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## Targeting interventions to high-risk populations: Benefits and costs<sup>☆</sup>

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### Abstract

Targeting prevention interventions to high-risk populations may increase intervention benefits, but identifying and/or finding the high-risk populations may increase intervention costs. We explore the costs and benefits of targeting in the context of human immunodeficiency virus (HIV) prevention in high-risk injection drug users (IDUs). Focusing interventions on such a population should maximize the number of HIV infections averted. Recruiting high-risk IDUs for such interventions, however, may be more difficult and costly. We base our analysis on an earlier model that determines the allocation of resources to two interventions, street outreach and methadone maintenance. The model seeks to minimize HIV incidence in a population of heterosexual IDUs and their non-injecting sex partners. We conclude that while targeting an inexpensive intervention like street outreach rarely proves to be cost-effective, even a costly targeting effort can increase cost effectiveness for an expensive, effective, narrowly focused intervention such as methadone maintenance.

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*Keywords:* Cost effectiveness; Intervention targeting; HIV prevention; Injection drug users; Resource allocation

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## 1. Introduction

Researchers have long suggested that targeting health care by risk or economic need would increase cost effectiveness of the program in question. In writing about the Rand Health Insurance Experiment, researchers concluded that “investing in more targeted programs such as hypertension detection and screening would be a more cost-effective method of saving lives (than would providing free health care to all)” [1]. Targeting a specific population for health care, however, may entail added costs related to identifying and recruiting individuals in that population. The tradeoffs between these costs, and the benefits of targeting health interventions, have received little explicit attention in the research literature. In this paper, we develop a model to more fully explore these tradeoffs in the context of targeting human immunodeficiency (HIV) interventions to high-risk injection drug users (IDUs).

Previous research has looked at a few aspects of targeting interventions and drawn several general and relevant conclusions. An analysis of home care goals identified the non-economic tradeoffs associated with targeting home- and community-based services to the neediest [2]. The author concludes that in a resource-constrained environment, increasing targeting to the neediest in the population will result in less access for those beneath the threshold. In other words, the tradeoffs are between the number of clients reached, and the number of services per client. The research in [2] also points out that targeting assumes the ability exists to distinguish those who are needy from those who are not. Further, the author emphasizes that the goal of targeting the neediest may conflict with the goal of equity if one group is disproportionately excluded from receiving services.

A discussion of the role of spatial targeting in malaria interventions suggests that using information on the distribution of malaria can greatly increase the cost effectiveness of prevention efforts [3]. Conversely, the lack of such information, resulting in omission of the foci of transmission, can result in the failure of control measures. The authors stress that the clustering of malaria risks means that untargeted prevention efforts will generally be inefficient. They outline those conditions that must hold for a successful targeting effort. It must, e.g., be possible to distinguish between high- and low-risk locations, as well as operationally possible to focus efforts on the high-risk locations. They also explain that some methods of control may benefit more from targeting than would others. Finally, they emphasize that the benefits of targeting may be greatest in low- to moderate-risk situations where transmission risks tend to be clustered, rather than in high-risk situations where the risk is more pervasive.

One of the earliest mentions of targeting with respect to prevention of HIV demonstrates the cost effectiveness of targeting subpopulations with higher levels of expected HIV prevalence [4]. While this analysis evaluated nine different target population scenarios, it assumed that each population was equally accessible.

A more recent analysis of vitamin A supplementation to high-risk children concludes that targeting the intervention is *not* cost-effective [5]. The authors include a discussion of some factors affecting the efficiency of targeting: whether the outcome of interest occurs primarily in the target population, the cost and side effects associated with the intervention, the cost and side effects of identifying the target population, and the possibility for misclassification of targets. The authors also discuss issues arising with selection of a cut-off point for the targeting criterion, and conclude that one should pick “...the point at which therapy has been shown to do more good than harm.”

While this statement is accurate, it addresses only the clinical tradeoffs. When implementing targeting under constrained resources, there are economic trade-offs as well. Intervention benefits *and* costs can increase as the target population is more restrictively defined. Whether targeting is advisable at all may depend on the intervention in question. Furthermore, the ability to target may affect how dollars should be allocated across interventions. We more fully explore these issues, within the context of HIV prevention in IDUs, in the analysis that follows.

IDUs can transmit HIV to both needle-sharing and sex partners. An estimated two million Americans have injected illegal drugs at some point in their lives, and 416,000 injected in the previous 3 years [6]. In studies taking place in the mid-1990s, between 40% and 50% of IDUs reported sharing needles [7,8], and most reported having sex regularly [9,10]. Consequently, the spread of HIV in this population remains a significant problem. Estimates of the percentage of new HIV infections that occur in IDUs range from 20% to 50% [10,11].

We define targeting to mean focusing interventions on a high-risk subset of IDUs, where risk is defined by needle-sharing behavior. We build on a previous analysis that used an epidemic model to determine the best allocation of resources to two different interventions as a function of intervention and epidemic characteristics [12,13], where the best allocation minimizes HIV incidence. In that model, the IDU population was characterized by homogeneous risk behavior.

The model presented here incorporates behavioral heterogeneity where the resource allocation decision can take that heterogeneity into account. In particular, this model defines high- and low-risk IDUs, and allows for different allocations to be made to those two groups. It also incorporates a targeting production function to model intervention recruitment. We explore how the targeting of interventions can improve the effectiveness of those allocations, and, perhaps, change the allocations themselves. For example, if we could recruit only very high-risk individuals, we would expect to see increased intervention benefits in the population. We may, in fact, choose a different intervention than we would for the general population. Conversely, if acceptance criteria are too rigid, the increased costs of any recruitment effort may outweigh the increased benefits of the intervention.

We develop a targeting production function that captures selected elements of these tradeoffs, e.g., the costs of targeting individuals when those costs are a function of the recruitment criteria. We consider cases where targeting is cost neutral or cost increasing. (Some authors have posited that targeting might, in fact, *decrease* intervention costs [14], e.g., for groups already receiving a given intervention.)

To assess the effectiveness of targeting, we focus on two interventions with very different characteristics: methadone maintenance and street outreach. Methadone maintenance (MM) is a relatively effective and expensive intervention [15] that seeks to stop injection behavior and needle sharing. Street outreach (SO), on the other hand, is a less effective and less expensive intervention [16,17]. Unlike MM, SO works to reduce both sex and injection risk. It includes condom and bleach distribution, as well as counseling intended to reduce injection rates and number of sex partners.

Section 2 outlines an extension to the earlier resource allocation model [12,13]. This extension allows for the representation of high- and low-risk IDUs, where the level of risk is defined by

needle-sharing behavior. We then use this expanded model to choose a targeting threshold (i.e., a definition of high risk) and allocate a budget between MM and SO.

The model presented in Section 3 then incorporates costs associated with a targeting program by introducing a targeting production function. This model addresses the overall problem of choosing a threshold, and allocating resources between intervention delivery and targeting. The results in Section 4 show how the optimal targeting threshold changes with intervention characteristics even when targeting is free. This section also presents results demonstrating the tradeoffs between the benefits that stem from a high threshold and the costs of implementing that threshold. We show that, ultimately, the effectiveness of a targeting strategy is a function of (1) the relationship between intervention and targeting costs and the budget, and (2) the relationship between intervention characteristics, HIV risk behavior, and the targeting threshold.

## 2. Methods

As described above, this analysis is based on an earlier model that seeks to determine the optimal allocation of resources between two interventions so that new HIV infections in a population are minimized [12,13]. The population in that model consists of heterosexual IDUs and their non-injecting sex partners (non-IDUs), and exhibits homogeneous risk behavior. Injection and sex risk are each described by two risk parameters: effective infectivity and activity level. We use the term ‘effective infectivity’ to refer to the probability of contracting HIV in one exposure to an infected person given typical protective behaviors, e.g., condoms or bleaching. Activity level represents the number of potentially infectious exposures per year: the number of sexual *partnerships* and the number of needle-sharing *episodes* (using a needle after someone else) [18]. Effects of the interventions are represented as relative decreases in one or more of these risk parameters, see Table 1.

As described more fully elsewhere [12,13], we assume that interventions exhibit increasing marginal costs because of the challenges of recruitment. Baseline intervention delivery costs are \$4750 per person for MM [19], and \$210 per person for SO [16].

In the remainder of this section, we outline a model to analyze the effectiveness of targeting interventions by needle-sharing behavior under varying assumptions.

Table 1  
Percentage reduction in HIV risk parameters for an individual receiving drug treatment or street outreach, by infectivity and activity level, and by risk behavior

Intervention	Efficacy (proportional decrease in risk)				Source
	Effective infectivity		Activity level		
	Sex	Injection	Sex	Injection	
Methadone maintenance	0.00	0.00	0.00	0.85	[15,24,25,26]
Street outreach	0.13	0.03	0.16	0.30	[17,27,28,29]

### 2.1. Modeling behavioral heterogeneity

We define targeting to be “focusing intervention(s) on IDUs exceeding a given risk threshold, termed the high-risk population.” The threshold is defined in terms of one of the risk parameters: the number of injections per year for which an IDU shares injection equipment. As described below, we estimate a distribution for the needle-sharing rate for San Francisco IDUs in the early 1990s. The targeting criterion is then stated in terms of deciles of that distribution. For example, a targeting threshold of “Top 10%” indicates that the interventions will be focused on the top 10% most frequent needle sharers.

The epidemic model tracks five characteristics of the population: intervention status, risk level, gender, injection status, and HIV status. Intervention status indicates which combination of the two interventions was received by the IDU: neither intervention, MM only, SO only, or both. Risk level indicates whether the IDU is high- or low-risk with respect to the targeting threshold. All males are IDUs; females are either IDU or non-IDU (sex partners of male IDUs). Justification for this assumption is detailed elsewhere [13]. Individuals are either HIV+ or HIV–.

### 2.2. No-cost targeting

We first analyze the case where targeting does not increase intervention cost. Given a total budget of \$1 M, the decision problem is to choose a targeting threshold and allocate the budget between the two interventions to minimize the number of new HIV infections in the model population. The allocation determines the number of high-risk IDUs to be reached by each intervention. While the decision variable applies only to IDUs, the outcome variable counts HIV infections in both IDUs and non-IDUs. (The non-IDUs do not receive interventions, and we assume behavioral homogeneity in that population.) Infection rates are based on effective infectivity, activity level, and HIV prevalence. The rates also account for any reductions in risk behavior generated by the interventions.

Parameter values describing IDU behavior and population dynamics in San Francisco in the early 1990s used in this analysis are fully described elsewhere [13]. We base our estimates for the average sharing rate, for those who share at all, on a study set in San Francisco during that time period [20]. This study suggests that approximately 35% of IDUs shared needles, with an annual injection rate of 256. We assume that those who share inject with previously used syringes for one-half of their injections, yielding a mean annual share rate of 128. This is a particularly conservative interpretation of these data and is likely to underestimate injection risk, potentially affecting the optimal resource allocation. We assume the rate for those who share at all is distributed exponentially with this mean (Fig. 1). This assumption allows us to represent the case where the majority of IDUs who do share do so in moderate numbers, as extremely heavy sharers are increasingly rare.

Parameterization of this model requires a definition of high risk, and average needle-sharing rates for both low- and high-risk IDUs. The targeting threshold affects the average share rate within the high- and low-risk groups. For example, the average share rate of the top 10% most frequent sharers differs from the rate for the top 20%. Table 2 demonstrates how the targeting threshold affects the average share rate in both groups given the estimated distribution.

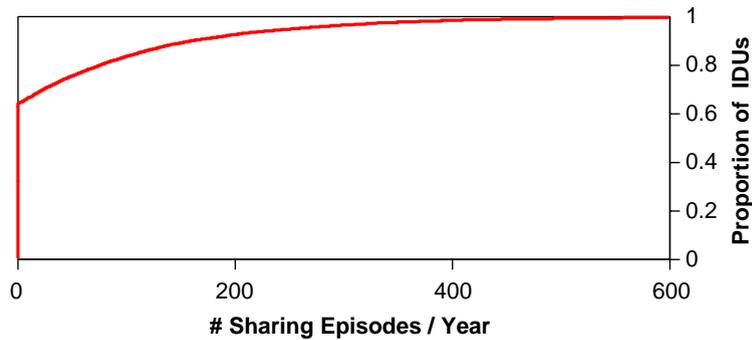


Fig. 1. Estimated cumulative distribution of annual needle-sharing rate for IDUs in San Francisco, early 1990s, assuming an exponential distribution with a mean of 128 shares per year and a sharing prevalence of 35% [20].

Table 2

Average number of needle-sharing episodes per year for target (high-risk) and non-target (low-risk) groups for different targeting thresholds given the estimated distribution of sharing rates in Fig. 1

Threshold description	Target	Non-target	Threshold value
Top 10%	290.4	18.5	159
20%	201.4	6.8	76
All sharers	127.8	0.0	1
All IDUs	45.7	0.0	0

### 2.3. Targeting with costs

The model described above allows us to explore the influence of budget, intervention costs, and effectiveness on the optimal targeting strategy when targeting does not increase overall costs. In this section, we incorporate the idea that more specific targeting criteria will lead to more difficult and costly recruitment. To this end, we develop a production function that represents the extra costs associated with recruiting IDUs who exceed a given risk threshold. The function is based on the assumption that targeted recruitment consists of sequential sampling from the general IDU population. This is just one possible approach to the conceptualization of targeting. The development of other approaches and conceptualizations remains an area for future study.

Given a targeting threshold and a level of investment in targeting, our proposed function determines how many IDUs exceeding the threshold can be found. In particular, the cost of finding *any* IDU is a constant. We assume that the probability of finding an IDU meeting the targeting criterion is proportional to the number of IDUs meeting the criterion. This implies that a higher targeting threshold requires that a greater number of IDUs be found in order to find one who exceeds the threshold.

We assume that the cost to find any IDU is  $m$ . Given a population of  $N$  IDUs, choosing a targeting threshold (e.g., top 10% of sharers) defines a target population,  $T_0 < N$ . We then choose a level of targeting expenditure,  $b$ , that determines how many of the  $T_0$  target IDUs we can reach,  $T(T_0, b)$ . The rate of change, with respect to  $b$ , of the population of *unfound*

high-risk IDUs,  $L$ , is given by

$$\frac{dL}{db} = \frac{-1}{m} \frac{L}{N}.$$

Solution of this equation determines the number of unfound IDUs remaining in the high-risk population after an expenditure of  $b$ :

$$L(b) = T_0 e^{(-1/mN)b}.$$

The targeting production function then describes the number of high-risk IDUs found, given  $b$ :

$$T(T_0, b) = T_0 - L(b) = T_0(1 - e^{(-1/mN)b}).$$

The form of this production function means that targeted recruitment exhibits increasing marginal costs, both as the threshold increases and as the target population is exhausted. Thus, a higher threshold and a greater number of IDUs recruited increase the targeting costs.

In sum, the resource allocation problem has four decision variables: targeting threshold, and expenditure levels for targeting ( $b$ ), and for delivery of MM and SO. The goal of the resource allocation is to minimize HIV incidence given a budget constraint. The epidemic model produces estimates of HIV incidence given values for these decision variables.

We solve the overall problem in an iterative fashion. First, a targeting threshold is chosen. The next step is to find the optimal allocation of resources between MM and SS for that threshold. To do this, we define  $b$  to be very small, and find the best allocation of the remaining budget to delivery of MM and SO to  $L(b)$  IDUs. We then incrementally increase  $b$ , resolving the resource allocation problem at each step. The increases in  $b$  continue until more IDUs are recruited for the intervention than can be served by remaining budget. These steps produce an optimal level for  $b$  and an optimal allocation of the remaining budget to MM and SO for a given threshold. We repeat this process for a discrete set of targeting thresholds.

### 3. Results

#### 3.1. No-cost targeting

The results presented in this section demonstrate how targeting an intervention to high-risk IDUs can increase the benefits of that intervention. Fig. 2 shows the estimated percentage of total HIV infections averted for different targeting thresholds when the entire budget is allocated to either SO or MM. The total budget remains constant across all targeting and intervention strategies. If the intervention cost is small relative to the total budget, and the targeting threshold is high, there may be more than enough funds to reach all high-risk IDUs. In this case, we allocate any remaining funds to low-risk IDUs.

Fig. 2 illustrates several points. The first is that, as we showed in previous analyses [12], SO dominates MM as an HIV prevention strategy in a resource-constrained environment in the epidemic scenario modeled. Second, the most effective MM targeting strategy is more “targeted” than the most effective SO strategy. Third, the best targeted MM strategy yields a nearly 400% relative increase in effectiveness vs. the untargeted MM strategy. Interestingly, the best-targeted SO strategy yields a relative increase of only 25% vs. the untargeted SO strategy.

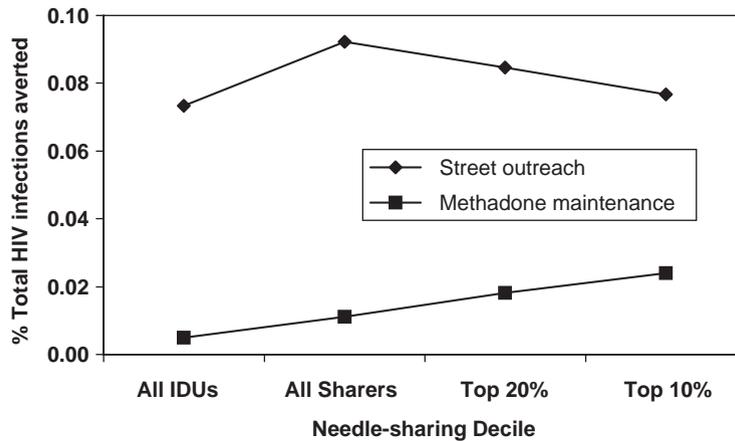


Fig. 2. Model predictions of percentage of total HIV infections averted by intervention and targeting threshold for no-cost targeting.

The first point noted above reflects the relative cost effectiveness of SO, which has been explored in [12,13]. The second and third points can be explained by (1) the relationship between total budget, population size, and intervention cost, and (2) the relationship between the targeting criterion and the intervention characteristics. A lower intervention cost makes it more likely that the most risky IDUs can be reached on a fixed budget. In this case, the most effective strategy is to be as *un*-selective as the budget allows. For example, with SO, enough budget exists to reach nearly all the IDUs who share. This is therefore the best targeting strategy. With the much more expensive MM, on the other hand, there exists enough budget to reach only 2% of all IDUs in the population, so the best strategy is to be as selective as possible. If the budget decreases, the added value of targeting to either intervention would clearly increase.

We have shown that the cost of an intervention and the budget both affect the increase in effectiveness that can be gained through intervention targeting. It is also the case that the behavioral focus of an intervention affects this increase. As described earlier, HIV risk is represented by four factors: sex and needle-sharing effective infectivity, and sex and needle-sharing activity level. The targeting threshold in this analysis is based on one of those factors, needle-sharing activity level. MM significantly decreases needle-sharing activity by decreasing injection behavior. SO, on the other hand, achieves much smaller decreases in all four risk parameters. If SO's effects were limited to decreasing needle-sharing activity, the value of targeting that intervention by needle-sharing activity would increase. Similarly, if SO had a greater effect on needle-sharing activity, the value of targeting that intervention would increase. In sum, the value added by targeting increases when the budget decreases, when the intervention focuses more exclusively on the risk embodied in the targeting threshold, and when the effects of the intervention on that risk increase.

### 3.2. Targeting with cost

The results in the previous section demonstrate that, in some cases, more specific targeting criteria (i.e., higher thresholds of needle-sharing rate) can lead to greater benefits in terms of the number of HIV infections averted. In this section, we ask whether targeting is still cost-effective

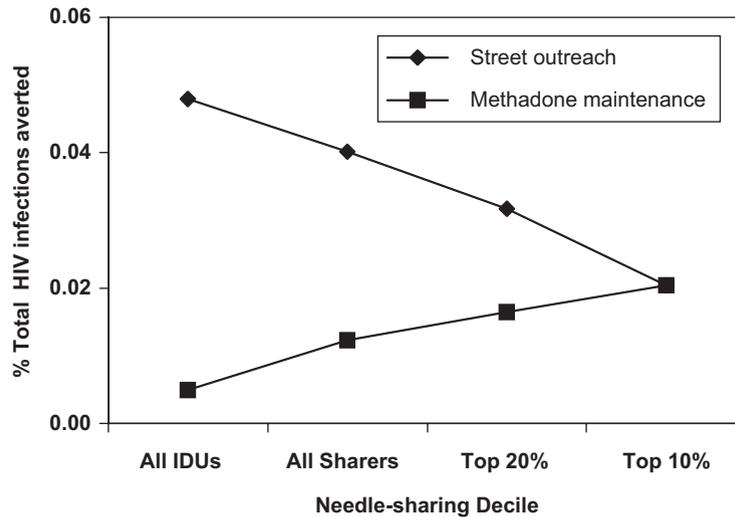


Fig. 3. Model predictions of percentage of HIV infections averted for treatment- and outreach-only strategies, varying targeting thresholds, and a contact cost of \$100 per IDU.

when we incorporate the increased costs associated with this more specialized recruitment. In our baseline analysis, we assume a value of \$100 for  $m$ , the cost to find any IDU, whether or not that person exceeds the targeting threshold. While estimates of the true value of this contact cost are not available, we vary this parameter widely in the analysis. This value represents approximately 50% of the per-person intervention delivery costs of SO and approximately 2% for MM.

Recall that the total budget for all analysis results is fixed. This means that increased intervention benefits (i.e., HIV infections averted) translate to increased cost effectiveness. Fig. 3 shows that, under these assumptions about targeting costs, targeting does not increase the effectiveness (or cost effectiveness) of SO. For MM, on the other hand, the most restrictive targeting strategy is the most effective. As before, the combination of the high cost of MM and the specificity of its effects increases the value of targeting for this intervention.

Fig. 4 shows the optimal targeting strategies for (a) SO and (b) MM for varying contact costs. Here, the contact costs are stated in terms of a percentage increase in the per-person intervention delivery costs. Note that the vertical scales for the two graphs differ. These graphs emphasize that even when targeting increases intervention costs proportionally, the value of targeting may differ significantly. For example, even when the contact cost is 50% of the MM intervention delivery cost, a targeted intervention is more effective than an untargeted intervention. By contrast, targeting SO is barely effective when the contact cost is as low as 2% of the intervention delivery cost.

In previous analyses, we studied the problem of allocating a budget between two interventions to maximize the number of HIV infections averted. In the current analysis, we have shown how targeting a single intervention may or may not increase effectiveness. In the next step of this analysis, we ask whether being able to combine *and* target interventions increases effectiveness.

Each point on the graph in Fig. 5 represents the best targeted allocation of resources to MM and SO under varying targeting strategies and assumptions about contact cost. Here, we see that when combining the two interventions, targeting is effective only when it imposes no additional

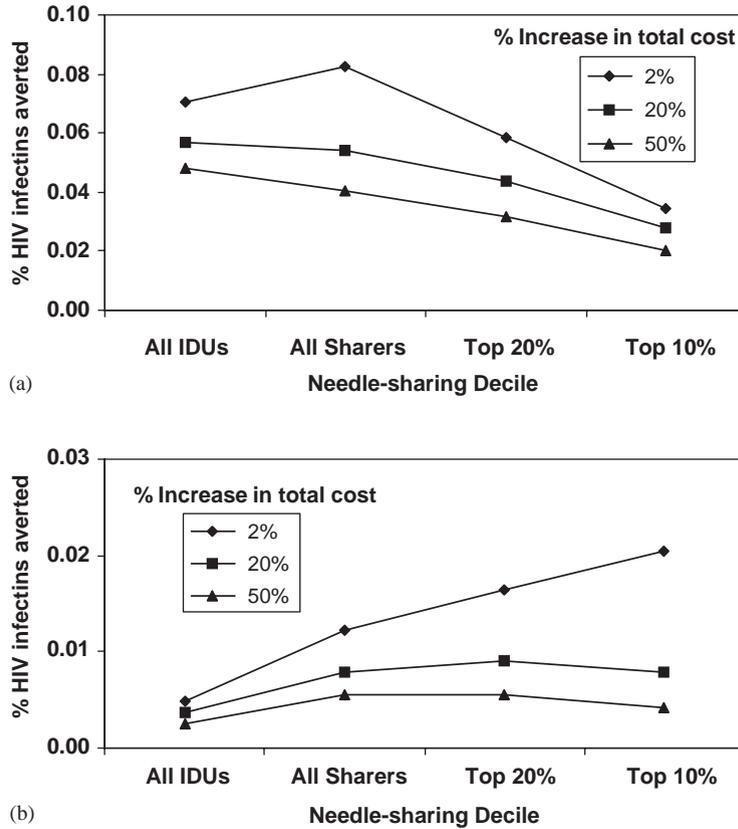


Fig. 4. Model estimates of percentage of total HIV infections averted by targeting threshold and targeting-related increase in intervention costs for (a) street outreach and (b) methadone maintenance.

costs and the threshold is low. This occurs primarily because SO is more cost-effective than MM in this scenario. The percentage of the budget allocated to SO delivery decreases as the targeting threshold increases. This occurs for two reasons. First, as contact cost increases, targeting costs increase and leave less for intervention delivery. For example, for all three values of contact cost analyzed, when the targeting rule is “All IDUs”, the optimal allocation does not include MM. Thus, the decrease in the percentage allocated to SO delivery represents the tradeoffs between intervention delivery and intervention targeting costs.

Second, as the threshold increases, the optimal allocation calls for increasing investment in MM. For example, when targeting is free and the targeting criterion is “Top 10%”, the optimal allocation reaches 84% of the most risky sharers with SO and 16% of that same group with MM. Clearly, the emphasis of this allocation is still on SO, but the high cost of MM means that reaching a few IDUs with that intervention consumes a significant portion of the budget.

#### 4. Discussion

Our analysis explored the costs and benefits of intervention targeting from the point of view of the HIV prevention policy maker whose goal is to allocate a budget to maximize the number of

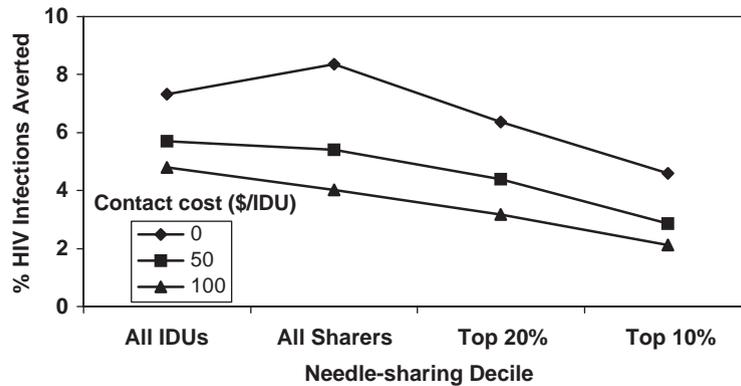


Fig. 5. Percentage of total HIV infections averted when allocating budget between street outreach and drug treatment for varying targeting thresholds and contact costs.

HIV infections averted. In particular, we considered targeting two interventions, street outreach and methadone maintenance, to prevent HIV in IDUs and their non-IDU sex partners. To accomplish the analysis, we expanded an earlier model developed to study the allocation of resources to interventions as a function of epidemic and intervention characteristics. The revised model incorporates behavioral heterogeneity, to represent high- and low-risk populations, and a targeting production function, to represent the costs of intervention targeting.

#### 4.1. No-cost targeting

We first explored how no-cost targeting can increase intervention effectiveness. We saw the greatest increases in effectiveness when the targeting criterion was closely related to the intervention effects and when the intervention cost was large relative to the budget. For example, a very targeted strategy maximized the effectiveness of MM. The delivery costs for this intervention are large relative to the budget and population size. The effects of the intervention coincide exactly with the targeting criterion, with the intervention having a significant effect on the related risk factor (needle sharing). For SO, on the other hand, the best targeting strategy is not very selective and yields only modest gains in effectiveness. The delivery costs for this intervention are low relative to the budget and population size. The effects of the intervention are broad with respect to the targeting criterion, and of small magnitude.

#### 4.2. Targeting with cost

We believe that more restrictive targeting criteria, e.g., higher risk thresholds, may increase intervention effectiveness but will be more expensive to implement. To incorporate these increased costs, we developed a production function that describes the number of IDUs that can be found given a threshold definition and a targeting expenditure level. This function represents two important aspects of targeted recruitment: (1) more restrictive targeting criteria make it more costly to find IDUs meeting those criteria, and (2) finding more IDUs from a given target population becomes more difficult as the target population is exhausted. The costs of targeted recruitment are therefore a

function both of the original target population definition and of the extent of recruitment in that population. The decision problem was then defined as (1) choosing a targeting threshold, and (2) allocating budget between targeting and the intervention delivery costs for SO and MM.

We first considered targeting single interventions under various assumptions regarding contact costs. We saw that, as in the no-cost case, the best targeting strategy varied greatly for the two interventions. Except for the case where targeting was free, it did not increase the effectiveness of SO and the best strategy was *not* to target the intervention. For MM, on the other hand, restrictive targeting policies were best even when targeting significantly increased overall costs. When combining *and* targeting interventions, we saw that, again, except for the case where targeting is extremely low cost, the best strategy was untargeted SO. This result is driven by the cost-effectiveness of SO and the factors we discussed earlier that make the targeting of that intervention less effective.

#### 4.3. Policy implications

There exist many interventions to prevent HIV in IDUs, e.g., street outreach, needle exchange, drug treatment, and counseling/testing. Because we limited this analysis to only two interventions, we cannot make specific policy recommendations for an overall targeted intervention strategy. While this analysis studied targeting in the very specific context of HIV prevention, policy makers can draw broad conclusions from the results. In particular, we addressed whether targeting is a good use of resources, and how to choose a targeting criterion. Results of this analysis demonstrated that answers to these questions are complex and deserve careful consideration.

The best targeting strategy depends on the relationship between the intervention effects and the targeting criterion, on the distribution of the population with respect to the criterion, and on the relationship between intervention delivery and targeting costs and the budget. The results for MM, for example, suggest that targeting can be worthwhile even when it is relatively expensive with respect to intervention delivery costs. Our analysis strongly suggests that the resource allocation problem for targeted interventions is not separable: targeting criteria should not be chosen independently of intervention characteristics, budget, and population characteristics. Conversely, if the targeting criterion is given, our analysis showed that the optimal *targeted* resource allocation might differ from the optimal *untargeted* allocation. In other words, a decision maker interested in implementing targeting should not proceed by simply “targeting” a prevention strategy that was optimal without targeting.

#### 4.4. Model limitations and future research

Two of the most significant limitations of this model are that it is constrained to two interventions, and that it relies on the sequential sampling model of targeting. While the model itself would not readily expand to three or more interventions, the analysis framework would allow for a series of pair-wise allocations of a budget among interventions. Alternatively, any number of interventions could be ranked by cost effectiveness by considering their effects on HIV incidence, one at a time. As mentioned earlier, this is the first analysis we know of to incorporate potential costs of targeting. We chose to model targeting as sequential sampling from the population both for conceptual and modeling simplicity. Furthermore, because sequential

sampling is not very “intelligent,” it should provide the most conservative estimates of the added value of targeting.

Intervention targeting for preventing HIV in IDUs is rich in opportunities for future study. There is, for example, increased interest in interventions targeted to HIV-positive individuals. When HIV prevalence is less than 50%, behavior change in HIV-positive individuals yields a greater effect on the epidemic than does an equivalent change in HIV-negative individuals [21]. The magnitude of such differentials is non-linear in HIV prevalence. A report from the Institute of Medicine reviewing domestic HIV prevention recommends emphasizing prevention services for HIV-positive individuals [22].

The Centers for Disease Control and Prevention have announced a program, the Serostatus Approach to Fighting the Epidemic (SAFE), that will emphasize prevention for HIV-positive individuals [23]. SAFE will focus on identifying those who do not know they are HIV-positive and those who are HIV-negative but continue in high-risk behaviors. Targeting HIV-positive individuals who do not know their status will generally entail additional HIV testing, thus increasing intervention costs. Identifying those individuals, and initiating treatment, will increase intervention benefits. Little research has addressed the tradeoffs between these additional costs and benefits. Nor have researchers explored whether a serostatus approach to targeting is more cost-effective than the risk-based approach described here.

As pointed out by others (e.g., [2,3]), areas for further study related to targeting in general include those related to equity, distribution of risk within the population, and misclassification of individuals with respect to a targeting criterion. A related area of study would incorporate the quality of the targeting information into the decision problem. As mentioned earlier, targeting requires the ability to reliably distinguish between targets and non-targets. One may have a low level of confidence in self-reported information about needle-sharing behavior but a high degree of confidence in another candidate criterion, e.g., HIV status. How does this uncertainty affect the “yield” of the targeting program? At what point would it be better to target by the less effective, but more reliable, targeting criterion? The value of targeting depends primarily on issues related to the cost and quality of the information required to do the targeting. While we have addressed some issues related to preventing HIV in IDUs, the above questions have been understudied in general. The potential benefit of targeting for preventing HIV and other grave conditions is great, and the economics and logistics of such strategies surely deserve further study.

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