Health Cobenefits and Transportation-Related Reductions in Greenhouse Gas Emissions in the San Francisco Bay Area

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Objectives. We quantified health benefits of transportation strategies to reduce greenhouse gas emissions (GHGE).

Methods. Statistics on travel patterns and injuries, physical activity, fine particulate matter, and GHGE in the San Francisco Bay Area, California, were input to a model that calculated the health impacts of walking and bicycling short distances usually traveled by car or driving low-emission automobiles. We measured the change in disease burden in disability-adjusted life years (DALYs) based on dose–response relationships and the distributions of physical activity, particulate matter, and traffic injuries.

Results: Increasing median daily walking and bicycling from 4 to 22 minutes reduced the burden of cardiovascular disease and diabetes by 14% (32 466 DALYs), increased the traffic injury burden by 39% (5907 DALYS), and decreased GHGE by 14%. Low-carbon driving reduced GHGE by 33.5% and cardiorespiratory disease burden by less than 1%.

Conclusions: Increased physical activity associated with active transport could generate a large net improvement in population health. Measures would be needed to minimize pedestrian and bicyclist injuries. Together, active transport and low-carbon driving could achieve GHGE reductions sufficient for California to meet legislative mandates. (*Am J Public Health.* 2013;103:703–709. doi:10.2105/AJPH.2012.300939)

Greenhouse gas emissions (GHGE) linked to global warming and climate change are the most significant threat confronting public health in the 21st century.[1] Approximately 7% of US GHGE are generated in California, which is the 12th largest emitter worldwide.[2,3] California's transportation sector is the single largest source (38%),[2] and personal passenger vehicles account for 79% of that sector's GHGE. The State of California has enacted legislation to achieve a 2050 goal of reducing GHGE to 80% below its 1990 level. Strategies to reduce GHGE include reducing carbon dioxide (CO_2) emitted per mile and reducing total car miles traveled.[2] Emerging technologies for lower carbon fuels and alternative-fuel vehicles (electric, fuel cell, or gas–electric hybrids) typify the former approach. The latter approach recognizes that a large proportion of urban automobile trips could be walked or bicycled, which affords opportunities for physical activity and reducing air pollution. Because physical inactivity is linked to obesity and chronic diseases, active transport could play an immensely important role in promoting public health while decreasing air pollution and transportation-related GHGE.

Several researchers have recently attempted to quantify the health benefits of reduced car travel and increased active transport,[4–8] focusing on physical activity and air pollution. However, none have simultaneously addressed a US population and its road traffic injuries,[7] which accounted for 3.1% of the overall US burden of disease and injury[9] in 2004 and had a disproportionate impact on pedestrians and bicyclists per mile traveled.[10] We quantified potential health cobenefits and harms of different strategies to reduce transport-related GHGE in the San Francisco Bay Area, California.

METHODS

We used a mathematical model that integrates data on travel patterns, physical activity, fine particulate matter, GHGE, and disease and injuries. Based on population and travel scenarios in the San Francisco Bay Area, we used the model to calculate the health impacts of walking and bicycling short distances usually traveled by car or driving low-emission automobiles.

Integrated Transport and Health Impacts Model

Previous research has identified physical activity, air pollution, and traffic injuries[4–8] as the main sources of health cobenefits and harms. Each is addressed in the integrated transport and health impacts model (ITHIM), which was developed out of the work reported in Woodcock et al.[7] The model's conceptual basis is comparative risk assessment.[7,11] It formulates a change in the disease burden, *DB*, resulting from the shift in the exposure distribution from a baseline scenario to an alternative scenario. This model is an extension of the population attributable risk formula, in which an exposure, *x,* has a continuous distribution.

$$(1)\quad \Delta DB = \frac{\int_{x_{\min}}^{x_{\max}} RR(x)P(x)dx - \int_{x_{\min}}^{x_{\max}} RR(x)Q(x)dx}{\int_{x_{\min}}^{x_{\max}} RR(x)P(x)dx} \times DB_{Baselines}.$$

The relative risk (RR) at exposure level x is weighted by the baseline and alternative population distributions, $P(x)$ and $Q(x)$, respectively, and integrated over all exposure levels. In this study, we measured the burden of disease in disability-adjusted life years (DALYs), which are the sum of years of life lost because of premature mortality (YLL) and years of living with disability (YLD). We obtained deaths and DALYs projected for the United States in 2010 in age, gender, and cause groups from the Global Burden of Disease database.[9] To account for differences in US and Bay Area health status, we scaled US deaths and DALYs to the Bay Area population and adjusted them in age–gender strata by the rate ratio of the San Francisco Bay Area to US mortality for specific chronic diseases and road traffic injuries. We used systematic reviews to identify causes that had strong evidence of an RR–exposure gradient for physical activity and air pollution. These causes included cardiovascular diseases,[12] colon cancer,[13] breast cancer,[14] lung cancer,[15] respiratory disease,[16,17] diabetes,[18] and dementia.[19]

The ITHIM characterized exposure distributions in several ways. Physical activity was described as quintiles of a log-normal distribution on the basis of the mean weekly active transport time per person, its standard deviation and coefficient of variation (the standard deviation divided by the mean), mean weekly nontransport physical activity, and the ratio between bicycling and walking times. The activity times were multiplied by weights to give metabolic-equivalent task hours, which reflect energy expenditures for walking and cycling at average speeds and for performing occupational tasks.[20] We obtained these descriptive statistics from published research on walking and bicycling speeds[7,21] and analysis of travel[22] and health[23] surveys with large probability samples for the Bay Area. At higher levels of active transport, the model reduced the coefficient of variation, increased travel speeds for walking, and assumed larger proportional increases in bicycling for older age groups and women. This follows a European pattern[24] in which population variability decreases as cycling and walking become prevalent and populations become more fit and capable of achieving faster walking speeds. Because the shape of the dose–response function at high physical activity levels was uncertain, the RR–metabolic-equivalent task hour gradient in the comparative risk assessment analysis was asymptotically limited using a square root function. Because health outcomes and physical activity are strongly influenced by age and gender, we performed these calculations in specific age and gender categories for which data were available on RR and exposure distributions.

To estimate exposure to air pollution, we used population-weighted means of airborne fine particulate matter ($PM_{2.5}$), based on models calibrated for Bay Area automobile emissions and air shed. The RR–$PM_{2.5}$ gradient in the comparative risk assessment analysis reflected the change in risk over an increment of 10 micrograms per cubic meter $PM_{2.5}$.[15]

For traffic injuries, we formulated injuries per mile traveled by victim and striking vehicle for the baseline scenario, R_0, as a rate for each pairwise combination of victim mode, *i,* and striking vehicle mode, *j:*

$$(2)\quad R_{0i,j} = \frac{\text{Injuries}_{0i,j}}{(\text{Personal Miles}_{0i} \times \text{Vehicle Miles}_{0j})^{1/2}}$$

The victim and striking vehicle modes were pedestrian, bicyclist, motorcycle, car, bus, and truck. For multivehicle collisions involving more than 2 travel modes, a decision rule assigned the striking party as the largest vehicle other than the one used by the injured party. Exposure distributions for scenarios were based on the square root of the change in scenario distances traveled by collision victims and striking vehicles. Exponential relationships between traffic injuries and mode share distance of pedestrians and bicyclists have repeatedly been observed in different populations.[25] We obtained the predicted number of injuries for a scenario, I_s, by multiplying the baseline rate by the square root of the change in scenario distances traveled by victims and striking vehicles in strata of injury severity and the roadway type (a proxy for roadway characteristics, including vehicular speed). Assuming a steady-state population and baseline injuries of I_0, the population attributable risk, PAR, is given by

$$(3)\quad PAR = \frac{I_S}{I_0}.$$

Injury severity was categorized as fatal (within 30 days of collision incident) or serious, based on the police report of a victim's incapacity to drive or walk away from the collision. We extracted data on injuries from a geocoded collision database of fatal and serious collisions reported to police.[26,27] We determined roadway type associated with the collision by a spatial join in mapping software (ArcGIS 10, ESRI, Redlands, CA) to a street layer (Tele Atlas, 's-Hertogenbosch, the Netherlands) and categorized it as highway, arterial, or local on the basis of federal and state classifications of facility type. We calculated the distribution of miles traveled by roadway type from travel demand models for Bay Area cars and trucks, administrative reports of revenue miles and trans-Bay (interstate highway) route information for buses, and published reports for bicyclists.[28]

We calculated daily distances walked, bicycled, and driven by drivers and passengers of cars, buses, and rail from geocoded coordinates of trip origins and destinations recorded in diaries of participants of the 2000 Bay Area Travel Survey. Because diaries did not record the exact route, we input a sample of coordinates to Google Maps to select a route taking the least amount of time for a specific mode (walk, bicycle, car, or other). We used the ratio of Google route miles to straight-line miles for unsampled trip segments.

We implemented ITHIM as an Excel (Microsoft, Redmond, CA) spreadsheet. Separate worksheets organized descriptive statistics of travel, the burden of disease, disease-specific RRs, transport- and nontransport-related physical activity, traffic injuries, and $PM_{2.5}$ concentrations. Technical documentation of ITHIM is available at the California Department of Public Health Web site.[29]

Population and Travel Scenarios

The San Francisco Bay Area is made up of 9 counties that border the San Francisco Bay estuary in northern California. In 2010, it had a population of 7.1 million. County population densities ranged from 181 people per square mile to 17 246 people per square mile. The cities of San Francisco, Oakland, and San Jose, California, are major metropolitan hubs.

Scenarios are described by total daily mileage by each travel mode divided by the total population. Active transport scenarios shifted miles traveled by car to miles walked and bicycled without affecting other modes of travel and held total travel distance constant.

Business as usual. The business-as-usual (BAU) scenario projects 2000 baseline travel patterns into the future, accounting for trends in demographics, economic development, and travel patterns and the likely consequences of implementation of existing policies, projects, and programs. Using travel demand models, the regional transportation planning agency (Metropolitan Transportation Commission)[30] has foreseen an increase by 2035 of 5% over the 2000 baseline per capita mean daily vehicle miles traveled for automobiles (Table 1). The year 2035 was chosen to coincide with the time horizon of the Metropolitan Transportation

TABLE 1—Predicted Per Capita Daily Travel Distances and Times and Aggregate Carbon Dioxide Emissions From Passenger Vehicles by Travel Mode and Scenario: San Francisco Bay Area, CA, 2035

	Travel Time, Min/D, Median		Travel Distance,[a] Miles/D, Mean			Reductions in
Scenario	Walk	Bicycle	Walk	Bicycle	Car[b]	Carbon Emissions,[c] %
Business as usual	3.7	0.7	0.35	0.17	22.6	-16.5
Low-carbon driving	3.7	0.7	0.35	0.17	22.6	-33.5
Short trips	6.4	6.0	0.63	1.58	20.9	-0.7
Carbon/physical activity goal	11.3	10.7	1.10	2.74	16.6	-14.5

[a]Other modes and total distance mi/person/d: bus = 0.62; rail = 0.79; heavy good vehicles = 1.0; total = 25.6.
[b]Passenger vehicles include automobiles, light trucks, and motorcycles
[c]2000 baseline of 27.9 million metric tons of carbon dioxide.

Commission's most recent regional transportation plan. Changes to personal passenger vehicles that affect GHGE involve improvements in drive train engineering, refrigerants, and accessories that incrementally improve fuel economy.

Low-carbon driving. Although distances are the same as in the BAU scenario, carbon emissions by automobiles and light trucks will be lower than in the other scenarios because of the increased adoption of gas–electric hybrid vehicles and light-duty diesel, biofuel, and electric vehicles.

Active transport. These 2 scenarios incorporate the same trends in travel distances as the BAU scenario while assuming that policies could achieve increases in active transport mode share. They do not describe the policies themselves. The short trip scenario assumes 50% of BAU miles traveled in car trips less than 1.5 miles are walked and 50% of BAU miles traveled in car trips 1.5 to 5 miles are bicycled. In 2000, Bay Area Travel Survey data indicated that 24% of car trips were less than 1.5 miles and 33.8% of car trips were between 1.5 and 5 miles.

The carbon/physical activity goal (C/PAG) scenario seeks to optimize both physical activity and CO_2 emission reductions by setting the time budget for physical activity from walking and bicycling to a level commuters would not find burdensome and similar to 2007–2009 commute times.[31]

Carbon dioxide emissions and copollutants. For incremental changes consistent with the BAU scenario, an absolute 16% reduction from the 2000 baseline is predicted by 2035.[33] The combination of all other technologies is predicted to reduce CO_2 emissions by an additional 9% to 33.5%. We estimated annual aggregate carbon emissions at baseline from CO_2 emission rates per mile traveled for passenger vehicles in the Bay Area and from the annual miles of car–driver travel estimated by the Bay Area Travel Survey. The methods for calculating these CO_2 emission rates are based on travel demand models and have been published elsewhere.[33] To determine aggregate CO_2 emission reductions for the BAU and low-carbon driving (LCD) scenarios, we applied percentage-wise reductions estimated by Lutsey[32] to the 2000 baseline. In the active transport scenarios, we reduced annual car–driver miles per person by the active transport miles per person and multiplied them by the emission factor of 1.175 pounds CO_2 per mile and the total projected population of 9.1 million for 2035.[34]

Estimates of average, annual airborne concentration $PM_{2.5}$ were based on 2 models. We used an emissions model, EMFAC2007,[35] to estimate Bay Area motor vehicle emissions for the baseline year of 2010 for a car fleet composed of model years from 1966 to 2010. The 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. We used a second model, the multipollutant evaluation method,[36] to predict population-weighted concentrations of total $PM_{2.5}$ in 4-kilometer grids in the Bay Area air shed on the basis of mobile and nonmobile sources. For each active transport scenario, we varied only car and light truck VMT and held constant VMT for all other vehicle classes and inputs for nonmobile sources. For each scenario, we ran the models to reflect $PM_{2.5}$ reductions proportional to those for car

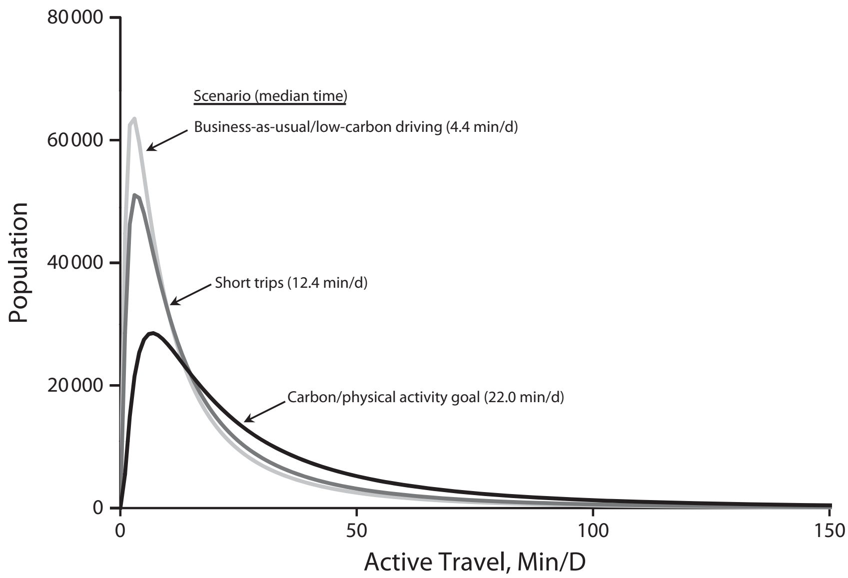

FIGURE 1—Model estimated population distribution of daily active travel time: San Francisco Bay Area, CA, 2035.

VMT. For LCD, we discounted VMT from the 2010 baseline by an amount equivalent to the 33.5% CO_2 reduction.

RESULTS

Daily physical activity time for transport-related walking and bicycling increased from the median of 4.5 minutes for BAU to 12.4 minutes for short trips and 22.0 minutes for C/PAG (Figure 1, Table 1). Daily per capita distances by active transport increased from approximately 0.5 miles to 3.8 miles. Active transport scenarios increased mode share (by distance) as much as 15% from the BAU of approximately 2.0%. Reductions in car VMT of 7%, 15%, and 33.5% for short trips, C/PAG, and LCD, respectively, corresponded to decreases of 21.7, 46.8, and 106.7 nanograms per cubic meter in population-weighted $PM_{2.5}$ concentrations from the Bay Area average of 9.3 micrograms per cubic meter. The combination of VMT reductions, population growth, and changes in automotive technologies would produce reductions in GHGE of as much as 33.5% for LCD and 14.5% for active transport for the C/PAG scenario.

Compared with BAU, the physical activity component of the C/PAG scenario generated large proportional decreases (>13%) in the annual number of premature deaths and DALYs for specific causes such as cardiovascular disease and diabetes (Table 2). For the Bay Area population, the ITHIM model predicted 2404 avoided premature deaths and 44 866 DALYs gained per year. Reduced $PM_{2.5}$ concentrations associated with LCD compared with BAU resulted in less than 0.1% reduction in premature deaths (22 deaths) and years of life lost (232 YLL) as a result of cardiovascular diseases, lung cancer, and nonmalignant respiratory diseases. The burden resulting from road traffic injuries increased under the short trip and C/PAG active transport scenarios by 11% and 39% (3320–5907 DALYs), respectively, compared with BAU, primarily as a result of an increase in car–pedestrian and car–bicycle collisions on local roads and arterials and, to a lesser degree, bicycle–bicycle and single bicyclist collisions.

Compared with LCD, the C/PAG scenario had the largest net decrease in the disease burden after factoring the independent contributions of physical activity, air pollution reduction, and road traffic injuries (Table 3). The reductions in premature deaths and gains of DALYs for the C/PAG scenario exceeded those of the LCD scenario by more than 100-fold.

TABLE 2—Predicted Annual Change in Burden of Disease From Physical Activity and Road Traffic Injuries Compared With Business as Usual by Scenario and by Cause of Death and Disability: San Francisco Bay Area, CA, 2035

	Change in Burden of Disease		Attributable Fraction (%)	
Cobenefit Source by Cause[a]	Short Trips	Carbon Goal	Short Trips	Carbon Goal
Physical Activity				
Premature deaths				
Cardiovascular disease	−1195	−1985	−8.5	−13.4
Diabetes	−122	−189	−8.6	−13.3
Dementia	−121	−218	−5.4	−9.6
Breast cancer	−31	−48	−3.1	−4.9
Colon cancer	−31	−53	−3.2	−5.6
Depression	−1	−1	−4.1	−7.4
Total	−1501	−2404	−3.0[b]	−4.8[b]
Years life lost				
Cardiovascular disease	−13 842	−21 503	−9.5	−14.8
Diabetes	−1902	−2961	−9.3	−14.4
Dementia	−808	−1387	−5.6	−9.6
Breast cancer	−614	−955	−3.3	−5.1
Colon cancer	−427	−728	−3.2	−5.5
Depression	−7	−11	−4.4	−7.5
Total	−17 600	−27 545	−2.4[b]	−3.8[b]
Years living with disability				
Cardiovascular disease	−2726	−4295	−9.9	−15.2
Diabetes	−2303	−3707	−9.4	−15.1
Dementia	−2414	−4029	−5.8	−9.6
Breast cancer	−158	−250	−3.2	−5.0
Colon cancer	−98	−166	−3.2	−5.5
Depression	−2703	−4784	−3.2	−5.7
Total	−10 402	−17 321	−1.7[b]	−2.9[b]
Injuries				
Deaths	61	113	9	17
Years life lost	2456	4524	9	17
Years living with disability	864	1382	19	31
Disability-adjusted life years	3320	5907	11	19

[a] *International Classification of Diseases, 10th Revision*[37] 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).
[b] Denominator is entire disease burden (136 causes of death and disability) in San Francisco Bay Area (premature deaths = 50 369; years of life lost = 721 469; years living with disability = 604 013; disability-adjusted life years = 1 325 482)

DISCUSSION

Health impacts modeling of different strategies for transport-related reductions in greenhouse gases demonstrated the enormous potential of active transport to generate health cobenefits and carbon reductions. At high but achievable levels of active transport, risk reduction of the magnitude predicted by ITHIM would rank among the most notable public health achievements in the modern era,[38] reduce the estimated $34 billion in California's annual costs from cardiovascular disease,[40] and other chronic conditions such as obesity, and

TABLE 3—Predicted Annual Health Cobenefits by Source of Cobenefits and Scenario Compared With Business as Usual, San Francisco Bay Area

	Counts			Rate per Million Population		
Risk Factor or Burden	LCD	Active Transport, C/PAG	LCD + C/PAG	LCD	Active Transport, C/PAG	LCD + C/PAG
Physical activity						
Premature deaths	0	−2404	−2404	0	−319	−319
YLL	0	−27 544	−27 544	0	−3653	−3653
YLD	0	−17 231	−17 231	0	−2285	−2285
DALYs	0	−44 776	−44 776	0	−5939	−5939
Air pollution ($PM_{2.5}$)						
Premature deaths	−22	−9	−29[a]	−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	4524	4524	0	600	600
YLD	0	1382	1382	0	183	183
DALYs	0	5907	5907	0	783	783
Total						
Premature deaths	−22	−2300	−2321[a]	−3	−305	−308
YLL	−232	−23 121	−23 337	−31	−3067	−3095
YLD		−15 849	−15 849	0	−2102	−2102
DALYs	−232	−38 971	−39 186	−31	−5169	−5197

Note. C/PAG = carbon/physical activity goal; DALY = disability-adjusted life years; LCD = low-carbon driving; $PM_{2.5}$ = airborne fine particulate matter; YLD = years living with disability; YLL = years of life lost.
[a]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)

achieve the US Surgeon General's recommendation that adults engage in 150 minutes of moderate to vigorous physical activity weekly.[41]

Wide-scale adoption of active transport could have as large an impact on carbon reduction as strategies based on LCD. The 14.5% reduction indicated by the C/PAG scenario falls in the range of the carbon reductions possibly achieved by reengineering automobiles and fuels. Although replacing short trips generated important health cobenefits, it did not substantially reduce total aggregate emissions from the 2000 baseline, largely because of anticipated population growth, which is a key driver of GHGE.[42] This finding highlights that reducing GHGE from transport will likely require a modal shift to active transport, LCD, and decreases in per capita travel distances that can be fostered by smart growth and other land use strategies.[43]

Of concern is a predicted increase in road traffic injuries to pedestrians and bicyclists at higher levels of active transport. The percentage of increase is higher than that found in previous research in London, despite more optimistic assumptions of safety in numbers. Even with a substantial population benefit of physical activity, active transport may not be embraced by a large segment of the population until safety concerns are met. Real and perceived risks reinforce this concern. In ITHIM baseline data, Bay Area pedestrians and bicyclists experienced 14.9% of fatal and serious road traffic injuries yet traveled only 2.1% of all roadway miles.[22,26] A significant percentage of US pedestrians and bicyclists currently report feeling threatened by the presence of motorists, crime, or inadequate infrastructure.[44] Most have also reported being dissatisfied with how their community is designed for safe bicycling. The experience of European countries with high rates of bicycling and walking suggests that policies, social and cultural norms, and robust investments in infrastructure, education, and enforcement may make people feel safer and reduce absolute risks.[45]

When cycling or walking along busy roadways, pedestrians and bicyclists may experience higher doses of vehicle exhaust than car occupants because of their higher respiration rates,[46] potentially acting against the benefits of physical exercise. On average, the health cobenefits of physical activity appear to far exceed harms caused by walking and bicycling in polluting traffic.[4,8] Reducing motor vehicle flow on routes that are likely to be used by pedestrians and cyclists could act to reduce both the harms from exposure to vehicle exhaust and road traffic danger and could increase the attraction of using active travel.

The findings of this study are consistent with those of other recent research in Midwestern US cities[5]; London, England[7]; the Netherlands[4]; and Barcelona, Spain.[6] Each study showed large health cobenefits of increased physical activity relative to those produced by reducing automobile emissions. The differences in health cobenefits are related in part to the amount of physical activity times envisioned in scenarios and whether all-causes or disease-specific mortality rate ratios were used to describe the risk gradient with physical activity. Had this study used an all-causes RR–physical activity gradient, the number of premature deaths and DALYs avoided would have increased by approximately one third.

Strengths and Limitations

ITHIM has relatively simple inputs derived from regional travel and health surveys and from a database of health outcomes. Its spreadsheet format can be implemented on a desktop computer, which 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, including land-use decisions and urban design.[47,48] ITHIM addresses limitations in simpler models that focus only on all-cause mortality, that assume a linear relationship between increasing activity and health outcomes, and that do not stratify the population into different age groups.

Scenarios were meant to be ambitious but achievable rather than realistic and did not prescribe particular policies, infrastructure, or contingencies (e.g., gasoline prices). Substituting miles in short trips and setting bounds of physical activity based on achieving health and environmental goals had an intuitive appeal. The median active transport time (22 min) for the C/PAG scenario is comparable to the overall Bay Area median commute time in 2007–2009.[31] We also evaluated scenarios on the basis of existing and projected travel patterns of cities in the Bay Area with the highest rates of walking and bicycling. These scenarios (not presented) involved active transport distances comparable to those in short trips.

As in most models, some key parameters were uncertain because of limitations in data quality and availability. In sensitivity analyses of physical activity, we varied the coefficient of variation and speeds of active transport time and metabolic-equivalent task hours for walking and bicycling. The absolute change in the burden of disease estimates for cardiovascular disease and diabetes was plus or minus 2%. For injuries, we varied the exponent describing miles at risk in the denominator of the injury rate. At values similar to those reported in the literature (0.33–0.5), injuries created a modest decrease in cobenefits compared with those gained from physical activity. As the relationship becomes linear, injuries subtract a sizable proportion from the overall benefits. Sharing road space with a large number of cotravelers may trigger anticipatory driving behaviors in motorists, pedestrians, and bicyclists—the so-called "safety in numbers" hypothesis.[25] Alternatively, policy change and improvements in safety infrastructure may be put into place before or because injuries occur.[49] Whatever the resolution of this polemic, a nonlinear relationship for modeling injuries appears to be the most realistic assumption.[10]

The model assumes that the health cobenefits occur in a single accounting year, although the changes in the physical activity distribution are likely to occur gradually over time, and ongoing cobenefits will be maintained in subsequent years. The model assumes that other factors influencing physical activity and metabolic-equivalent task hours are time invariant, including nontransport 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.

We also did not consider other health impacts of active transport and LCD. These impacts include other copollutants (ozone, nitrogen oxide, sulfur dioxide, ultrafine particles, elemental carbon) and their adverse health impacts[50] on the general population and subpopulations of bicyclists and pedestrians with near-roadway exposures, noise, and indirect impacts of GHGE on climate change. We also did not include effects of 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 with nonusers.[51]

Conclusions

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 a modal shift in favor of active transport with LCD technologies, the Bay Area and other locales will be better able to achieve carbon reduction goals. ■

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Contributors

N. Maizlish was responsible for the analysis and interpretation of data on physical activity and traffic injuries and for drafting the article. J. Woodcock was responsible for conceptualizing and designing the study, interpreting the data on physical activity and traffic injuries, and revising the article. S. Co contributed to analysis and interpretation of travel scenarios. B. Ostro, A. Fanai, and D. Fairley contributed to the analysis and interpretation of the air pollution component of the study.

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Human Participant Protection

No protocol approval was necessary because no human participants were directly engaged in this work.

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