Health Co-Benefits and Transportation-Related Reductions in Greenhouse Gas Emissions in the Bay Area:

Technical Report

by

Neil Maizlish, PhD
Center for Chronic Disease Prevention and Health Promotion
California Department of Public Health
Richmond, California

with contributions from

James Woodcock, PhD
UKCRC Centre for Diet and Activity Research (CEDAR)
Institute of Public Health
Cambridge, United Kingdom CB2 0SP

Sean Co, MS TTP
Metropolitan Transportation Commission
Oakland, CA

Bart Ostro, PhD
Centre for Research in Environmental Epidemiology (CREAL)
Barcelona 08003, Spain

Amir Fanai, C. Eng. I. Mech. E
David Fairley, PhD
Bay Area Air Quality Management District
San Francisco, CA

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Executive Summary

Background

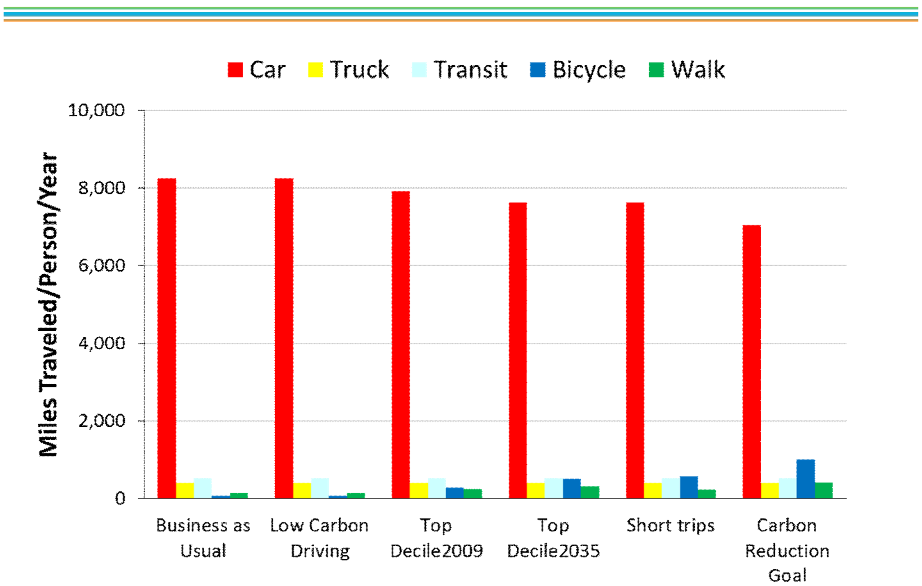
Greenhouse gas (GHG) emissions linked to global warming are a significant public health threat. In California, the transportation sector accounts for 38% of GHG emissions, and within transportation, personal passenger vehicles account for most GHGs. Strategies to reduce GHG emissions include reducing both the amount emitted per mile of travel ("low carbon driving") and reducing the overall miles traveled. Low carbon driving includes improvements in fuels and fuel efficiency, and the wider adoption of low- and zero-emissions vehicles. Bicycling and walking for transport including links to public transit is called "active" transport. Substituting active transport for short trips taken in automobiles could play an important role in decreasing GHG emissions, reducing air pollution, and increasing physical activity levels with concomitant reductions in chronic diseases. The health gains from physical activity and cleaner air are known as health co-benefits, and this “win-win” is likely attractive to both the public and policy makers who confront difficult choices in achieving carbon emission reduction goals

A public health research team recently developed the Integrated Transport and Health Impacts Model (ITHIM) that makes it possible to estimate the health co-benefits and potential harms from active transport and low carbon driving in urban populations. The California Department of Public Health partnered with the developers of ITHIM, the Metropolitan Transportation Commission, and the Bay Area Air Quality Management District to apply this model to possible scenarios of active transport and low carbon driving that could unfold in the nine county San Francisco Bay Area by 2035.

Methods

The active transport scenarios use regional travel surveys and census data to describe and project travel patterns in Bay Area cities that are already in the top decile of walking and bicycling. Substituting walking and bicycling for half of the numerous short automobile trips in the range of walking and bicycling was also considered. Ambitious, but achievable scenarios of both active transport and low carbon driving were combined to optimize GHG reductions. These scenarios were contrasted with Business-as-Usual (BAU), which envisions a 5% per capita increase in vehicle miles traveled by 2035 and little percentagewise change in walking

Annual Per Capita Miles Traveled by Mode and Scenario



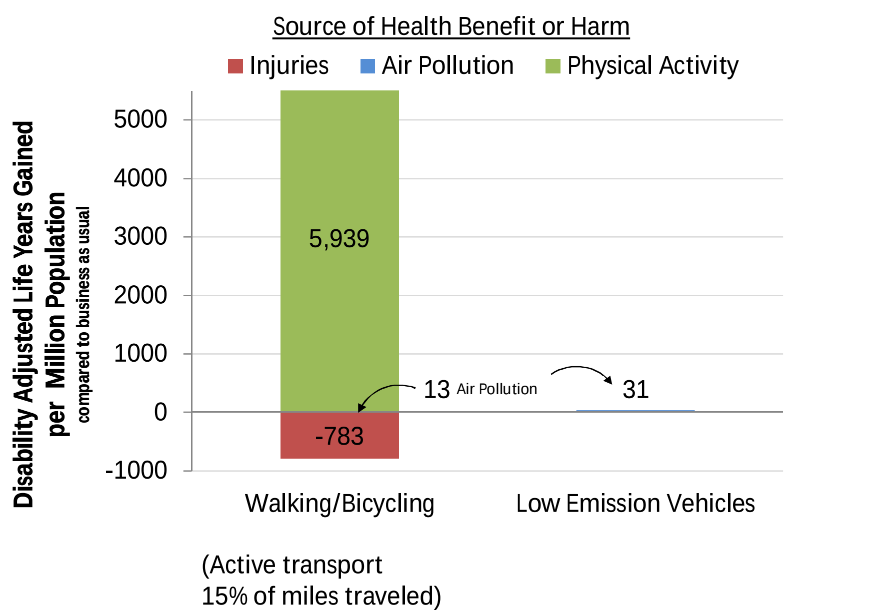
and bicycling. As inputs, ITHIM uses regional data from health surveys, traffic collision databases, vital statistics, and the results of regional models for travel demand, vehicle emissions, and air pollution. ITHIM then relates physical activity, air pollution, and travel behaviors to specific health outcomes based on established cause-effect relationships reported in the scientific literature for heart and respiratory disease; stroke; diabetes; cancers of the breast, colon, and lung; dementia; and depression.

Findings

The health impacts model was applied to a range of active transport scenarios that from a 2% baseline would attain a combined walking and bicycling mode share of up to 15% of travel distance. This corresponds to an increase in an average person's (median) weekly walking and bicycling from 31 minutes to 154 minutes.

At high levels of active transport compared to BAU, the model predicts 13% fewer premature deaths and 15% fewer years of life lost for cardiovascular disease and diabetes, 10% fewer deaths and years of life lost for dementia, and 5% reductions in each of three other chronic diseases. After accounting for a 19% increase in the disease burden from fatal and serious traffic injuries to pedestrians and bicyclists, the Bay Area would still experience 2,300 fewer deaths and 23,121 years of life gained. Almost all (99%) of the health benefit arises from increased physical activity rather than from less air pollution. While low carbon driving generated smaller health co-benefits, it is estimated to reduce GHG emissions 9% to 33.5% from the 2000 baseline. The most ambitious active transport scenario would achieve from 9% to 14.5% in GHG reductions.

Annual Health Benefits of Active Transport and Low Carbon Driving in the Bay Area Predictions from the Woodcock Model



Reducing risks from chronic disease of the magnitude suggested by ITHIM would rank among the most notable public health achievements in the modern era, and reduce the estimated $34 billion annual cost in California from cardiovascular disease and other chronic conditions such as obesity. The ambitious active transport scenario would also achieve the U.S. Surgeon General's recommendation that adults engage in at least 150 minutes of at least moderate physical activity weekly. Together, the ambitious scenarios of active transport and low carbon driving could achieve a 45% GHG reduction by 2035 that puts California on track for the 80% reduction by 2050 mandated by AB32 (Global Warming Solutions Act) and Executive Order S-3-05.

INTRODUCTION

Background

Climate change associated with the emission of greenhouse gases is the most significant threat confronting public health during the 21st century[1]. In California, the transportation sector accounts for 38% of the these emissions, outpacing all other sectors, including energy production[2]. Within transportation, personal passenger vehicles account for 79% of greenhouse gas (GHG) emissions, and strategies to reduce carbon dioxide (CO_2) and other greenhouse gases include reducing both CO_2 emitted per mile and the overall miles traveled [2]. In urban settings, a large proportion of automobile trips cover distances well within those feasible for walking and bicycling, which are opportunities for integrating physical activity into daily routines. Because physical inactivity is strongly linked to obesity, cardiovascular disease, some cancers, and other chronic diseases that together account for most of the disease burden in the United States (U.S.) population, active transport through walking and bicycling could in principle play a very important role in promoting public health while decreasing transportation-related GHG emissions and air pollution. The physical activity and air pollution reduction portions of this "win-win" situation is known as a health co-benefit and is attractive to both the public and policy makers who confront difficult choices in achieving carbon reduction goals[3].

Although the health co-benefits of active transport are recognized by many transportation and public health professionals and community advocates, few attempts have been made to quantify its health benefits and potential harms. A recent report suggested that by 2030 London could achieve a 60% reduction in 1990 levels of GHGs and a 10% to 19% reduction in premature deaths and disability from major chronic diseases if low carbon emitting motor vehicles were widely adopted and residents increased active transport mode share of distance to 19% from a baseline of 4% [4]. This project led to the development of the Integrated Transport and Health Impacts Model (ITHIM). The ITHIM model focuses on three pathways that impact health outcomes associated with increased walking and bicycling and driving lower carbon automobiles: physical activity, air quality, and road traffic injuries.

California has been at the forefront of State actions to reduce greenhouse gas emissions. The California Global Warming Solutions Act of 2005 (AB32) set carbon reduction goals for the state. Complementary legislation, SB 375, requires regional transportation planning agencies to incorporate CO_2 reduction targets and land use strategies into the updates of their existing transportation plans. The California Climate Action Team is a multi-agency body that coordinates climate change activities across state agencies. As a member of the Climate Action Team, the California Department of Public Health (CDPH) seeks to address the potential health promoting and/or adverse health consequences of climate mitigation and adaptation strategies. The availability of the ITHIM modeling tool offered an opportunity for collaboration between CDPH, developers of ITHIM, and the Metropolitan Transportation Commission, a regional transportation planning agency covering nine counties in the San Francisco (SF) Bay Area to assess projected health impacts of various transportation scenarios in the Bay Area.

Population and Transportation Infrastructure

The SF Bay Area is comprised of nine counties that border the San Francisco Bay estuary in northern California. The counties occupy 1,038 mi^2 and had a population of 7.1 million in 2010. County population densities range from 181 persons/mi^2 to 17,246 persons/mi^2. The cities of San Francisco, Oakland, and San Jose are major metropolitan hubs, and 54 cities have populations greater than 20,000. The transportation infrastructure includes 42,000 lane miles of roadways. Over 70 freeway locations, mostly interstate highways dominated by single occupancy vehicles, are chronically congested during morning and evening commutes. There are 28 public transit operators with 509 million boardings per year [5]. The bicycling infrastructure includes over 1,000 miles of a regional bikeway network [6].

MATERIALS AND METHODS

Description of the ITHIM Model

The modelling approach used in ITHIM has been described in detail elsewhere [4, 7, 8]. In brief, the conceptual basis is called comparative risk assessment (CRA), which formulates the percent of disease and disability that is attributable to a shift in the exposure distribution from a baseline scenario to an alternative. The attributable fraction, AF, is applied to a population-based measure of the burden of disease at baseline.

$$AF = \frac{\int_{\mathrm{Xmin}}^{\mathrm{Xmax}} R(x)P(x)dx - \int_{\mathrm{Xmin}}^{\mathrm{Xmax}} R(x)Q(x)dx}{\int_{\mathrm{Xmin}}^{\mathrm{Xmax}} R(x)P(x)dx}.$$

A measure of the disease risk, R, corresponding to a specific exposure level (x), is weighted by the baseline and alternative populations, P(x) and Q(x), respectively. These weighted risks are summed over all exposure levels and divided by those of the baseline. Exposure corresponds to levels of physical activity or levels of air pollution. A variant of this model was also used for the analysis of road traffic injuries (described below). The population-based measure of the burden of disease and disability is the sum of years of life lost due to premature mortality, YLL, and years of living with disability, YLD. Together they comprise disability adjusted life years, or DALYs. The health benefits or harms between different transport-related physical activity scenarios is given by

$$\mathbf{AF} \times \mathbf{DALY}_{\mathbf{Baseline}}\ .$$

Because health outcomes and physical activity are strongly influenced by age and gender, the above calculations are done in specific age and sex categories, and then summed.

In ITHIM, the baseline distribution of physical activity is generated at quintiles of a log-normal distribution from the overall population mean weekly active transport time per person, its standard deviation and coefficient of variation (CV), the ratio between bicycling and walking times, and a weight that reflects energy expenditures for walking and cycling at average speeds. The use of quintiles refines methods used previously[4] that used only the population median. Activity times for bicycling and walking are made age and sex specific by distributing the population mean time according to ratios relative to one age-sex group and the ratio of walking to bicycling times. Scenarios with increased active transport have a right-shifted distribution of physical activity times based on the mean time per person it takes to cover the mean scenario distance at given travel speed. At increasing levels of active transport, the model reduces the standard deviation, increases travel speeds for walking and cycling, and increases age-sex travel time ratios in older age groups. This follows a European pattern in which population variability decreases as cycling and walking become prevalent and populations become more fit and capable of achieving faster walking and bicycling speeds.

Road Traffic Injuries

The health co-benefits of active transport primarily arise from increased physical activity related to walking and bicycling. However, increasing exposure of pedestrians and bicyclists to motorized transport can increase the risk of traffic injuries. ITHIM quantifies the number of injuries to pedestrians and bicyclists[4] using a topology of collisions that accounts for the mode of travel of both the injury victim and the striking vehicle:

	Striking Vehicle					
Injury Victim	Bicyclist	Ped.	Motorcycle	Car	Bus	Truck
Bicycle	$n_{b,b}$	$n_{b,p}$	$n_{b,m}$	$n_{b,c}$	$n_{b,bus}$	$n_{b,t}$
Pedestrian	$n_{p,b}$	$n_{p,p}$	$n_{p,m}$	$n_{p,c}$	.	.
Motorcycle	$n_{m,b}$	$n_{m,p}$	$n_{m,m}$	.	.	.
Car	$n_{c,b}$	$n_{c,p}$	.	.	etc.	.
Bus	$n_{bus,b}$	.	.	.	.	.
Truck	$n_{t,b}$	.	.	.	.	.

For each matrix cell, the risk of an injury at baseline, R_0, can be expressed as the ratio of the number of injuries and distance traveled by the victim and the striking vehicle - person miles traveled, PMT, and vehicle miles traveled, VMT, respectively.

$$R_0 = \frac{Number\ of\ \ Injuries_{Victim0}}{PMT_{Victim0} \times VMT_{Striking\ Veh0}}$$

In a scenario in which the miles traveled by victim and striking vehicle change, the number of injuries, I_S, for a given collision matrix cell is:

$$I_S = R_0 \times PMT(victim)_S \times VMT(Striking\ vehicle)_S$$

Empirical evidence suggests that injury rates of pedestrians and bicyclists do not increase linearly with increasing distance they travel. A power function in the range of a square to cubic root of distance describes this relationship in many U.S. and western European populations.[9] Because the risk of injury is related to both speed and volume of motor vehicles[10], the above matrix can be stratified by roadway type: highways, arterials, and local streets, including feeder roads. In California these roadway types have posted speeds of 55-65, 30-55, and 25 miles per hour, respectively, and tend to correlate with traffic volume. The matrix can also be stratified by injuries severity: fatal and non-fatal but serious.

The number of severity-specific injuries is summed over matrix cells of each roadway type for the baseline and scenario. If the baseline and scenario populations are considered to be static, the attributable risk (population) for fatalities is given by:

$$AR_{Fatal} = \frac{\Sigma I_S}{\Sigma I_0}$$

where I_s and I_0, are the number of fatal injuries at baseline and under the scenario, respectively.

A similar calculation can be made for serious injuries, $AR_{Serious}$. To equate the attributable risk to the change in disease burden, Woodcock et al multiply the AR_{Fatal} by years of life lost and $AR_{Serious}$ by years living with disability.

Air Pollution

The comparative risk assessment (CRA) model previously described[4] was applied to estimate the attributable fraction of the disease burden associated with a shift in population-weighted mean $PM_{2.5}$ levels in scenarios compared to business as usual (BAU). The concentration-response relationships to determine the values of the relative risks used in the CRA have the functional form of:

$$RR=\exp(b(x_1-x_2))$$

where RR, is the relative risk, b is the estimated risk coefficient, x_1 is the mean $PM_{2.5}$ in a scenario and x_2 is the mean $PM_{2.5}$ concentration of the BAU. The risk coefficients were derived from California or U.S. epidemiologic studies that relate long-term exposure to PM2.5 to the likelihood of certain diseases.

Data Sources

Data sources and ITHIM inputs are summarized in Table 1 and Figure 1.

Burden of Disease and Disability

Years of life lost are based on life expectancy tables and actual ages at death from death certificates. Years living with disability are based on the incidence of the disease or injury, its duration, and a standardized severity weight. DALYs have been compiled by the World Health Organization for the United States in age-sex categories for 136 specific causes of death and disability[11]. U.S. deaths, YLLs, and YLDs projected for 2010 were scaled to the SF Bay Area population. To account for the observation that residents of the SF Bay Area generally have better health outcomes than the U.S. population [12], the burden of disease measures were adjusted by the ratio of the mortality rates of the SF Bay Area and the U.S. population for each age and sex strata[13]. Due to unstable estimates based on small numbers, age-sex cells with less than 10 Bay Area deaths were not adjusted (i.e. RR = 1).

Relative Risks

Epidemiologic evidence of association between chronic diseases and physical activity and air pollution has been published and summarized elsewhere[4, 8]. In brief, bibliographic databases of medical literature were searched through March 2009 for diseases and illnesses whose risk factors were assessed in study of the global burden of disease [7]. Systematic review articles were identified for cardiovascular diseases[14]; colon cancer [15]; breast cancer [16]; diabetes [17]; and dementia [18], lung cancer [19], respiratory disease[20, 21], while relative risk for depression was based on a review of epidemiological studies described in Woodcock et al [8]. The reviews compiled multiple epidemiologic studies, which, after selecting those of highest quality, were pooled to derive dose-response relationships between disease risk and level of physical activity. Except for breast cancer, the shape of the dose-response function was not well researched. Based on a conservative biologic assumption, a square root linear relationship was used to describe steep risk reduction at moderate levels of physical exercise that taper to marginal risk reduction at very high levels. For cardiovascular diseases and diabetes, relative risks were based on studies of walking alone, and, for the other diseases, relative risks were based on a broader range of physical activities. The specific disease entities and diagnostic codes used in ITHIM based on the Global Burden of Disease database[11] and the International Classification of Diseases are shown in Table 2.

Physical Activity Distribution

Energy Expenditure METS

In epidemiologic studies, physical activity is best described in units of energy (calories) expended per kilogram of body weight per hour of activity (kcal/kg/h) during a typical week. One kcal/kg/h is also called a metabolic equivalent task (MET). In laboratory and field settings, researchers have measured METS for many physical activities, including walking and bicycling at various speeds and for occupational activities [22]. In calculating the attributable fraction, physical activity of less than 2.5 METs per week was recorded as a zero exposure. The basis for this assumption is that epidemiological studies generally classified persons with such a low exposure as sedentary.

Outside of laboratory settings, population distributions of METS per week for active transport are estimated from surveys based on distances, speeds, and duration of walking and bicycling. Travel surveys usually cover the details of just one or two days of travel using travel diaries. This poses a methodological challenge because one-day travel diaries may not record trips of longer duration that occur infrequently. Compared to seven days of observation, this is likely to inaccurately characterize variability. To overcome these challenges, two different surveys were used to describe weekly distribution of walking and bicycling times for SF Bay Area residents and its coefficient of variation.

Physical Activity Time – Travel Related

First, the Bay Area Travel Survey (BATS), conducted in 2000, was a probability sample of 15,064 households and 34,680 SF Bay Area residents [23]. The survey instrument covered household and personal demographics and included a two-day travel diary in which respondents recorded the type of activity or travel, start and end times for each activity, mode of travel, and information to geocode origins and destinations of trips. The two days of travel were consecutive and covered each day of the week, but had no Saturday-Sunday combination (Fri-Sat and Sun-Mon were included). BATS was used to estimate mean travel distances per person. In conjunction with published values of average speeds, population mean travel times were calculated for bicycling and walking [24, 25].

The data are structured into 5 data files: household, person, activity, unlinked trips, and linked trips. The linked file consolidated trip segments that had a common purpose but with potential intermediate transitions or stops along the way to drop off passengers or switch modes of travel. In the case of multi-modal trips, the linked file incorporated a single predominant mode based on the mode with the longest trip segment.

Physical Activity – Nontravel Related

Second, the California Health Interview Survey (CHIS), 2005 was administered to 10,128 adults representing 5.1 million SF Bay Area adults. In addition to demographics, the survey included items on walking for fun and for transport, moderate and vigorous physical activities, hours worked per week, and type of occupation. The reference period was one week and respondents recalled the number of days per week of physical activities and average minutes per day on days of activity. CHIS was used to estimate the standard deviation and CV of weekly active transport time, taking into account the complex survey design [26].

CHIS was also used to estimate physical activity not associated with transport. At quintiles of the transport-related physical activity times, medians were calculated for the total of other physical activity based on responses to questions for leisure time moderate and vigorous exercise and weekly hours worked and occupation, which were weighted by standard MET values [22]. Total physical activity summed the distributions of active travel and other physical activity for all causes except cardiovascular disease and diabetes. For these two, the analysis of physical activity was limited to travel because their relative risks were based only on walking.

Travel Distances, Times, and Speeds by Mode

BATS was used to estimate the baseline for distances traveled by walking, bicycling, bus and rail travel, and cars (automobiles and light trucks). Car miles were subdivided among car-driver and car-passenger miles. Heavy goods vehicles were not included in the BATS 2000. Daily estimates of miles traveled by heavy goods vehicles in the Bay Area was provided by the Urban Land Transportation Center (University of California, Davis) based on a goods movement model for heavy trucks (FHWA classes 8-13), comprised of a tractor and trailer with 4 or more axles.[27] Annual miles were estimated by multiplying the daily amount by 365.

Bicycle and Walking

Travel Speeds

Due to the design of the travel diary and reporting biases, respondents probably overestimated active travel times in BATS by including time not spent in physical activity or motion related to stop-and-go nature of urban driving, traffic delays, and waiting at signals, and parking at trip ends. Instead of using BATS to estimate speeds and travel times, the age- and sex-specific walking speeds published by Oberg and Karsznia [25] were adjusted to 2010 SF Bay Area population (2.78 mi/h). Mean bicycling speed at baseline was 7.4 mi/h, based on a synthesis of several European populations [8]. At the most ambitious active transport scenario, walking speed increased to 3.2 mi/h and bicycling speeds increased to 8.5 mi/h. These average speeds were multiplied by the average walking and bicycling distances in scenarios to generate the mean active transport time.

Relative Travel Times

BATS was used to calculate relative travel times by dividing the mean age-sex specific travel time by a reference group mean (females aged 15 to 24 years).

Road Traffic Injuries

The California Statewide Integrated Traffic Records System (SWITRS)[28] is a compilation of electronic records of police-investigated traffic collisions in California. Information is collected by local, county, and state police who use a standardized form (CHP555) that itemizes attributes of collision, the parties involved, and each party's' victims. Information includes the street names and intersections where the collision occurred, the modes of transport of the parties (motorized vehicles, pedestrians, bicyclists), and the injury severity (fatal, serious, other visible, complaint of pain, and property damage only). Fatal injuries are deaths occurring within 30 days of the collision. Severe injuries are defined as those having a severe wound that "prevents the injured party from walking, driving, or performing activities he/she was normally capable of before the collision."

Distances Traveled by Mode and Roadway Type

In the analysis of road traffic injuries, person miles traveled by the victim and vehicle miles traveled by the striking vehicle were derived from the following data sources:

Mode	Victim Person Miles Traveled (PMT)	Striking Vehicle Miles Traveled (VMT)
Car	BATS2000 (driver + passenger)	BATS2000 (driver only)
Motorcycle	VMT estimate * occupancy from NHTS, 2001	BATS2000 car-driver × proportion of motorcycle VMT in NHTS car + motorcycle drivers
Bus	BATS2000	Revenue miles for motor and electric buses in 2005 reported by 25 Bay Area transit operators
Truck	UCD travel model, 2008 for FHWA classes 6-13 (medium and heavy goods vehicles)	UCD travel model, 2008 for FHWA classes 6-13 (medium and heavy good vehicles)
Walk	BATS2000	BATS2000
Bicycle	BATS2000	BATS2000

Because the Bay Area Travel Survey, 2000[23] included motorcycles in the automobile category, the National Household Transportation Survey, 2001, California Add-On[29] was used to estimate the ratio of motorcycle to car vehicle miles in California. This ratio was applied to the BATS car-driver miles to estimate the miles traveled by motorcycles. To estimate motorcycle PMT, motorcycle PMT in NHTS was divided by motorcycle VMT in NHTS. This occupancy measure was multiplied by the estimated BATS per capita annual motorcycle VMT to yield the estimate of the BATS per capita motorcycle PMT (driver + passenger). Truck VMT and PMT were assumed to be the same (i.e., no occupants beside the driver). Vehicle miles traveled by Bay Area electric and motor buses have been published by transit system operators.[30] The California Statewide Travel Demand Model was used to estimate Bay Area VMT and PMT by medium and heavy duty vehicles (FHWA Classes 6-13).[27]

<u>Distribution Traveled by Roadway Type</u>

Several data sources were used to estimate miles traveled by roadway type by mode. (Travel surveys used to estimate miles traveled by mode did not have information on the route taken.)

Mode	Data source
Car	Loaded travel demand model of Bay Area highway network (2005) by facility type
Motorcycle	Assumed to be same as car-driver
Bus	Revenue miles reported by transit operator and analysis of WestCat, AC Transit, and Golden gate transit TransBay routes in Google maps to identify miles traveled on highways 80, 580, 101, 84, 92 on the stops preceding TransBay terminal; no miles on local streets assumed
Truck	Loaded highway network (2005) by facility type applied to UCD medium and heavy goods vehicle miles
Walk	Assumed distribution
Bicycle	2009 study of Portland bicyclists

To estimate car, motorcycle, and truck miles driven, output of the 2005 Bay Area "fully loaded" travel demand model was used.[31] The file estimates the volume of motor vehicle traffic by vehicle type on every major segment of the Bay Area roadway transportation network during 5 daily time periods of weekday travel. The length and facility type of each segment, except local roads within a transportation analysis zone, TAZ, (equivalent to a census tract) are included in the model. Facility type is broken down into 10 categories that in turn were aggregated into three categories: highway (freeway, freeway to freeway connector, expressway, freeway ramp, metered ramp), major arterial, and local (collector, dummy link). Travel within a TAZ travel was estimated to be 10% of total network travel and was added to the totals. A SAS program (Appendix B) was written to provide the percentage distribution of miles traveled by facility type by cars (classes DA, S1,S3, S3) and trucks (classes SV, HV).

Bus miles by roadway type was derived from specific TransBay routes of 3 transit operators (WestCat, AC Transit, Golden Gate Transit). Bus route frequencies for in-bound and out-bound weekday and weekend travel and distances between the transit stops immediately preceding and succeeding the 3 Bay Bridges, estimated using Google maps, were used to estimate total annual distances traveled on interstate and major highways. These distances were subtracted from the total revenue miles to give miles traveled on arterials. It was assumed that there was no bus travel on local streets.

For distribution of walked miles, it was assumed that pedestrian traffic on interstates was incidental to roadside emergencies (breakdowns, out of gas), and was estimated at 0.00000667% following the value used by Woodcock et al.[4] It was assumed that 25% of pedestrian miles were on arterials and 75% on local roads. For bicycles, Dill's[24] reported distribution for Portland bicyclists was applied to the Bay Area: 47% arterials and 53% local roads.

Air Pollution

Estimates of average, annual airborne concentration of fine particulate matter (aerodynamic diameter of 2.5 microns, $PM_{2.5}$) were based on two models. First, an emissions model, EMFAC2007[32], was used to estimate Bay Area motor vehicle emissions for the baseline year of 2010 for the car fleet composed of model years from 1966 to 2010. The model output included vehicle class-specific daily vehicle miles traveled (VMT) and tons per day of primary $PM_{2.5}$ emissions and constituents of secondary $PM_{2.5}$ (reactive organic gases, nitrogen oxides, sulfur dioxide, and tire and brake wear). All operating conditions (start, run, idle, evaporative emissions) were included. A second model, called the Multi-Pollutant Evaluation Method (MPEM)[33], was used to predict population-weighted concentrations of total $PM_{2.5}$ (primary and secondary) in 4 kilometer grids in the Bay Area air shed based on mobile and non-mobile sources. For each active transport scenario, only car and light truck VMT were varied and VMT for all other vehicle classes and inputs for non-mobile sources were held constant at the 2010 baseline level. $PM_{2.5}$ concentrations were assumed to change with scenarios VMT in a proportional, linear manner. Population-weighted mean $PM_{2.5}$ concentrations were calculated for the Bay Area based on 2010 census tract populations.

Population and Population Projections

<u>Bay Area Population 2004</u>

The global burden of disease measures are based on 2004 data projected to 2010. ITHIM prorates 2004 U.S. population data[34] to the 2010 projections using the overall 2004 Bay Area population as estimated by the California Department of Finance[35].

Bay Area Population 2010

Age-sex specific walking speeds[25] and relative travel times for walking and bicycling are age-sex standardized to the Bay Area 2010 population. The 2010 Bay Area county specific population counts were obtained from U.S. Census Bureau website[36], and were used to populate an MS Access database [37]. A query was written to subset the nine-county Bay Area population in sex and 5-year age groups, which were aggregated to match the 8 age categories used in the Woodcock model (<5, 5-14, 15-29, 30-44, 45-59, 60-69, 70-79, 80) and copied to a separate Excel spreadsheet.

Bay Area Population 2035

Decadal projections of California population (2000 to 2050) by county have been produced by the California Department of Finance[38]. The 2035 estimate was the arithmetic average of the 9-county 2030 and 2040 populations.

Travel Scenarios

In ITHIM scenarios are described by annual mean miles traveled per person for each mode of travel. The modes of travel are car, walking, bicycling, bus, rail, and heavy goods vehicles (HGV), comprising the Federal Highway Administration Classes 8-13. Total annual miles traveled by mode divided by the total population gives average miles traveled per person per year. Total travel distance was held constant in each scenario, and active transport scenarios shifted miles traveled by car to miles walked and bicycled without affecting other modes of travel.

- The baseline scenario describes travel patterns in a base year.
- Business as usual (BAU) projects 2000 baseline travel patterns into the future accounting for trends in demographics, economic development, and travel patterns, and/or the likely consequences of implementation of existing policies, projects, and programs.
- Low carbon driving (LCD) assumes engineering changes to fuels and cars that reduce carbon emissions, but do not fundamentally alter miles traveled by car or active transport from BAU.
- Active transport describes a range of scenarios which represents a significant change in travel patterns with an increased share of miles walked and bicycled replacing miles driven by automobiles and light trucks.

Business As Usual

Based on travel demand models of the MTC [39], the BAU scenario for 2035 foresees an increase of 5% over the BATS 2000 per capita mean vehicle miles traveled for automobiles (Table 3). Miles driven per capita for other motorized transport and active transport are assumed not to change over time from the BATS baseline. Changes to passenger vehicles that impact GHG emissions involve improvements in drive train engineering, refrigerants, and accessories that incrementally improve fuel economy [40].

Low Carbon Driving (LCD)

Although distances are the same as in BAU, carbons emissions by automobiles and light trucks will be lower than other scenarios (described below).

Active Transport

This scenario incorporates the same trends in travel distances as the BAU and assumes that qualitative and quantitative changes in existing implementation strategies could achieve increases in active transport mode share. It does not describe the implementation strategies themselves. The assumption of fixed travel miles per capita was used to represent the potential for health gains and carbon emissions alone from a direct modal shift. In practice a major modal shift might be accompanied by changed land uses and shorter travel distances. Three approaches were used to create options for modeling active transport.

Local Benchmarks

In previous research, Woodcock et al [4] used the walking and cycling patterns of European cities with high walking and bicycling rates to inform a future London that emulates current-day European exemplars. Likewise, among the 53 largest SF Bay Area cities, many already achieve high rates of walking and cycling in the commute to work based on the American Community Survey (ACS) (Figure 2) [41].

The "Top Decile$_{2009}$" scenario envisions that by 2035 all SF Bay Area cities achieve the active transport levels that the top decile of cities achieved in 2009 (Table 4). For bicycling to work, the top decile included 5 cities that ranged from 40,000 to 800,000 in population and included San Francisco and university towns of Berkeley and Palo Alto. The midpoint of the range of bicycling to work was 4.9% (range 2.8% to 7.4%). For walking to work, the top decile included 5 cities that ranged from 37,000 to 800,000 in population and included San Francisco and Oakland. The midpoint of the range of bicycling to work was 10.5% (range 4.4% to 16.6%). San Francisco, Berkeley, and Palo Alto were in the top decile for both walking and bicycling.

An ambitious extension called "Top Decile$_{2035}$" projects that all SF Bay Area communities will achieve the levels of this top decile, taking into account their expected growth in active transport by 2035. The annual growth rates between 2000 and 2009 for the top decile of cities for bicycling and walking to work were calculated using simple linear regression and extrapolation to 2035. The midpoint of the range for bicycling in 2035 was 8.8% and the midpoint for walking was 13.9% for all work trips.

BATS data were analyzed for the employed population aged 16 years and older and distance of trip segments with a purpose of commuting to work. To project walking and bicycling miles traveled in this scenario, ACS mode share of the work commute or journey to work (JTW) for the midpoint of the mode share range of the top decile of cities was multiplied by ratios of BATS mode share, miles traveled to work, and total miles:

$$\textbf{Total Miles Scenario} = \textbf{Scenario JTW\%}_{ACS} \times \frac{\textbf{JTW Miles}_{BATS}}{\textbf{JTW Mode Share \%}_{BATS}} \times \frac{\textbf{Total Miles}_{BATS}}{\textbf{JTW Miles}_{BATS}}$$

.

Total active transport scenario (work and non-work) miles were then subtracted from automobile and light trucks and allocated to bicycling and walking.

Active Transport Carbon Reduction Goal (AT_C)

This scenario envisions the optimal use of active transport to reduce carbon emissions with the constraint that bicycling distance not exceed 1,000 miles per person per year and walking not exceed 400 miles per person per year. This level of active transport corresponds to an approximate mean of 30 min/person/d and a mode share of 15% of total travel distance, including work and non-work trips. (This scenario was revised from a more ambitious scenario in which total active transport miles was 2,361 mi/person/yr to maximize carbon reduction (-21.5% from 2000 baseline) and car-driver miles/person/yr was 4,502. The excess miles (961) was distributed to rail and bus in the ratio in the BAU scenario and assumed no additional CO_2 from emissions from public transit.)

Short Trips

This scenario assumes 50% of BAU miles traveled in car trips < 1.5 miles in length are walked and 50% of BAU miles traveled in car trips 1.5 to 5 miles in length are bicycled. BATS data were analyzed for the distribution of car-driver and car-passenger miles by trip length (Table 5). For each mode (walking and bicycling), the fraction of miles in the distance range was multiplied by the total BAU car-drive and car-passenger miles to estimate the miles traveled per person per year traveled in that distance range. For bicycling, 11.4% of car-driver miles were in trips 1.5 to 4.9 miles in length, and 15.3% of car-passenger miles were in trips 1.5 to 4.9 miles in length. For walking, 2.2% of car-driver miles were in trips less than 1.5 miles in length, and 3.3% of car-passenger miles were in trips less than 1.5 miles in length.

Carbon Dioxide Emissions

For cars and light trucks, Lutsey[40] estimated CO_2 reductions from 2000 to 2050 expected from incremental engineering changes (drive train, accessories, refrigerants), penetration of gas-electric hybrid vehicles and light duty diesels, increased biofuels usage, and the penetration of electric vehicles. For incremental changes consistent with the BAU scenario, a 16% reduction is predicted by 2035. The combination of all other technologies is predicted to reduce CO_2 emissions by an additional 9% to 33.5%.

Annual aggregate carbon emissions at baseline were estimated from CO_2 emission rates per mile traveled for passenger vehicles in the SF Bay Area and from the annual miles of car-driver travel estimated by BATS. The methods for calculating these carbon dioxide emission rates are based on travel demand models and have been published elsewhere[42]. Aggregate CO_2 emission reductions for the BAU and LCD scenarios applied percentage-wise reductions estimated by Lutsey [40] to the 2000 baseline (Table 6). In the active transport scenarios, annual car-driver miles per person were reduced by the active transport miles per person and multiplied by the emission factor of 1.175 lbs. CO_2/mi and the total projected population for 2035 [38]. Active transport miles were credited entirely to car-driver miles holding car-passenger miles constant at BAU levels. (Active transport miles were not apportioned to car-driver and car-passenger miles in their BAU ratio.)

Statistical Analysis

Physical Activity

Travel Distances by Mode

Although actual distances were not recorded in BATS, geocoded coordinates of trip origins and destinations were available to estimate distances using a SAS program[43] that interacted with the Google maps **(**http://.maps.google.com) and returned the distance of the route taking the least amount of time specific to mode. Because of the large number of X-Y origin-destination pairs (>250,000) for car travel, walking, and public transit, random samples of XY pairs were taken to estimate the ratio between best route and straight line distances. In the case of bicycling, it was possible to process all 3,058 coordinate pairs in Google maps. The coordinates' sampling rates for car-driver, car-passenger, bus/taxi, rail, and walk were 2%, 5%, 50%, 50%, and 10%, respectively. For every straight line mile traveled, Google maps estimated 1.36±0.008 (standard error) car-driver miles, 1.35±0.018 car-passenger miles, 1.29±0.02 bus/taxi miles, 1.27±0.009 rail miles, 1.26±0.05 walk miles, and 1.42±0.014 bicycle miles.

Approximately 28% of all trip segments had either a missing travel time or an ungeocoded origin or destination. To impute missing data, mean speeds on segments with known distance and time were calculated for each mode of travel. After excluding segments with unlikely velocities (see below), the mean speed by mode on known trip segments were applied to segments with missing time or distance. This method of imputation is similar to that used in the National Household Travel Survey.[44]

In 8% of bicycle trip segments, there was a non-zero duration of activity but trip beginnings and ends with identical geographical coordinates. These trips were most likely loops for recreational travel. A sample of text descriptions of the locations of these loops were manually inspected and they appeared to be valid trips. To calculate the distance of these loops, the average speed was also applied. Loop trips were also prevalent for walking, and a similar approach was applied to calculate distances.

Trip distances were aggregated for each travel day. Two-day average distance was multiplied by 7 to give weekly mean miles traveled per person, and by 365 to give annual mean miles traveled per person. The sample weight (PFACTOR5) reflected the probability of each resident's selection in the survey and adjustments to make the BATS sample consistent with the age, sex, and racial make-up of the 2000 Census Bay Area population. The analysis was repeated for each mode in the survey: car driver, car passenger, bus, taxi, rail, walking and bicycling. Data processing was carried out with the SAS 9.2 statistical package (SAS Corp., Carey, NC). No adjustment was made for trip underreporting, which in a similar statewide survey in 2000 reported that only 64.7% of all car trips recorded in travel diaries were corroborated by GPS devices distributed to a sample of survey respondents.[45]

Walking and Cycling Times

ITHIM models the distributions of travel times in age-sex groups in both BAU and alternative scenarios using the following inputs:

- overall population arithmetic mean travel time, $\overline{x}_T$, and its standard deviation, σ_T for bicycling and walking
- the overall population travel time coefficient of variation, $CV_T = \frac{\sigma_T}{\overline{x}_T}$
- age$_i$-sex$_j$ specific mean travel times, $\overline{x}_{i,j}$ for walking and bicycling.

Using the inverse logarithmic function for a normally distributed population and a known arithmetic mean and standard deviation, it is possible to estimate the physical activity level at population percentage intervals along the distribution (i.e. quintiles). Making the assumption that the coefficient of variation for the population total, CV_T, also applies to age-sex subgroups, the age-sex mean travel times and the overall coefficient variation can be used to predict the age-sex specific standard deviations ($\sigma_{i,j} = \overline{x}_{i,j} \times CV_T$). Age-sex relative mean times (using females 15-29 years as the reference) can be used to distribute the overall mean to age-sex specific groups. Applying the inverse logarithmic function to the age-sex specific means and standard deviations allows distributions of travel times to be calculated for each age-sex group. The ratio of bicycling to walking can be used to further parse the activity times for bicycling and walking along the quintile distribution.

CV of Travel Time

BATS

The standard deviation and coefficient of variation of the overall mean weekly active travel time per person was estimated from complex survey with household (HHID) as the primary sample unit (cluster) and "superdistrict" variable (R_SD) as stratification variable. (Superdistricts were combinations of census tracts or traffic analysis zones, TAZ). The SD calculation uses a variance derived from the complex survey information and assumes random sampling of a population of equal size to that of the BATS2000 survey.[46] The raw BATS data unlinked data file was read into STATA Version 7, which performed the calculation. (This standard deviation should not be confused with the standard error of a mean, which is the usual interest in the analysis of complex surveys, and whose ratio with the survey mean is often called the relative standard error, and is less frequently called the coefficient of variation of a survey mean.)

CHIS

CHIS did not have specific questions on bicycling, so age-sex ratios of walking to bicycling derived from BATS were applied to CHIS data to estimate total active transport time. CHIS was used to estimate the standard deviation and CV of weekly active transport time, based on an algorithm that took into account the complex survey design[46]. CHIS data were analyzed in SAS and a .csv datafile was exported for analysis of the CV in STATA.

Relative Travel Time

Age-sex and mode-stratified means per person per week were generated from survey weights reflecting the probability of selection and reweighting to reflect the 2000 Census Bay Area population by age, sex, and race. Age-sex relative travel times by mode were calculated by dividing age-sex travel times by that of females aged 15 to 29 years.

Relative Travel Speed

Relative age-sex specific travel speeds per person by mode were calculated from the age-sex total distances and age-sex total travel times. Age-sex relative speeds by mode were calculated by dividing age-sex speeds by that of females aged 15 to 29 years.

<u>Non-Transport Related Physical Activity</u>

Days per week and minutes per day of walking for leisure, moderate physical activity and vigorous physical activity were expressed in hours of activity per week and weighted for physical activity intensity using the age specific MET values. Physical activity at work was estimated from the number of reported work hours in the past week and usual occupation. Following the methods of Woodcock et al, each nominal work day (8 hours) was considered to involve 5 hours of physical activity at the MET value for that type of occupation. Zero hours of daytime physical activity beyond that indicated for leisure time were assigned to persons who reported doing household work, unemployed, retired, or those on vacation during the CHIS survey interview day.

Hours per week for each type of non-travel physical activity were weighted by representative MET values and summed for each individual.

Quintiles of transport related MET-weighted physical activity time were created, and the median MET of non-transport related physical activity was calculated for each quintile of transport-related MET-weighted physical activity time. This represents the additional nontransport-related physical activity that, when added to the transport related physical activity, makes up total physical activity. Age-sex specific quintiles and medians of the population distribution were calculated using sample weights (RAKED0WT).

Walking and Bicycling Miles Traveled for Top Decile Scenarios

The distance traveled in the commute to work by bicycle and walking in the population aged 16 years and older was calculated using the BATS2000 linked trip, activity, household and person files. In the linked file, the trip segments with a common purpose are linked and classified by the predominant mode (longest trip segment) and assigned a purpose at trip origin and destination (trip end). Bicycle and walking predominant modes with a purpose of the first (earliest) trip end of work were selected as work commutes. The BATS 2000 linked trip file did not have x-y coordinates of trip origins or destinations. However, the coordinates of the first trip end (i.e. earliest end time) could be identified by linking the person ID, day of travel, and mode to the BATS activity file, which did have the x-y coordinates. In a manner previously described, straight line distance between the residence and the work destination for each travel day were averaged for each person and weighted by the probability of selection in the survey (PFACTOR5). The sum of the distances was then adjusted to reflect the ratio of Google miles to straight line miles for walk-miles and bicycle-miles and trip underreporting.

The percentage of the population aged 16 years and older who commuted to work by bicycle or walked were also calculated from the BATS linked trip file. These were the individuals with work purpose trip end on travel days. The percentage of the population was determined for each of the two travel days and averaged, and weighted for the probability of selection in the survey.

The ratio of work commute miles and non-work commute miles by bicycle were calculated from the total miles in the baseline scenario (Table 2).

The components of the above formula to calculate total miles traveled for the top decile scenarios were entered into cells of an Excel worksheet to make the calculations.

Data Quality

SAS programs were routinely interrupted so that files could be manually inspected for programming errors and erroneous and missing data. While only 2% of the 3,639 bicycle segments had missing travel times and coordinates of origins and destinations, 6% had missing coordinates but non-missing travel times, and 15% had missing travel times but non-missing coordinates. Missing data of comparable magnitude were also recorded for other travel modes. To reduce the amount of potentially missing data, average speed was calculated from the segments with both complete travel times and distances. Impossibly high speeds identified were sometimes an indication of unlikely travel (e.g. cycling from Oakland to Eureka in 4 hours.) Bicycle speeds over 24 mph were considered unlikely, and were excluded from the average. The average speed was then applied to the 21% of segments that were missing either a travel time or travel distance. This approach was also applied to all other modes using maximum probable speeds: walking (6 mph), cars (75), bus/taxi (45), and rail (45).

Data Processing

The details of data processing and file management are presented in Appendix A. The instructions for configuring ITHIM are presented in Appendix B. Key model inputs are presented in Appendix C. SAS programs for converting haversine miles to Google miles and analyzing BATS data for travel distance, times, and speeds by mode are presented in Appendix D. STATA programs for determining the standard deviation and coefficient of variation in BATS and CHIS complex survey data are presented in Appendix E. SAS programs for the analysis of non-transport physical activity using CHIS data are shown in Appendix F. The data dictionary for the subset of variables used in BATS and CHIS are presented in Appendix G.

Road Traffic Injuries

Injury Matrix

A SAS program (Appendix H) was written to stratify injuries by severity and roadway type and aggregate injuries by mode of transport by the victim and striking vehicle. Missing data on striking vehicles and roadway type were reallocated to each cell based on the distribution of known values. Collisions in which only one party was listed in SWITRS were considered collisions not involving another vehicle. For two party and higher collisions, a decision rule based on the following precedence order was used to identify the striking vehicle among the parties:

truck > bus > car > motorcycle > bicycle >pedestrian.

The rule also specified that the largest vehicle other than the one operated by the victim was classified as the striking vehicle. For example, in the simplest case, in a car-bicycle collision in which only the bicyclist is injured, the car is the striking vehicle. In a three-party collision involving two trucks and a car, and injuries to one truck driver and one car occupant, this rule decides that the injured truck driver is struck by the other truck and the car occupant is struck by a truck. Also, applying this decision rule, a bicyclist who grazes a pedestrian and is subsequently injured when he crashes his bicycle onto the street, would have the pedestrian as the striking "vehicle". A small number of collisions with trains were not included in the matrix.

Baseline Injury Risks

Because the injury data covered the period from 2000 to 2008 and modal miles traveled were based on the 2000 BATS, the injury risk was calculated for a 2004 baseline year by taking the annual average of injuries for the 9-year injury period (numerator) and by scaling the BATS 2000 aggregate modal miles by the ratio of the 2004 to 2000 Bay Area population (7,053,477/6,641,061) as estimated by the California Department of Finance (www.dof.ca.gov/research/demographic/reports/estimates/e-3/by_year_2000-08/).

Data Processing

The files and locations of programs used to process injury and travel data are listed in Appendix I. Appendix J is a SAS program that uses data from the National Household Transportation Survey, 2001[29] to estimate the ratio of motorcycle to car vehicle miles in California. Appendix K is a SAS program that uses output from the MTC travel demand model to provide the percentage distribution of miles traveled by facility type by cars (classes DA, S1,S3, S3) and trucks (classes SV, HV).

Injury Matrix

The Safety Transportation Research and Education Center at the University of California, Berkeley has compiled and geocoded all fatal and serious collisions from 2000 to 2008 for California in its Traffic Injury Mapping System (TIMS).[47] Three SWITRS files for collisions, parties, and victims were downloaded from the TIMS website and used to populate an MS Access database (Appendix L). The collision file contained duplicates which were manually identified and removed. Case IDs provided by UCB SafeTREC had a number of digits beyond that allowed as a long integer storage type in MS Access, and a consecutive GEOID was created as a key to link GIS output with injury information.

Geocoding

Each geocoded injury was spatially joined in ArcGIS (Version 10) to a California 2008 TeleAtlas street layer (Appendix M), which has the federal facility type code for each street segment in the Bay Area, shown in the following table:

Roadway Type	Federal Facility Type Codes in Bay Area Street Segments
Interstate	A12, A15, A16
Arterial	A21, A25, A30, A31, A34, A35, A36, A37, A38
Local	A40, A41, A42, A44, A45, A51, A60, A62, A63, A64, A70, A71, A72

ArcGIS default settings were used to assign the street segment nearest to the geocoded collision point. Because the zip code of street segments was the only geographic area identifier in the TeleAtlas file, zip codes of Bay Area counties from USPS postal lists were used in definition queries to restrict spatial joins to streets within Bay Area counties (Appendix N).

Road Traffic Injury (RTI) Calculator

The output from the SAS program (Appendix H) to aggregate SWITRS data for the RTI matrix was manually entered into an Excel spreadsheet in the format required by ITHIM. (ITHIM Version October 7, 2011 was designed only to contrast scenarios against a baseline, rather than a business as usual scenario that might differ from the baseline. Because of this limitation the RTI calculator was used.) Formulae were created to distribute collisions with missing data on victims, striking vehicles, and roadway type. Separate worksheets were added to:

- provide distance by roadway type for each active transport scenario
- calculate the baseline risk (stratified by severity and roadway type) for each cell in the matrix and apply the baseline risk to distances traveled by the victim and striking vehicle for each scenario, and
- use pivot tables to sum up injuries by severity, type of victim and striking vehicle, and roadway

type for each scenario.

Additional worksheets are copies of the U.S. Global Burden of Disease, scaled and adjusted to the Bay Area population, taking into account the differences in U.S. and Bay Areas mortality rates. The RTI calculator allows the user to specify the value of the exponent in the power function that describes the relationship between the number of injuries and distances traveled. The default value is 0.5 (square root).

Air Pollution ($PM_{2.5}$)

Personnel from the Bay Area Air Quality Management District ran the EMFAC2007 model for vehicle emissions and the MPEM model for airborne $PM_{2.5}$ concentrations for active transport and low carbon driving scenarios. Population-weighted means were applied to the appropriate age groups in the ITHIM model, which was used to calculate attributable fractions and health outcomes in the Global Burden of Disease database.

Calculations for deaths and years of life lost were carried out in ITHIM version October 7, 2011. To assess the independent impact of air pollution on ischemic heart disease, hypertensive heart disease, and stroke, relative risks for physical activity were held constant at 1.0 in each scenario.

RESULTS

Physical Activity

Figure 3 presents model-estimated distributions of daily physical activity for each active transport scenario. Active transport miles per person per year range from 189 in BAU to 1,400 for the carbon goal (AT_C), representing an increase from 2.1% to 15% of total miles (Table 3). Per capita miles traveled increased 16-fold for bicycling and 3-fold for walking comparing BAU to AT_C.

Age and sex specific medians of weekly active transport times are presented in Table 7. Median times for the entire population ranged from 31 min/wk/person at baseline to 154 min/wk/person with AT_C. Median active transport times decrease with age. At baseline, walking accounts for a large share of active travel time, but the ratio of walking to bicycling times narrows as travel time increase in other scenarios.

Table 8 summarizes cause-specific and all causes co-benefits for premature deaths and disability adjusted life years for active transport scenarios compared to business as usual. Because there is no change in the physical activity distribution between BAU and the low carbon driving scenario, the latter does not generate any health co-benefits related to physical activity.

The largest attributable fractions were observed for ischemic heart disease, stroke, and diabetes, increasing from 6% to 15% for progressively increasing levels of active transport. Even the least ambitious active transport scenario would annually avert 892 deaths and 17,068 DALYs in the SF Bay Area population.

To assess the impact of uncertainties in the value of key parameters such as the coefficient of variation in active transport time and the MET output at various speeds of walking and bicycling, we performed sensitivity analyses, varying CV and speeds of active transport time, and METS for walking and bicycling. The absolute change in the burden of disease estimates for cardiovascular disease and diabetes was ± 3% (Table 9).

Road Traffic Injuries

Annual mean modal distances are presented in Table 9 for baseline, BAU, and each scenario of active transport. Modal distributions by roadway type are presented in Table 10. An example of the road traffic matrix is presented in Table 11, using fatal injuries on Bay Area arterial roads from 2000 to 2008. Table 12 gives the annual number of injuries by injury severity and mode of victim and striking vehicle assuming a square root function between injuries and distances traveled.

Both fatal and non-fatal serious injuries increase with increasing levels of active transport. A large share of the increase is borne by bicyclists and pedestrians being struck by cars on arterials and local streets (Tables 13-14). As active transport substitutes for increasing car miles, there are fewer injuries in car-car collisions, but this does not offset the increased injuries to pedestrians and bicyclists in car collisions. Compared to BAU, the attributable fraction of fatal injuries ranged from 9% to 17% for the range of active transport scenarios (Table 15). For serious injuries, the attributable fraction ranged from 14% to 31%.

The values for the exponential power function were varied from 0.33 to 1 (Table 16). At a value of 0.33, the attributable fraction of fatal injuries comparing BAU with active transport scenarios ranged from 5% to 8%. Attributable fractions for non-fatal injuries ranged from 8% to 15%. At a value 1.0, the attributable fraction for fatal injuries ranged from 25% to 85%, and that for nonfatal injuries ranged from 42% to 182%.

Air Pollution

Table 17 gives the percent reductions in vehicle miles traveled and corresponding levels of constituents of $PM_{2.5}$ estimated from the EMFAC emissions model. Table 18 gives the overall population weighted mean $PM_{2.5}$ concentrations for the Bay Area by scenario and county-specific reductions. Table 19 gives cause-specific and totals for reductions in premature deaths and years of life lost due to $PM_{2.5}$ reductions from the BAU scenario for low carbon driving and active transport scenarios.

There was an overlapping range of co-benefits from low carbon driving and active transport. For the most ambitious adoption of low carbon driving and active transport, low carbon driving would achieve more than double the co-benefits of active transport.

All Components

The net health impacts of co-benefits of physical activity and low carbon driving and harms from pedestrian and bicyclist injuries is presented in Table 20 and Figure 4. In the most ambitious active transport and low carbon driving strategies, the Bay Area would avoid 2,321 deaths, 23,337 years of life lost, and 15,849 years living with disability. The overwhelming share of the co-benefit is from physical activity associated with active transport. Air-pollution related reductions in the disease burden are less than 1% of those from physical activity. Road traffic injuries are a harm that diminishes the physical activity co-benefits by approximately 13%.

DISCUSSION

The main findings are that active transport scenarios generate significant health co-benefits and carbon reductions for the SF Bay Area. For the scenario with the highest levels of physical activity (AT_C), ITHIM predicted a 15% reduction in disease burden due to cardiovascular diseases and diabetes, a 10% reduction due to dementia, and approximately 5% reductions each for breast cancer, colon cancer, and depression. Risk reduction of this magnitude would rank among the most notable public health achievements in the modern era [48], and reduce the estimated $34 billion in California annual costs from cardiovascular disease[49, 50] and other chronic conditions such as obesity. If adopted widely, active transport alone could achieve over half of the 20% reduction in cardiovascular disease rates set as a national goal in Healthy People 2020[51], and decrease the overall disease burden from all causes by 2.9%. The AT_C scenario would also achieve the U.S. Surgeon General's recommendation that adults engage in at least 150 minutes of at least moderate physical activity weekly[52]. ITHIM predicts that even scenarios with modest increases in active transport over BAU achieve important health co-benefits.

The ITHIM model predicts an increase in road traffic injuries to pedestrians and bicyclists with increasing levels of active transport. In the most ambitious active transport scenario, this potential harm is approximately 14% of the benefit from physical activity. The experience of European countries with high rates of bicycling and walking suggests that robust investments in infrastructure, education, and enforcement may substantially reduce this harm[53]. The model also indicates that co-benefits from air pollution reductions due to low carbon driving or active transport are less than 1% of those gained from physical activity.

The other principal finding is that wide scale adoption of active transport could have as large an impact on carbon reduction as strategies based on low carbon driving. The 14.5% absolute reduction indicated by the AT_C scenario is mid-range among the carbon reductions possibly achieved by reengineering automobiles and fuels. Although the top decile and short trips scenarios make important per capita carbon reductions, these scenarios do not substantially reduce total aggregate emissions from the 2000 baseline, largely because of population growth. This highlights that reducing greenhouse gas emissions from transport will require both a modal shift and lower carbon driving. Further reductions would require decreases in per capita travel distances.

This is the first application of ITHIM in the United States, and there are noteworthy similarities and differences with previous research. In London, compared to BAU, active transport distances increased from 3% (128 mi/person/y) to 19% (1,128 mi/person/y). In the SF Bay Area, active transport distances increased from 2% (189 mi/person/y) to 15% (1,400 mi/person/y). Although the relative increase in walking was similar, bicycle miles increased 9-fold in London and in 16-fold in the SF Bay Area. On a per capita basis at BAU, SF Bay Area residents traveled 2.5 times farther per year by automobile than Londoners (8,247 mi vs. 3,146 mi). Injury risks to pedestrians and bicyclists at baseline also appear to be higher in the Bay Area than London (RR=3.3). These differences account for SF Bay Area having higher share of burden from injuries than London and more modest reductions in carbon emissions, despite covering longer active transport distances.

Strengths and Limitations

Among its strengths, ITHIM has relatively simple inputs derived from travel and health surveys and an international database of health outcomes. Its spreadsheet format can be implemented on desktop computers. The aim of model is to quantify health co-benefits rather than prescribe scenarios. This allows ITHIM to complement travel demand and other models that lack a health component but predict how mode share and travel distances change in response to policies, projects, and programs. Nonetheless, neither ITHIM nor the scenarios we developed provide details on the kinds of changes to policy, infrastructure, or systems that would accompany increased active travel. Bay Area cities already in the top decile of walking and bicycling model best practices that include separate bicycle lanes, traffic calming in residential areas, intersection improvements (cross walks, count down signals, signage, bulb-outs, etc.) and community level programs for youth and adolescent safety education and for organized transport in conjunction with state and local health departments, public schools, public works and transportation agencies, and law enforcement personnel (e.g., Safety Routes to School, Complete Streets).

The model assumes that the health co-benefits occur in a single "accounting year", although the changes in the physical activity distribution and low carbon driving are likely to gradually occur over time, and that these co-benefits will be maintained in subsequent years. The model assumes that other factors influencing physical activity, METS and pollution levels are time invariant, including non-transport physical activity and body weight distributions. Secular trends in disease rates are not factored into the model. Thus, ITHIM makes several simplifying assumptions to project the 2010 burden of disease to a future steady-state in which only active transport varies between the baseline and alternative scenarios.

Physical Activity

As in most models, some key parameters were uncertain due to limitations data quality and availability. Because the CV of mean weekly active transport time could not be calculated directly from two-day travel surveys, CHIS offered an alternative because it queried physical activity over a week. The resulting CV was much larger than values found in previous studies based on English and European populations [4]. This suggests that compared to London, the SF Bay Area population may have a higher proportion of physically inactive individuals and an equal or greater share of very active walkers or bicyclists. Speeds calculated from distances and self-reported travel times in BATS were low for all modes of travel, suggesting a systematic artifact related to travel diary design or recall bias. The increasing use of global position devices in travel surveys may improve data quality. Published data were available for walking speeds, but not for bicycling speeds. Dill [24] reported an average speed of 10.8 mi/h for 166 Portland, OR bicyclists. But because Dill's sample may have represented more enthusiastic cyclists than the norm, we used lower speeds based on London and Dutch bicyclists [8].

To assess the impact of these uncertainties, we performed sensitivity analyses, varying CV and speeds of active transport time, and METS for walking and bicycling. The absolute change in the burden of disease estimates for cardiovascular disease and diabetes was ± 3% (Table 9).

Injuries

The findings for road traffic injuries are sensitive to the value chosen for the exponent in the relationship between injuries and miles traveled. At exponent values similar to those reported in the literature (0.33 to 0.5), road traffic injuries create a modest decrease in co-benefits compared to those gained from physical activity. However, as the relationship becomes linear, the number of injuries increases to a level that subtracts a sizable proportion of the potential benefits from physical activity. While the exponential relationship between injuries and pedestrian and bicyclist travel is broadly acknowledged in the literature, there is debate to whether the relationship is causal, given that it is based largely on cross sectional epidemiologic data. Some researchers believe that sharing road space with a large number of co-travelers triggers anticipatory driving behaviors in motorists, pedestrians, and bicyclists – the so called "safety in numbers" hypothesis.[9] Others posit a dialectic process in which policy change and improvements in safety infrastructure are put into place before and/or because injuries occur.[54] Whatever the resolution of this debate, a nonlinear relationship for modelling injuries appears to be the most realistic assumption.

In Woodcock's previous research, only injuries occurring to London residents in the geographic boundaries of greater London were included in the road traffic injury matrix. Unfortunately, SWITRS reports injuries by location of occurrence and does not include information on the residence of parties. A large share of road traffic injuries of Bay Area residents are likely to occur within the 9 county Bay Area. However, non-residents, including tourists, visiting the Bay Area, may have been included in SWITRS collisions. It is generally recognized that no one data source is likely to ascertain all injuries related to traffic collisions.[55] Some parties forgo medical treatment and some injuries become apparent to victims only after police reports are filed. Because this study focused on fatal and serious injuries, the level of underascertainment is likely to be much lower had less serious injuries been included. While minor injuries and complaints of pain may add to the burden of disease, their contribution to DALYs is minor.[4]

Air Pollution ($PM_{2.5}$)

A number of simplifying assumptions were used to generate average $PM_{2.5}$ exposure levels for the Bay Area population. These include 1) reductions in VMT occurring proportionately along all road segments in the roadway network in all geographic areas and 2) ambient $PM_{2.5}$ concentrations are those actually experienced by residents. The latter assumption is often used, however, for epidemiology studies of air pollution.

Assuming geographic uniformity in VMT reductions can introduce a dilution effect that biases concentrations downward. There may be geographic hot spots where car-related $PM_{2.5}$ makes an important contribution to the overall $PM_{2.5}$ levels, and the burden of disease will be higher in those areas. Active transport is more likely to impact local roads, collectors, and arterials, so $PM_{2.5}$ -related to short trips on local roads and arterials are more likely to be impacted than longer trips on highways. This assumption on uniform VMT reductions in the entire roadway network is more likely to be met with Low Carbon Driving.

The level of geographic resolution differs between emission and air shed models. County appears to be the finest level of resolution in the EMFAC; the air shed model predicts $PM_{2.5}$ concentrations in 2 km grids. At this time the models can only be reconciled at the air basin or county level. $PM_{2.5}$ levels are subject to temporal variation of season, day of week, and time of day, which may influence average and peak levels and the burden of disease. Additional health effects related to ozone, NO_x, SO_2, and reactive organic gases were not included, so the overall impact may have been underestimated.

Some researchers have suggested that increased active transport along busy roadways exposes pedestrians and bicyclists to the harmful effects of automotive exhaust, potentially cancelling out the benefits of physical exercise.[56] However, on a population basis, the health co-benefits of physical activity appear to far exceed harms caused by walking and bicycling in polluting traffic [57].

Other

The scope of current effort also did not include indirect effects of changes in physical activity on obesity, changes in use of public transit, active transport in the journey to school, potential health impacts in children, and greenhouse gases from heavy trucks and public transit. Several of these factors add to the population distribution of physical activity, such as increased walking in public transit users compared to non-users[58]. Future improvements in ITHIM may address some of these limitations.

Summary and Conclusion

In summary, ITHIM demonstrated that active transport has the potential to substantially lower both the burden of disease and carbon emissions, and can be used to complement other modeling strategies in the transportation sector. By combining active transport with low carbon driving technologies the Bay Area (and California) will be better able to achieve its carbon reduction goals.

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FIGURES AND TABLES

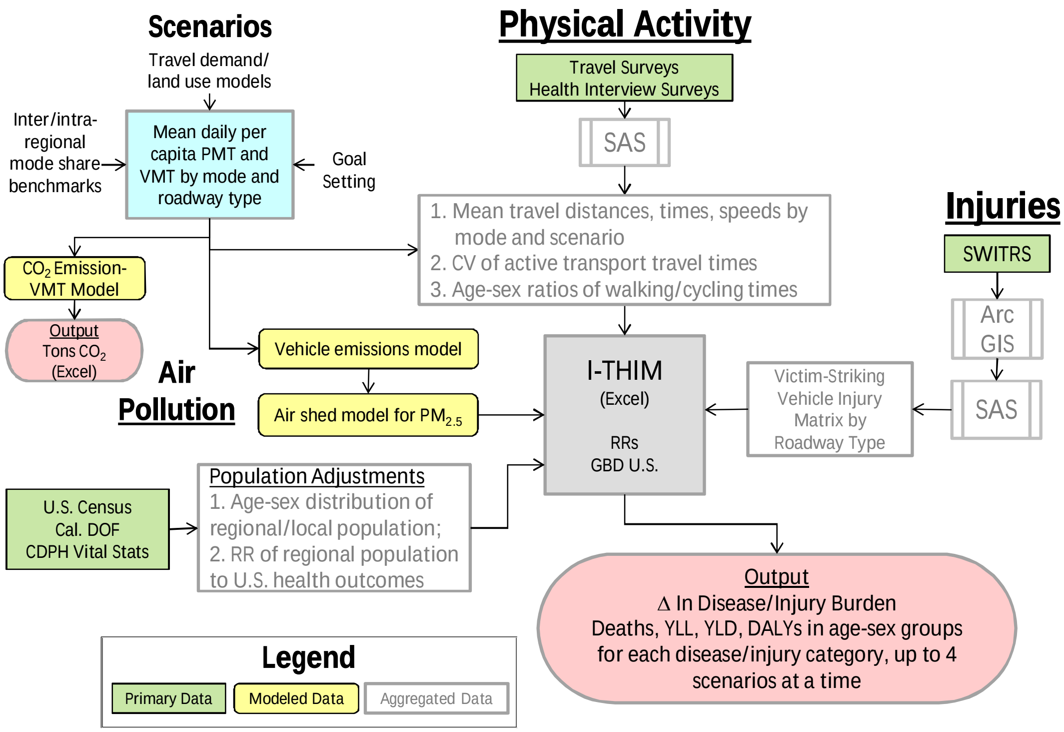

Figure 1. Inputs and Outputs of the Integrated Transport and Human Health Model (ITHIM).

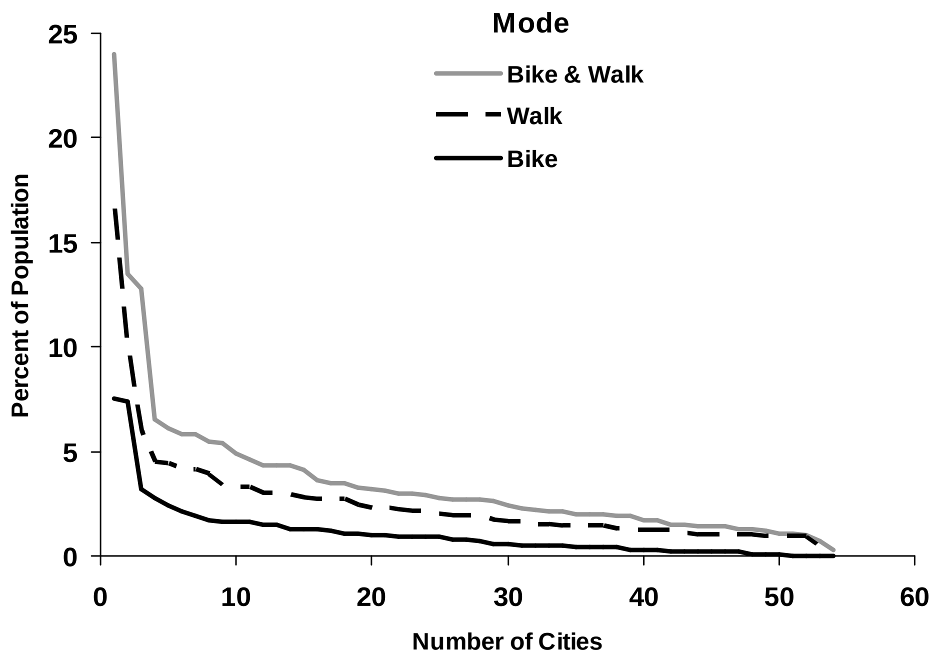

Figure 2. Percent of Population Aged ≥16 Years with a Journey to Work by Bicycle or Walking, 54 SF Bay Area Cities, 2007-2009.

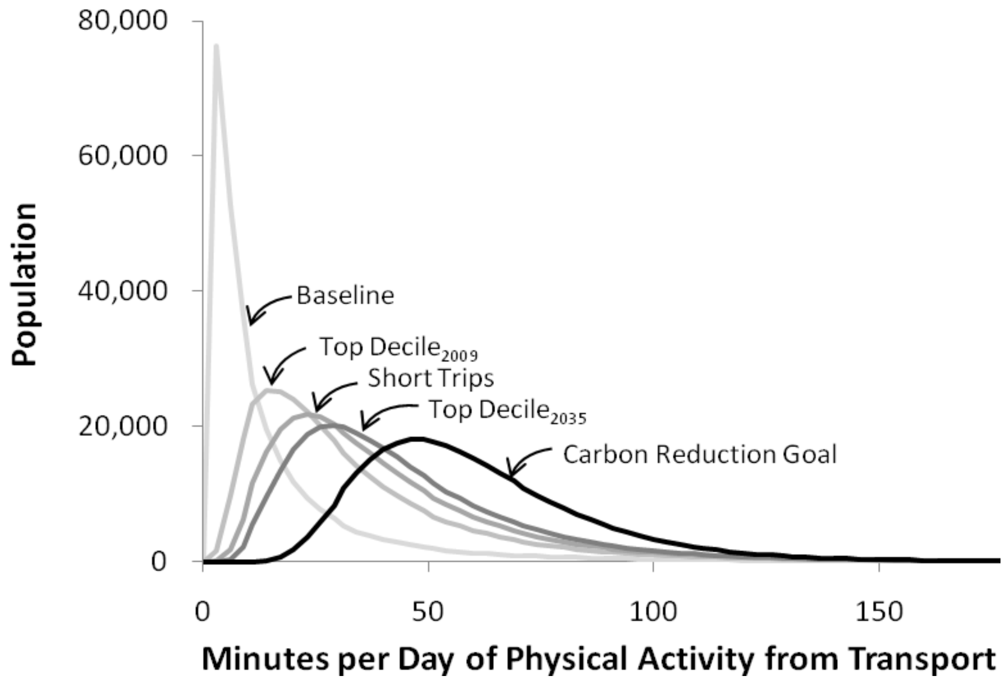

Figure 3. Model-Estimated Daily Physical Activity Distributions For Active Transport Scenarios.

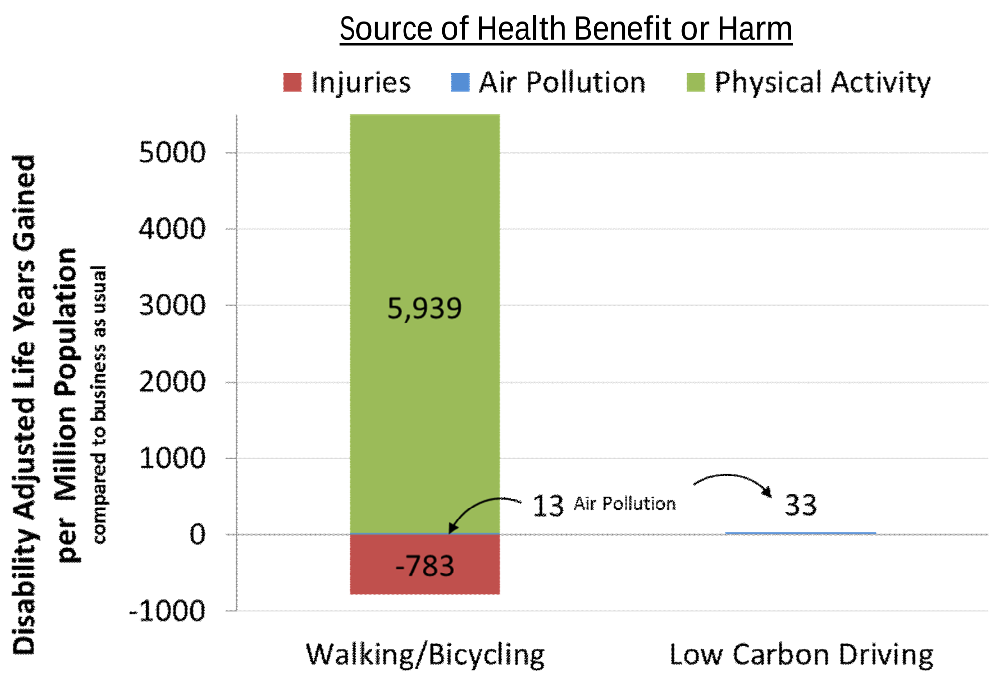

Figure 4. Annual Health Co-Benefits of Active Transport and Low Carbon Driving, Bay Area.

Table 1. Summary of Data Sources and ITHIM Model Inputs

Model Parameter	Data Source(s)
Health Outcome	
DALY, condition specific	• Global Burden of Disease database, WHO
Age-sex specific mortality rate ratios of Bay Area and U.S. for diseases of interest, 2004	• Global burden of disease database for U.S. mortality rates 2004 and California Dept. of Public Health for Bay Area mortality rates, 2004
U.S. and Bay Area population, 2004	• U.S. (Census Bureau) and Bay Area (Department of Finance), 2004
Road Traffic Injuries	• Statewide Integrated Traffic Records System (SWITRS)
Disease specific RRs	• Meta-analyses from an exhaustive literature review
Travel Distances for Scenarios	
Distance traveled by mode for BAU/Baseline/LCD	• Bay Area Travel Survey, 2000; Statewide Travel Model for heavy goods vehicles (UCD)
Top Decile$_{2009/2035}$	• Census Bureau, 2000; American Community Survey, 2005-2007, 2007-2009 and BATS
Travel distance by roadway type	• MTC fully loaded travel demand model 2006 for cars and trucks; Bay Area bus system operator annual reports of revenue miles and TransBay routes
Travel Times and Speeds	
Population mean active transport time	• Derived from distance traveled per person divided by standard speeds for walking (Oberg) and bicycling (synthesis of Dutch/English bicyclists)
Coefficient of Variation of overall mean active transport time	• CHIS Adult Survey 2005 walking data (walking for fun & transport) and BATS 2000 age-sex specific ratios of walking to bicycling
Population distribution of active travel time	• Population weights from 2010 U.S. Census of Bay Area Counties
Absolute travel speeds for walking and cycling	Age-standardized (Bay Area 2000 population) walking speeds from Oberg age-sex specific rates; bicycling speeds based on age-sex ratios of English Dutch cyclists
Relative travel speeds for walking and cycling	• BATS 2000
Ratios of cycling: walking times	• BATS 2000 for baseline and modeled data for high active transport scenarios
Non-Transport Physical Activity Time	• CHIS 2005 Adult survey data of SF Bay Area Counties
Energy Expenditures for Physical Activities	• Compendium of physical activities ((walking and cycling at varying speeds and non- transport physical activity)
Carbon emissions	• BAU and Low Carbon Driving scenario (Lutsey); Active transport scenarios use MTC's BASSTEGG model for emission factor and BATS distances
$PM_{2.5}$ Concentration	• EMFAC2007 vehicle emissions model and BAAQMD air shed model

Table 2. Global Burden of Disease Cause Categories and Corresponding ICD-10 Codes Used in ITHIM

Title in Global Burden of Disease Database	GBD Code	ICD-10*	CDPH VSQS#
Colon and rectum cancers	U064	C18-C21	C18-C21
Breast Cancer	U069	C50	C50
Cardiovascular Disease	U106-U108		
Hypertensive heart disease	U106	I10-I13	I10-I13
Ischemic heart disease	U107	I20-I25	I20-I25
Cerebrovascular disease	U108	I60-I69	I60-I69
Alzheimer and other dementias	U087	F01, F03, G30-G31	F01, F03, G30-G31
Diabetes mellitus	U079	E10-E14	E10-E14
Depression (Unipolar depressive disorders)	U082	F32-F33	F30-F39
Road Injuries	U150	V01-V89, Y85	[V01-V99,Y85 (Transport)] – [V90-V94 (Water)] – [V95-V97 (Air)]
Cardio-respiratory: a. Lower respiratory infections, upper respiratory infections	U39-U40	J10-J18, J20-J22, J00-J06	J00-J06; J09-J11; J12-J18; J20-J22, U04.9
b. Same as cardiovascular above + inflammatory heart diseases	U106-U109	I10-I13, I20-I25, I60-I69, I30-I33, I38, I40, I42	Same as above I30-I31,40; I33; I36-I38; I42; [J09-J98] – [J09-J11; J12-J18; J20-J22, U04.9]
c. Chronic obstructive pulmonary disease, Asthma, Other respiratory diseases	U112-U114	J40-J44, J45-J46, J30-J39,J47-J98	
Lung cancer (Trachea, bronchus and lung)	U67	C33-C34	C33-C34
Acute Respiratory Infections (children < 5 years) Lower respiratory infections, upper respiratory infections	U39-40	J10-J18, J20-J22, J00-J06	J00-J06; J09-J11; J12-J18; J20-J22, U04.9

* International Classification of Diseases 10th Revision

California Department of Public Health Vital Statistics Query System equivalents

Table 3. Annual Mean Miles Traveled Per Person by Mode and Percent Mode Share for Health Co-Benefit Model Scenarios, 2035

Scenario	Units	Automobile/ Light Truck Driver*	Automobile/ Light Truck Pas-senger	Heavy Goods Vehicles	Bus/ Taxi	Rail	Bicycle	Walk	Total
Baseline	Miles	5,820	2,034	385	228	290	62	127	8,947
	%	65.1	22.7	4.3	2.5	3.2	0.7	1.4	100.0
Business as Usual	Miles	6,111	2,136	385	228	290	62	127	9,339
	%	65.4	22.9	4.1	2.4	3.1	0.7	1.4	100.0
Low Carbon Driving	Miles	6,111	2,136	385	228	290	62	127	9,339
	%	65.4	22.9	4.1	2.4	3.1	0.7	1.4	100.0
Active Transport									
Top Decile$_{2009}$	Miles	5,869	2,052	385	228	290	274	241	9,339
	%	62.8	22.0	4.1	2.4	3.1	2.9	2.6	100.0
Top Decile$_{2035}$	Miles	5,652	1,976	385	228	290	488	320	9,339
	%	60.5	21.2	4.1	2.4	3.1	5.2	3.4	100.0
Short trips	Miles	5,694	1,937	385	228	290	575	230	9,339
	%	61.0	20.7	4.1	2.4	3.1	6.2	2.5	100.0
Active Transport Carbon Reduction Goal AT$_C$	Miles	4,502	1,574	385	650	829	1,000	400	9,339
	%	48.2	16.8	4.1	7.0	8.9	10.7	4.3	100.0
Active Transport Carbon Reduction Goal AT$_C$ – No Pub. Transit	Miles	5,214	1,823	385	228	290	1,000	400	9,339
	%	55.8	19.5	4.1	2.4	3.1	10.7	4.3	100.0

Note: Assumes a constant car-driver to car-passenger mile ratio (2.9:1) of the BAU scenario

Table 4. Percent of the Population Aged ≥16 Years Journey to Work by Bicycling and Walking, Baseline and 2035 Linear Extrapolation, Highest Decile of SF Bay Area Cities

Mode/City	Total Pop., 2007-2009	Baseline Period 2000*	2007#	2009†	2035§
Bicycle					
Berkeley	101,426	5.6	6.0	7.4	11.8
Mountain View	70,890	2.0	3.1	3.2	7.6
Palo Alto	58,879	5.6	6.2	7.5	12.5
Rohnert Park	40,583	1.0	1.0	2.4	5.7
San Francisco	807,515	2.0	2.2	2.8	5.1
Midpoint of range				4.9	8.8
Walking					
Berkeley	101,426	14.9	15.4	16.6	21.2
Morgan Hill	37,865	1.0		4.5	16.3
Oakland	403,267	3.7	4.3	4.4	6.6
Palo Alto	58,879	3.2	5.8	6.0	16.0
San Francisco	807,515	9.4	9.5	10.0	11.8
Midpoint of range				10.5	13.9

* 2000 US Census
# 3-year average 2005-2007, American Community Survey
† 3-year average 2007-2009, American Community Survey
§ Linear annual increase in journey to work population from 2000-2009 extrapolated to 2035 (~0.15%/yr for bicycle and ~; 0.25%/yr for walking)

Table 5. Distribution of Car Miles Traveled by Trip Length, BATS 2000

Distance (mi)	Car-Driver Miles (2-day)*	Car-Driver Percent	Car-Passenger Miles (2-day)	Car-Passenger Percent
>0-1.49	5,091,609	2.2	2,555,593	3.3
1.49-4.99	26,083,020	11.4	11,907,764	15.3
5+	197,105,237	86.3	63,235,406	81.4

* Aggregates all trip segments reported in two-day period of travel diary

Table 6. Annual Aggregate and Per Capita Annual Greenhouse Gas Emissions from Different Transport Scenarios*, San Francisco Bay Area, 2035

Scenario	Aggregate Transport CO_2 Emissions (Million Metric Tons)	Percent CO_2 Emissions Reduction from 2000 baseline	Population Millions	Transport CO_2 Emissions Per Person: Metric Tons	Transport CO_2 Emissions Per Person: %
Baseline, 2000	27.9	0.0	6.6	4.2	0.0
2035:					
Business as Usual	23.3	-16.5	9.1	2.6	-39.1
Low Carbon Driving	18.5-25.4	-9 to -33.5	9.1	2.0-2.8	-33.6 to -51.5
Active Transport					
Top $Decile_{2009}$	28.1	+0.9	9.1	3.1	-26.4
Top $Decile_{2035}$	26.7	-4.2	9.1	2.9	-30.1
Short Trips	26.7	-4.1	9.1	2.9	-30.6
Carbon Reduction Goal#	23.8	-9 to -14.5	9.1	2.6	-37.6
Combined†	15.8	-43.1	9.1	1.7	-58.5

* Automobiles and light duty trucks

9% reduction assumes active transport miles distributed among car-passenger and car-driver in same ratio as BAU (2.9); 14.5% reduction assumes active transport miles distributed only to car-driver

† Combined is adding low carbon driving (-33.5%) to active transport (-14.5%), adjusting to avoid double counting (i.e. substitution of active transport miles is in proportion to LCD and non-LCD miles).

Table 7. Median* Weekly Active Transport Time in Minutes by Age and Sex and Scenario

Age in Years	Baseline		Top Decile$_{2009}$		Short Trips		Top Decile$_{2035}$		AT_C	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
15–29	44	42	97	92	118	103	126	129	187	188
30–44	36	31	81	73	99	86	99	100	161	158
45–59	33	26	75	63	94	73	94	101	152	149
60–69	23	30	61	67	75	73	91	116	142	158
70–79	24	24	56	55	65	60	86	96	123	120
80+	21	15	45	32	46	33	65	56	94	71
Total†	33	29	74	66	99	76	100	100	140	129
Walking	26	26	49	50	45	45	63	64	69	69
Bicycling	7	3	25	16	54	31	37	36	71	58
Both Sexes:										
Total	31		70		87		100		154	
Walking	26		50		45		64		79	
Bicycling	5		21		42		36		75	

* Medians were back-transformed to $\log_{10}$ scale.
† All ages, 0 to 80+
AT_C, Active Transport Carbon Reduction Goal

Table 8. Annual Physical Activity Health Co-Benefits and Attributable Fractions (AF) of Active Transport Compared to Business As Usual by Scenario by Cause of Death and Disability, Bay Area

	Burden of Disease				Attributable Fraction, Percent			
Item by Cause*	TD_{2009}	TD_{2035}	Short Trips	Carbon Goal	TD_{2009}	TD_{2035}	Short Trips	Carbon Goal
Premature Deaths								
Ischemic Heart Disease	-444	-794	-728	-1,154	-5.2	-9.3	-8.5	-13.4
Hypertensive Heart Disease	-85	-152	-141	-224	-5.2	-9.2	-8.5	-13.6
Stroke	-195	-354	-326	-517	-4.9	-9.0	-8.3	-13.1
Diabetes	-73	-129	-122	-189	-5.2	-9.1	-8.6	-13.3
Dementia	-63	-140	-121	-218	-2.8	-6.2	-5.4	-9.6
Breast Cancer	-15	-32	-31	-48	-1.5	-3.3	-3.1	-4.9
Colon Cancer	-17	-34	-31	-53	-1.8	-3.0	-3.2	-5.6
Depression	-0.4	-1	-1	-1	-2.2	-4.8	-4.1	-7.4
Total	-892	-1,636	-1,501	-2,404	-1.8	-3.2	-3.0	-4.8
Years Life Lost								
Ischemic Heart Disease	-5,214	-8,810	-8,348	-12,959	-5.9	-10.0	-9.5	-14.8
Hypertensive Heart Disease	-1,216	-1,998	-1,897	-2,990	-6.1	-10.1	-9.6	-15.1
Stroke	-2,200	-3,780	-3,597	-5,554	-5.7	-9.8	-9.3	-14.4
Diabetes	-1,190	-1,986	-1,902	-2,961	-5.8	-9.7	-9.3	-14.4
Dementia	-410	-911	-808	-1387	-2.8	-6.3	-5.6	-9.6
Breast Cancer	-315	-647	-614	-955	-1.7	-3.4	-3.3	-5.1
Colon Cancer	-240	-462	-427	-728	-1.8	-3.5	-3.2	-5.5
Depression	-4	-7	-7	-11	-2.3	-4.9	-4.4	-7.5
Total	-10,789	-18,601	-17,600	-27,545	-1.5	-2.6	-2.4	-3.8

* International Classification of Disease, 10th Revision cause codes: cardiovascular disease (hypertensive heart disease, I10-I13; ischemic heart disease, I20-I25; cerebrovascular disease, I60-I69), diabetes (E10-E14); dementia (Alzheimer's disease, G30-G3, organic dementias, F01, F03), breast cancer (C50), colon cancer (C19), depression (F32, F33).

† Denominator is entire disease burden (136 causes of death and disability) in SF Bay Area (Premature Deaths: 50,369; YLL: 721,469; YLD: 604,013; DALYs: 1,325,482)

Table 8. Annual Physical Activity Health Co-Benefits and Attributable Fractions (AF) of Active Transport Compared to Business As Usual by Scenario by Cause of Death and Disability, Bay Area (Continued)

	Burden of Disease				Attributable Fraction, Percent			
Item by Cause*	TD_{2009}	TD_{2035}	Short Trips	Carbon Goal	TD_{2009}	TD_{2035}	Short Trips	Carbon Goal
Years Living With Disability								
Ischemic Heart Disease	-444	-746	-715	-1,100	-6.1	-10.3	-9.9	-15.2
Hypertensive Heart Disease	-236	-248	-226	-365	-4.8	-8.8	-8.0	-12.9
Stroke	-1,157	-1,876	-1,785	-2,830	-6.5	-10.5	-10.0	-15.9
Diabetes	-1,529	-2,424	-2,303	-3,707	-6.2	-9.9	-9.4	-15.1
Dementia	-1,206	-2,662	-2,414	-4,029	-2.9	-6.4	-5.8	-9.6
Breast Cancer	-85	-167	-158	-250	-1.7	-3.4	-3.2	-5.0
Colon Cancer	-55	-106	-98	-166	-1.8	-3.5	-3.2	-5.5
Depression	-1,666	-2,946	-2,703	-4,784	-2.0	-3.5	-3.2	-5.7
Total	-6,378	-11,175	-10,402	-17,231	-1.1	-1.9	-1.7	-2.9
DALYs								
Ischemic Heart Disease	-5,658	-9,556	-9,064	-14,059	-6.0	-10.1	-9.5	-14.8
Hypertensive Heart Disease	-1,352	-2,246	-2,123	-3,355	-6.0	-9.9	-9.4	-14.8
Stroke	-3,357	-5,655	-5,382	-8,384	-5.9	-10.0	-9.5	-14.9
Diabetes	-2,719	-4,410	-4,205	-6,668	-6.0	-9.8	-9.3	-14.8
Dementia	-1,617	-3,573	-3,222	-5,416	-2.9	-6.4	-5.7	-9.6
Breast Cancer	-400	-815	-773	-1,205	-1.7	-3.4	-3.2	-5.1
Colon Cancer	-295	-568	-524	-894	-1.8	-3.5	-3.2	-5.5
Depression	-1,670	-2,954	-2,709	-4,795	-2.0	-3.5	-3.2	-5.7
Total	-17,068	-29,777	-28,002	-44,776	-1.3	-2.2	-2.1	-3.4

* International Classification of Disease, 10th Revision cause codes: cardiovascular disease (hypertensive heart disease, I10-I13; ischemic heart disease, I20-I25; cerebrovascular disease, I60-I69), diabetes (E10-E14); dementia (Alzheimer's disease, G30-G3, organic dementias, F01, F03), breast cancer (C50), colon cancer (C19), depression (F32, F33).

† Denominator is entire disease burden (136 causes of death and disability) in SF Bay Area (Premature Deaths: 50,369; YLL: 721,469; YLD: 604,013; DALYs: 1,325,482)

Table 9. Sensitivity Analysis of CV and METS (walking/cycling speeds) and Burden of Disease Measures

		Deaths				YLL				YLD				DALYS			
		Low CV + Hi METS*		Hi CV + Low METS#		Low CV + Hi METS		Hi CV + Low METS		Low CV + Hi METS		Hi CV + Low METS		Low CV + Hi METS		Hi CV + Low METS	
		N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Breast Cancer	M	0	5.1	0	3.6	0	5.0	0	3.7	0	5	0	3.6	0	5.0	0	3.7
	F	-50		-36		-935		-691		-246		-180		-1,181		-870	
Colon Cancer	M	-30	6.0	-22	4.3	-377	5.6	-268	4.0	-125	6	-88	4.0	-502	5.9	-357	4.2
	F	-26		-18		-363		-262		-97		-71		-460		-333	
CVD	M	-1,030	14.5	-801	10.8	-13,217	15.6	-9,804	11.5	-1,965	16	-1,444	11.7	-15,183	15.7	-11,248	11.5
	F	-1,021		-732		-9,992		-7,317		-2,068		-1,474		-12,060		-8,791	
Depression	M	-1	8.5	-0	5.9	-4	8.2	-3	5.8	-1,239	6	-842	3.9	-1,243	5.6	-845	3.9
	F	-1		-1		-8		-6		-3,478		-2,477		-3,487		-2,483	
Dementia	M	-75	11.0	-56	7.6	-486	10.8	-369	7.6	-1,364	10.5	-1,030	7.5	-1,850	10.6	-1,398	7.5
	F	-175		-116		-1,071		-728		-3,033		-2,106		-4,104		-2,834	
Diabetes	M	-103	14.3	-77	10.6	-1,568	15.1	-1,136	11.0	-1,395	15	-1,018	11.0	-2,963	15.3	-2,153	11.0
	F	-99		-72		-1,529		-1,111		-2,395		-1,691		-3,924		-2,802	
Total	M	-1,209	0.6	-935	0.5	-15,463	0.6	-11,433	0.5	-5,555	0.4	-4,012	0.3	-21,018	0.5	-15,445	0.4
	F	-1,304		-929		-13,482		-9,825		-10,137		-7,161		-23,619		-16,986	

* Sensitivity Analysis Scenario 3 (ATc): Baseline CV = 1.17, METS = 6 Bicycle, walk speeds start with Oberg and increase , bike speeds ~7 MPH

Sensitivity Analysis Scenario 3 (ATc): Baseline CV = 1.85, METS = 4 Bicycle, walk speeds start with Oberg and increase , bike speeds ~7 MPH

Table 10. Person Miles and Vehicle Miles Traveled Per Person Per Year for Baseline and Scenarios†

Mode	Person Miles Per Person Per Year						Vehicle Miles Per Person Per Year					
	Baseline	BAU	TD2009	TD2035	Short Trips	AT_C	Baseline	BAU	TD2009	TD2035	Short Trips	AT_C
Pedestrian	127	127	241	320	230	400	127	127	241	320	230	400
Bicycle	62	62	274	488	575	1,000	62	62	274	488	575	1,000
Car	7,854	8,247	7,921	7,628	7,631	7,036	5,820	6,111	5,869	5,652	5,694	5,214
Bus*	228	228	228	228	228	228	12	12	12	12	12	12
Truck#	737	737	737	737	737	737	737	737	737	737	737	737

* Bus VMT based on 2005 revenue miles divided by Bay Area 2004 population

Truck VMT from UCD Statewide travel model 2008 for medium and heavy trucks (FHWA vehicle classes 6-13)

Table 11. Distribution of Miles Traveled by Mode and Roadway Type

Mode	Roadway Type		
	Highway	Arterial	Local
Pedestrian	0.00	0.25	0.75
Bicycle	0.00	0.47	0.53
Motorcycle	0.60	0.31	0.09
Car	0.60	0.31	0.09
Bus	0.04	0.96	0.00
Truck	0.67	0.26	0.08

* 6.67×10^{-6}% of miles traveled by pedestrians are assumed to be on highways.
A similar percentage is assumed for bicycles.

Table 12. Example of the Road Traffic Injury Matrix for Raw and Imputed Missing Data, SWITRS,Bay Area Counties, 2000-2008

A. Raw Data

			Striking$_j$									
Roadway	Severity	Victim$_i$	Ped (1)	Bicycle (2)	Motor-cycle (3)	Car (4)	Bus (5)	Truck (6)	Train	No Other Vehicle (7)*	Missing (8)	Total
Arterial	Killed	Pedestrian (1)		2	5	353	12	16			73	461
Arterial	Killed	Bicycle (2)		2		59	4	12		15	10	102
Arterial	Killed	Motorcycle (3)			8	115	1	11		99	3	237
Arterial	Killed	Car (4)				460	9	82	3	402	7	963
Arterial	Killed	Bus (5)						1		4		5
Arterial	Killed	Truck (6)				1		5		7		13
Arterial	Killed	Train*										0
Arterial	Killed	Missing (8)							2	48	67	117
Arterial	Killed	Total	0	4	13	988	26	127	5	575	160	1898
		% Missing	0.00	0.00	0.01	0.57	0.01	0.07	0.00	0.33		1.00

B. Imputed for Missing Data

			Striking$_j$									
		Victim$_i$	Ped (1)	Bicycle (2)	Motor-cycle (3)	Car (4)	Bus (5)	Truck (6)	Train	No Other Vehicle (7)*	Missing (8)	Total
Arterial	Killed	Pedestrian (1)	0.0	2.5	6.2	434.8	14.8	19.7	0.0	0.0		477.9
Arterial	Killed	Bicycle (2)	0.0	2.3	0.0	67.8	4.6	13.8	0.0	18.7		107.1
Arterial	Killed	Motorcycle (3)	0.0	0.0	8.4	120.7	1.0	11.5	0.0	113.3		255.0
Arterial	Killed	Car (4)	0.0	0.0	0.0	480.3	9.4	85.6	5.2	457.7		1038.3
Arterial	Killed	Bus (5)	0.0	0.0	0.0	0.0	0.0	1.0	0.0	4.5		5.6
Arterial	Killed	Truck (6)	0.0	0.0	0.0	1.0	0.0	5.2	0.0	7.9		14.1
Arterial	Killed	Train*	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0
Arterial	Killed	Missing (8)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Arterial	Killed	Total	0.0	4.8	14.6	1104.7	29.8	136.9	5.2	602.1	0.0	1898.0

Table 13. Injuries by Severity and Victim and Striking Vehicle Mode and Scenario*

	Injured						Killed					
Victim/Struck by:	**Baseline**	**BAU**	**TD2009**	**TD2035**	**Short Trips**	**ATC**	**Baseline**	**BAU**	**TD2009**	**TD2035**	**Short Trips**	**ATC**
Total	**2,001**	**2,058**	**2,345**	**2,504**	**2,459**	**2,700**	**485**	**497**	**542**	**564**	**543**	**581**
Bicyclist	**179**	**181**	**379**	**506**	**553**	**723**	**19**	**19**	**39**	**52**	**56**	**74**
NOV	44	44	90	120	130	171	4	4	8	10	11	15
Bicycle	4	4	17	31	37	64	0	0	1	2	3	4
Bus	2	1	3	4	4	5	1	1	1	2	2	2
Car	123	127	257	335	365	459	12	12	24	32	34	44
Motorcycle	2	2	4	5	5	7	0	0	0	0	0	0
Pedestrian	1	1	2	3	3	5	0	0	0	0	0	0
Truck	3	3	6	9	9	12	2	2	5	6	7	9
Bus	**4**	**2**	**2**	**2**	**2**	**2**	**1**	**1**	**1**	**1**	**1**	**1**
NOV	1	1	1	1	1	1	1	1	1	1	1	1
Bicycle	0	0	0	0	0	0	0	0	0	0	0	0
Bus	2	1	1	1	1	1	0	0	0	0	0	0
Car	1	1	0	0	0	0	0	0	0	0	0	0
Motorcycle	0	0	0	0	0	0	0	0	0	0	0	0
Pedestrian	0	0	0	0	0	0	0	0	0	0	0	0
Truck	0	0	0	0	0	0	0	0	0	0	0	0
Car	**1,101**	**1,140**	**1,106**	**1,076**	**1,063**	**1,013**	**280**	**290**	**282**	**275**	**271**	**259**
NOV	491	503	493	484	476	465	138	142	139	136	134	131
Bicycle	0	0	0	0	0	0	0	0	0	0	0	0
Bus	6	4	4	4	4	4	2	2	2	2	2	2
Car	543	570	547	527	523	486	116	122	117	113	112	104
Motorcycle	0	0	0	0	0	0	0	0	0	0	0	0
Pedestrian	0	0	0	0	0	0	0	0	0	0	0	0
Truck	62	63	62	61	60	58	24	24	24	24	23	23

Table 13. Injuries by Severity and Victim and Striking Vehicle Mode and Scenario (continued)

	Injured						Killed					
Victim/Struck by:	**Baseline**	**BAU**	**TD2009**	**TD2035**	**Short Trips**	**ATC**	**Baseline**	**BAU**	**TD2009**	**TD2035**	**Short Trips**	**ATC**
Motorcyclist	**335**	**347**	**344**	**340**	**341**	**333**	**63**	**65**	**65**	**64**	**64**	**63**
NOV	136	139	139	139	139	139	29	30	30	30	30	30
Bicycle	0	0	0	0	0	0	0	0	0	0	0	0
Bus	2	1	1	1	1	1	0	0	0	0	0	0
Car	180	189	185	181	182	174	29	30	30	29	29	28
Motorcycle	10	11	11	11	11	11	2	2	2	2	2	2
Pedestrian	0	0	0	0	0	0	0	0	0	0	0	0
Truck	7	7	7	7	7	7	3	3	3	3	3	3
Pedestrian	**361**	**366**	**493**	**559**	**480**	**608**	**116**	**116**	**150**	**167**	**145**	**178**
NOV	0	0	0	0	0	0	0	0	0	1	0	1
Bicycle	4	4	11	16	15	26	0	0	1	2	2	3
Bus	9	6	8	10	8	11	4	2	3	3	3	3
Car	332	340	451	507	435	542	103	106	136	150	131	159
Motorcycle	5	5	7	8	7	9	1	1	1	1	1	2
Pedestrian	0	0	0	0	0	0	0	0	0	0	0	0
Truck	12	12	15	17	15	19	7	7	8	9	8	10
Truck	**21**	**21**	**21**	**21**	**21**	**20**	**6**	**6**	**6**	**6**	**5**	**6**
NOV	8	8	8	8	8	8	4	4	4	4	4	4
Bicycle	0	0	0	0	0	0	0	0	0	0	0	0
Bus	0	0	0	0	0	0	0	0	0	0	0	0
Car	3	3	3	3	3	2	0	0	0	0	0	0
Motorcycle	0	0	0	0	0	0	0	0	0	0	0	0
Pedestrian	0	0	0	0	0	0	0	0	0	0	0	0
Truck	9	9	9	9	9	9	2	2	2	2	1	2

Table 14. Total Injuries by Roadway and Victim Type for Each Scenario*, Bay Area Injury Model

Roadway/Victim	Baseline	BAU	TD2009	TD2035	Short Trips	ATC
1. Highway	609	630	615	601	583	572
Car	465	481	468	455	438	430
Motorcyclist	86	89	89	88	88	86
Pedestrian	42	43	43	42	42	40
Truck	10	10	10	10	9	10
Bicyclist	5	5	5	5	5	5
Bus	1	1	1	1	1	1
2. Arterial	1,086	1,122	1,309	1,415	1,391	1,546
Car	557	578	561	545	546	512
Pedestrian	229	234	320	365	311	398
Motorcyclist	185	192	190	188	189	185
Bicyclist	106	108	229	306	335	440
Truck	8	8	8	8	8	8
Bus	2	2	2	2	2	2
3. Local	625	634	770	848	828	944
Car	268	276	268	260	261	245
Pedestrian	174	174	237	270	230	294
Motorcyclist	100	104	103	101	102	99
Bicyclist	74	74	157	209	229	299
Truck	6	7	6	6	6	6
Bus	1	0	0	0	0	0
Total	2,320	2,386	2,695	2,863	2,802	3,062

Table 15. Change in Burden of Injury from BAU by Scenario, Bay Area*

	GBD_{2010}	TD2009		TD2035		Short Trips		ATC	
	N	AF[#]	N	AF	N	AF	N	AF	N
Injuries									
Deaths	671	9	60	13	90	9	61	17	113
YLL	26,921	9	2,424	13	3,611	9	2,456	17	4,524
YLD	4,439	14	617	22	960	19	864	31	1,382
DALY	31,360	10	3,042	15	4,571	11	3,320	19	5,907

GBD, Global Burden of Disease

* Time and population constant from the 2004 baseline

AF, Attributable Fraction (percent)

Table 16. Change in Attributable Fractions with Change in the Exponent "a" for Injuries = (Victim Distance)^a $\times$ (Striking Vehicle Distance)^a by Scenario*

	TD2009		TD2035		Short Trips		ATC	
	AF[#]	N	AF	N	AF	N	AF	N
"a" = 0.33								
Deaths	5	36	8	50	5	32	8	56
YLL	5	1,442	8	2,022	5	1,268	8	2,259
YLD	8	360	12	523	10	451	15	673
DALY		1,803		2,546		1,718		2,932
"a" = 1.0								
Deaths	25	169	46	309	38	258	85	572
YLL	25	6,765	46	12,401	38	10,349	85	22,937
YLD	42	1,850	83	3,671	86	3,823	1.82	8,099
DALY		8,615		16,073		14,172		31,036

AF, Attributable Fraction (percent)

Table 17. Daily Output of Vehicle of Emissions that are Primary and Secondary components of PM2.5 by Scenario, Bay Area

	Scenario												
	BAU			TD2009		TD2035		Short Trips		AT Carbon Goal		Low Carbon Driving†	
Item	Cars*	Other	Total	Cars	Total	Cars	Total	Cars	Total	Cars	Total	Cars	Total
VMT Reduction, %	-0.0			-3.96		-7.5		-6.8		-14.7		-33.5*	
NO_x	68.2	112.4	180.6	65.5	177.9	63.1	175.5	63.6	175.9	58.2	170.6	45.4	157.7
$PM_{2.5}$	2.5	3.0	5.5	2.4	5.4	2.3	5.3	2.3	5.3	2.1	5.1	1.7	4.7
Tire wear	0.3	0.2	0.5	0.3	0.5	0.3	0.5	0.3	0.5	0.3	0.5	0.2	0.4
Brake wear	0.9	0.2	1.0	0.8	1.0	0.8	1.0	0.8	1.0	0.7	0.9	0.6	0.7
SO_2	0.7	0.2	0.9	0.7	0.9	0.7	0.9	0.7	0.9	0.6	0.8	0.5	0.7
ROG#	79.8	17.6	97.4	76.6	94.2	73.8	91.4	74.3	92.0	68.1	85.7	53.1	70.7

* Car includes, automobiles, light duty trucks, and motor cycles (classes LDA-TOT, LDT1-TOT, LDT2-TOT, MYC-TOT); Other includes medium and heavy duty trucks, buses, and motorhomes

† The range of reductions is projected to be 9% to 33.5%

ROG, Reactive Organic Gases

Table 18. Estimated Population-Weighted Mean PM2.5 Concentrations (µg/m^3) by Scenario, Bay Area*

	Scenario					
	2010 Baseline	TD2009	TD2035	Short Trips	AT_C	Low Carbon Driving
Bay Area	9.3000	9.2871	9.2759	9.2783	9.2532	9.1933-9.2717
		Reductions (ng/m^3)				
Bay Area	9.3	12.9	24.1	21.7	46.8	106.7
Alameda	9.4	11.9	22.3	20.1	43.4	98.8
Contra Costa	8.4	11.2	20.9	18.8	40.6	92.5
Marin	9.5	7.7	14.5	13.1	28.2	64.4
Napa	9.2	6.8	12.7	11.4	24.7	56.2
San Francisco	10.4	15.3	28.6	25.7	55.4	126.1
San Mateo	9.0	12.9	24.1	21.7	46.8	106.6
Santa Clara	9.4	17.3	32.4	29.1	62.8	143.0
Solano	9.0	6.5	12.2	11.0	23.7	54.1
Sonoma	8.6	9.5	17.9	16.1	34.7	79.2

* Based on Bay Area Air Quality Management District air shed model

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Table 19. Premature Deaths and Years of Life Lost and Attributable Fractions (AF) Due to Reduced Air Pollution from Low Carbon Driving and Active Transport Scenarios, Compared to Business As Usual by Scenario by Cause of Death, Bay Area

	Burden of Disease					Attributable Fraction, Percent				
Item by Cause*	LCD	TD_{2009}	TD_{2035}	Short Trips	Carbon Goal	LCD	TD_{2009}	TD_{2035}	Short Trips	Carbon Goal
Premature Deaths										
Ischemic Heart Disease	-8	-1	-2	-2	-3	-0.09	-0.01	-0.02	-0.02	-0.04
Hypertensive Heart Disease	-2	0	0	0	-1	-0.09	-0.01	-0.02	-0.02	-0.04
Stroke	-4	0	-1	-1	-2	-0.09	-0.00	-0.02	-0.02	-0.04
Inflammatory Heart Disease	-1	0	0	0	0	-0.09	-0.00	-0.00	-0.00	-0.00
Lung Cancer	-4	1	-1	-1	-2	-0.13	-0.00	-0.03	-0.03	-0.06
Acute Resp. Infections	0	0	0	0	0	-0.00	-0.00	-0.00	-0.00	-0.00
Respiratory Disease	-3	0	-1	-1	-1	-0.09	-0.00	-0.02	-0.02	-0.04
All causes†	-22	-1	-5	-5	-9	-0.04	<-0.01	<-0.01	<-0.01	-0.02
Years Life Lost										
Ischemic Heart Disease	-80	-10	-18	-16	-35	-0.09	-0.01	-0.02	-0.02	-0.04
Hypertensive Heart Disease	-18	-2	-4	-4	-8	-0.09	-0.01	-0.02	-0.02	-0.04
Stroke	-35	-4	-8	-7	-15	-0.09	-0.00	-0.02	-0.02	-0.04
Inflammatory Heart Disease	-10	-1	-2	-2	-4	-0.09	-0.01	-0.02	-0.02	-0.04
Lung Cancer	-59	-7	-13	-12	-26	-0.13	-0.02	-0.03	-0.03	-0.06
Acute Resp. Infections	-1	0	0	0	0	-0.10	-0.00	-0.00	-0.00	-0.00
Respiratory Disease	-29	-4	-7	-7	-13	-0.09	-0.01	-0.02	-0.02	-0.04
All Causes†	-232	-28	-52	-48	-101	-0.02	<-0.01	<-0.01	<-0.01	-0.01

* International Classification of Disease, 10th Revision cause codes: ischemic heart disease, I20-I25; hypertensive heart disease, I10-I13; stroke, I60-I69, Inflammatory heart disease (I30-I33, I38, I40, I42); Respiratory Disease (J10-J18, J20-J22, J00-J06, J40-J44, J45-J46, J30-J39, J47-J98); Acute Respiratory Infections in children (J00-J06, J10-J18, J20-J22)
† Denominator is entire disease burden (136 causes of death and disability) in SF Bay Area, 50,369 deaths; 721,469 YLL
LCD, Low carbon driving; TD, top decile of cities

Table 20. Annual Physical Activity Health Co-Benefits of Low Carbon Driving and Active Transport (Carbon Goal) Compared to Business As Usual by Scenario, Bay Area

	Counts			Rate per Million Population		
Risk Factor/Burden*	Low Carbon Driving, LCD	Active Transport Goal, AT_C	LCD+ AT_C	Low Carbon Driving, LCD	Active Transport Goal, AT_C	LCD+ AT_C
Physical activity						
Premature deaths	0	-2,404	-2,404	0	-319	-319
YLL	0	-27,544	-27,544	0	-3,653	-3,653
YLD	0	-17,231	-17,231	0	-2,285	-2,285
DALYs	0	-44,776	-44,776	0	-5,939	-5,939
Air pollution						
Premature deaths	-22	-9	-29†	-3	-1	-4
YLL	-232	-101	-317	-31	-13	-42
YLD	0	0	0	0	0	0
DALYs	-232	-101	-317	-31	-13	-42
Road traffic crashes						
Premature deaths	0	113	113	0	15	15
YLL	0	4,524	4,524	0	600	600
YLD	0	1,382	1,382	0	183	183
DALYs	0	5,907	5,907	0	783	783
Total						
Premature deaths	-22	-2,300	-2,321†	-3	-305	-308
YLL	-232	-23,121	-23,337	-31	-3,067	-3,095
YLD		-15,849	-15,849	0	-2,102	-2,102
DALYs	-232	-38,971	-39,186	-31	-5,169	-5,197

* YLL, years of life lost; YLD, years living with disability; DALY, disability-adjusted life years

† Adjusted to avoid double counting of cardiovascular disease (air pollution and physical activity) and mode choice (active transport replacing LCD trips based on proportion of vehicle miles traveled)