

Using Simulation to Compare 4 Categories of Intervention for Reducing Cardiovascular Disease Risks

Gary Hirsch, SM, Jack Homer, PhD, Justin Trogdon, PhD, Kristina Wile, MS, and Diane Orenstein, PhD

The Prevention Impacts Simulation Model (PRISM) projects the multiyear impacts of 22 different interventions aimed at reducing risk of cardiovascular disease. We grouped these into 4 categories: clinical, behavioral support, health promotion and access, and taxes and regulation. We simulated impacts for the United States overall and also for a less-advantaged county with a higher death rate. Of the 4 categories of intervention, taxes and regulation reduce costs the most in the short term (through 2020) and long term (through 2040) and reduce deaths the most in the long term; they are second to clinical interventions in reducing deaths in the short term. All 4 categories combined were required to bring costs and deaths in the less-advantaged county down to the national level. (*Am J Public Health*. 2014;104:1187–1195. doi:10.2105/AJPH.2013.301816)

Public health decision-makers often have to decide among multiple and potentially competing interventions to strategically direct their prevention programs. Interventions vary by private or public costs, political acceptability, ease of implementation, and the magnitude, time frame, and uncertainty surrounding their health impacts.¹ They also vary in terms of their aim (e.g., individual, social environment, physical environment).

We used a computer simulation model to explore how 4 distinct categories of interventions differ in terms of their potential for reducing the risks of cardiovascular disease (CVD) in a population over a 30-year time horizon. The Prevention Impacts Simulation Model (PRISM),^{2,3} originally developed to represent the entire US population, includes 22 intervention levers, which we found could be usefully grouped according to a 2 × 2 conceptual representation (Figure 1). On 1 axis, some of the levers act at the individual level (clinical, behavioral support), whereas others act at the population level (taxes and regulation, health promotion and access). On a second axis, some of the levers are prescriptive (clinical, taxes and regulation), whereas others are facilitative (behavioral support, promotion and access). Facilitative levers require a certain awareness, motivation, and creativity on the

part of the individual, whereas prescriptive levers affect behavior more simply or directly.

The impacts of public health interventions may be mediated, in part, by the socioeconomics of the target population.⁴ Although PRISM does not include interventions to modify socioeconomic factors, it is possible to illustrate the importance of such factors by recalibrating the model to represent a local area whose socioeconomics are different from those of the nation overall. After testing the 4 categories of interventions at the US level, we compared the national results with those of the model calibrated to represent the demographics, risk factor prevalence, and CVD events and deaths of a less-advantaged county that has a higher death rate than the nation overall. Assuming the same intervention effect sizes in the national and less-advantaged county models, the comparison allowed us to explore 2 questions:

(1) Do the starting differences between the less-advantaged county and the United States overall lead to different conclusions about the relative effectiveness of the different categories of interventions? (2) Is it possible to close the current CVD health gap between the less-advantaged county and the rest of the nation, and, if so, what combination of interventions would this require?

PRISM AND ITS INTERVENTION LEVERS

PRISM^{2,3} is a model that simulates the multiyear impacts of a wide variety of interventions aimed at reducing risks for CVD (i.e., coronary heart disease, stroke, heart failure, and peripheral arterial disease) and other chronic conditions and diseases (e.g., hypertension, diabetes, renal disease, obstructive pulmonary disease, certain cancers). It is a compartmental system dynamics model, representing groups of people in categories rather than each individual separately. Like other such models, it depicts processes of multiple and nonlinear influence, accumulation, delay, and feedback that result in movements (flows expressed as people per year) between healthy and ill population subgroups.^{5–7} The model produces outputs from 1990 to 2040 and has been calibrated to represent the United States overall as well as some local areas.^{8–10}

PRISM is built on the best available evidence, and its credibility also rests on the fact that it (1) reproduces national survey data on CVD deaths (1990–2008), CVD incidence (2003 and 2006), and the changing prevalence of a variety of chronic conditions (1990–2010) and (2) produces realistic future projections telling an internally consistent story.^{2,3} The model's user-friendly interface provides instant output to “what if” questions to individual users and groups using it interactively in workshops and study sessions. This capability has influenced the thinking and actions of decision-makers at the national and local levels.^{8–10} PRISM has been used by the Centers for Disease Control and Prevention (CDC) to estimate future trajectories for health and economic outcomes for Communities Putting Prevention to Work and for strategic planning for Community Transformation Grants.

In PRISM, the population is segmented by 6 childhood and adult age categories, by

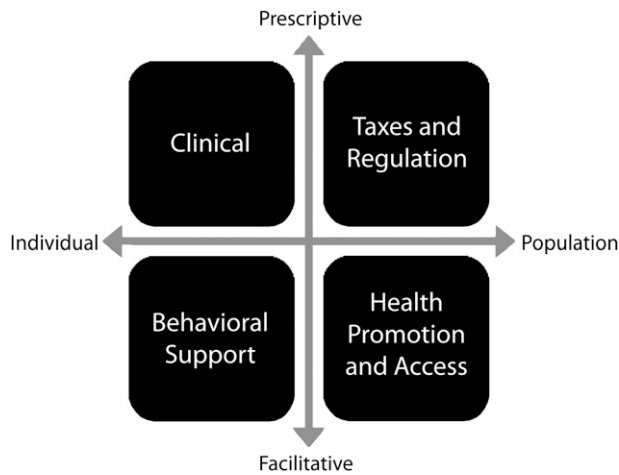


FIGURE 1—Two axes defining 4 categories of interventions for reducing risks of cardiovascular disease: Prevention Impacts Simulation Model.

gender, and by CVD event status (not-yet or “non-CVD” vs already-had or “post-CVD”). The model depicts changes in the population through birth, migration, aging, movement from non-CVD to post-CVD status, and death. PRISM models the changing age structure of the population; the results reported are not age adjusted. It also depicts flows into and out of the following (each by age, gender, and CVD status):

- 3 blood pressure categories (hypertensives: people who have ever had persistent systolic blood pressure [SBP] > 140 mmHg or diastolic blood pressure [DBP] > 90 mmHg; prehypertensives: not hypertensive but ever had persistent SBP > 130 or DBP > 85; and normotensives: all others),
- 3 blood cholesterol categories (high cholesterol: those who have ever had low-density lipoprotein [LDL] cholesterol > 130 mg/dL; borderline cholesterol: not high cholesterol but ever had LDL > 110; and normal cholesterol: all others),
- 3 blood sugar categories (diabetes: those who have ever had fasting blood glucose [FBG] > 126 mg/dL; prediabetes: not diabetes but ever had FBG > 100; and with normoglycemia: all others);
- 4 smoking categories (never-smokers, smokers, recent ex-smokers [quit less than 10 years ago], and long-term ex-smokers [quit 10 or more years ago]), and

- 2 body mass index (BMI) categories (non-obese and obese; for youths, obese defined as BMI greater than or equal to the 95th percentile on standard growth charts [by gender and age] established in the 1970s; for adults, obese defined as BMI ≥ 30 kg/m²).

The endpoints of the model include risk-related mortality and cost. The model simulates by quarter-year increments through more than 4000 intermediate and final output variables.

The version of PRISM used for our analysis (version 2u) included 22 intervention levers that may prevent or mitigate certain well-established cardiovascular risks—high blood pressure, high cholesterol, diabetes, obesity, poor nutrition, inactivity, psychological distress, smoking, second-hand smoke, and small particulate air pollution. All interventions in the model, as well as their effects, were based on peer-reviewed literature. In some cases, discussions with experts helped to quantify the size of intervention effects (Table A, available as a supplement to the online version of this article at <http://www.ajph.org>). As seen in Figure 1, the interventions fell into 4 broad categories, as determined by the 2 axes “individual–population” and “prescriptive–facilitative.” Individual-level interventions included clinical services (prescriptive) and behavioral support services (facilitative), with the former involving more medical treatments and the latter involving more motivational counseling for lifestyle change. Population-level

interventions included taxes and regulations to limit unhealthy behaviors (prescriptive) and interventions promoting or providing greater access to healthy behaviors (facilitative).

Table 1 displays PRISM’s 22 levers organized for the 4 categories, showing for 2010 the target population and also, for the clinical and behavioral support interventions, the existing recipient population and cost per recipient. The target population is the number of potential recipients, estimated by applying the risk factor prevalence to the total population size. The recipient population is the estimated portion of the target population already receiving the service in question. For example, for the first intervention listed, the use of quality blood pressure care among non-CVD individuals, we estimated that out of the 57.7 million non-CVD adults with hypertension, 27.8 million were already receiving quality care to reduce their blood pressure. The 3 clinical levers act to prevent first-time or repeat cardiovascular events and to improve acute and rehabilitative care when cardiovascular events do occur. The 4 levers for behavioral support act to help individuals quit smoking, move from obese to nonobese through a combination of diet and exercise, and ameliorate psychological distress, which can lead directly or indirectly to cardiovascular events. Although these 4 levers are classified as behavioral support, there are pathways from the clinical interventions to these levers, as providers often recommend or initiate these behavioral support services. The 8 levers for health promotion and access act to discourage smoking and consumption of energy-dense food and to encourage and improve access to fruits and vegetables and physical activity. The 7 levers involving taxes and regulation are aimed at reducing smoking, secondhand smoke, small particulate air pollution, and the consumption of energy-dense food, sodium, and trans fats.

We acknowledge that each lever has advantages and limitations or challenges in terms of cost and ease of implementation. For example, levers aimed at individuals have been shown to be effective at preventing morbidity and mortality, especially if they involve the use of advanced products and procedures, but they may be costly to the individuals or to third-party payers. In addition, levers involving taxes or regulation may have strong impacts and cost relatively little to implement on an ongoing basis, but the ability

TABLE 1—PRISM Interventions' Target Populations and Risk Factor Management Costs

Intervention Class and PRISM Interventions	Intervention Levers	Estimated Target Population in 2010 (Recipient Population in 2010), ^a in Millions	Unit Cost Per Recipient Per Year (2008), ^b \$
Clinical (n = 3 interventions)			
Preventive care for precardiovascular event	Use of quality BP care, non-CVD	57.7 (27.8)	440
	Use of quality cholesterol care, non-CVD	89.4 (26.9)	420
	Use of quality diabetes care, non-CVD	17.4 (6.9)	1700
Preventive care for postcardiovascular event	Use of quality BP care, post-CVD	21.0 (11.6)	440
	Use of quality cholesterol care, post-CVD	19.2 (8.8)	420
	Use of quality diabetes care, post-CVD	9.0 (4.3)	1700
	Use of quality CVD care, post-CVD	27.4 (19.2)	2000
Acute care and rehabilitation for cardiovascular event	Use of quality acute and rehab care	3.7 (3.0)	26 050
Behavioral support (n = 4)			
Smoking quit services	Use of quit counseling and NRT by smokers	51.1 (5.1)	619
Weight loss services	Use of weight loss services by obese	75.3 (7.5)	650
Distress support services precardiovascular event	Use of counseling and support services by distressed, non-CVD	28.0 (3.8)	2080
Distress support services postcardiovascular event	Use of counseling and support services by distressed, post-CVD	6.9 (1.4)	2080
Health promotion and access (n = 8)			
Smoking countermarketing	Smoking countermarketing index	253.4	
Energy-dense ("junk") food countermarketing	Energy-dense ("junk") food countermarketing index	295.4	
Fruit and vegetable promotion	Fruit and vegetable promotion index	295.4	
Fruit and vegetable access	Fruit and vegetable access index	295.4	
Physical activity promotion	Physical activity promotion index	295.4	
Physical activity facilities access	Physical activity facilities access index	295.4	
Physical activity in schools	Physical activity in schools index	50.1	
Physical activity in child care facilities	Physical activity in childcare facilities index	16.9	
Taxes and regulation (n = 7)			
Tobacco taxes	Tobacco tax rate	253.4	
Tobacco marketing restrictions	Tobacco marketing restriction index	253.4	
Workplace smoking bans	Fraction of workplaces allowing smoking	253.4	
Air pollution restrictions	Air pollution ($\mu\text{g}/\text{m}^3$ PM _{2.5})	295.4	
Energy-dense ("junk") food taxes	Energy-dense ("junk") food tax rate	295.4	
Sodium reduction in processed food	Nonhypertensives, mean sodium consumption (mg/d)	216.8	
	Hypertensives, mean sodium consumption (mg/d)	78.6	
Trans fat reduction in processed food	Trans fat fraction of calories	295.4	

Note. BP = blood pressure; CVD = cardiovascular disease; NRT = nicotine replacement therapy; PM_{2.5} = particles of ≤ 2.5 μm diameter; PRISM = Prevention Impacts Simulation Model.

^aSources for target and recipient populations are available from PRISM reference guide for model version 3p, August 2013, Table 1-1.ⁱⁱ

^bSources for unit costs available from PRISM reference guide for model version 3p, August 2013, Table 1-8.ⁱⁱ

of governments to implement them—partially or fully—may be limited because of concerns about individual liberties or they may have financial impacts on affected industries and businesses. However, for the purposes of the PRISM analysis, we limit consideration to the effects of the interventions on deaths and downstream (or “consequence”) costs.

“Deaths” refers to deaths from CVD events as well as deaths attributable to other complications of CVD risks, including

1. deaths from chronic obstructive pulmonary disease due to smoking (current or former), secondhand smoke, or small particulate air pollution;
2. deaths from lung and other respiratory-system cancers due to smoking, secondhand smoke, or small particulate air pollution;
3. deaths from kidney failure due to hypertension or diabetes, as well as other noncardiovascular deaths from hypertension or diabetes;

4. deaths from colorectal cancer due to obesity, diets poor in fruits and vegetables, or physical inactivity;
5. deaths from breast cancer due to physical inactivity; and
6. deaths from suicide associated with psychological distress.

To give a sense of the relative magnitude of the deaths included in the model, we estimate that in 2010 there were about 616 000 CVD deaths and about 525 000 other deaths

attributable to CVD risk factors. For a detailed discussion of how data on cause of death from the National Vital Statistics System were incorporated into PRISM, see Homer.³

“Costs” refers to discounted (at 3% per year) direct medical costs for risk factor management and preventive care, acute care for CVD events and other risk factor-related hospitalizations, and post-CVD long-term care, as well as productivity costs due to disability from CVD events and premature deaths from CVD events and other risk factor complications.³ These costs do not include the administrative and other nonmedical implementation costs of interventions. One source has estimated these nonmedical costs as one tenth to one hundredth of the medical costs, and we therefore would not expect their addition to meaningfully affect the relative costs of various interventions.¹²

METHODS

We first tested the 4 categories of interventions—including all of the intervention levers within each class—using the version of PRISM calibrated to represent the entire United States. Each intervention starts out at a baseline value representing its 2010 level and is then ramped up over a 5-year period from 2011 to 2016 to reach full implementation, and remains at that level through the end of the simulation in 2040 (Table B, available as a supplement to the online version of this article at <http://www.ajph.org>). Full implementation represents the best plausible level of reach and effectiveness of an intervention as suggested by the literature and subject matter experts. For example, when “smoking quit services” is selected as an intervention, on the basis of the prevailing scientific literature, it is assumed that promotion and subsidization of quit lines, counseling, and nicotine replacement therapy will increase the annual use of such services from 10% of smokers to 20%.³ The interventions affect the flow of people into and out of the modeled risk groups (e.g., smoking quit services increase the flow from current to recent former smoker; tobacco taxes do the same and also reduce the flow from nonsmoker to current smoker) (Table A).

In addition to differences in the best plausible lever strengths across interventions, the

interventions also differ in their underlying effect size (Table A) and target populations (Table 1), which have different levels of CVD risk. For example, some interventions may have large effect sizes for a smaller, higher-risk segment of the population whereas others have smaller effects on the entire population. These factors will drive the differences in outcomes across the intervention categories.

The PRISM model contains 84 parameters that could affect intervention results and that are associated with some degree of uncertainty (Table A). We first tested the model with all of these parameters at their “best estimate” default settings (a single simulation) and then performed a Monte Carlo–style sensitivity analysis in which each of the 84 parameters was allowed to vary over its uncertainty range (200 simulations). We report 95% sensitivity bounds (2.5 percentile to 97.5 percentile) of results from the 200 Monte Carlo simulations.

We next performed the same set of intervention and sensitivity tests using a version of PRISM recalibrated to represent a less-advantaged county that has a higher death rate than the nation overall. PRISM has recently been recalibrated to represent 6 local populations within the United States that differ substantially in terms of population density, poverty level, racial composition, and all-causes mortality, and which we selected as representative of 6 different clusters of localities we have analyzed. (For a similar clustering approach, see Murray et al.¹³) One of these local populations is a county that has a significantly higher death rate and is also poorer (although not less educated), more urban, and more African American than the US average. The demographic differences between this county and the United States overall, and the difference in terms of all-causes mortality, may be seen in the top half of Table 2. Although PRISM is built around health care and public health interventions and does not include antipoverty initiatives, a comparison of results from the 2 models may clarify whether socioeconomic factors are likely to affect the relative importance of different categories of interventions for reducing cardiovascular risks.

The lower half of Table 2 compares the United States and the less-advantaged county in terms of certain cardiovascular risk factors.

For small particulate air pollution (PM_{2.5}, or particles of 2.5 μm diameter or less), the data presented here are averages for the year 2008 based on direct measurement by the Environmental Protection Agency. For all other risk factors in this table—high blood pressure, high cholesterol, diabetes, smoking, obesity, and distress—we derived the estimates from the National Health and Nutrition Examination Survey (NHANES), broken out by population segment (age, gender, CVD status) and weighted to approximate the US and local populations in the year 2008. We constructed synthetic estimates at the local level by first stratifying NHANES data and estimating risk factor prevalence for each unique age, gender, CVD status, poverty status, and race/ethnicity cell, in a manner similar to other studies.^{17,18} We then combined these strata using population counts for each cell in the less-advantaged county,^{14,15} producing the synthetic estimates for the less-advantaged county seen in Table 2.

The synthetic estimates, which we used to calibrate PRISM for the less-advantaged county, suggest that the less-advantaged county has a higher prevalence of uncontrolled high blood pressure than the national average, a lower prevalence of uncontrolled high cholesterol, a higher prevalence of uncontrolled diabetes, about the same prevalence of smoking, a higher prevalence of obesity, and a slightly higher prevalence of distress. It also has a significantly higher level of particulate air pollution than the national average.

When the differences in cardiovascular risk factor prevalence (and the slight differences in age structure) in Table 2 are taken into account, the PRISM model—without further adjustment—would suggest that the less-advantaged county should have a CVD death rate that is 23% greater than that of the United States overall, and a death rate from other complications of cardiovascular risk factors barely greater than that of the United States overall. However, data from *Vital Statistics* indicate that in fact these gaps are 55% for CVD deaths and about 20% for deaths from other complications. For PRISM to replicate these actual gaps, it is necessary to introduce adjustment multipliers for the less-advantaged county of 1.25 on CVD deaths and 1.20 on deaths from other complications in the county’s baseline simulation. These

TABLE 2—Comparison of Demographics and Cardiovascular Risk Factors for Entire United States and for Less-Advantaged County

Characteristics	United States	Less-Advantaged County
Demographics		
Age, y, %		
< 18	24.8	23.6
18–64	61.7	62.5
≥ 65	13.5	13.9
Race/ethnicity, %		
White non-Hispanic	65	52
African American non-Hispanic	13	42
Hispanic	16	4
Other	6	2
Urban or suburban location, %	82	89
Income below poverty line, %	14.3	16.5
Median household income, \$	50 221	43 312
Education (not mutually exclusive), %		
High school graduate	85	87
College graduate	28	29
All-causes death rate, per 1000 population	8.2	11.1
Cardiovascular risk factors (population aged ≥ 18 y)		
High blood pressure, %		
Ever told or measured systolic blood pressure ≥ 140 mmHg or diastolic blood pressure ≥ 90 mmHg	33	40
Controlled fraction of adults with high blood pressure ^a	54	52
High cholesterol, %		
Ever told or measured low density lipoprotein ≥ 130 mg/dL	47	45
Controlled fraction of adults with high cholesterol ^a	35.5	37
Diabetes, %		
Ever told or measured fasting glucose ≥ 126 mg/dL	11	14
Controlled fraction of adults with diabetes ^a	42	40
Current smoker (> 100 cigarettes in lifetime and any cigarette smoking currently), %	23	24
Obesity: body mass index ≥ 30 kg/m ² , %	32	37
Distress: Kessler-6 ≥ 6, ^b %	14.5	16
Particulate air pollution ^c : μg/m ³ PM2.5	10.9	16.1

Note. Data and synthetic estimates are from various sources, 2000 to 2010. Demographic metrics are from Census 2010, except (a) urban-rural split from the Central Intelligence Agency's *World Factbook 2009*¹⁴ for the United States in 2008 and from Census 2000 for less-advantaged county,¹⁵ and (b) death rates from *Vital Statistics 2010*. *Vital Statistics* are compiled by the National Center for Health Statistics (NCHS) from vital registration systems operated in the various jurisdictions legally responsible for the registration of vital events—births, deaths, marriages, divorces, and fetal deaths. Cardiovascular risk factor estimates for high blood pressure, high cholesterol, diabetes, smoking, obesity, and distress are based on National Health and Nutrition Examination Survey (NHANES) 2005–2008 for non-cardiovascular disease (CVD) adult population and NHANES 2001–2008 for post-CVD population (additional years included to account for post-CVD's smaller sample size), and applying population weights, including post-CVD percentages from National Health Interview Survey (NHIS) 2007–2009. For United States overall, the population weights use 2008 US percentages by gender, adult age group, and CVD status. For less-advantaged county, the estimates are synthetic, starting from US estimates and applying further population weights reflecting poverty rates and race/ethnicity percentages in the less-advantaged county.

^aThe controlled fraction represents the portion of the high-risk population (those ever told or currently measured to have hypertension, high cholesterol, or diabetes) now under the high-risk threshold for each respective condition.

^bThe Kessler-6 index measures nonspecific psychological distress and is intended to identify persons with mental health problems severe enough to cause moderate to serious impairment in social, occupational, or school functioning and to require treatment.¹⁶

^cParticulate air pollution (PM2.5, or particles of ≤ 2.5 μ) estimates for the United States from Environmental Protection Agency (EPA) Air Trends report for 2008, and for the less-advantaged county averaging across all of its EPA monitoring stations for 2008.

multipliers do not reflect differences in risk factors and are not affected by interventions. They are reflective of socioeconomic status (SES) differences and other factors not represented in the model, such as the racial and ethnic composition of the population. Use of these multipliers also does not affect the interpretation of results because the multipliers are contained in both the baseline simulation and simulations with various interventions, and all results are reported with respect to changes from baseline values. Presentation of comparative results effectively factors out any influence of these multipliers.

RESULTS

Table 3 shows testing results for each class of interventions at 2 points in time and for 2 key output variables. Because the CVD effects of many of the interventions can take years to manifest after full implementation, results are shown for 2020 and 2040, to contrast the short-term (i.e., 10-year) and long-term (i.e., 30-year) effects of the interventions. The table shows percentage reductions (relative to no intervention) in cumulative (starting in 2011) average annual per capita metrics for deaths and costs. As is evident in Table 3, the percentage reduction for each class of intervention is less than the sum of the reductions of the individual interventions that are included. We made no assumptions about the potential synergies or redundancies of the interventions. Rather, the combinations of interventions are less than additive because certain “upstream” interventions that reduce risks will reduce the populations that require action and therefore the impact that “downstream” interventions can have.

Of the 4 categories of interventions, the clinical interventions are projected to be the most effective at reducing deaths in the short term and second to taxes and regulation at reducing deaths in the long term. On the other hand, the net cost reductions of the clinical interventions are relatively modest, third behind (1) taxes and regulation and (2) health promotion and access, in the short and long term. Although the costs of CVD events and other chronic disease morbidity and mortality are reduced, the significant costs of treating and managing hypertension, high cholesterol,

TABLE 3—PRISM Simulated US Results by Intervention Class for Years 2020 and 2040, With 95% Sensitivity Bounds

Intervention Class	Year	
	2020	2040
Percentage reduction from base run in per capita deaths ^a		
Clinical	11.0 (10.0, 12.4)	14.4 (13.0, 16.7)
Behavioral support	1.1 (1.1, 1.1)	2.2 (2.2, 2.3)
Health promotion and access	2.1 (1.8, 2.3)	5.9 (4.9, 7.1)
Taxes and regulation	7.9 (7.3, 8.7)	15.4 (14.2, 16.7)
All interventions	19.2 (17.9, 21.0)	31.3 (29.2, 33.3)
Percentage reduction from base run in per capita costs ^a		
Clinical	3.2 (2.7, 3.8)	3.9 (3.5, 4.7)
Behavioral support	1.6 (1.6, 1.6)	1.3 (1.0, 1.3)
Health promotion and access	2.1 (1.9, 2.2)	5.4 (4.8, 6.2)
Taxes and regulation	7.3 (6.9, 7.9)	14.2 (13.2, 15.3)
All interventions	9.1 (8.5, 9.8)	17.8 (16.7, 19.1)

Note. PRISM = Prevention Impacts Simulation Model.

^aCumulative average starting in 2011. Comparisons are to results of base run in which all interventions remained at their 2010 levels.

diabetes, and CVD—summed across millions of people—are at the same time increased.

The behavioral support interventions can quickly reduce smoking, obesity, and distress, but their reach (Table 1) and effectiveness at the population level (Table A) are limited, and their per capita cost (Table 1) is relatively high due to the intensive and individual nature of these services. Of the 4 intervention categories, they are projected to be the least effective in reducing deaths and costs.

The health promotion and access interventions are projected to reduce deaths and costs relatively little in the short term, although still more than the behavioral support interventions. In the long term, however, their impacts grow and they become second only to taxes and regulation in their ability to reduce costs.

The taxes and regulation interventions, which address smoking, nutrition, and air pollution, are projected to be effective at reducing deaths and costs in the short term and even more so in the long term. Of the 4 intervention categories, they are projected to be the second most effective at reducing deaths in the short term but the most effective at reducing deaths in the long term. The model shows these interventions as the most effective at reducing costs in both the short and long terms.

Table 3 also presents the projected benefits of combining all 4 intervention categories—that

is, all 22 intervention levers. Deaths are reduced relative to the base run (within 95% sensitivity bounds) by 18% to 21% by 2020 and 29% to 33% by 2040. Costs are reduced 9% to 10% by 2020 and 17% to 19% by 2040. In the short term, more than half of the reduction in deaths comes from the clinical interventions alone, but by 2040 the other intervention categories (taxes and regulation, behavioral support, and health promotion and access) account for more than half of the reduction in deaths. In the short and long term, tax and regulation interventions by themselves would achieve 80% of the cost reduction that could be achieved with all interventions combined. This is separate from any revenues generated through new taxes.

Table 4 presents the results of testing the 4 categories of interventions on the version of PRISM calibrated to represent the less-advantaged county. The top part of the table shows percentage reductions in average annual per capita death and cost metrics relative to the no-intervention base run. These projected intervention impacts for the less-advantaged county may be compared with those projected in Table 3 for the nation overall. In most cases, the projected intervention impacts are somewhat greater for the county than for the nation. When all of the intervention categories are combined, deaths

in the county are reduced relative to the base run (within 95% sensitivity bounds) by 21% to 24% by 2020 and 34% to 38% by 2040. Costs in the county are reduced 13% to 15% by 2020 and 23% to 25% by 2040. The bottom part of the table shows the effects of various interventions on the ratios of deaths and costs for the county relative to those for the United States overall.

These percentage reductions are greater than those for the United States overall, because in several ways there is more room for improvement for the county than for the United States, and thus more potential reach of interventions. First, the less-advantaged county starts with a higher prevalence of uncontrolled high blood pressure and diabetes, more obesity and distress, and more air pollution (Table 2). Thus, the same relative risk reduction caused by a set of interventions would lead to a larger absolute reduction in the less-advantaged county than in the United States overall. Second, more of the population in the less-advantaged county also starts without convenient access to or ability to afford physical activity facilities or fresh fruits and vegetables. Third, the less-advantaged county, compared with the United States overall, starts with a greater fraction of workplaces allowing smoking (30% vs 25%) and with a lower tax rate on tobacco (15% vs 34%).

Although the percentage reductions are somewhat greater in the less-advantaged county than in the United States, the relative importance of the 4 intervention categories is unchanged on the whole. For reduction of deaths in the short term, the clinical class is still the most powerful, followed by taxes and regulation. For reduction of deaths in the long term, taxes and regulation are still the most powerful, followed by clinical interventions. Note, however, that taxes and regulation contribute even more to the reduction in deaths in the county than they do in the United States overall, because of the greater room for improvement in reducing air pollution and workplace smoking through regulations and in raising the tobacco tax rate.

For reduction of costs in the short and long term, taxes and regulation are still the most powerful, followed by clinical interventions in the short term and health promotion and access in the long term. All 3 of these

TABLE 4—PRISM Simulated Results for the Less-Advantaged County for Years 2020 and 2040, With 95% Sensitivity Bounds, and Comparison With US National Base Run

Intervention Class	Year	
	2020	2040
Percentage reduction from county base run		
Deaths per capita, ^a mean (95% CI)		
Clinical	12.1 (11.0, 13.6)	14.9 (13.7, 17.1)
Behavioral support	1.3 (1.2, 1.3)	2.4 (2.4, 2.6)
Health promotion and access	2.6 (2.6, 2.9)	6.8 (6.3, 7.7)
Taxes and regulation	10.4 (9.6, 11.1)	19.6 (18.3, 21.0)
All interventions	22.5 (21.3, 24.3)	35.4 (33.8, 37.6)
Costs per capita, ^a mean (95% CI)		
Clinical	5.2 (4.8, 5.9)	6.1 (5.8, 7.0)
Behavioral support	-1.2 (-1.2, -1.2)	0.8 (0.7, 0.8)
Health promotion and access	2.6 (2.6, 2.8)	6.3 (6.0, 7.0)
Taxes and regulation	9.7 (9.1, 10.1)	18.2 (17.1, 19.3)
All interventions	13.7 (13.1, 14.5)	23.7 (22.8, 24.9)
Per capita ratio to national base run		
Deaths		
County base run	1.40	1.41
Clinical	1.23	1.20
Behavioral support	1.38	1.37
Health promotion and access	1.36	1.31
Taxes and regulation	1.25	1.13
All interventions	1.08	0.91
Costs		
County base run	1.26	1.27
Clinical	1.20	1.20
Behavioral support	1.28	1.28
Health promotion and access	1.23	1.19
Taxes and regulation	1.14	1.04
All interventions	1.09	0.97

Note. CI = confidence interval; PRISM = Prevention Impacts Simulation Model.

^aCumulative average starting in 2011.

intervention categories have a greater impact on reducing costs for the county than for the United States overall. This is especially so for the clinical interventions, which contribute more to the reduction in costs in the county than they do in the United States overall, because of a greater relative reduction in CVD-related disability and extended care.

Whereas the top half of Table 4 addresses the question, “To what extent can the interventions reduce deaths and costs in the less-advantaged county?,” the bottom half addresses the question, “To what extent can the interventions in the county bring its deaths and costs down to those of the United States?” In

particular, the bottom half of the table presents ratios comparing the county results (best estimates without sensitivity bounds) with those of the US base run. With interventions remaining at their 2010 levels, the death metric in the county base run is 40% greater in 2020 and 41% greater in 2040 than in the US base run. Modeling shows that the clinical interventions alone can reduce the county-versus-US death ratios to 1.23 in the short term and 1.20 in the long term, and the taxes and regulation interventions alone can reduce them to 1.25 in the short term and 1.13 in the long term. When all 22 of the interventions are combined, they bring the county-versus-US death ratio down to

1.08 in the short term and 0.91 in the long term. With ratios such as 1.08 and 0.91, the interventions help to largely erase the effects of SES differences on deaths as well as reducing the effects of risk factors.

With interventions remaining at their 2010 levels, the cost metric is 26% greater in 2020 and 27% greater in 2040 than the US base run. The taxes and regulation interventions alone can reduce the cost ratios to 1.14 in the short term and 1.04 in the long term. When all 22 of the interventions are combined, they bring the less-advantaged county-versus-US cost ratio down to 1.09 in the short term and 0.97 in the long term.

Whereas the top half of Table 4 (compared with Table 3) indicates that the percentage reductions in deaths and costs are greater for the county than for the United States overall, the bottom half indicates that it would take all of the interventions together to close the baseline gaps. Put another way, no single class of interventions by itself is sufficient to close the gaps between the less-advantaged county and the United States.

DISCUSSION

Conceptual models of public health have suggested that interventions that affect a larger number of people have the greatest potential to improve population health.¹⁹ We used PRISM, a simulation model of cardiovascular risk factors and consequences, to test this hypothesis. First, we divided the model’s 22 health care and public health interventions into 4 categories corresponding to a 2 × 2 representation defined by the axes “individual-population” and “prescriptive-facilitative.” Second, we tested the model as calibrated to represent the United States overall with the 4 categories of interventions, individually and combined, to determine the relative importance of the 4 categories in affecting deaths and costs in both the short term (2011–2020) and the long term (2011–2040). Third, we repeated this process with the model calibrated to represent a less-advantaged county with a more urban population, lower average income, larger proportion of African Americans, and higher cardiovascular and all-causes death rates than in the United States overall.

The model testing indicates that, of the 4 categories of interventions, those that use taxes and regulations to influence change at the population level (upper-right quadrant of Figure 1) are projected to do the most to reduce costs in both the short and long term and the most to reduce deaths in the long term; they are second only to clinical interventions in reducing deaths in the short term. The short-term impacts come primarily from improved hypertension control from sodium reduction, improved cholesterol control from trans fat reduction, and fewer cases of coronary ischemia from reductions in trans fat consumption, secondhand smoke in the workplace, and particulate air pollution. The long-term impacts come primarily from an accelerated reduction in smoking prevalence related to tobacco taxes, marketing restrictions, and workplace smoking bans. Energy-dense food taxes also contribute in the long term by reducing the prevalence of obesity and, in turn, hypertension, high cholesterol, and diabetes.

Interventions for health promotion and access at the population level are shown to have multiple positive effects over time. They reduce the prevalence of smoking and, by improving physical activity and the quality of diet, also reduce the prevalence of obesity, hypertension, high cholesterol, and diabetes in adults. They are not very powerful in the short term but are second only to taxes and regulations for reducing costs in the long term.

The 3 clinical interventions in combination have a relatively quick and powerful effect in reducing the number of CVD events (through improved preventive care) and reducing their fatality (through improved acute and short-term rehabilitation care). Of the 4 intervention categories, they do the most to reduce deaths in the short term and are second in the long term, but are less effective at reducing costs.

Compared with the other categories, the individual-level behavioral support interventions are least effective at reducing deaths and costs. Like clinical interventions, they are relatively costly, but their impact is facilitative rather than prescriptive and, unlike clinical interventions, have only indirect impact on key risk factors, including high blood pressure and diabetes.

The model testing also demonstrates that the less-advantaged county could be brought in line with the US average on per capita

cardiovascular-related deaths and costs only through a concerted effort along all categories of interventions; no single class of interventions by itself could do so. This result may be seen as offering hope to less-advantaged parts of the country that their health problems are not unsolvable, but it may also be seen as underscoring the huge gap that currently exists between certain specific segments of the population with regard to cardiovascular health.

In the case of the county in question, the cardiovascular health disadvantage does not lie with the socioeconomic factors of income or education. The poverty rate in the less-advantaged county is only a couple of percentage points higher than that in the United States overall and its educational attainment is actually higher. The biggest demographic difference is in racial composition; its proportion of African Americans is 42% compared with 13% for the United States overall. It may be that African Americans differ from other races with respect to mortality from CVD and other chronic disease, even when they have similar income and living conditions.²⁰ Such persistent race-based disparity—not explained by other established risk factors—has been observed in several areas of health.^{20–22}

These results are subject to several limitations. First, they reflect modeling assumptions about the structure of the system and effect sizes. All causal effects were based on the peer-reviewed literature. Where published data on effect sizes were lacking or incomplete, we supplemented with expert opinion. This was done in an effort to reduce the uncertainty about effect sizes that we faced in some cases. We included wide sensitivity ranges for the effect size parameters in the probabilistic sensitivity analysis (Table A). Furthermore, results for categories are affected by the choice of interventions assigned to each category. The selection of interventions in each category was based on an extensive review of the literature, but a different assignment of interventions to categories might produce different results.

Second, although the consequence costs calculated in PRISM include many types of direct medical costs and lost productivity costs, as well as the costs of clinical and behavioral support interventions, they do not include the implementation costs of interventions.

One study suggests that comprehensive population-level prevention (preventing smoking, increasing physical activity, and improving nutrition) could be accomplished for only \$10 per person per year, or about \$3 billion per year.¹² This cost may be compared with the roughly \$85 billion per year in additional clinical costs that PRISM calculates would be required immediately as a result of implementing the clinical and behavioral support interventions.

Third, the comparisons presented here have used certain specific outcome measures for deaths and costs. These are arguably good measures, but others, such as years of potential life lost or cost per quality-adjusted life year, might conceivably yield different results.

Fourth, lack of representative, measured risk factor data at the local level meant that we relied on synthetic risk factor estimates for the less-advantaged county. The synthetic estimates involved adjusting nationally representative estimates for demographics, but other local factors, such as climate, air pollution, and regional diet, could also affect risk factor prevalence rates.

Finally, although the analysis comparing the less-advantaged county with the United States overall indicates an association between SES and deaths and costs, it is not possible with PRISM to tease apart the influences of income, education, urban versus rural setting, and race/ethnicity or to test interventions that would affect them. It is one thing to say that social position is an important driver of outcomes but more difficult to quantify the potential impact of interventions that attempt to alter social position—for example, through antipoverty or anticrime programs or enhanced social support services. Some research has been done to help separate the contributions of poverty, race, population density, and other social determinants of health,^{13,23} but much more is needed.

Despite these limitations, PRISM offers a unique capability to test, in a single integrated dynamic framework, many potential interventions for reducing cardiovascular risk. This capability allows one to perform extensive sensitivity testing to determine the relative significance of uncertain parameters. We have found here and elsewhere² that most policy conclusions from PRISM are insensitive

to such uncertainties. PRISM is one in a class of simulation models dealing with population health that have been developed over the past decade using the system dynamics modeling approach. Other simulation models have been used to examine alternative interventions for other chronic conditions such as diabetes and heart failure,^{6,7} and to project the impacts of interventions in early childhood caries.²⁴ Another model called HealthBound was developed for the CDC to demonstrate the importance of including prevention as part of national health reform.^{25,26} Other areas of public health have also benefited from this type of modeling⁵ and present opportunities for further application and interactive use with real-world decision-makers.



About the Authors

Gary Hirsch is an independent consultant based in Wayland, MA. Jack Homer is with Homer Consulting, Voorhees, NJ. At the time of the study, Justin Trogdon was with RTI International, Research Triangle Park, NC. Kristina Wile is with Systems Thinking Collaborative, Stow, MA. Diane Orenstein is with the Centers for Disease Control and Prevention (CDC), Atlanta, GA.

Correspondence should be sent to Gary B. Hirsch, Independent Consultant, Creator of Learning Environments, 7 Highgate Rd, Wayland, MA 01778 (e-mail: GBHirsch@comcast.net). Reprints can be ordered at <http://www.ajph.org> by clicking the "Reprints" link.

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Contributors

G. Hirsch assisted with model development, ran simulations, and analyzed their results. J. Homer built the simulation model and collaborated on the writing of the article. J. Trogdon managed the various aspects of the modeling project, assisted with modeling, and led the writing of the article and design of the figures. K. Wile assisted with modeling, developing the analysis framework, and designing the figures. D. Orenstein oversaw projects using and building PRISM at the CDC, served as technical consultant, and contributed to manuscript writing and review. All authors conceptualized ideas, framed the structure of the model, and edited drafts of the article.

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Human Participant Protection

No protocol approval was necessary because only secondary data were used in this work.

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