



Improved Allocation of HIV Prevention Resources: Using Information About Prevention Program Production Functions

MARGARET L. BRANDEAU

Department of Management Science and Engineering, Stanford University, Stanford, CA 94305 USA

GREGORY S. ZARIC*

Ivey School of Business, University of Western Ontario, London, Ontario N6A 3K7, Canada

E-mail: gzaric@ivey.uwo.ca

VANDA DE ANGELIS

Dipartimento di Statistica, Probabilità e Statistiche Applicate, Università di Roma la Sapienza, Piazzale Aldo Moro, 5, Rome, Italy

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Abstract. To allocate HIV prevention resources effectively, it is important to have information about the effectiveness of alternative prevention programs as a function of expenditure. We refer to this relationship as the “production function” for a prevention program. Few studies of HIV prevention programs have reported this relationship. This paper demonstrates the value of such information. We present a simple model for allocating HIV prevention resources, and apply the model to an illustrative HIV prevention resource allocation problem. We show that, without sufficient information about prevention program production functions, suboptimal decisions may be made. We show that epidemiologic data, such as estimates of HIV prevalence or incidence, may not provide enough information to support optimal allocation of HIV prevention resources. Our results suggest that good allocations can be obtained based on fairly basic information about prevention program production functions: an estimate of fixed cost plus a single estimate of cost and resulting risk reduction. We find that knowledge of production functions is most important when fixed cost is high and/or when the budget is a significantly constraining factor. We suggest that, at the minimum, future data collection on prevention program effectiveness should include fixed and variable cost estimates for the intervention when implemented at a “typical” level, along with a detailed description of the intervention and detailed description of costs by category.

Keywords: HIV/AIDS prevention, resource allocation, epidemic modeling

1. Introduction

HIV prevention is a critical problem worldwide. More than 42 million people are infected with HIV/AIDS; 5 million people became newly infected in the year 2002 alone [26]. The World Health Organization estimates that another 45 million people will become infected by 2010 unless prevention efforts are significantly improved [26].

However, resources for HIV prevention are limited. Available funds are insufficient to meet all prevention needs. Thus, policy makers must determine how best to allocate available prevention funds among competing programs and populations. Although political and social goals may be important when allocating HIV prevention funds [16,22], a key goal is to prevent new HIV infections. Thus, policy makers need to know how many HIV infections are likely to be averted as a consequence of different allocations of funds.

The problem of allocating HIV prevention resources to avert the maximum number of HIV infections is complex, so decision makers often use simple rules to help guide the allocation of HIV prevention resources [11,14,16]. In some cases, such decision rules do not take into account any information

about program effectiveness. For example, some HIV Prevention Community Planning Groups have been reported to assign priorities to population groups (e.g., based on HIV incidence) and to allocate resources according to those rankings, without explicit regard to the effectiveness of programs that target those population groups. In this paper we demonstrate how increased knowledge of prevention program effectiveness—in particular, knowledge of the number of HIV infections likely to be averted for different levels of investment in a prevention program—leads to improved allocation of HIV prevention resources.

In order to know how many HIV infections will be averted by any given allocation of prevention resources, decision makers need information about the effectiveness of competing prevention programs. They need to know how effective a given prevention program is in preventing new HIV infections, and how the program’s effectiveness will vary as a function of expenditure. We refer to the latter relationship as the “production function” for the prevention program.

Some authors have defined the production functions for HIV prevention programs as the function that relates dollars invested in a program to the number of HIV infections averted [12–14,16]. However, studies of prevention program effectiveness often report only intermediate measures of program

*Corresponding author.

effectiveness (e.g., condom use, number of new sexual partners over time, or needle sharing episodes over time) rather than HIV infections averted. Thus, we define production functions in terms of an intermediate outcome—risk reduction—that determines infections averted.

Some models for allocating HIV prevention resources implicitly assume that the relationship between resources expended on a program and the resulting risk reduction is linear (e.g., [12,22,25]). Thus, for example, doubling the investment in a given prevention program is assumed to double the risk reduction. In some cases this may be a good approximation. For example, each incremental treatment slot added to an already established methadone maintenance program is likely to yield an approximately constant reduction in risk if the number of incremental slots is small relative to the size of the existing program. Under these conditions, it is reasonable to assume that each person newly enrolled in the program reduces risky behavior by the same amount as individuals already in the program.

However, the relationship between the level of investment in a prevention program and the corresponding reduction in risk may not always be linear. For example, a minimum level of investment in a prevention program may be needed before any behavior change occurs: increased expenditure has no impact if the total is below the fixed cost. The fixed cost may represent the initial cost of establishing a prevention program (for example, salary for a program administrator, rent for office space, or the fixed cost of educational materials) as well as the minimum level of investment required before any individual's behavior changes. A new HIV prevention program may become relatively more effective once some threshold level of investment has been reached. Such a program has increasing returns to scale. An existing program may have been very effective initially, but may have already reached most of the people that it is likely to help, so the program may have decreasing returns to scale. A program may also have decreasing returns to scale because of the behavior of individuals reached by the program: if, with each additional dollar invested in a program, the resulting incremental risk reduction of each individual diminishes, then the program has decreasing returns to scale. Kaplan [13] estimated that the New Haven needle exchange program had decreasing returns to scale. A prevention program could also incorporate all of these effects: some startup is required; then the program exhibits increasing returns to scale as more money is invested; but eventually, as more money is spent, the program becomes relatively less effective and exhibits decreasing returns to scale.

Numerous evaluations of HIV prevention programs have appeared in the literature. The results of many of these studies have been summarized in a number of reviews and meta-analyses [4,6,7,9,10,17,19,20,23,24,30]. All of these studies report the average level of behavior change induced by a prevention program for a single level of investment per person (or, equivalently, for a single program intensity). Very few studies report program effectiveness as a function of investment. Moreover, for many published HIV prevention program evaluations, program cost is not explicitly stated, even for the

single level of investment that is considered. Instead the studies report measures such as the number and type of sessions comprising the intervention (e.g., [19]) or the total number of hours of the sessions (e.g., [20,24]). The cost of the programs must be inferred from the description of the intervention.

Only a few published studies have estimated prevention program production functions. Richter [21] estimated production functions for counseling and testing programs targeted to injection drug users and non-users. Wilson and Kahn [28,29], in analyzing the allocation of resources between a methadone maintenance program and street outreach, estimated that the programs would have decreasing returns to scale but no fixed cost. Using data from several sources, Zaric and Brandeau [31] estimated production functions for a condom availability program and for a methadone maintenance program. Kaplan [13] analyzed data from the New Haven needle exchange program to estimate a production function for the program. By and large, however, good information about prevention program production functions has not been gathered.

In this paper we demonstrate the value of such information. Previous analyses have shown how the form of the optimal resource allocation (e.g., whether all funds should be devoted to a single program or a single population) is affected by the production functions for the prevention programs [2,32]. In this paper, we show how improved knowledge of prevention program production functions can improve decisions about allocating HIV prevention resources. We use a simple resource allocation model that is solved in a spreadsheet. We apply the model to an illustrative HIV prevention resource allocation problem. We show that, without basic information on prevention program production functions, suboptimal decisions may be made. We provide qualitative insight into when knowledge of production functions is most important, and discuss needs for future data collection on prevention program effectiveness.

2. A simple resource allocation model

We considered two populations to which HIV prevention programs are to be directed. We assumed that the two populations are independent: infection transmission does not occur between the two populations. The epidemic in each population is modeled by a simple susceptible/infected (SI) model where, for each population i , $S_i(t)$ denotes the fraction of individuals in population i at time t who are susceptible, $I_i(t)$ denotes the fraction of individuals in population i at time t who are infected, λ_i is the sufficient contact rate, and δ_i is the replacement rate. The rate λ_i is the rate of contact between two individuals (one susceptible, one infected) sufficient for disease transmission; its value incorporates rate of contact and chance of infection transmission per contact. The rate δ_i is the rate at which people enter and leave the population: total entry into the population equals total exit from the population. All new entrants are assumed to be uninfected, whereas exit occurs from both the infected and susceptible groups. The rate δ_i reflects exit from the population for any reason (e.g., death

from any cause or maturation out of the population); exit due to death from disease is not distinguished from exit due to other reasons.

The equations of the SI model [1] for each population i ($i = 1, 2$) are

$$\begin{aligned} \frac{dS_i(t)}{dt} &= \delta_i - \lambda_i S_i(t) I_i(t) - \delta_i S_i(t) \\ \frac{dI_i(t)}{dt} &= \lambda_i S_i(t) I_i(t) - \delta_i I_i(t) \\ S_i(t) + I_i(t) &= 1 \end{aligned}$$

Using the above notation, $S_i(0)$ and $I_i(0)$ denote the fraction of individuals who are susceptible and infected, respectively, in population i at time zero. We assume that $0 < I_i(0) < 1$ for each population i .

We assume that for each population, one HIV prevention program is available. The prevention program targeted to population i reduces λ_i , the sufficient contact rate in that population. We let v_i denote the amount of money invested in the program targeted to population i . A fixed budget B is available to invest. This budget cannot be exceeded, so $v_1 + v_2 \leq B$.

We denote the production function for prevention program i by $f_i(v_i)$. We assume that the production function acts as a multiplier on the sufficient contact rate: thus, $f_i(0) = 1$ (investing nothing in population i leaves the sufficient contact rate unchanged), and $f_i(B) > 0$ (the sufficient contact rate cannot be reduced below zero). We assume that the function $f_i(v_i)$ is continuous and nonincreasing in v_i : incremental investment can never increase the sufficient contact rate. We assume that investment in program i changes λ_i immediately and that this change lasts over the time horizon of the problem.

We assume that the production function for each prevention program i is given by a function of the form illustrated in figure 1. A certain level of investment F_i is required before any behavior change occurs; this is illustrated by the horizontal

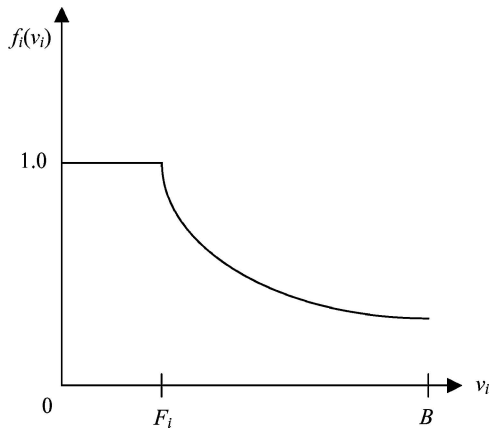


Figure 1. Prevention program production function. The function $f_i(v_i)$ is a multiplier on the sufficient contact rate in population i (λ_i) as a function of investment in prevention program i (v_i).

line at the beginning of the function. Then, above this level of investment, risky behavior begins to decrease. (Because of the initial fixed cost, the program has, in effect, increasing returns to scale near the point where fixed cost is replaced by variable cost.) Once risky behavior begins to decrease, the program has diminishing returns to scale: each incremental amount invested leads to less reduction in risky behavior. This is illustrated by the convexity of the curved part of the function in figure 1. Eventually, no more behavior change can be achieved. This is illustrated by the horizontal asymptote of $f_i(v_i)$ as v_i gets large.

We assume that the goal in allocating resources is to minimize the total number of new HIV infections that occur in the two populations over a given time horizon (from time zero until time T). The number of new infections that occur in population i up to time T given investment v_i is

$$N_i \int_0^T f_i(v_i) \lambda_i I_i(t) S_i(t) dt,$$

where N_i denotes the (constant) size of population i .

The resource allocation problem can be written as

$$\begin{aligned} \min_{v_1, v_2} & N_1 \int_0^T f_1(v_1) \lambda_1 I_1(t) S_1(t) dt \\ & + N_2 \int_0^T f_2(v_2) \lambda_2 I_2(t) S_2(t) dt \\ \text{s.t.} & v_1 + v_2 = B \\ & v_i \geq 0 \quad i = 1, 2 \end{aligned}$$

where the functions $S_i(t)$ and $I_i(t)$ are determined by the equations of the SI model. The budget constraint is binding in an optimal solution because the production functions are monotonically nonincreasing; thus the budget constraint is expressed as an equality in the above formulation.

We now illustrate the application of the simple resource allocation model. Section 3 describes the data we used and our assumptions about the production functions. Section 4 shows how different levels of knowledge of prevention program production functions lead to different decisions about allocating HIV prevention funds, and thus to different levels of health benefit.

3. Data

3.1. Epidemic data

We considered two independent populations, one of men who have sex with men (MSM) and one of injection drug users (IDUs). We fit the SI models to data from 2001 California estimates of HIV prevalence, incidence, and risk group sizes [8]. These estimates were generated during Consensus Meetings on HIV/AIDS Incidence and Prevalence in California that brought together experts from universities, local health departments, private research entities, and the

California Department of Health Services [8]. Replacement rates were based on published mortality rates [27]. Population 1 comprised 759,500 MSM, and Population 2 comprised 230,000 IDUs. For the MSM population, we assumed 20% initial HIV prevalence and replacement rate $\delta_1 = .104$. For the IDU population, we assumed 8% initial HIV prevalence and replacement rate $\delta_2 = .134$. We calculated the sufficient contact rates that would yield incidence rates equal to those in the California consensus estimates. For the SI model, the approximate number of new infections in one year is $N_i \times \lambda_i \times S_i \times I_i$, so we estimated $\lambda_i = (\text{number of new infections}) / (N_i \times S_i \times I_i)$. The MSM population was estimated to have 5150 new HIV infections annually [8], so we estimated $\lambda_1 = (5150) / (759000 \times .80 \times .20) = .042$; the IDU population was estimated to have 1049 new infections annually [8], so we estimated $\lambda_2 = (1049) / (230000 \times .92 \times .08) = .062$.

3.2. Complete knowledge of production functions

We assumed that the exponential function would be a good representation of the cost-effect relationship in a region where the prevention program has decreasing returns to scale. The exponential function exhibits constantly decreasing returns to scale and, with proper parameter selection, can be used to reflect a wide variety of cost-effect relationships. Accordingly, we represented the complete production functions (figure 1) by

$$f_i(v_i) = \begin{cases} 1 & 0 \leq v_i \leq F_i \\ a_i + b_i e^{-c_i(v_i - F_i)} & F_i < v_i \leq B \end{cases} \quad i = 1, 2$$

where a_i , b_i , and c_i are parameters characterizing the shape of the exponential part of the function, and F_i is the fixed cost. The value a_i is the minimum value that the function can take; it represents the maximum attainable level of behavior change. The maximum value of the function is given by $a_i + b_i$; since we assume that the maximum value is 1 (which occurs when no money is spent on program i), we have $b_i = 1 - a_i$. The parameter c_i characterizes the shape of the exponential curve: larger values of c_i lead to a flatter function, meaning that less money must be spent to achieve a given level of behavior change (all other things being equal).

We estimated parameters for the above functions based on published sources. A wide range of risk reduction from HIV prevention programs has been reported. The results of many of these studies have been summarized in a number of reviews and meta-analyses [4,6,7,9,10,17,19,20,23,24,30]. A review of prevention programs targeted to MSM found an overall risk reduction of 26%, with separate odds ratios of .61 for condom use and .74 for number of sexual partners [10]. A meta-analysis of programs intended to reduce sexual risk behaviors among IDUs found an odds ratio of .86 [24]. Two studies of programs targeting IDUs found significant reductions in injection risk [3,18]; one of those studies found larger reductions associated with injection risk than with sexual risk [18]. Kaplan and

O'Keefe [15] estimated that the New Haven needle exchange program led to a 33% reduction in risk among program participants. In the base case we assumed that a typical prevention program, at a typical level of investment, would lead to a 25% reduction in risk behaviors among those targeted. We varied this number in sensitivity analysis.

None of the above studies reports program cost, though many of them report information related to cost such as the number, size, and type of sessions involved in the prevention programs. From this information, a wide range of program costs can be inferred. A meta-analysis of programs targeted to adolescents found that 11 of 16 programs involved more than six group sessions, and these were frequently conducted in a classroom setting [19]. A study of programs targeted to adult heterosexuals found that half the programs investigated involved five or more hours of group sessions [20]. A study of prevention programs targeted to IDUs found that the interventions required an average of ten hours over five sessions [24]. In the base case, we assumed that the counseling sessions would be conducted by a registered nurse and would require one hour per participant. (This could be an individual one-hour session or a total of ten hours of group sessions for ten people, or any other combination that yields one hour per person). We thus assumed that a 25% average risk reduction would be achieved with one hour of intervention per person, which we estimated would cost \$20 per person. In terms of the above production functions, this means that we estimated $f_i(20 \times N_i) = .75$.

In sensitivity analysis we also considered both \$65 and \$125 as the cost to achieve the 25% average risk reduction. The New Haven Needle Exchange program cost approximately \$125 per IDU in the program (\$150,000 annual cost/1,200 IDUs served [15]) and achieved a 33% reduction in risk. We assumed, therefore, that an upper limit on the expenditure required to achieve a 25% reduction in risk would be \$125 per person. We also considered an intermediate cost (between \$20 and \$125) of \$65 per person.

We assumed that 5% of the \$20 (or \$1 per person) comprised fixed cost (the amount that must be spent before any behavior change is achieved); this is equivalent to $f_i(1 \times N_i) = 1$. In sensitivity analysis, we assumed that the fixed cost fraction (the fraction of the cost per person required to achieve the 25% risk reduction which comprises fixed cost) could be as high as 50%.

Few studies in the literature report risk reduction greater than 40% for HIV prevention programs targeted to MSM and IDUs, although odd ratios as low as .26 have been reported [24]. We assumed that the maximum level of risk reduction among both MSM and IDU would be 50%; this is equivalent to $f_i(\infty) = .5$. We varied this number in sensitivity analysis.

We used these data points to estimate the following parameter values for the above production functions: $a_1 = a_2 = .5$, $b_1 = b_2 = .5$, $c_1 = 4.80 \times 10^{-8}$, $c_2 = 1.59 \times 10^{-7}$, $F_1 = 759,500$, $F_2 = 230,000$. For both production functions, the maximum risk reduction is 50% (equivalent to a multiplier of .5), so $a_1 = a_2 = .5$, and the minimum risk reduction is zero (equivalent to a multiplier of 1), so $b_1 = b_2 = .5$. We assumed that, in both populations, \$1 per person would have to be spent

before any behavior change occurs, so $F_1 = N_1 = 759,000$, and $F_2 = N_2 = 230,000$. We assumed that, in both populations, spending \$20 per person would yield a 25% reduction in risk (equivalent to a multiplier of .75). When taking into account the different sizes of the two populations ($N_1 = 759,000$, $N_2 = 230,000$), we obtain $c_1 = 4.80 \times 10^{-8}$, $c_2 = 1.59 \times 10^{-7}$. The value c_2 is larger than c_1 , meaning that less total money must be spent in the IDU population (Population 2) than in the MSM population (Population 1) to achieve the same risk reduction (this is because the IDU population is smaller).

3.3. Incomplete knowledge of production functions

A planner wishing to allocate HIV prevention resources may not have good information about how a prevention program’s effectiveness will vary as a function of investment in the program and may have to rely on a poor approximation of the production function in order to make a decision. We considered four cases for knowledge of the production functions, illustrated in figure 2.

In the first case (figure 2(a)), we assumed that no information about prevention program effectiveness would be taken into account when the resource allocation decision is made. We assumed that in this case, resources would be allocated in proportion to relative HIV incidence in the two populations. This is similar to the allocation criterion reportedly used by some HIV Prevention Community Planning Groups

[11,14,16]. Thus,

$$v_1 = B \left[\frac{N_1 \lambda_1 S_1(0) I_1(0)}{N_1 \lambda_1 S_1(0) I_1(0) + N_2 \lambda_2 S_2(0) I_2(0)} \right]; \quad v_2 = B - v_1$$

In the absence of any new investment, 5150 new infections are projected to occur in the MSM population, and 1049 new infections are projected to occur in the IDU population. An allocation based on these incidence figures gives 83% of the budget to MSM (who would accrue 5150, or 83%, of the total 6199 new infections projected to occur), and 17% to IDUs (who would accrue 1049, or 17%, of the 6199 new infections projected to occur). Funds are allocated to each population in proportion to the number of new HIV infections projected to occur in that population, as a fraction of the total number of new HIV infections projected to occur in all populations under consideration.

In the second case (figure 2(b)), we assumed that a planner would have a single cost-effectiveness data point from the production function, and would use this data point to estimate a linear production function with no fixed cost. Using the above estimate that a \$20 per person expenditure will yield a 25% average reduction in risk behavior, we fit a linear production function of the form

$$f_i(v_i) = 1 - a_i v_i$$

to the points $f_i(0) = 1$ and $f_i(20 \times N_i) = .75$. This yielded $a_1 = 1.65 \times 10^{-8}$ and $a_2 = 5.43 \times 10^{-8}$.

In the third case (figure 2(c)), we assumed that a planner would also have information about the maximum level

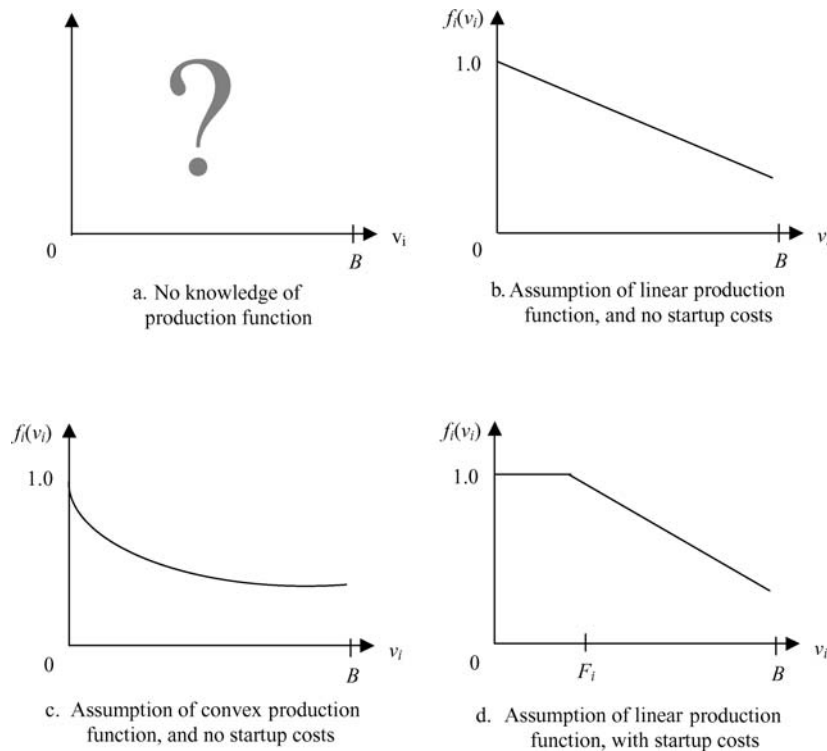


Figure 2. Alternative assumptions about production functions for prevention programs.

of behavior change that could be achieved by each prevention program, so that a production function with decreasing returns to scale could be estimated. With this information, we fit an exponential production function of the form

$$f_i(v_i) = a_i + b_i e^{-c_i v_i}$$

to the points $f_i(0) = 1$, $f_i(20 \times N_i) = .75$, and $f_i(\infty) = .50$. This yielded $a_1 = a_2 = .5$, $b_1 = b_2 = .5$, $c_1 = 4.56 \times 10^{-8}$, $c_2 = 1.51 \times 10^{-7}$.

The above three functions do not take into account knowledge of the programs' fixed cost. In the fourth case (figure 2(d)), we assumed that a planner would have information about a single fixed point on the production function, along with information about program fixed cost, but would not have information about the maximum achievable level of behavior change. This yields a function of the form

$$f_i(v_i) = \begin{cases} 1 & 0 \leq v_i \leq F_i \\ a_i - b_i v_i & F_i < v_i \leq B \end{cases}$$

Based on the data points $f_i(1 \times N_i) = 1$ and $f_i(20 \times N_i) = .75$, we estimated $a_1 = a_2 = 1.013$, $b_1 = 1.73 \times 10^{-8}$, $b_2 = 5.72 \times 10^{-8}$.

4. Allocating HIV prevention resources: The effect of production function knowledge

The model was implemented in a spreadsheet and solved numerically. We considered a budget of \$1 million, and a time horizon of one year. The budget was allocated using the fully specified production functions, and also considering the four cases for incomplete knowledge of the production functions. The SI model has a closed-form solution [1]. We used this formula to calculate the number of infections that would occur in one year for any given allocation of resources. To determine the optimal allocation of resources under different assumptions about the production functions, we set $v_2 = B - v_1$ and searched over values of v_1 in increments equal to 5% of the total budget.

When the allocation is made based on the fully specified production functions (last row of table 1), 100% of the budget is allocated to the IDU population, and 61.5 infections are averted.

If the allocation is made proportional to the baseline incidence figures (first row of table 1), with no knowledge of potential behavior change accruing from the prevention programs, 83% of the budget is allocated to MSM, and 17% is allocated to IDUs. This results in 9.0 infections averted (measured using the true (fully specified) production functions). When the allocation is made using the linear production functions, which incorporate our estimate that a \$20 per person investment can achieve a 25% reduction in risk, 100% of the budget is allocated to the program targeted to MSM, and 30.0 infections are averted (second row of table 1). When the allocation is made based on the exponential production functions, which additionally incorporate information about the maximum attainable level of behavior change, 100% of the budget is allocated to the program targeted to MSM, and 30.0 infections are averted (third row of table 1).

Table 1
Allocations based on varying levels of knowledge of production functions.*

Knowledge of production functions	% of budget allocated to MSM	% of budget allocated to IDU	Number of infections averted**
No knowledge of production functions			
Allocation proportional to incidence	83	17	9.0
Incomplete knowledge of production functions			
Linear	100	0	30.0
Exponential	100	0	30.0
Linear with fixed cost	0	100	61.5
Complete knowledge of production functions			
Exponential with fixed cost	0	100	61.5

* Results in this table assume a \$1 million budget.

** This column shows the number of infections that would actually be averted, were the allocation to be made. The number of infections averted was calculated using the fully specified production functions (which are exponential with fixed cost; see text), because we assume that these are the true production functions (the functions that will occur when investment is made).

The above three allocations do not take into account knowledge of the programs' fixed cost. Because of this fixed cost, it is not worthwhile to allocate any funds to the MSM population. When the allocation is made using the linear production functions that incorporate fixed cost (fourth row of table 1), 100% of the budget is allocated to the IDU population, and 61.5 infections are averted. In this case, the allocation is the same as the allocation achieved when the fully specified production functions are used, even though the production functions do not have exactly the same form as the true production functions.

For this example, when fixed cost is not considered, it appears optimal to allocate all funds to the MSM population. However, no behavior change occurs until at least \$1 per person has been spent. For the MSM population, this is equivalent to \$759,000 (76% of the total budget). Not taking fixed cost into account makes it appear that the risk reduction in the MSM population is significantly higher than it actually will be: using the linear production function with no fixed cost, it appears that spending \$1 million on the MSM population will reduce risk in that population by 1.65% (linear production function value .9835) and that it is optimal to spend all funds on the MSM population; when the fixed cost is taken into account, the risk reduction associated with spending \$1 million on MSM is found to be, in fact, only about .43% (value of the linear production function with fixed cost is .9957) and it is found to, in fact, be optimal to allocate all funds to the IDU population.

This example illustrates how increasing knowledge of the production functions can improve the allocation of resources. The poorest allocation occurred when no knowledge of the production functions was used when making the allocation decision. Using a linear production function improved the allocation; incorporating knowledge of fixed cost further improved the allocation.

We performed sensitivity analysis on all parameters of the problem. As the budget becomes sufficiently large (or,

Table 2

Sensitivity analysis: Percentage of maximum number of infections averted when allocation is made under different levels of knowledge of production functions, with different levels of fixed cost per person and different cost per person to achieve a 25% risk reduction.*

Proportion FC**	Assumed production function	Cost/person to achieve 25% risk reduction		
		\$20	\$65	\$125
5%	No Form Assumed***	99.9	93.5	87.8
	Linear	98.1	100.0	100.0
	Exponential	100.0	100.0	100.0
	Linear, FC	98.1	100.0	100.0
	Exponential, FC	100.0	100.0	100.0
10%	No Form Assumed***	99.9	88.6	72.2
	Linear	98.9	100.0	100.0
	Exponential	100.0	100.0	100.0
	Linear, FC	98.9	100.0	92.0
	Exponential, FC	100.0	100.0	100.0
25%	No Form Assumed***	98.3	57.6	0.0
	Linear	100.0	100.0	0.0
	Exponential	98.3	100.0	0.0
	Linear, FC	100.0	97.2	100.0
	Exponential, FC	100.0	100.0	100.0
50%	No Form Assumed***	91.3	0.0	0.0
	Linear	100.0	0.0	0.0
	Exponential	90.8	0.0	0.0
	Linear, FC	100.0	100.0	100.0
	Exponential, FC	100.0	100.0	100.0

* Assumes a budget of \$20 million. Percentage of maximum number of infections averted is calculated as number of infections averted given the current allocation as a percent of the number of infections that would be averted if the allocation were made using the fully specified production functions (exponential with fixed cost).

** Percentage of cost per person (rightmost columns) that represents fixed cost. For example, if the cost to achieve a 25% risk reduction is \$20/person, then the row 5% (first row) corresponds to a production function with \$1 fixed cost/person (before any behavior change is achieved).

*** Allocation is proportional to HIV incidence.

equivalently, as the cost of achieving the 25% risk reduction becomes sufficiently small), knowledge of production functions becomes less important because sufficient funds are available to avert most infections. Similarly, when HIV prevalence and/or incidence become sufficiently small, knowledge of production functions becomes less important because there are few infections to avert.

Table 2 shows the results of sensitivity analysis on program costs—in particular, the cost per person to achieve a 25% reduction in risk, and the fraction of that cost that represents fixed cost. Our base case analysis (table 1) assumed that a 25% reduction in risk would be achieved for a cost of \$20 per person, and that 5% of this cost (\$1) would comprise fixed cost. Table 2 shows results for cases when the cost required to achieve a 25% risk reduction is \$20, \$65, and \$125, and for cases when the fraction of that cost comprising fixed cost is 5%, 10%, 25%, or 50%. All of the non-base-case analyses in table 2 assume more expensive programs than the base case: either it costs more to achieve a 25% reduction in risk and/or it costs more to achieve any behavior change at all (because of a higher fixed cost). Thus, we considered a budget of \$20

million for the analyses in Table 2. (Note that if the cost per person to achieve a 25% risk reduction is \$20 (first column of table 2), then the \$20 million budget is enough to reduce risk among all 989,000 individuals by 25%; if the cost per person to achieve a 25% risk reduction is \$65 (second column of table 2), then \$65 million would be required to reduce risk by 25%; and if the cost to achieve the 25% risk reduction is \$125 (third column of table 2), then approximately \$125 million would be required to reduce risk by 25%.) The optimal allocations for the problems in table 2 varied: in some cases, the entire budget is allocated to IDUs; in some cases, the budget is split between IDUs and MSM; and in other cases, the entire budget is allocated to MSM.

As programs become increasingly expensive relative to the budget (i.e., moving across columns of table 2), the allocations based on incidence or linear or exponential production functions with no fixed cost become worse relative to the optimal allocation. Similarly, as the fixed cost becomes increasingly large relative to the budget (i.e., moving down the sections of table 2), the allocations based on incidence or a linear or exponential production functions with no fixed cost become worse relative to the optimal allocation. The effect is most pronounced when total cost and fixed cost are both relatively high. For example, if fixed cost is 50% of the cost per person needed to achieve a 25% risk reduction (bottom section of table 2), then when the cost per person required to achieve a 25% risk reduction increases to \$65 or \$125, the allocations based on incidence or a linear or exponential production functions with no fixed cost all avert no new HIV infections.

When the cost to achieve behavior change is relatively small (low fixed cost or low cost to achieve a 25% risk reduction) compared to the budget (upper and leftmost entries in table 2), then knowledge of production functions is less important than when the cost to achieve behavior change is large compared to the budget (lower and rightmost entries in table 2). If the fixed cost is much larger than we assumed and the cost per person to achieve a 25% risk reduction is larger than we assumed, then the allocations that do not consider fixed cost (i.e., the allocation proportional to incidence and the allocations based on linear and on exponential production functions) all avert no new infections because they do not allocate sufficient funds to either population to exceed the fixed cost. Conversely, if the fixed cost is small (e.g., 5%), then the allocations based on the linear and exponential production functions avert almost as many infections as the allocations when fixed cost is considered. The analyses in table 2 assume a budget of \$20 million. Results are qualitatively similar when a smaller budget is considered: when fixed cost is high and/or it is relatively expensive to achieve a 25% reduction in risk, knowledge of production functions becomes increasingly important.

In almost all cases, the allocation proportional to initial HIV incidence yielded the lowest health benefit. (In a few instances the allocation proportional to incidence was not the poorest allocation, but this only occurred in situations when all allocation methods performed relatively well, and when this occurred the allocation proportional to incidence yielded health benefits close to those of worse allocations.) The allocations based on

the linear and exponential production functions with no fixed cost were similar to one another and yielded good solutions except when the fixed cost was high (25% or higher) and the budget constraint became tighter (\$65 or \$125 per person to achieve a 25% risk reduction). The allocations based on the linear production function with fixed cost were optimal or close to optimal (in terms of HIV infections averted) in almost all cases. These results suggest that the most important production function information to incorporate in the allocation decision is the prevention program fixed cost and a single estimate of cost and resulting risk reduction. These two data points allow one to fit a linear production function with a fixed cost component. If the fixed cost is small, use of a linear production function can provide a near-optimal allocation. Our results also suggest that knowledge of production functions is most important when fixed cost is high and/or when the budget is a significantly constraining factor.

5. Discussion

We have presented a simple model for allocating HIV prevention resources that allows one to incorporate knowledge of production functions for the prevention programs. We have shown that improved knowledge of production functions leads to improved allocation of HIV prevention resources. In the example we presented, incorporating no knowledge of program effectiveness into the allocation decision led to significantly less health benefit than the maximum that could be achieved. Assuming constant returns to scale and no fixed cost (a linear production function with no fixed cost) yielded good allocations except when the fixed cost was high or the budget was significantly constraining. In the latter cases, inclusion of a fixed cost estimate in the production function led to significantly improved solutions.

HIV prevention needs and resources vary widely in different regions of the world, but all decisions about allocating HIV prevention resources share a common trait: information on program effectiveness is essential to determining the allocation of resources that maximizes health benefit. Our analyses showed that epidemiologic data, such as estimates of HIV prevalence or incidence, may not provide enough information to support optimal allocation of HIV prevention resources. Our results suggest that good allocations can be obtained based on fairly basic information about prevention program production functions. This includes an estimate of fixed cost plus a single point on the production function curve.

Little data is available on production functions for HIV prevention programs. This paper has shown that the value of such information can be significant. A first step toward the generation of such functions is for program evaluations to include cost estimates for the intervention when implemented at a "typical" level, specifically the fixed cost of the program and the variable cost. The results of such evaluations will be most useful to planners considering the application of such prevention programs in other settings if a detailed description of the intervention (e.g., initial brief counseling session followed by

a half-hour counseling session) and detailed cost categories are provided (e.g., types of fixed and variable cost, and associated effort levels, if relevant). More comprehensive evaluations could include estimates of how program effectiveness changes as a function of investment, and estimates of the maximum behavioral change that could be achieved.

In the absence of comprehensive information on prevention program production functions, decision makers can improve allocation decisions with basic estimates of fixed cost and a point estimate of program cost and associated behavior change. When applying estimates from past studies to future programs, decision makers must make assumptions about how the new program setting will affect the production function. For a new prevention program, the population served and details of the program implementation may differ from that in the study program. For an expanded prevention program, it is important to understand the extent to which prevention services can be added to an additional program: in some cases, little fixed cost may be incurred; in other cases, significant fixed cost may be incurred. Although such production function estimates are inherently uncertain, sensitivity analysis on key parameters of the production functions can be used to identify regions for the parameters over which allocations are robust. Sensitivity analysis can also identify the most important parameters for which further data are needed.

The simple model that we have presented allows one to explore the consequences of different assumptions about prevention program production functions. Other simple resource allocation models can also be used (for example, that of Kaplan [14] or the approximations in Zaric and Brandeau [32]). Analyses of this type can help decision makers understand the health consequences of different allocations of HIV prevention funds, and thus make informed allocation decisions. Such analyses can also be extended to other communicable diseases such as other sexually transmitted diseases.

Our analysis has several limitations. Our goal has been to illustrate the importance of using production function information when making resource allocation decisions. For actual resource allocation decisions, more sophisticated modeling of the epidemic, prevention programs, and target populations may be needed. When a significant amount of disease transmission occurs between population subgroups, or when individuals who do not know they are HIV infected behave very differently from individuals who do know they are infected, the SI model may be inappropriate as a foundation for resource allocation. In such cases, a more sophisticated epidemic model (e.g., [5,33,34]) could be used. Similarly, we illustrated our ideas assuming that all MSM and all IDUs could potentially be reached by the interventions. Decision makers might wish to consider interventions that reach only some individuals within a population group (e.g., those at highest risk for acquiring or transmitting HIV infection, or those who can be most easily reached). However, even if a different epidemic model or different types of interventions are considered, our qualitative results regarding the importance of prevention program production functions are unlikely to change.

Our model estimates the number of HIV infections averted for a given allocation of resources. Although health benefit is of key importance in resource allocation decisions, political, social, and other factors may also be important. Our model can be used to quantify the reduction in health benefits associated with restrictions on the allocation of prevention resources.

In response to the HIV epidemic, significant amounts of money and effort have been devoted to evaluation of HIV prevention programs. However, most existing evaluations report the level of risk reduction achieved for a single level of effort, but do not report the cost of that effort, nor the extent to which risk is reduced for different levels of investment. Our analysis has shown that, without knowledge of such production functions, poor allocation decisions may be made. Moreover, our analysis suggests that even very basic knowledge of production functions can lead to allocations with greatly improved health outcomes. To help policy makers make the best use of limited prevention resources, more effort should be devoted to collecting good data on the production functions for HIV prevention programs.

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