the spread of smart driving behaviors beyond the behavior change induced by the devices that MTC distributes.

Analysis steps

Smart driving educational campaign

Smooth acceleration and deceleration

In order to estimate CO_2 reductions due to smooth acceleration and deceleration, the methodology:

1. Estimated the total number of media impressions by multiplying the media ad-buy for smooth acceleration and deceleration by the estimated number of impressions per million dollars of media spend (28 million impressions/$1 million).
2. Estimated the number of residents who internalize the campaign messaging by dividing the total media impressions by the estimated number of views required for engagement (12).
3. Estimated the number of potential adopters by multiplying the total number of residents who internalized the campaign messaging by the percent of Bay Area residents who responded that adopting smooth acceleration and deceleration behaviors would be easy or very easy.
4. Estimated the number of residents who adopt the behavior by multiplying the number of potential adopters by the by the assumed adoption rate (5%).
5. Estimated the total daily VMT affected by the smart driving behavior by multiplying the number of behavior adopters by the regional average daily VMT per capita.
6. Estimated the equivalent quantity of VMT reduced due to smooth acceleration and deceleration by multiplying the total daily VMT affected by the assumed fuel efficiency savings of smooth acceleration and deceleration (3%).
7. Calculate the CO_2 emissions reduced by multiplying the equivalent VMT reduced by the EMFAC exhaust emissions CO_2 factor.

Trip linking

In order to estimate CO_2 reductions due to trip linking, the methodology:

1. Repeated Steps 1-4 of the smooth acceleration and deceleration calculations above, substituting using the appropriate assumptions for trip linking, to estimate the number of residents who adopt the behavior.

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[36] Ibid.

[37] Barkenbus, Jack, 2010. *Eco-driving: An overlooked climate change initiative.* Journal of Energy Policy, 38 (2010) 762–769.

2. Estimated the annual vehicle trips reduced by the behavior adopters by multiplying the total number of behavior adopters by the assumed number of trips reduced per week (2) and the number of weeks per year (52).
3. Calculated the total annual VMT reduced by multiplying the annual vehicle trips reduced by the average length of a shopping trip in the region (approximately 4.6 miles; varies by year and scenario).
4. Divided the results of steps 2 and 3 by the assumed number of driving days per year (300) to calculate total daily trips and VMT reduced.
5. Summed the product of trip-end emission rates and daily vehicle trip reductions and the product of exhaust emission rates and daily VMT reductions to calculate total CO_2 emission reductions.

Fuel economy meters

In order to estimate CO_2 reductions due to trip linking, the methodology:

1. Estimated the total number of devices to be distributed by dividing the total investment by the assumed price per device (including program management fees).
2. Calculated the total daily VMT affected by the smart driving behavior by multiplying the number of behavior adopters by the regional average daily VMT per vehicle.
3. Estimated the equivalent quantity of VMT reduced due to fuel economy meters by multiplying the total daily VMT by the assumed fuel efficiency savings of the fuel economy meters (3%).
4. Calculated the CO_2 emissions reduced by multiplying the equivalent VMT reduced by the EMFAC exhaust CO_2 emissions factor.

Results

Table 17 and Table 18 summarize the CO_2 reductions due to MTC's efforts to promote smart driving.

Table 17: Daily emissions reductions due to smart driving (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	0	-677	-669
Main Streets	0	-681	-677
Big Cities	0	-672	-663
EEJ	0	-662	-655

Table 18: Per capita emissions reductions from 2005 baseline due to smart driving (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	0%	-0.72%	-0.67%
Main Streets	0%	-0.72%	-0.68%
Big Cities	0%	-0.71%	-0.67%
EEJ	0%	-0.70%	-0.66%

Targeted Transportation Alternatives

Targeted transportation alternatives programs employ a variety of strategies, including individual travel consultation, organized events, and distribution of outreach and informational materials to encourage people to shift from driving alone to carpooling, transit, biking, or walking for any of their trips. These programs are "targeted" because they tailor activities and materials to focus on the travel needs and transportation options that are available in specific job centers or residential neighborhoods. Several MPOs and large cities in the U.S. administer these programs, partnering with local governments, transit agencies, employers and transportation management associations to customize projects to different communities. Examples from other jurisdictions operating programs for ten years or more with positive results include Portland Metro's Regional Travel Options program, the City of Portland's SmartTrips program and the City of Seattle's InMotion program.

In addition, several public agencies in the Bay Area currently have marketing programs in place. Two of the Climate Initiative Innovative Grant pilot projects funded by MTC from 2011-13, GoBerkeley and Connect, Redwood City!, include targeted transportation alternatives components. The former involved working with property managers to market travel options and provide free bus passes to residents of multifamily transit-oriented developments, while the latter included focused outreach to employers with billboard and print advertising to promote alternatives to driving alone. These two projects were among the most effective Climate Initiative projects at reducing CO_2 emissions, and the targeted transportation alternatives components of these projects stood out for their cost effectiveness and results.

MTC's Targeted Transportation Alternatives Program is considering a similar implementation approach to Portland Metro's Regional Travel Options grant program, which issues grants to public agencies, transportation management associations, and non-profits to implement projects that make it easier for travelers to get around without driving alone.[38]

Off-model analysis is necessary to capture CO_2 reductions from targeted transportation alternatives programs. MTC's last travel survey which informs the travel model, was conducted in 2010, and does not capture the impacts of new strategies that change travel behavior such as this one. These strategies might be captured by a future model once they have been implemented to the extent that they influence people's behavior and can be captured by the travel surveys, and once the model framework has been altered to include inputs that represent the presence of behavior change strategies.

Assumptions and Methodology

Data from two community-based travel marketing programs from the Portland, OR metropolitan area was used to estimate CO_2 reductions for a regional targeted transportation alternatives program in the Bay Area. Since travel marketing programs are typically targeted toward employees or households; this strategy includes both workplace and residential components, and uses data from different programs to assess each component. Employee-focused programs can be more cost-effective at reaching workers

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[38] http://www.oregonmetro.gov/tools-partners/grants-and-resources/travel-options-grants

who are concentrated at large employers, making outreach efficient. However, residential programs can produce greater CO_2 reductions per person reached because they affect all trips, not just commute trips.

Evaluation data from employer-focused projects in Portland Metro's Regional Travel Options program[39] was used to assess the impact of programs that target employers and data from the City of Portland's SmartTrips program,[40] which focuses on households, to assess the impacts of residential programs. These are longstanding programs, and each has conducted multiple rounds of evaluation, with each round covering multiple projects. Information was collected on the cost per year of marketing to an individual household/employee, the percentage of residents/employees receiving program information who change behavior (penetration rate), and the reduction in SOV mode share for those residents/employees from evaluations of these two programs. These were then applied to the daily number and distance of trips for all trips (for households) and for commute trips (for employees) to estimate VMT impacts. Evaluations of targeted transportation alternatives programs typically focus on impacts during the year after programs are implemented; long-term evaluations that provide information on how long behavior change persists due to marketing programs is not currently available. Therefore, the methodology uses a conservative assumption that behavior change lasts for five years before participants revert to their previous travel patterns. Table 19 summarizes these assumptions.

Table 19: Summary of Targeted Transportation Alternatives assumptions

	Households	Employees
Average cost per year of marketing to a household/employee	$3.11	$4.34
Average penetration rate	29%	33%
Average reduction in SOV mode share among participants	11%	9%
Average daily one-way driving trips affected	5.47	2
Average one-way trip length (miles)[41]	6.4	10.6
Number of years for which behavior change persists[42]	5	5

MTC's investment in this strategy is the primary input in the CO_2 estimates. Based on the budget available and the amount of CO_2 reductions that it needs to achieve, MTC anticipates investing $2.15 million in this strategy per year, with $2 million going to residential programs and $150,000 going to employee programs. Since this is a new strategy, MTC will be working with consultants to develop an approach to implementation.

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[39] Metro, Regional Travel Options Program Evaluation Report, 2012, http://www.oregonmetro.gov/sites/default/files/appendix_d_rto_evaluation_2012.pdf.
[40] Portland Bureau of Transportation, Past SmartTrips 2004-2010, http://www.portlandoregon.gov/transportation/56703.
[41] This is an output from MTC's travel model, and the value varies for different scenarios and years. The values shown are for the Proposed Plan in 2035; values for other scenario/year combinations range from 6.2-6.5 (household) and 10.2-11.2 (employee)
[42] For 2020, we used a value of 3 since the strategy will take effect in 2017, and will only have been in place for 3 years.

Analysis steps

The amount of CO_2 reductions that MTC realizes through this strategy depends on the amount that it invests. To calculate CO_2 reductions based on the amount invested, the methodology:

1. Allocated the investment between household and employee programs.
2. Divided the respective household/employee investments by the average cost per year of marketing to a household/employee and multiplied by the penetration rate in order to calculate the total number of participants.
3. Multiplied the total number of participants by the average reduction in SOV mode share among participants and the average daily one-way driving trips affected to calculate the average daily number of vehicle trips reduced due to programs funded that year.
4. Multiplied the average daily number of vehicle trips reduced by the number of years for which behavior change persists to estimate the total average daily number of vehicle trips reduced in any given year. This accounts for the fact that programs funded in previous years produce ongoing vehicle trip reductions.
5. Multiplied daily vehicle trips reduced by the average one-way trip length to calculate the average daily VMT reductions.
6. Summed the product of trip-end emission rates and daily vehicle trip reductions and the product of exhaust emission rates and daily VMT reductions to calculate total CO_2 emission reductions.

Results

Table 20 and Table 21 summarize the CO_2 reductions due to Targeted Transportation Alternatives.

Table 20: Daily CO_2 emissions reductions due to Targeted Transportation Alternatives (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	-954	-1,604	-1,578
Main Streets	-958	-1,598	-1,586
Big Cities	-952	-1,581	-1,553
EEJ	-948	-1,574	-1,552

Table 21: Per capita CO_2 emissions reductions from 2005 baseline due to Targeted Transportation Alternatives (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-1.17%	-1.71%	-1.59%
Main Streets	-1.17%	-1.70%	-1.60%
Big Cities	-1.16%	-1.68%	-1.57%
EEJ	-1.16%	-1.67%	-1.57%

Trip Caps

Trip caps set limits on the number of vehicle trips to and from workplaces, and enforce these limits via regular traffic counts and penalties for non-complying workplaces. By limiting the number of vehicle trips to a level below unrestricted access, trip caps can reduce CO_2 emissions. Local governments have the ability to set trip caps on new development projects through development agreements, but their

authority to enact caps on existing development is more limited. Trip caps therefore typically focus on minimizing the traffic impacts of new office or commercial development. Several South Bay cities, including Mountain View, Sunnyvale, Cupertino and Menlo Park, have enacted trip caps,[43] as has the City of Los Angeles. Stanford University and Santa Clara County have had a trip cap in effect for over ten years. Most of these caps focus on individual development projects, but Mountain View's trip cap covers an entire business district, providing a promising template for a program to encourage trip caps in employment centers throughout the Bay Area.[44] They are an increasingly popular strategy to reduce vehicle trips in the Bay Area's high-growth employment centers, and MTC can promote their use throughout the region, reducing CO2 emissions.

Trip caps complement, but do not duplicate, other commute transportation demand management strategies included in the off-model analysis, such as the Commuter Benefits Ordinance (CBO). These other strategies act as "carrots" that provide employees incentives to use sustainable commute modes; trip caps are a "stick" that require employers to reduce trips by employees or face fines. Trip caps also apply to different employers than other TDM strategies; for example the CBO applies to all employers with 50+ employees throughout the Bay Area whereas trip caps apply to all new businesses, regardless of size, in designated employment areas. In order to implement trip caps across the region, MTC is considering offering assistance to local governments through its existing planning grant programs.

Off-model analysis is necessary to capture CO_2 reductions from trip caps because MTC's last travel survey, which informs its model, was conducted in 2010, and does not capture the impacts of new strategies that change travel behavior such as this one. These strategies might be captured by a future model once they have been implemented to the extent that they influence people's behavior in a way that can be captured by the travel surveys, and once the model framework has been altered to include inputs that represent the presence of behavior change strategies.

Assumptions and Methodology

Estimating CO_2 reductions due to trip caps involves multiplying the number of employees affected by trip caps by the average reduction in vehicle trips for employees subject to caps, and then converting the result to CO_2 reductions.

In order to determine the number of employees affected, two assumptions were made where trip caps can apply:

1. Trip caps generally apply in employment centers where there is a high enough concentration of businesses to justify the effort in adopting a cap. All traffic analysis zones (TAZs) with more jobs than residents are assumed to represent employment centers.
2. Trip caps are feasible in areas where there is a high enough density of jobs and land uses to support transit, carpooling and other sustainable commute options which is assumed to be the case in all TAZs designated as either urban or suburban in MTC's travel model.

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[43] For a summary of South Bay trip cap programs, see Cities21, Palo Alto Comp Plan Transport Element, Extended Comments, September 1, 2015, http://www.cities21.org/cms/PA_Transp_Elem_C21.pdf.
[44] City of Mountain View, North Bayshore Transportation Demand Management (TDM) Plan Guidelines, February 2015, http://www.mountainview.gov/civicax/filebank/blobdload.aspx?BlobID=15164.

Trip caps would apply to all new employees located in TAZs that met both of these criteria.

The next step was to determine the reduction in vehicle trips due to the trip cap. The baseline number of vehicle trips per employee in each TAZ where trip caps apply were estimated. To this, the average vehicle trip reduction from the City of Mountain View's North Bayshore Transportation Demand Management (TDM) Plan Guidelines was applied, which is based on a target of 45 percent drive-alone mode share and 10 percent carpool mode share.[45] According to MTC's travel model, the current regional average carpool occupancy is 2.58 people per carpool, and the cap is equivalent to 0.98 vehicle trips per employee per day. This represents a 40 percent decrease from the current level of 1.62 vehicle trips per employee per day, which was calculated based on the current mode share for home-based work trips to the superdistrict containing the North Bayshore area—76 percent drive alone and 14 percent carpool, according to MTC's travel model.

The 40 percent reduction in the North Bayshore trip cap represents an average estimate for the effectiveness of trip caps that should apply throughout the region, because it reflects both the opportunities and challenges that will be present in many Bay Area locations. On one hand, the area is experiencing high demand for commercial development and the City of Mountain View took a proactive approach to minimizing the traffic impacts of new development through the trip cap. On the other hand, the North Bayshore area is very challenging to serve with alternatives to driving given that it is cut off from the rest of Mountain View by the Bayshore Freeway and is home to the Shoreline Amphitheatre, the Google campus, and other land uses that are not conducive to walking, bicycling or transit.

Analysis steps

To calculate CO_2 reductions due to trip caps, the methodology:

1. Identified all TAZs where trip caps are likely to apply: urban and suburban TAZs with more jobs than households.
2. Identified the current drive-alone and carpool mode share for home-based work trips to each of the trip-capped TAZs.
3. Calculated the average number of daily vehicle trips per employee in each trip-capped TAZ by dividing carpool mode share by current average carpool occupancy, adding the result to the drive-alone mode share, and multiplying the sum by two to account for round trips to and from work.
4. Estimated the reduction in daily vehicle trips per employee by applying the trip cap reduction factor derived from the Mountain View North Bayshore TDM Plan (40%) to the result of Step 4.
5. Multiplied the result of step 4 by the number of new employees projected for the TAZ between 2015 and the scenario year to estimate the total reduction in daily vehicle trips for each trip-capped TAZ.
6. Multiplied the result of step 5 by the average trip distance for home-based work trips for each trip-capped TAZ to estimate the total reduction in daily VMT for each trip-capped TAZ.
7. Summed the total reduction in daily vehicle trips across all trip-capped TAZs.
8. Summed the total reduction in daily VMT across all trip-capped TAZs.
9. Summed the product of trip-end emission rates and daily vehicle trip reductions and the product of exhaust emission rates and daily VMT reductions to calculate total CO_2 emission reductions.

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[45] City of Mountain View 2015, p. 4-3.

Results

Table 22 and Table 23 summarize the CO_2 reductions due to Trip Caps.

Table 22: Daily CO_2 emissions reductions due to trip caps (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	-120	-688	-856
Main Streets	-150	-764	-1,111
Big Cities	-143	-646	-836
EEJ	-150	-622	-761

Table 23: Per capita CO_2 emissions reductions from 2005 baseline due to trip caps (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-0.15%	-0.73%	-0.86%
Main Streets	-0.18%	-0.81%	-1.12%
Big Cities	-0.18%	-0.69%	-0.84%
EEJ	-0.18%	-0.66%	-0.77%

Expanded Bike Share System

Bike share systems provide bicycles that members of the public can borrow and use for limited durations (typically under a day) in exchange for a fee. In most systems, bike share bicycles must be borrowed from and returned to designated docking stations, though some systems have payment technology and locks mounted on bicycles to allow users to leave them anywhere in the service area. In August 2013, in collaboration with MTC, the Air District implemented a bike share system in the Bay Area on a limited pilot basis called Bay Area Bike Share (BABS). BABS consists of approximately 700 bikes deployed across 70 stations; approximately half in San Francisco and the other half in South Bay cities. Stations are located at key destinations such as transit hubs and employment and commercial areas. In 2015, Motivate, a private company, took over management of BABS, and with corporate sponsorship, rebranded and will expand the system tenfold, including new service areas in the inner East Bay.[46] MTC will be promoting bike sharing through its existing or new outreach programs.

Bike share reduces CO_2 emissions by enabling users to take short-distance trips by bicycle instead of by car, and in some cases bike share can eliminate longer trips by enabling users to connect to transit. As the bike share system expands, further CO_2 reductions will be realized. Motivate's plans for the bike share system are still evolving, but CO_2 reductions are quantified based on information currently available to MTC about the planned system.

Assumptions and methodology
Based on information from Motivate, the criteria for service area expansion in Berkeley, Emeryville, Oakland, San Francisco and San Jose includes transit-rich, densely developed areas, in addition to some targeted neighborhoods for equitable access. Since the service areas are still being decided, the priority

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[46] http://www.bayareabikeshare.com/expansion

development areas (PDAs) or areas in which most of the region's growth is anticipated to occur, were used to identify neighborhoods in each city that met these criteria. A contiguous bike share service area was then mapped that included these neighborhoods. Summarized below are the boundaries of the service area for each city:

- Berkeley: bike share covers the area east of College Ave., south of Cedar St., west of 6th St., and extends south to the city limits for contiguity with the Emeryville/Oakland bike share network.
- Emeryville: bike share covers the entire city east of Interstate 80.
- Oakland: North of Interstate 580, bike share covers the area west of College/Broadway. South of Interstate 580, the bike share service area is bounded in the southeast by 55th Ave. and in the southwest by 12th St. / San Leandro St., except for the area around Jack London square, where it extends down to the harbor.
- San Francisco: bike share covers most of the city, excluding hilly residential neighborhoods around Twin Peaks / Mt. Sutro, the Sunset, industrial lands along the Bayfront, and major parks. Though the Sunset meets the criteria for density and transit service, it was excluded as it is isolated from the rest of the service area.
- San Jose: bike share covers downtown and the residential neighborhoods surrounding it. The service area is bounded by Interstates 680 and 101 in the northeast, Tully Rd. in the southeast, Monterey Highway and Meridian Ave. in the west, and Berryessa Rd. and Hedding St. in the northwest.

With these geographic areas mapped, the number of residents and jobs in each using 2010 Census and Longitudinal Employer-Household Dynamics data were calculated. Information from Motivate on the approximate number of bikes in each city and the number of bikes per station was used to estimate the number of planned stations for each city.

The Institute for Transportation and Development Policy (ITDP) *Bike-Share Planning Guide* includes data on the effectiveness (in terms of the number of trips per 1,000 residents) of different bike share systems and compares effectiveness to different system characteristics.[47] ITDP finds that station density best explains bike share usage, and uses linear regression analysis to identify the relationship between station density and effectiveness. ITDP's data from U.S. systems was used to determine the equation best describing the relationship between station density and daily trips per 1,000 residents for U.S. systems:

Daily trips per 1,000 residents = 1.74 * station density + 17.2

This equation was then applied to the station density and number of residents in each bike share service area to estimate the total number of bike share trips per day. Table 24 summarizes the data and calculations for each service area.

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[47] Institute for Transportation and Development Policy, *The Bike-Share Planning Guide*, Fig. 3, p. 45, https://www.itdp.org/the-bike-share-planning-guide-2/.

Table 24: Summary of bike share service areas by city

City	Number of bikes	Bikes per station	Total stations	Area (km2)	Stations per km2	Estimated daily bike share trips per 1000 residents	Current number of residents	Estimated current daily bike share trips (pop-based)
Berkeley	400	10	40	11.5	3.5	23.1	79,090	1,823
Emeryville	100	10	10	2.6	3.8	23.7	8,596	204
Oakland	850	10	85	34.8	2.4	21.3	207,116	4,401
San Francisco	4,500	15	300	67.0	4.5	24.8	659,773	16,356
San Jose	1,000	10	100	46.3	2.2	20.8	188,213	3,907
Total	**6,850**		**535**	**162**			**1,142,788**	**26,691**

The average regional population growth was applied to estimate the number of bike share trips in each scenario year. This results in a conservative estimate of bike share trips since bike share serves many of the Bay Area's highest-growth communities.

The bike share trips were then converted to VMT reductions based on results from MTC's evaluation of BABS, which found that each bike share trip reduced an average of 1.3 VMT.[48] Many bike share trips do not reduce any VMT because they do not displace vehicle trips, while others only reduce short trips, but the evaluation found that a significant share of bike share trips enables users to connect to transit, eliminating longer trips.

Analysis steps

To calculate CO_2 reductions due to bike sharing, the methodology:

1. Identified a service area for each city with planned bike share and collected data on the area, number of planned bike share stations, and population for each service area.
2. Divided the number of bike share stations by the area of each service area to calculate the number of stations per square kilometer.
3. Applied a regression formula derived from ITDP to estimate the number of daily trips per 1,000 residents in each service area.
4. Multiplied the results by the number of residents in each area to estimate the number of daily bike share trips in each service area, and summed results across all service areas.
5. Multiplied total daily bike share trips by average population growth for the scenario year to estimate future total daily bike share trips.
6. Multiplied the result by the average VMT reduced per bike share trip to estimate total VMT reductions due to bike share.
7. Multiplied exhaust emission rates by daily VMT reductions to calculate total CO_2 emission reductions.

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[48] MTC Climate Initiatives Program Evaluation: Pilot Bike-sharing Program, Prepared for MTC by Eisen-Letunic, 2015.

Results

Table 25 and Table 26 summarize the CO_2 reductions due to the expanded bike share system. CO_2 reductions do vary slightly between the different EIR alternatives assessed, but the differences between alternatives are not visible at the level of precision shown in the tables.

Table 25: Daily CO_2 emissions reductions due to the expanded bike share system (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	-18	-21	-22
Main Streets	-18	-21	-22
Big Cities	-18	-21	-22
EEJ	-18	-21	-22

Table 26: Per capita CO_2 emissions reductions from 2005 baseline due to the expanded bike share system (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-0.02%	-0.02%	-0.02%
Main Streets	-0.02%	-0.02%	-0.02%
Big Cities	-0.02%	-0.02%	-0.02%
EEJ	-0.02%	-0.02%	-0.02%

Expanded Bicycle Infrastructure

Bicycle infrastructure makes it safer, more convenient, and more pleasant for people to bike instead of driving. Research has found that many people are interested in bicycling more, but are concerned about being hit by motor vehicles.[49] Building new infrastructure allows trips by bicycle instead of driving. As of 2005, the Bay Area had over 6,500 miles of bike lanes and trails, and this number is projected to increase to over 11,300 miles by 2035, significantly increasing the number of bicyclists and reducing VMT and CO_2 emissions as a result. Off-model analysis is required to account for CO_2 reductions due to improving bicycle infrastructure. MTC's model estimates bicycle trips based on based on trip distance alone, and does not capture the quality of bicycle infrastructure nor how infrastructure affects travel.

MTC's Regional Bicycle Plan 2009 Update[50] estimated the cumulative cost of building out the regional bikeway network as $1.4 billion dollars. Local governments are assumed to fund projects not included in the regional bikeway network.

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[49] Dill, J., and N. McNeil, Four Types of Cyclists? Testing a Typology to Better Understand Bicycling Behavior and Potential, Oregon Transportation Research and Education Consortium, August 10, 2012, http://web.pdx.edu/~jdill/Types_of_Cyclists_PSUWorkingPaper.pdf.

[50] Metropolitan Transportation Commission. Regional Bicycle Plan for the San Francisco Bay Area 2009 Update. March 2009. http://www.pedbikeinfo.org/pdf/PlanDesign_SamplePlans_Region_SFBayArea2009.pdf

Assumptions and methodology

In order to estimate CO_2 reductions due to expanded bicycle infrastructure, current and planned bicycle infrastructure in the region data was collected. Data on current infrastructure comes from MTC's Regional Bicycle Plan, which included an inventory of bicycle lanes and trails in the region. Data on planned infrastructure comes from an inventory of planned local and regional facilities conducted in 2013, and may underestimate future infrastructure because it does not capture facilities included in more recent plans. The impact on bicycle mode share was then estimated based on research conducted by Dill and Carr,[51] which estimates the absolute increase in bicycle mode share based on the number of bicycle lane-miles per square mile of land. Dill and Carr observed that if bike lane density increases by one lane-mile per square mile, bicycle mode share goes up by an absolute one percent, e.g., if the baseline mode share is two percent, it will increase to three percent. This increase in bicycle mode share was then converted to a reductions in vehicle trips, VMT and CO_2 emissions.

Analysis steps

To calculate CO_2 reductions due to expanded bicycle infrastructure, the methodology:

1. Divided miles of current bicycle lanes by the land area of the region to calculate the current bicycle facility density, in terms of the number of bicycle lanes and trails per square mile.
2. Repeated the step above for the scenario year.
3. Calculated the percent change in bicycle facility density between the current and scenario year.
4. Divided the percent change in bicycle facility density by 100 to estimate the change in bicycle mode share.
5. Multiplied the change in bicycle mode share by the baseline number of daily vehicle trips to estimate the number of daily vehicle trips reduced.
6. Multiplied the result by the average length of bicycle trips for the scenario year to estimate the average daily VMT reduced.
7. Summed the product of trip-end emission rates and daily vehicle trip reductions and the product of exhaust emission rates and daily VMT reductions to calculate total CO_2 emission reductions.

Results

Table 27 and Table 28 summarize the CO_2 reductions due to expanded bicycle infrastructure.

Table 27: Daily CO_2 emissions reductions due to expanded bicycle infrastructure (short tons)

EIR Alternative	2020	2035	2040
Proposed Plan	-24	-50	-52
Main Streets	-24	-51	-54
Big Cities	-22	-48	-51
EEJ	-24	-51	-53

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[51] Dill, J., and T. Carr. 2003, Bicycle Commuting and Facilities in Major U.S. Cities: If You Build Them, Commuters Will Use Them – Another Look, *Transportation Research Board* 1828, National Academy of Sciences, Washington, D.C.

Table 28: Per capita CO$_2$ emissions reductions from 2005 baseline due to expanded bicycle infrastructure (percent)

EIR Alternative	2020	2035	2040
Proposed Plan	-0.03%	-0.05%	-0.05%
Main Streets	-0.03%	-0.05%	-0.05%
Big Cities	-0.03%	-0.05%	-0.05%
EEJ	-0.03%	-0.05%	-0.05%