



Incentivizing hospital infection control

Sarah E. Drohan^{a,1}, Simon A. Levin^{a,b,c,1}, Bryan T. Grenfell^{b,d}, and Ramanan Laxminarayan^{c,e,1}

^aProgram in Applied and Computational Mathematics, Princeton University, Princeton, NJ 08544; ^bDepartment of Ecology and Evolutionary Biology, Princeton University, Princeton, NJ 08544; ^cPrinceton Environmental Institute, Princeton University, Princeton, NJ 08544; ^dFogarty International Center, National Institutes of Health, Bethesda, MD 20892; and ^eCenter for Disease Dynamics, Economics & Policy, Washington, DC 20036

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Healthcare-associated infections (HAIs) pose a significant burden to patient safety. Institutions can implement hospital infection control (HIC) measures to reduce the impact of HAIs. Since patients can carry pathogens between institutions, there is an economic incentive for hospitals to free ride on the HIC investments of other facilities. Subsidies for infection control by public health authorities could encourage regional spending on HIC. We develop coupled mathematical models of epidemiology and hospital behavior in a game-theoretic framework to investigate how hospitals may change spending behavior in response to subsidies. We demonstrate that under a limited budget, a dollar-for-dollar matching grant outperforms both a fixed-amount subsidy and a subsidy on uninfected patients in reducing the number of HAIs in a single institution. Additionally, when multiple hospitals serve a community, funding priority should go to the hospital with a lower transmission rate. Overall, subsidies incentivize HIC spending and reduce the overall prevalence of HAIs.

nosocomial infection | antimicrobial resistance | subsidy | game theory

Healthcare-associated infections (HAIs) are a serious danger to patient safety (1–3). In the United States roughly 1.7 million patients admitted to hospitals each year contract an HAI (4). HAIs cause increased mortality, longer hospital stays, and a large financial burden for patients and healthcare systems (5). Furthermore, HAIs are linked to the development of antimicrobial resistance in pathogenic bacteria (6).

Patients and healthcare workers act as vectors that transmit infections between healthcare institutions. Since the pathogens responsible for HAIs can persist on body surfaces for long periods of time (1), when patients discharged to the community are rehospitalized, they can spread infection and colonization between hospitals and long-term care facilities (7, 8). Controlling HAIs is especially challenging since many individuals admitted are already colonized from other institutions (9).

A hospital that invests in hospital infection control (HIC) lowers transmission in its own wards, which decreases the basic reproduction number \mathcal{R}_0 of the disease (the number of secondary cases). This in turn lowers the number of individuals colonized in the community. Therefore the benefits of HIC in a single hospital are shared by all institutions that share the same catchment population. As a result, there is an economic incentive for each hospital to invest less in HIC, free riding on the efforts of others. This concept has been supported by mathematical models and data-driven approaches that have shown HAIs are a regional problem that requires a coordinated effort at the local scale (9–13).

Policymakers can offer subsidies as an incentive to encourage spending and control the spread of HAIs (14, 15). We develop coupled mathematical models of epidemiology and hospital behavior in a game-theoretic framework to investigate how hospitals may change spending behavior in response to various implementations of subsidies. Our focus is to understand how to use subsidies to incentivize optimal infection control.

Mathematical Model and Analysis

Single-Hospital Game. Consider a single-hospital population admitted from a large catchment population. Assuming HAI transmission occurs only within hospitals, we can approximate

the proportion of patients admitted from the community already colonized as a constant value κ . The dynamics of the proportion of patients colonized within the hospital (represented by the variable X) are governed by Eq. 1:

$$\frac{dX}{dt} = \sigma(\kappa - X) + \beta(c)X(1 - X) - \lambda X. \quad [1]$$

σX describes the discharge of patients at a rate σ where $1/\sigma$ is the average length of stay in a hospital. $\sigma\kappa$ represents new colonized admissions to the hospital. Hospital occupancy is assumed to be constant, so that admissions balance discharges. Finally, the clearing of colonization occurs at a rate λ . This is a chemostat hospital model similar to those explored by other researchers (3, 16, 17).

Infection control lowers the transmission rate of the pathogen, but with diminishing marginal returns. Mathematically, the function $\beta(c)$ describes the transmission rate of the pathogen. This rate depends on the total money invested in HIC (c), which is a function of the hospital's spending, h , and the value of a subsidy, s . The relationship between c , h , and s will depend on the type of subsidy described below being offered. For the purposes of the following preliminary calculations we take this relationship to be of the form $\beta(c) = \frac{a}{1+b\sqrt{c}}$, where a and b are scaling factors. This functional form originates from Smith, Levin, and Laxminarayan (9) and was chosen because it is a decreasing function of c with diminishing

Significance

As populations age and hospitalization becomes more common, healthcare-associated infections, including many caused by drug-resistant pathogens, are increasing in importance. Because healthcare facilities share patients, healthcare-associated pathogens spread easily between facilities. Each institution, therefore, has an incentive to free ride on the infection control efforts of other institutions. A feasible policy is to compensate hospitals for infection control. Here we explore the effect of different forms of subsidies on hospitals' infection control. Under a limited budget, we find that the most effective subsidy is a dollar-for-dollar matching subsidy. Additionally, we show that a subsidy should be preferentially given to hospitals with lower transmission rates. Economic incentives strongly influence hospital behavior and understanding these is a useful complement to epidemiological analysis alone.

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¹To whom correspondence may be addressed. Email: sedrohan@princeton.edu, slevin@princeton.edu, or ramanan@cddep.org.

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returns and is useful for algebraic characterization of equilibria. Additionally, this functional form does not show sudden discontinuous shifts in return to spending. In the absence of data to which we could fit a candidate function, hence the form chosen is the most parsimonious. More general functions could be considered in future work, particularly those that do not have a slope discontinuity at $c=0$, and may allow for larger bounds on the results that follow. We did not include the clearance rate to isolate the influence of spending on the dynamics of the system. $\beta(0)=a$ is the intrinsic transmissibility of the pathogen when no effort is made to control infection.

Equilibrium analysis and optimization. A hospital will choose an optimal value h such that the total costs are minimized. If the average hospital stay is short [in the United States it is ≈ 5 d (18)], the system will converge relatively fast to the equilibrium and we can ignore the transient dynamics. The total costs to the hospital at equilibrium are the sum of investment in HIC and the cost incurred for each infected patient. Therefore, the optimization problem without a subsidy ($s=0$) is equivalent to finding the minimum of $h + D\bar{X}(c)$, where D describes the excess cost per patient per day at the equilibrium \bar{X} (9). Local minima of this function occur if $1 + D\frac{d\bar{X}}{dh}(c) = 0$. In this simple case, the exact solution can be found via the quadratic formula. For further details refer to Smith, Levin, and Laxminarayan (9).

If the proportion of community admissions is nonzero, then Eq. 1 has two equilibria: One is negative and the other is strictly positive and therefore the only relevant equilibrium. If $\kappa=0$, then there are two feasible equilibria, one at $X=0$ and one at $X = 1 - \frac{\lambda + \sigma}{\beta(c)} = 1 - \frac{1}{\mathcal{R}_0}$. Since $\beta(c)$ is in the denominator in this expression, increasing spending decreases the number of patients infected at equilibrium. \mathcal{R}_0 , the basic reproduction number, is defined as a threshold such that when $\mathcal{R}_0 > 1$, the nonzero equilibrium is positive and stable while the trivial equilibrium is unstable. That is to say, when $\mathcal{R}_0 > 1$, the number of secondary cases one infected individual generates in a wholly susceptible population is more than one and thus the infection will spread. When $\mathcal{R}_0 < 1$, there is no nontrivial feasible equilibrium. As \mathcal{R}_0 varies the system undergoes a transcritical bifurcation.

Subsidies. In general, when a subsidy is offered by a policymaker, the total investment in infection control is a function of both the hospital spending h and the subsidy s . The policymaker is concerned solely with reducing the number of people infected, usually given some limited budget. We consider three specific formulations of a subsidy for HIC: a fixed-amount subsidy, a subsidy for each uninfected patient at equilibrium, and a dollar-for-dollar matching subsidy.

Under a fixed subsidy a predetermined amount of money s is given to the hospital to spend on HIC. The total investment in this scenario is then $c = h + s$ and the total costs to the hospital are $h + D\bar{X}$. As shown in *SI Appendix*, a fixed subsidy will simply replace a hospital's own optimum spending, even for more general forms of $\beta(c)$. Total costs remain the same and hospital spending decreases linearly with the subsidy.

A subsidy for each uninfected patient at equilibrium has total investment $c = h$, but the total costs to the hospital are $h + D\bar{X} - s(1 - \bar{X})$. This type of subsidy is equivalent to increasing the cost D per infected patient. Effectively, this is a tax on infected patients (*SI Appendix*) and may result in a negative cost. As formulated here, we assume that the subsidy value is predetermined and reduces a hospital's total cost after equilibrium has been reached. Redirecting these funds into HIC without causing complicated recursion is better suited for a repeated game, which we do not consider here.

Finally, a dollar-for-dollar matching subsidy implies that for every dollar a hospital spends on HIC, the policymaker will provide s dollars to also be spent on HIC. The total investment is $c = h(1 + s_m)$, where $s = s_m h$ to distinguish between the multiplicative constant and the cost to the policymaker. The costs to the hospital are $h + D\bar{X}$, the same as in the case of a fixed subsidy.

As can be seen in Fig. 1, a dollar-for-dollar matching subsidy appears to outperform the other subsidy types. The number of patients infected at equilibrium given a limited budget from the policymaker is lower for the matching grant for the parameter range and functional forms considered. For this reason, we focus on this type of subsidy.

We consider a subsidy to be effective if it encourages a hospital to spend more than it would without a subsidy $\frac{\partial h_{opt}}{\partial s} > 0$. An ineffective subsidy is one where the hospital decreases spending as the matching subsidy increases. Even if the total amount being spent on infection control is growing, the proportion paid for by the institution is constant or decreasing. An ineffective subsidy is an example of policy resistance in which a policy worsens a problem as a result of feedback and unintended incentives (19).

Theorem 1 describes the existence criteria for when a matching subsidy will be effective in the extreme case when $\kappa = 0$. A hospital will invest at the cheaper option of either the minimum of the cost function or the amount required to reduce \mathcal{R}_0 below 1 and eliminate the pathogen. When the intrinsic transmissibility is high, there will be an interval of effective matching grant values bounded below by zero.

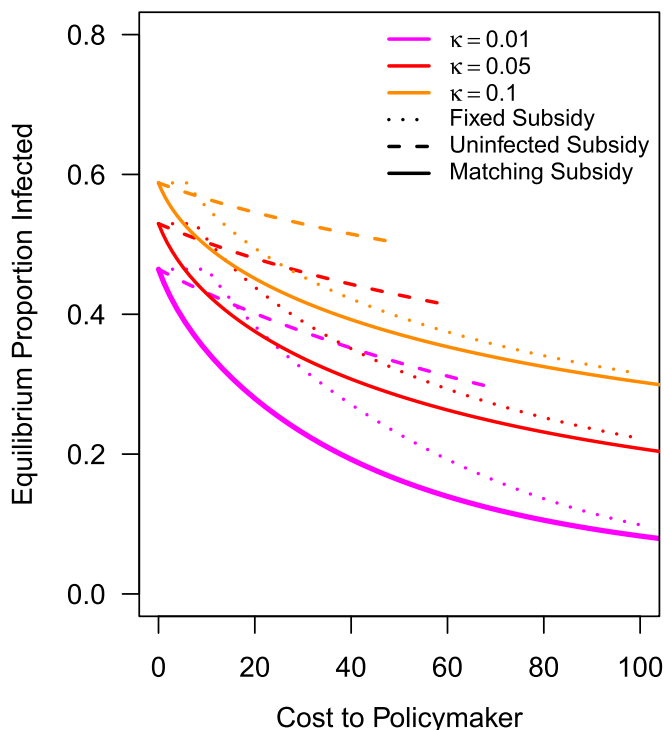


Fig. 1. For three values of κ (colors), the equilibrium proportion of hospitalized patients infected is given as a function of the cost to the policymaker. To achieve the same number of infected patients, a policymaker spends the least by using a matching subsidy (solid lines), followed by a fixed subsidy (dotted lines), and then finally a subsidy for uninfected patients (dashed lines). The end points of these curves vary because the same range of subsidy spending produces different costs for the policymaker, depending on the subsidy type. The parameters used to generate this plot are $a = 0.6$, $b = 0.2$, $\lambda = 0.0005$, $\sigma = 0.2$, and $D = 100$.

Theorem 1. A region of effective subsidies will exist for $\kappa = 0$ when

$$a > \frac{\lambda + \sigma}{2} \left(1 + \sqrt{1 + 2Db^2} \right) = a^*. \quad [2]$$

Proof: The minimum of the cost function occurs when $1 + D \frac{\partial X}{\partial h} = 0$. Solving this equation gives

$$h = \left(\frac{Db(\lambda + \sigma)}{2a} \right)^2 (1 + s_m). \quad [3]$$

The amount needed to eliminate the pathogen (the zero equilibrium to be stable) is

$$h = \left(\frac{a - (\lambda + \sigma)}{b(\lambda + \sigma)} \right)^2 \cdot \frac{1}{1 + s_m}. \quad [4]$$

A hospital will switch strategies from eradicating the pathogen to minimizing the cost function when the costs of these two strategies are equal. We can solve for the subsidy value at which this occurs:

$$s_m^* = \frac{2a(a - (\lambda + \sigma))}{Db^2(\lambda + \sigma)^2} - 1. \quad [5]$$

If a ($\beta(0)$) is sufficiently high, this switching point does not exist and the hospital will always choose to eradicate the infection. For $s_m > s_m^*$, $\frac{\partial h_{opt}}{\partial s_m} < 0$, but for $s_m < s_m^*$, $\frac{\partial h_{opt}}{\partial s_m} > 0$. Therefore the region of effective subsidies is $0 < s_m < s_m^*$ which exists when $s_m^* > 0$ or equivalently $a > a^*$ as stated in Eq. 2. \square

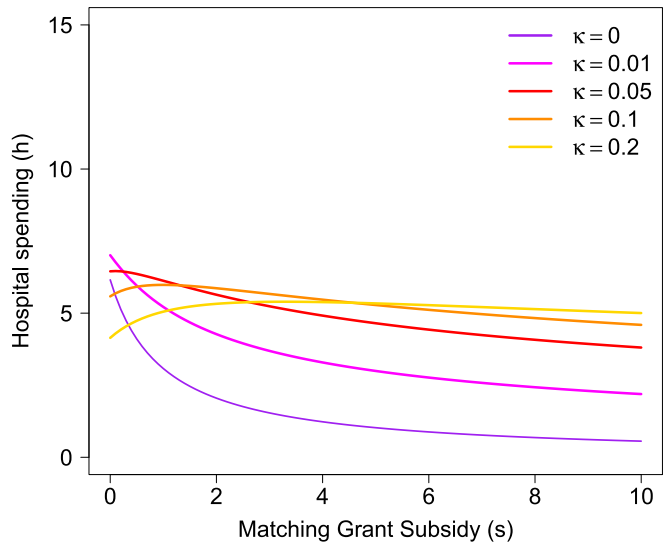
This existence condition can be rearranged to $\mathcal{R}_{0ns} > \frac{1}{2} (1 + \sqrt{1 + 2Db^2})$, where \mathcal{R}_{0ns} represents \mathcal{R}_0 when there is no subsidy. The biological parameters are now on the left (a, λ, σ) and the economic parameters (b, D) are on the right. Biologically, for effective subsidies to exist \mathcal{R}_{0ns} must be high enough such that it is not always economically optimal to eliminate the pathogen.

A closed-form analytical solution is no longer possible when $\kappa \neq 0$, as seen in Fig. 2. Additionally, this condition is particular to the choice of functional form. Our numerical solutions for $\kappa \neq 0$ seem to support the existence of effective subsidies for $a > a^*$. However, clearly κ also determines the region of effective subsidies since even when $a < a^*$ there may also exist a region of effective subsidies when κ is high. When the proportion colonized in the community is high and overwhelms new nosocomial colonizations, there may be a point at which any subsidy value is effective. Regardless of the intrinsic transmissibility, the peak of hospital spending decreases as the proportion colonized increases.

In general, a hospital may be “free riding” if a subsidy is not effective since it lowers its own spending as more subsidy is offered. Fig. 2, *Top* and *Bottom* shows that behavior may differ between a “free rider”—a hospital which does not increase spending when others do—and a “cooperator”—a hospital that increases spending when others do. In the language of game theory and economics, for a free rider a subsidy is a strategic substitute for the hospital’s own HIC resources and the institution is displaying policy resistance. For a cooperator a subsidy is a strategic complement and the institution is displaying policy reinforcement.

The strongest characteristic influencing into which category a hospital falls is the intrinsic transmissibility. This attribute may be associated with hospital size, ward size, or hospital type. However, the proportion colonized in the community, κ , also plays a role in determining hospital behavior. Hospitals with low intrinsic transmissibility may act as cooperators if the proportion admitted colonized is high.

$a = 0.3$



$a = 0.6$

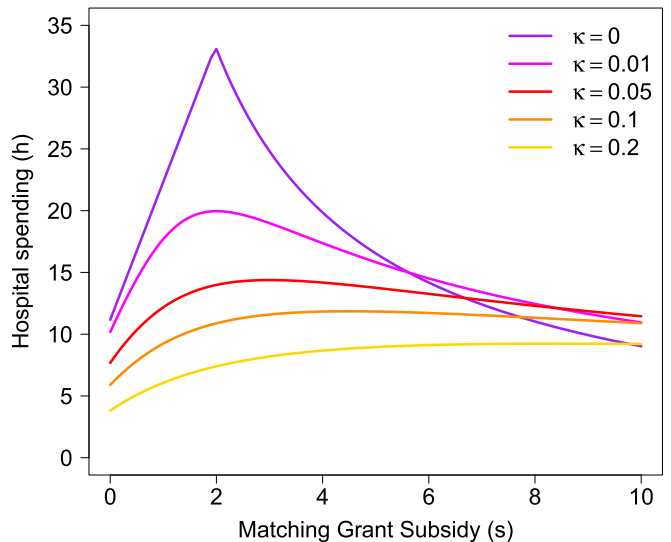


Fig. 2. Illustration of how hospitals change their spending behavior in response to a matching subsidy. *Top* shows a hospital with low intrinsic transmissibility and *Bottom* shows a hospital with high transmissibility. We consider an effective subsidy to correspond with points on these curves for which the slope is positive. This occurs for a larger range of κ when intrinsic transmissibility is high as opposed to when intrinsic transmissibility is low. The parameters used to generate this plot are the same as in Fig. 1 other than intrinsic transmissibility (a).

Multinstitutional Games. The single-hospital case offers a stylized model to understand how identical hospitals all receiving subsidies may interact. We then explore a two-player game as a case study in subsidy allocation.

Let X and Y be the proportions colonized in a focal hospital and all other hospitals, respectively, such that the total number of hospitals is n . Z replaces the constant κ as a variable describing the proportion colonized in the community. Patients are still discharged into a common catchment population, but are admitted to each institution at a rate r . The dynamics for hospitals are the same as in the single-hospital case; however, each has its own transmission function and choice of amount to invest. Differences between hospitals could be defined in multiple

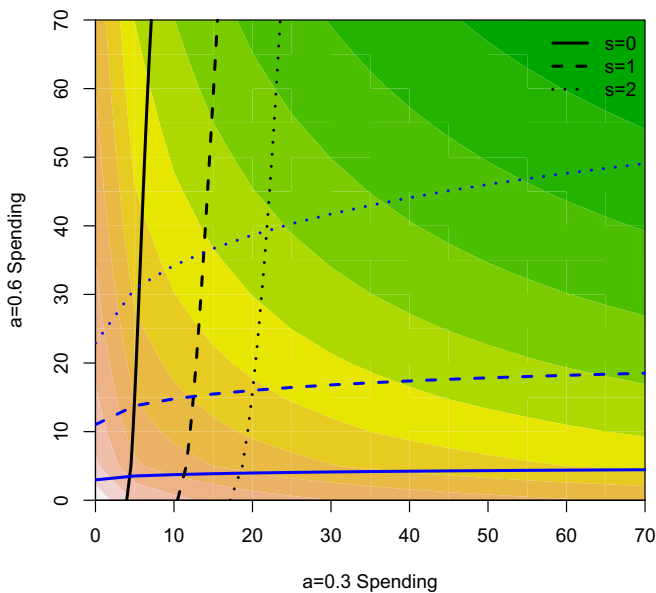


Fig. 3. In a game-theoretic framework, hospitals are investing at a Nash equilibrium that is determined by the offered subsidy (s) values. The black lines show the response of the free rider ($\beta(c) = \frac{0.3}{1+0.2\sqrt{c}}$) to the amount of money being invested by the cooperator ($\beta(c) = \frac{0.8}{1+0.2\sqrt{c}}$). Conversely, the blue lines show the response of the cooperator to the amount of money being invested by the free rider. The solid, dotted, and dashed lines indicate various matching subsidy values. Any intersection of a black and a blue line would represent Nash equilibrium spending at the specified parameters. The asymmetry of these curves is a result only of the scaled transmission rate function, which could also act as a proxy for hospital size or other environmental differences. The background heat map indicates the total number of patients infected after 30 y (white indicates high infection and green corresponds to low infection). The initial conditions used are $X = 0, Y = 0, Z = 10^{-5}$.

different ways, i.e., different sizes (different contributions to the community) or different propensity to admit from a recently hospitalized population (primary vs. tertiary care). Having nonidentical transmission functions provides an easy way to describe these differences and is analogous to having different values of \mathcal{R}_0 .

The system of differential equations describing the situation is

$$\frac{dX}{dt} = \beta(c)X(1 - X) - \lambda X - \sigma(X - Z) \quad [6]$$

$$\frac{dY}{dt} = \tilde{\beta}(\tilde{c})Y(1 - Y) - \lambda Y - \sigma(Y - Z) \quad [7]$$

$$\frac{dZ}{dt} = r \left(\frac{X}{n} + \frac{Y(n-1)}{n} - Z \right) - \lambda Z. \quad [8]$$

The dynamics are now more complicated and thus we use a cumulative cost function of the form below,

$$\int_0^T \left[h + DX(t, h(1+s), \tilde{h}(1+\tilde{s})) \right] dt. \quad [9]$$

To generate example response curves, we simulate this system and generate numerically the outcome when hospitals ($n = 2$) are playing against each other in a two-player game. This is done using nonlinear minimization of Eq. 9, given the strategy \tilde{h} of all other hospitals.

When two heterogeneous hospitals, i.e., one with low intrinsic transmissibility and one with high intrinsic transmissibility, play against each other, their responses to the other hospital's actions will be very different. Fig. 3 shows the response curves for three different subsidy values laid over a heat map of the resulting

equilibrium of infection. Nash equilibria occur at the intersection of the response curves. By comparing the level of infection at the Nash equilibria, we note that if a subsidy can be offered to only one hospital, the optimal solution for reducing infection is to offer it to the hospital with the lower transmission rate. We assume that any combination of matching grant values can be offered to this pair of hospitals.

When the hospitals have identical transmission functions, the response curves are entirely symmetrical. When hospitals have the same transmission rate, the best outcome is obtained by offering the entire subsidy to a single hospital rather than splitting it equally between the two.

The number of infected patients at Nash equilibria spending for a range of subsidy values is shown in Fig. 4. The axes are the total amount of money a public health authority would provide to either hospital in the same heterogeneous case as in Fig. 3. The asymmetry of the heat map shows that the lowest prevalence appears to be obtained when more money is given to the hospital with lower transmissibility (predisposed to free riding). While some benefit is gained no matter to whom the subsidy is given, the worst outcome seems to occur when each one receives similar amounts of incentive. In the case of a limited budget, sloping downward diagonal lines in Fig. 4 denote equal total amounts of money spent by the public health authority (the sum of money given to each hospital). The point at which infection is lowest is along the axis corresponding to most of the budget being devoted to the hospital with low intrinsic transmission.

Discussion

In this paper, we explored how public subsidies for HIC could alter the behavior of hospitals and how best to deploy limited subsidy resources.

We considered three types of subsidies: a subsidy for each uninfected patient, a fixed subsidy, and a matching subsidy. Assuming a fixed level of subsidy resources, the least effective at reducing infection was a subsidy tied to the number of uninfected patients at equilibrium, which is equivalent to a tax on infected patients. A fixed subsidy was moderately effective; however, it simply replaces a hospital's own spending. The fixed subsidy has no effect on the transmission of HAIs until the subsidy contributes all of the HIC spending and the hospital invests zero.

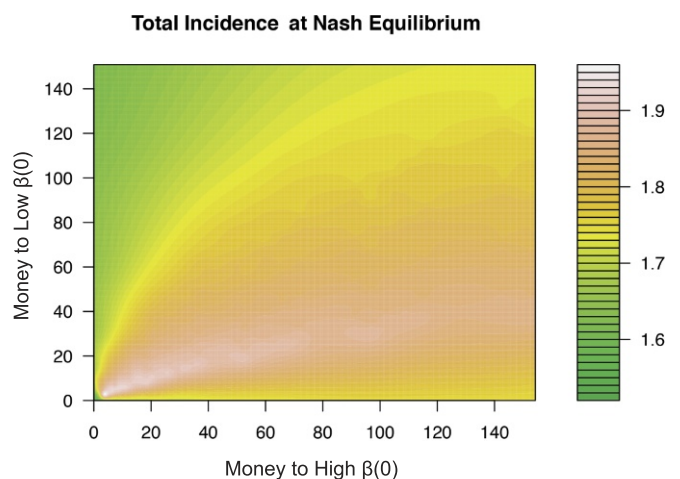


Fig. 4. Given the same two hospitals and parameters as displayed in Fig. 3, this plot shows the total incidence at Nash equilibrium spending. The units of incidence are the sum of the proportion of X and Y infected (the maximum is 2). We iterated over a range of subsidy values from 0 to 10, found the Nash equilibria, and then simulated the times series. The asymmetry of the heat map indicates that most of the subsidies should optimally go to the hospital with the lower transmission rate (free rider).

The matching subsidy was the best at reducing infection for the same cost to the policymaker. Furthermore, we derived a theoretical rule for when a matching subsidy will be effective. For hospitals with high transmission and/or high levels of patients being admitted already infected, a matching subsidy will result in a hospital increasing its own spending.

In our study, we observed two kinds of behaviors on the part of hospitals: Free riders spend less when offered funding and cooperators spend more when offered funding. An intuitive approach to deploying scarce subsidy resources might be to offer encouragement to a hospital that increases spending when others do. However, the results of our mathematical model suggest that in a two-hospital system incentivizing the institution with a lower transmission rate is better for the overall outcome of the system. Since this two-player game acts as a case study in subsidy allocation, future work should explore the nuances of more complex network combinations of n hospitals with various transmission functions. Furthermore, an optimal control model may be able to tease apart the feedbacks between local and global infection control efforts as well as the differences between optimal and suboptimal spending conditions.

Previous work has explored similar epidemiological optimal allocation problems in metapopulations with varying conclusions (20, 21). In a two-patch susceptible-infected-susceptible system with an annual budget for treatment it may be optimal under certain conditions to devote the entire budget to the least-infected group (22–24). A similar theoretical question is addressed by Klepac, Laxminarayan, and Grenfell (25) with respect to vaccine allocation between two patches. In their model a limited budget should initially be allocated to the patch closest to the herd immunity threshold.

In the context of this paper, the group that has the lower transmission rate should receive the incentive. This group is closest to eradicating the infection and significantly reduces the proportion of patients infected in the community. In effect, this is focusing on reducing the local infection in a single patch to reduce the total global prevalence. Individuals colonized in the community play a large role in the transmission dynamics and so reducing the community prevalence is most effective at reducing the global prevalence. If the money from a subsidy was split, then there would not be as strong an impact on patients admitted already colonized. Thus, the marginal return on an additional subsidy dollar is much higher for a lower transmission rate.

We have made two strong assumptions to support analytic tractability. First, hospitals are identical in all ways other than their transmission rate as a function of investment. Moreover, within a hospital we assume the patient population is well mixed. The differences in transmission rate between institutions may be a reflection of hospital size or function (such as tertiary care facilities); however, they cannot reflect nonrandom admittance from the catchment population. If patients are more likely to be admitted to one hospital over another, that hospital may contribute disproportionately to colonization. Implementing any of these heterogeneities is important for future work. We predict that such an extension will not qualitatively change our results and that the subsidy would still be allocated to a single institution. Our second major assumption is that hospitals must choose a level of investment which cannot be changed once implemented. Future work could extend this model to an optimal control problem that may determine the most effective investment as a function of time.

Unfortunately, we lacked data to confirm how hospital spending decisions are made. Such data could reveal whether there are changes in hospital budgeting when comparing those with different financial incentives or community structure. Our model predicts that rational actors would respond optimally when presented with incentives; however, there may be other factors at play in decision making.

Our results are applicable not only to individual hospitals. Large multifacility systems managed by healthcare corporations could also benefit from considering the behavior change resulting from infection control incentives. Additionally, this type of framework could be applied to consider vaccination or treatment in a metapopulation.

Within the overlap of epidemiology and economics, this research provides another example of the way in which incentives can alter behavior (sometimes in unexpected ways) and fundamentally change the outcome of an epidemic. More broadly we offer a model that can guide policymakers in enacting subsidy programs which result in encouraging investment in hospital infection control.

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