Initiation versus Cessation Control Policies: Deriving Optimal Resource Allocation Strategies to Decrease Smoking Prevalence Under a Fixed Budget

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Abstract

Background. Over several decades the tobacco control community has recommended and implemented smoking initiation and cessation interventions to reduce the smoking toll. It is necessary to study the combined effect of these interventions to allocate resources optimally. However, there is a paucity of studies that address the right combination of initiation and cessation policies over time to reduce smoking prevalence. **Objective.** To derive optimal trajectories of initiation and cessation interventions that minimize overall smoking prevalence over a specified period while satisfying a budget constraint. **Methods.** Using an established dynamic model of smoking prevalence, we employ an optimal control formulation to minimize overall smoking prevalence within a specified time period. The budget constraint is handled through an iterative application of a penalty function on above-budget expenditures. We further derive the optimal cost ratio of initiation versus cessation programs over time. To parameterize our model, we use results from two empirical interventions. The demographic data are from the National Health Interview Survey in the United States. **Results.** For our example, our results show that the optimal cost ratio (initiation over cessation) starts around 2.02 and gradually increases to 5.28 in 30 years. Smoking prevalence decreases significantly compared with the status quo, 8.54% in 30 years with no interventions versus the estimated 6.43% with interventions. In addition, the optimal units of initiation and cessation interventions increase over time. **Conclusions.** Our model provides a general framework to incorporate policy details in determining the optimal mix of smoking interventions.

Keywords

Optimal control, tobacco control, smoking prevalence, smoking cessation

Cigarette smoking has remained as the leading preventable cause of disease and premature death in the United States. It can lead to many adverse health consequences such as lung cancer, cardiovascular diseases, and respiratory diseases.[1–3] In the United States alone, in 2015, more than 16 million individuals lived with a smoking-related disease. According to the estimates given by the 2014 Surgeon General's report, the annual number of smoking-attributable deaths is around 480,000 and has stayed above 400,000 for more than a decade.[4] Besides

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mortality, smoking imposes a substantial financial burden on society. Smoking-attributable economic costs resulting from loss of productivity, premature deaths, and direct medical cost added up to around $300 billion over the 2009 to 2012 period.[4,5] To private employers in the United States, a smoking employee costs an extra $5,816 per year, considering excess absenteeism, presenteeism, and lost productivity due to smoking breaks, excess health care costs, and pension benefits.[6]

The primary focus of tobacco control policies in the United States has been to reduce the number of smokers. Reducing smoking prevalence can be achieved either by encouraging smokers to quit or by preventing nonsmokers from taking up the habit. Smoking cessation interventions aim at the first goal while smoking initiation interventions target the latter. Cessation programs can be divided into two categories: pharmacological and nonpharmacological interventions. Pharmacological interventions are those in which smokers take prescribed drugs to help with their nicotine withdrawal syndromes. Popular treatments include nicotine-replacement treatment, bupropion, and varenicline.[7,8] Nonpharmacological interventions usually involve motivational interviews and counseling as well as cognitive behavioral therapy.[9,10] Scholars have identified a few barriers for successful nonpharmacological interventions, including lack of social support, cultural norms, and stressful working/living situations.[11,12] Initiation/prevention programs aimed at reducing the risk of youth becoming smokers. Some popular programs include cigarette taxation, mass media campaigns, and school-based education programs.[13–16] Studies show that smoking initiation occurs during teenage and young-adulthood years, but is very rare after age 24 years.[17,18] As a result, smoking initiation programs mainly target teenagers at school.

Smoking prevalence in the United States in 2015, after 50 years of smoking control efforts, has decreased to 15.1% from 43% in 1964.[19] To accelerate the eradication of the smoking epidemic, more efficient ways to implement smoking interventions are needed. Previous studies reveal that initiation and cessation programs are implemented and evaluated independently. Few studies look at the combined impact of multiple interventions targeting both initiation and cessation. The right combination of interventions could accelerate the process of reducing smoking prevalence while allocating limited resources efficiently. However, given the constant change of the environment in which these policies will act, there is a need to anticipate those changes and propose interventions that will adapt over time to this dynamic environment.

Optimization techniques, such as Optimal Control, can be useful in deriving appropriate solutions to this dynamic problem. Optimal control theory deals with problems of finding the paths of control variables that satisfy certain optimality criterion. In the context of dynamic models, the solutions represent a path for the control variables over time. Some scholars have applied optimal control theory to investigate empirical policies. For example, Juusola and Brandeau used optimal control to determine the best mix of investment in HIV treatment and prevention given a fixed budget. Their model maximizes the net present quality-adjusted life years.[20] Similarly, Basu and Kiernan investigated how financial incentives motivate health behavior changes by optimizing marginal return on investments.[21] When we deal with smoking policies, we can figure out the best combination of initiation and cessation programs over time to minimize prevalence given a budget constraint. To the best of our knowledge, we are the first study to adopt optimal control techniques to address the problem of reducing smoking prevalence over time while subjected to a budget constraint.

The organization of this article is as follows. First, we propose an optimal control dynamic model of ordinary differential equations (ODEs) and solve it analytically. Second, we identify and discuss an initiation and a cessation intervention to use as controls in the model. We then parameterize the model and solve it numerically for optimal trajectories. Finally, we present and discuss our results.

Methods

Theoretical Model

Based on previous work,[22,23] we employ the following expression to represent the path of smoking prevalence over time:

$$\dot{S} = I(t) - [\mu(t) + \nu(t)]S(t) \qquad (1)$$

where $S(t)$ stands for the number of smokers in the population at time t, $I(t)$ is the number of new smokers at time t, and $\mu(t)$ and $\nu(t)$ are the time-variant death and smoking cessation rates, respectively.

The original model has S and I as number of people while μ and ν are rates. Assuming a constant population of size M and dividing by M on both sides of expression (1),

$$\frac{\dot{S}}{M} = \frac{I(t)}{M} - [\mu(t) + \nu(t)]\frac{S(t)}{M},$$

where

$$s(t) = \frac{S(t)}{M}$$

is the time-variant smoking prevalence and

$$i(t) = \frac{I(t)}{M}$$

is the initiation rate. Because we assume M to be constant,

$$\dot{s} = \frac{d\left(\frac{S(t)}{M}\right)}{dt} = \frac{1}{M}\frac{dS(t)}{dt} = \frac{1}{M}\dot{S}.$$

We can write the transformed Equation (1) as

$$\dot{s} = i(t) - [\mu(t) + \nu(t)]s(t). \tag{2}$$

Empirical policies are generally designed with a proposed goal and a budget constraint. To incorporate these characteristics, our model aims to minimize the overall toll of smoking prevalence over time, subject to a budget constraint. In order to construct a performance measure that takes both factors into account, we assign weights to these two aspects. σ_1 is the weight assigned to smoking prevalence and σ_2 is the one for cost: $\sigma_1 + \sigma_2 = 1$ and $\sigma_1, \sigma_2 \geqslant 0$. The values of weights are determined by the policy as well as the corresponding budget. If the policy has no budget constraint, then $\sigma_1 = 1$ and $\sigma_2 = 0$. If the policy aims at reducing smoking prevalence with a budget constraint, then weights can be determined retrospectively by calculating the total cost over time and penalizing over-expenditures. The algorithm can be divided into two steps. The first step is to calculate the total cost retrospectively by summing up the area under the cost curve. In the second step, through adjusting weights, we can write a loop to find the minimum weight in front of costs that satisfy the proposed budget constraints. In this way, we can decrease smoking prevalence efficiently while satisfying the budget constraint. In addition, reducing cost requires us to include costs of interventions. γ_1 is the price per unit of initiation intervention and γ_2 is the unit price of cessation intervention $\gamma_1, \gamma_2 > 0$.

After defining our performance measure, we add some constraints to our model. Besides Equation (2), we have two more equations: $i(t) = \alpha_0 + \alpha_1 u_1(t)$ and $\mu(t) + \nu(t) = \beta_0 + \beta_1 u_2(t)$.[22] The death rate $\mu(t)$ is assumed to be constant over time and we include its value in β_0. We denote $\mu + \nu(t)$ as $\theta(t)$ to simplify the notation. $u_1(t)$ is the total units of initiation intervention

over time and $u_2(t)$ is the units for cessation intervention over time. Unit here is a technical term; one interpretation for unit is the scope of the intervention. For example, if γ_1 is the cost of one initiation intervention per 1,000 individuals, then we can have $\mu_1 = 2$ to represent the cost of an intervention for 2,000 individuals. Similarly, unit can stand for number of interventions. We can implement three interventions of the same size simultaneously and consider the impact as 3 units of one intervention. We have α_1 and β_1 to represent the effectiveness of interventions in the form of their impact on adult smoking initiation and cessation rates. α_0 is the initiation rate at t_0 and β_0 includes both death rate and smoking cessation rate at t_0.

Now we are ready to write our problem in the mathematical form:

$$\min_{u_1, u_2 \geqslant 0} \int_{t_0}^{t_T} \sigma_1 s(t) + \sigma_2\left(\gamma_1^2 u_1^2(t) + \gamma_2^2 u_2^2(t)\right) dt$$

subject to

$$\begin{aligned} \dot{s} &= i(t) - \theta(t)s(t) \\ i(t) &= \alpha_0 + \alpha_1 u_1(t) \\ \theta(t) &= \beta_0 + \beta_1 u_2(t) \\ \delta_1 + \delta_2 &= 1, \quad \delta_1, \delta_2 \geqslant 0 \\ \gamma_1, \gamma_2 &> 0 \\ \alpha_1 &< 0, \quad \beta_1 > 0 \end{aligned} \tag{3}$$

We can combine the first three constraints into one:

$$\dot{s} = \alpha_0 + \alpha_1 u_1(t) - (\beta_0 + \beta_1 u_2(t))s(t)$$

We choose to use the quadratic form for cost to penalize for extreme values. It is also a conventional form to represent cost in optimal control problems[24]. Then we can simplify the above problem into:

$$\min_{u_1, u_2 \geqslant 0} \int_{t_0}^{t_T} \sigma_1 s(t) + \sigma_2\left(\gamma_1^2 u_1^2(t) + \gamma_2^2 u_2^2(t)\right) dt$$

subject to

$$\begin{aligned} \dot{s} &= \alpha_0 + \alpha_1 u_1(t) - (\beta_0 + \beta_1 u_2(t))s(t) \\ \delta_1 + \delta_2 &= 1, \quad \delta_1, \delta_2 \geqslant 0 \\ \gamma_1, \gamma_2 &> 0 \\ \alpha_1 &< 0, \quad \beta_1 > 0 \end{aligned} \tag{4}$$

We obtain the augmented integrand function as

$$
\begin{aligned}
& g_a(s(t), u_1(t), u_2(t), p(t)) \\
&= \delta_1 s(t) + \delta_2\big(\gamma_1^2 u_1^2(t) + \gamma_2^2 u_2^2(t)\big) \\
&\quad + p(t)[\dot{s} - \alpha_0 + \alpha_1 u_1(t) + (\beta_0 + \beta_1 u_2(t))s(t)].
\end{aligned}
$$

Using the Euler-Lagrange equation,[24] we derive the following set of necessary conditions for the optimal solution:

$$
\begin{cases}
2\delta_2\gamma_1^2 u_1(t) - \alpha_1 p(t) = 0 \\
2\delta_2\gamma_2^2 u_2(t) + \beta_1 p(t)s(t) = 0 \\
\alpha_0 + \alpha_1 u_1(t) = \beta_0 + \beta_1 u_2(t)s + \dot{s} \\
\delta_1 + p(t)\beta_0 + p(t)\beta_1 u_2(t) - \dot{p} = 0
\end{cases}
\tag{5}
$$

The first two constraints give us the value of $u_1(t)$ and $u_2(t)$ in terms of other parameters:

$$
\begin{cases}
u_1(t) = \dfrac{\alpha_1 p}{2\delta_2\gamma_1^2} \\[2mm]
u_2(t) = \dfrac{\beta_1 ps}{2\delta_2\gamma_2^2}
\end{cases}
\tag{6}
$$

plugging these values back into the last two ODE constraints, we have

$$
\begin{cases}
\dot{s} = \alpha_0 + \dfrac{\alpha_1^2 p}{2\delta_2\gamma_1^2} - \beta_0 s + \dfrac{\beta_1^2 ps^2}{2\delta_2\gamma_2^2} \\[3mm]
\dot{p} = \delta_1 + \beta_0 p - \dfrac{\beta_1^2 ps}{2\delta_2\gamma_2^2}
\end{cases}
\tag{7}
$$

The time-variant optimal control problem we start with now becomes a set of ODE equations with initial and parameter values. One qualitative analysis we can conduct here is to compare if we should invest more in initiation intervention or cessation intervention, aka comparing $\gamma_1 u_1(t)$ with $\gamma_2 u_2(t)$. Since we already know the expression of $u_1(t)$ and $u_2(t)$, we plug these values into the equation:

$$
\begin{aligned}
\frac{\gamma_1 u_1}{\gamma_2 u_2} &= \frac{\dfrac{-\alpha_1 p}{2\delta_2\gamma_1}}{\dfrac{\beta_1 ps}{2\delta_2\gamma_2}} \\[3mm]
&= \frac{-\alpha_1\gamma_2}{\beta_1\gamma_1 s} \\[3mm]
&= \frac{|\alpha_1|\gamma_2}{\beta_1\gamma_1 s}
\end{aligned}
\tag{8}
$$

Here we have $p < 0$ from $u_1 > 0$, $\beta_1, \delta_1, \delta_2, \gamma_1, \gamma_2 > 0$ and $\alpha_1 < 0$. The reasoning is the following. We know the

weights, δ_1 and δ_2, are always nonnegative by definition, the same for prices, γ_1 and γ_2. α_1 is the effectiveness of the initiation intervention, which aims at decreasing initiation rate, thus $\alpha_1 < 0$. β_1, the parameter measuring the effectiveness of the cessation intervention, should increase the cessation rate by having $\beta_1 > 0$. The ratio of

$$
\frac{|\alpha_1|\gamma_2}{\beta_1\gamma_1 s}
$$

is the optimal proportion of the budget that should be spent on initiation intervention versus cessation intervention.

Numerical Simulations

Here we consider one initiation intervention and one cessation intervention in our model to illustrate the optimal path of u_1 and u_2 with respect to time. The optimal paths also solve the problem of allocative efficiency over time. This numerical simulation example using empirical results illustrates how our model optimizes intervention units u_1 and u_2 over time to minimize smoking prevalence while satisfying a budget constraint. These simulation examples are not intended to be exhaustive or represent implementable interventions, but to illustrate how this method can be used to develop optimal combinations over time to achieve certain goals. Especially how the policies should change over time to achieve these goals.

To parameterize our simulation example, we use the 2014 estimates from the National Health Interview Survey (NHIS; 16.8% smoking prevalence and 0.35% initiation rate). Here we define the initiation rate as the 18 to 24 prevalence taken as a proportion of the entire adult population. We use the permanent cessation rate (net of relapses) of 4.5% estimated by Mendez et al.[23] As our policy example, we use cost and effectiveness values from the 12 + 12 weeks of varenicline treatment for smoking cessation and the US truth campaign for smoking prevention. In our analysis, one intervention unit covers 1 million individuals. This unit size is arbitrary and can be scaled up or down.

The values of α_1 and β_1 are a bit more complicated. The effectiveness of the interventions needs to be scaled properly to be applied to the entire adult population since smoking prevalence is a population-level measure. We use two sets of demographic data to fit our model, NHIS and NSDUH (National Survey on Drug Use and Health). According to the coding documents for NHIS survey in 2014, the population data used was the 2010 Census. Combining the 2010 Census population size estimates with smoking prevalence from NHIS, we estimate

Table 1 Parameter Values in the Simulation Example

Population Smoking Initiation Rate in 2014	Effectiveness of the US Truth Campaign	Population Smoking Cessation Rate in 2014	Death Rate in 2014	Effectiveness of the 12 + 12 Weeks Varenicline Treatment	Unit Cost of the US Truth Campaign	Unit Cost of the 12 + 12 Weeks Varenicline Treatment
α_0 (%)	α_1 (%)	β_0 (%)		β_1 (%)	γ_0 (2014 USD)	γ_1 (2014 USD)
0.35	−0.0633358	4.5	0.89	0.6289097	20.168 million	67.968 million

a total of 39.6 million adult smokers in 2014 and the adult population size is approximated to be 234 million.

Last, we determine the values of δ_1 and δ_2. Since $\delta_2 = 1 - \delta_1$, we have just one unknown. We assume a total budget of 1 billion dollars over the time span of 30 years. Using the algorithm mentioned earlier, we first start with an initial guess of δ_1 and calculated the corresponding total cost retrospectively. We found the minimum weight in front of costs that satisfy the proposed budget constraints to be 0.01 in our example. The exact value of the minimum weight changes with respect to the units of cost used.

Simulations

Smoking Initiation Intervention

The truth campaign is a national youth smoking prevention campaign launched by the American Legacy Foundation starting from 2000. The truth campaign is a national tobacco counter-marketing campaign targeted primarily 12- to 17-year-olds. The campaign sent its anti-smoking message by TV commercials, advertisements, promotional items, street marketing, and a website.[25] Studies evaluating the US truth campaign found that 22% of the overall decline in youth smoking that occurred between 1999 and 2002 can be attributed to the campaign. In addition, the campaign was estimated to prevent 300,000 youth from smoking by 2002.[26] The total cost including travel costs is approximately 324 million dollars in 2002. Using 2014 US dollars, we estimated the per person cost to be 179 dollars.

Smoking Cessation Intervention

Among available smoking cessation alternatives, varenicline treatment, commonly branded as Chantix in the United States, is viewed by many as the most effective smoking cessation aid.[27] A randomized, double-blind trial published in 2006 recruited 1210 adult smokers to receive a 12 + 12 weeks of varenicline treatment. These smokers were assessed after 28 weeks where 603 patients were randomized to varenicline maintenance and 607 randomized to placebo. Researchers found that the 1-year abstinence estimate for the 12 + 12 weeks of varenicline treatment is 27.7%, compared with the 9.3% with placebo treatment. In addition, the average cost of the course of varenicline treatment was estimated at $603.89 in 2010. Knight and colleagues estimated the treatment cost as the sum of the initial 12 weeks of costs (covering one physician visit and 12 weeks of varenicline) and a further 12 weeks of maintenance therapy (another physician visit and 12 weeks of varenicline) for successful quitters.[28]

Table 1 shows all the parameter values in our simulation example.

Results

The figures show results obtained by employing the parameters derived from the NHIS data. Figure 1 shows the projected path of smoking prevalence without any intervention (status-quo path) over the next 30 years versus the projected trajectory derived from an optimal combination of initiation and cessation interventions over the same time period (optimal path).

Figure 1 confirms that the numeric simulation is consistent with our theoretical results. With interventions, smoking prevalence decreases to 6.43% in 30 years versus the status quo of 8.54%. Figure 2 shows how the units of optimal interventions change over the 30-year span. The upper graph in Figure 2 shows the optimal units of initiation intervention over time while the lower one presents the optimal cessation units. We can see that both curves are monotonically increasing functions. In addition, both curves are convex. Convexity implies that as time goes on, the increases in units for both interventions accelerates.

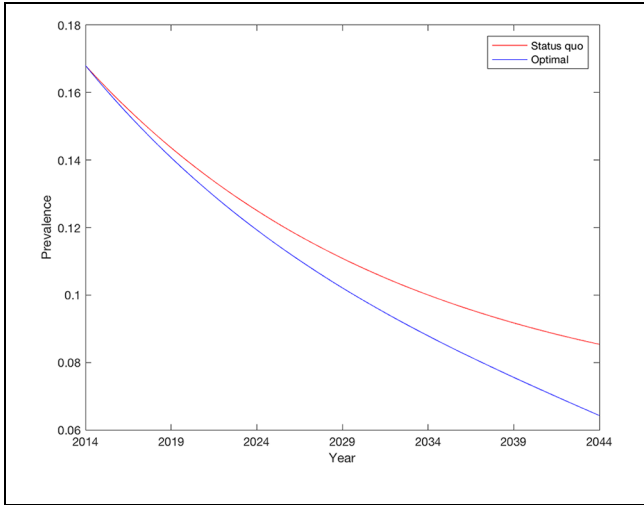Figure 3 shows the optimal cost ratio over time to achieve allocative efficiency. Based on our earlier

Figure 1 Smoking prevalence among adults (≥ 18) in the United States from the National Health and Interview Survey (NHIS).

analysis, if $\gamma_1 u_1 > \gamma_2 u_2$, we should spend more money on initiation instead of cessation, and if not, we should spend more on cessation interventions. The figure indicates that for our example, we should always invest more on the US truth campaign and shift more

emphasis to this prevention program over time. This result is due to a combination of program effectiveness and smoking prevalence. Parameter values in this numerical example can be easily adjusted to reflect different population characteristics and policy effectiveness. Figure 4 presents the total cost of interventions over time. To ensure we indeed derived optimal policy trajectories, we tested alternative interventions that yielded the same terminal smoking prevalence. All of them show higher costs than our optimal trajectories. One of them is here for illustration. The blue curve in the graph is the cost function for our optimal combination and the red curve is the one for the alternative combination. The area under the curve is the total amount of cost over 30 years; it is obvious that our optimal solution has a lower total cost. Similar results are obtained from the NSDUH data. We conducted a sensitivity analysis for the cost as well as the effectiveness of interventions and we found the results to be robust.

Discussion

This study establishes an optimal control model to investigate the best combination of smoking interventions to minimize smoking prevalence over 30 years while
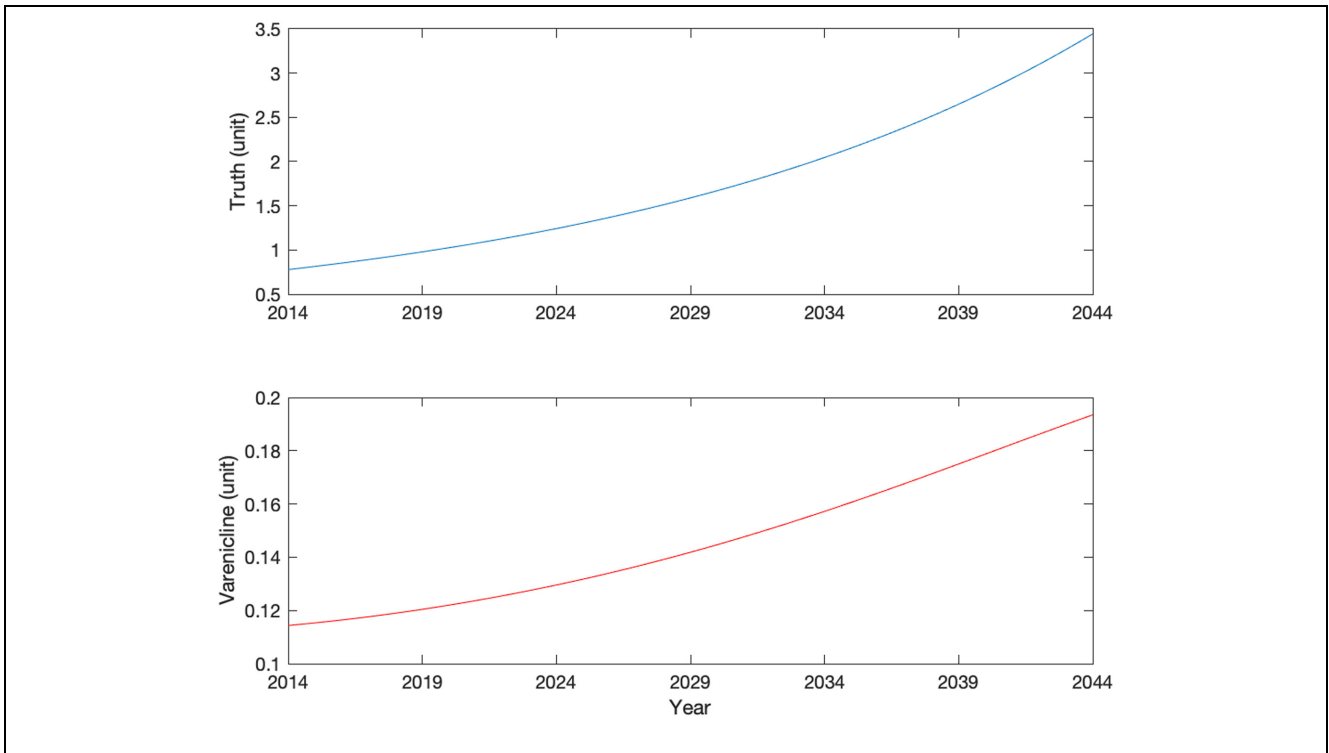

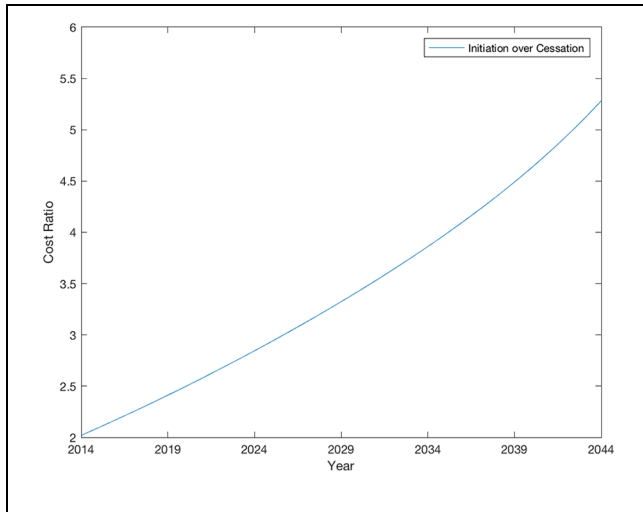**Figure 2** Optimal intervention units over time, initiation versus cessation.

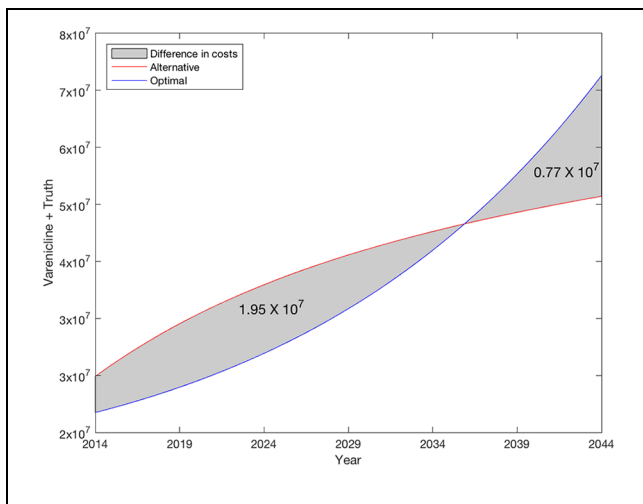**Figure 3** Optimal cost ratio between initiation and cessation.

Figure 4 Optimal cost versus alternative cost over time.

satisfying a budget constraint. By solving the model analytically using the Euler-Lagrange equation, we obtain a set of necessary conditions in forms of ODE. In addition, allocative efficiency is revealed in forms of the ratio between $\gamma_1 u_1$, and $\gamma_2 u_2$, which equals to

$$\frac{|\alpha_1|\gamma_2}{\beta_1\gamma_1 s}.$$

The numerical simulations, based on interventions from the US truth campaign and the $12 + 12$ weeks varenicline treatment combined with demographic data from NHIS and NSDUH, offer a few important observations.

First, this simulation example verifies our theoretical results. With optimal interventions, smoking prevalence is reduced to 6.43% in 30 years compared to the original 8.54% while satisfying the budget constraint of 1 billion US dollars over 30 years.

Next, we observe the optimal trajectories of intervention units. $u_1(t)$ and $u_2(t)$ both increase over time in the form of convex curves. This indicates that an optimal implementation strategy needs to expand initiation and cessation programs over time. Because the death rate is lower than the birth rate in the United States, our estimate of the optimal number of prevention units is a conservative one.[29,30] We speculate that more emphasis should be put on prevention due to a growing population. In addition, the optimal ratio of costs changes as well. In this numerical example with the truth campaign and the varenicline treatment, the strategy is to always spend more money on prevention interventions and gradually shift more emphasis to prevention over time. On examination, these results seem logical. When we start with a substantial number of smokers in the population, it is important to encourage them to quit. When we have fewer smokers later on, the policy should shift more focus to prevention. The analytical form of the ratio is consistent with this intuition. Effectiveness of interventions, program costs, and smoking prevalence together determine the allocative efficiency between initiation and cessation programs. Here smoking prevalence is in the denominator, meaning the higher the prevalence, the more we should spend on cessation.

This study shows that optimal control methods can help us determine more efficient ways to address the smoking problem. The general framework established here can be applied to other problems in future research. Additionally, more features can be added when evaluating specific interventions. However, out study presents certain limitations. First, we employ a linear model of prevalence and constant policy effectiveness values. Linear ODEs are proven to be reasonable formulations for predicting smoking prevalence both domestically and globally. However, as prevalence declines, nonlinear effects might become more important in describing the system's dynamics. Another limitation is that our formulation considers prevalence as a surrogate of population health effects, thus ignoring the timing differences between initiation and cessation related health benefits. Despite these limitations, our work presents a meaningful framework to analyze the issue of efficient allocation in tobacco control.

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