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Optimal Environmental Health Regulations with Heterogeneous Populations: Treatment versus "Tagging"[1]

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In this paper, we develop a model of population level environmental health risk with individuals that are heterogeneous in their susceptibility to environmental toxins. This framework allows us to determine when it is optimal to target vulnerable subgroups of the population with special exposure-reducing treatments. Our analytic results show that the potential economic gains from targeted policies will depend critically on the quality of existing capital, the degree of returns to scale in treatment technologies, and the size and sensitivity of the vulnerable population. An empirical application of the model is extended to the case of cryptosporidium in drinking water supplies.

I. INTRODUCTION

In recent times, there has been a simultaneous increase in social concerns about environmental health risks and the expenditure necessary to reduce these risks (Executive Order 12866; Risk Assessment Improvement Act of 1996). As a result, the employment of differentiated policy tools, as opposed to uniform ones, and the ability to evaluate and prioritize intervention strategies have become critical.

In this paper, we present a model of environmental health risk policy, which explicitly models the health risk generation process (contamination, exposure, and dose–response) as a function of policy control variables, with aggregation from heterogeneous individuals to population level analysis. Specifically, the population is heterogeneous in its susceptibility to environmental toxins and the government has two policy alternatives: (1) employ a uniform policy, where all members of the population are equally subject to the treatment scheme governing disease preven-

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tion; (2) offer discriminatory polices, where health protection strategies are subpopulation specific. This latter policy will be referred to as "tagging," a term popularized by Akerlof [1] in his seminal work on income taxes and welfare programs. This approach has been extended to a diversity of settings characterized by decision making under heterogeneous conditions but has not included applications to environmental health.[3]

While there is a substantial public health literature pertaining to the environmental health risk generation process and risk assessment in general (for a good review see Bogen [4] or Hallenback and Cunningham [5]), the economic literature in this area is still emerging.[4] Lichtenberg and Zilberman [8] have provided a conceptual framework for the economics of environmental health and its policy implications. Their model illustrates some important relationships between pollution reduction and human exposure regulation, but it results in generic conclusions due to the abstract nature of their formulation. The economic literature also contains several applications of this type of health risk model. These include two studies on pesticide poisonings (Harper and Zilberman [9]; Sunding and Zivin [10]) and a study by Lichtenberg *et al.* [11] on groundwater contamination. All of these studies emphasize the importance of uncertainty but do not address observable heterogeneity in vulnerability among the population. Our goal is to present a model of the health risk production process that includes structural specifications which allow for an explicit examination of population heterogeneity and how it can be incorporated into the policy process.

The theoretical presentation is followed by an empirical application of the model to the case of cryptosporidium in drinking water supplies. Cryptosporidium was chosen because of its salient characteristic as a disease that exhibits a large degree of variability in human infectivity: immunocompromised individuals are significantly more susceptible than the immunocompetent. An analysis of five different municipal water districts is made to highlight the conditions that define the optimal mix of intervention strategies, i.e., individual end-point filtration systems versus high-tech treatment facilities.

Our paper demonstrates that discriminatory policies, for example, targeting a vulnerable subset of the population with special treatment, can be employed to achieve a given government standard at a lower cost than uniform ones. Further, by varying the government health standard, we are able to obtain an efficient health–cost trade-off curve. The optimal mix of policies is shown to differ by municipality due to regional differences in the quality of capital, scale effects via population size, and the size and sensitivity of the vulnerable population. The empirical results suggest that small municipal water districts could benefit from tagging policies, with substantial annual compliance cost savings, ranging from 38% to 99%. Due to scale effects in treatment costs and substantial vulnerable populations, it is generally optimal for large water districts to adopt new, uniform technologies.

[3] See for example, the work by Stavins and Jaffe [2] on natural resource management and the emerging literature in agricultural economics on precision farming (National Research Council [3]).

[4] There is an expansive economic literature on environmental health, which does not examine the health risk generation process, but relies on a reduced form relationship between environmental contaminants and health (e.g., Viscusi [6] and Van Houtven and Cropper [7]).

II. ENVIRONMENTAL HEALTH RISK MANAGEMENT

The term health risk refers to an increase in probability that an individual exposed to a particular environmental contaminant will become ill (e.g., probability of morbidity or mortality). In conventional health risk assessment, health risk is commonly represented as the product of three risk generating components: (i) ambient contamination (C), (ii) human exposure (E), and (iii) the dose–response relationship (D). Thus, total population morbidity (M) is merely $C*E*D$.[5] This multiplicative formulation is reasonable when the increased risk is relatively small and is particularly germane to cases where there is preexisting background risk (Van Ryzin [13]; Crump and Howe [14]; Krewski and Van Ryzin [15]).

Further, the two regulatory options discussed earlier affect different components of the risk generating process. The uniform policy, henceforth referred to as water treatment, affects contamination, and the precision policy, henceforth referred to as tagging, affects exposure. Thus, the impacts of regulation on population morbidity can be expressed in the following relationship: $M(\text{regulation}) = C(\text{treatment})*E(\text{tagging})*D$, where D is the distribution of population dose–responses (vulnerabilities).

The objective of the government is to minimize the costs of regulation such that population morbidity is below some maximum allowable rate. This methodology, commonly called the cost-effectiveness criterion or the "containment of risk" principle, is consistent with much of the health protection legislation (Grant and Jarabek [16]). This framework is essentially an adoption of the safety-fixed model first popularized in the economics literature by Kataoka [17].

III. THE MODEL

Consider an environmental health risk that is imposed on a finite and well-defined population, for example, a pathogen in the drinking water supply that may threaten the health of residents served by the water district. Denote the probability that an *individual* gets sick, given their vulnerability and the level of government contamination treatment, as $R(T, D)$. This is referred to as *individual* health risk. Contamination treatment (T) should be thought of as a wide range of government policies designed to reduce contamination levels of environmental hazards. In our case, treatment policies include traditional filtration and ozone gas treatment at a drinking water processing facility. The key feature that distinguishes these policies from the tagging policy that we will develop later is their inability to be applied in a discriminatory manner, i.e., they are uniform policies. Treatment regimes are clean-up strategies that reduce environmental contamination, and they should be viewed as public goods that are nonexcludable and apply to all members of the population equally.[6] For example, the use of filtration and coagulation technologies at a drinking water plant reduces water contaminants equally for all users in the water district.

The population is heterogeneous in their vulnerability (dose–response) to this risk, i.e., for the same exposure, some people are more likely to get sick than

[5] In practice, each component can be expressed as a distribution representing both uncertainty and heterogeneity, where the standard rules of probability theory apply (Bogen and Spear [12]).

[6] This condition is nonrestrictive and is only meant to define the population region.

others. This is a common feature of most health risks, where it is rare to see an entire population of people respond identically to a given toxic exposure (Grandjean [18]). We define the range of vulnerabilities as between zero and one, and let $g(D)$ represent the population distribution of these vulnerabilities. In other words, $g(D)$ indicates the percentage of people within the given population at each level of vulnerability.

Thus, the expected *population* morbidity rate for a given level of treatment is simply the integral of individual sickness probabilities over the entire distribution of vulnerabilities, i.e., the average individual risk of illness in the population. Multiplying this rate by the population would give the total expected cases of illness in the population. Formally, we represent the *population* morbidity rate as

$$M(T, D) = \int_{D=0}^{1} g(D) \cdot R(T, D)\, dD.$$

In the example of drinking water supplies, this equation represents the expected percentage of a given population (supplied by the same water source) that will experience a specific adverse health outcome (e.g., cryptosporidiosis). As will be discussed in greater detail in a later section, tagging is represented as a choice on the upper bound of vulnerability for those still remaining in the general treatment population.

The objective of the policymaker is to minimize costs subject to a health risk target, i.e., where $M(T, D) \leq k$ The variable k represents the government standard on the level of population health risk that is still considered reasonable. This formulation is consistent with Lichtenberg and Zilberman [8] and is essentially a generalization of the standards and charges approach to environmental regulation under uncertainty (Baumol and Oates [19]). The variable k is an average health risk target for the entire population, which in the empirical work is defined as all the residents served by a given municipal water supply.[7] This target is set to a predetermined morbidity rate, i.e., an allowable percentage of adverse health outcomes.

Given our minimization objective, it is useful to think of this morbidity as the output of a health risk production process, with water treatment and tagging as inputs in this process. Thus, the derivatives of M can be discussed using the language of production economics, i.e., M_T is the marginal productivity of treatment on population morbidity, $M_{D_{\max}}$ is the marginal productivity of tagging, M_{TT} represents returns to scale in treatment, etc.

The cost of water treatment, c_1, is an increasing function of the treatment level, $c_{1T} > 0$, and a decreasing function of plant efficiency, $c_{1\Theta} < 0$. Further, we assume that marginal treatment costs are increasing with the treatment level, $c_{1TT} > 0$, and decreasing in plant efficiency, $c_{1T\Theta} < 0$, where the efficiency measure is designed to capture the age and quality of facilities as well as the size of the population

[7] It is important to note that the health standard must be defined in the context of a specified population, or subpopulation. In some cases, the regulator's objective may be to control risk for the most vulnerable subgroup. However, heterogeneity is likely to persist even within a given subgroup. Furthermore, there are alternative ways to consider heterogeneity among individuals: by age, earning power, human capital, etc. The literature on the value of life grapples with these issues (e.g., Mishan [20]; Broome [21]). Given the lack of consensus on the appropriate social weighting of life values, we employ an expected risk criterion that treats all lives equally.

served by the plant. The latter component is particularly important for the case of drinking water treatment because fixed costs are high and the economic feasibility of treatment hinges on the ability to spread costs among many users; i.e., there is an element of returns to scale. Thus, population size is likely to be important in determining the relative attractiveness of treatment versus tagging policies.

A. *Treatment Only*

In this case, the only policy option the government has is to treat the pollutant.[8] Thus, the government objective is to meet the health risk standard in the least-cost manner. Expressing the government's problem as a Lagrangian maximization, we obtain

$$\max_T L = -c_1(T, \Theta) + \lambda[k - M(T, D)],$$

where λ is the shadow value of the government health standard and measures the impact of maintaining this standard on the cost-minimization objective. The logical interpretation of this variable is as an implicit representation of the government's value of reduced population morbidity, i.e., the value of health. It is important to recognize that this shadow value does not necessarily reflect a value of risk reduction in a willingness-to-pay sense. Recall that k is the maximum permissible level of risk.

The minimization problem yields the following first-order conditions:

$$\frac{\partial L}{\partial T} = -\frac{\partial c_1}{\partial T} - \lambda\left[\int_{D=0}^{1} g(D)\frac{\partial R}{\partial T}\,dD\right] = 0 \tag{1}$$

$$\frac{\partial L}{\partial \lambda} = k - \int_{D=0}^{1} g(D)\cdot R(T, D)\,dD = 0. \tag{2}$$

Equation (1) says the marginal cost of water treatment equals the marginal benefit of reduced population morbidity times the value of health. The term in brackets can be interpreted as the marginal productivity of water treatment on population morbidity. Equation (2) merely restates the constraint.

The impacts of changes in the maximum permissible level of risk and the plant efficiency are obtained through comparative static analysis. For ease of exposition we provide the answers in proposition form, followed by some intuition. The mathematical proof is provided in an appendix.

PROPOSITION 1.

(1a) $\frac{dT}{dk} < 0$;
(1b) $\frac{dT}{d\Theta} = 0$;
(1c) $\frac{d\lambda}{dk} < 0$;
(1d) $\frac{d\lambda}{d\Theta} < 0$.

Expressions (1a) and (1c) indicate that as the government health standard becomes more stringent (smaller k), the level of water treatment and the shadow

[8] In practice, T can be continuous, such as the disinfectant to water ratio, or T can represent discrete technology jumps, such as a switch from filtration technologies to reverse osmosis or from chlorination to ozonation.

value of health increase. Assuming the constraint is binding, expression (1d) shows that more efficient plants result in smaller shadow values, and (1b) indicates that changes in treatment plant efficiency have no effect on the level of treatment. This latter result occurs because the health standard must be met regardless of cost,[9] and water treatment is the only policy option available to meet that standard. Further in the paper we will relax the assumption of a single policy option, thereby allowing the dependence of treatment on costs.

B. *Treatment and "Tagging"*

In this case, we expand the policy options to include "tagging." As stated earlier, tagging refers to the identification of a vulnerable subpopulation and offering them an alternative form of health protection.[10] In the case of water quality regulations, tagging options could include end-point filtration systems or the provision of bottled water.

Tagging is represented as a choice on the upper bound of vulnerability for those still remaining in the general treatment population, denoted as $D_{\max}$. An important distinction between tagging and treatment policies is that water treatment changes the toxic exposure level for everyone, while tagging, assuming it is fully effective, changes the number of people exposed to the toxin. Another way to express this is that water treatment reduces *population* morbidity rates by reducing all members' *individual* morbidity rates, while tagging reduces *population* morbidity rates by significantly reducing, or eliminating, the *individual* morbidity rates of only a subset of the population.

We assume that the tagging treatment is fully effective; i.e., the health risk to the population selected for tagging is zero. The cost of tagging, c_2, is an increasing function of the tagging level, $c_{2D_{\max}} < 0$. Further, we assume that the marginal costs of tagging are increasing at an increasing rate (increasing marginal costs of tagging), $c_{2D_{\max}D_{\max}} < 0$. This is likely to be the case when it is fairly easy to identify very vulnerable people, but is progressively more difficult to identify less vulnerable people.

The government's problem is represented as

$$\max_{T,\,D_{\max}} L = -c_1(T,\Theta) - c_2\left[\int_{D_{\max}}^{1} g(D)\,dD\right] + \lambda\left[k - M(T,D,D_{\max})\right],$$

where the percentage of people in the tagged subpopulation is represented as $\int_{D_{\max}}^{1} g(D)\,dD$. Given the complete effectiveness of tagging, the maximum allowable risk level only applies to the remaining population. This is attractive because the

[9] Cost irrelevance is a common feature of these types of health regulations. For example, many EPA regulations employ a maximum individual risk target (e.g., 10^{-6} risk) that is set independent of compliance costs. More recently, costs have begun to enter the health risk management debate, implying that in fact the maximum allowable risk is a function of treatment costs, $k(T)$. The ultimate fate of these concerns is unknown. Thus, for simplicity, we maintain the assumption that k is independent of costs.

[10] In the case where individual vulnerabilities are not known but can be ascertained through some reasonable identification process, the costs of identification are included in the costs of the tagging policy. As identification technologies change, conditions that were previously unidentifiable may become amenable to tagging policies.

nontagged population is less vulnerable to health risks, thereby requiring less traditional water treatment to meet the health standard. The ultimate decision to tag will involve some weighting of the benefits and additional costs of tagging. Unlike the earlier case of a single policy tool, treatment plant efficiency and one of its principal components, population size, will have an important impact on intervention choice through its influence on relative intervention costs.

The maximization problem above yields the following first-order conditions:

$$\frac{\partial L}{\partial T} = -\frac{\partial c_1}{\partial T} - \lambda\left[\int_{D=0}^{D_{\max}} g(D)\frac{\partial R}{\partial T}\,dD\right] = 0 \tag{3}$$

$$\frac{\partial L}{\partial D_{\max}} = c_2 g(D_{\max}) - \lambda\left[g(D_{\max})\cdot R(T, D_{\max})\right] = 0 \tag{4}$$

$$\frac{\partial L}{\partial \lambda} = k - \int_{D=0}^{D_{\max}} g(D)\cdot R(T, D)\,dD = 0. \tag{5}$$

Equation (3) says the marginal cost of water treatment equals the marginal benefit of reduced morbidity from traditional water treatment times the value of health. Equation (4) states that the per person cost of tagging times the number of people on the margin at vulnerability $D_{\max}$ equals the probability of people who on the margin of $D_{\max}$ will no longer get sick times the government value of health. Restated, Eq. (4) says that the marginal cost of tagging equals the marginal benefit from reduced morbidity times the value of health, i.e., the value marginal product (VMP) of tagging. The terms in brackets in Eqs. (3) and (4) represent the marginal productivity of water treatment and tagging on population morbidity, respectively. Equation (5) is the constraint.

In order to conduct a comparative static analysis, it will be important to characterize the properties of the population morbidity production function, $M(T, D, D_{\max}) = \int_0^{D_{\max}} g(D)R(T, D)\,dD$. Recall that tagging refers to choosing a vulnerability upper bound on the nontagged population. Essentially, tagging starts with the rightmost person(s) in the vulnerability distribution (the most vulnerable) and works its way leftward. Clearly, the change in morbidity will depend on the shape of the vulnerability distribution. For example, if the distribution of vulnerabilities is bimodal, the effect of a small change in tagging will depend on whether the slope of the distribution is increasing or decreasing at this point. For simplicity, we assume that the vulnerability distribution is unimodal and the relevant range for incremental policy changes is in the right-hand tail of the distribution (to the right of the maximum).

This assumption has some clear implications for the second derivatives of the morbidity production function. As water treatment levels increase they impact proportionally more vulnerable people. Since the population size is decreasing in vulnerability, if the dose–response function has a threshold where below a certain contamination level no health response occurs, higher levels of treatment affect fewer people, implying a decreasing marginal productivity of treatment, $M_{TT} > 0$. If, as in our case study presented later, the dose–response function is convex such that changes in the dose–response with respect to contamination levels are increasing at an increasing rate, the marginal productivity of treatment is still

decreasing.[11] Similarly, we can determine the sign of the substitution effect between policies. By construction, water treatment reduces morbidity for all members of the nontagged population, including those people on the tagging margin at $D_{\max}$. This implies $M_{TD_{\max}} = M_{D_{\max}T} < 0$: the two regulatory policies are substitutes.

The impact of a change in tagging levels on the marginal productivity of tagging is less clear. This effect can be broken down into two opposing components,

$$\frac{\partial^2 M}{dD_{\max}^2} = \frac{\partial g}{\partial D_{\max}} R(T, D_{\max}) + g(D_{\max}) \frac{\partial R(T, D_{\max})}{\partial D_{\max}},$$

where the first term is the extensive margin and the second term is the intensive margin of change. The extensive component corresponds to the impacts on new, tagged segments of the population. As tagging levels increase, due to the shape of the vulnerability distribution, the marginal number of additional people tagged increases, implying increasing marginal productivity. The intensive component captures the reduced morbidity for those people at the marginal vulnerability, $D_{\max}$. As tagging levels increase, the new individuals being tagged are progressively less vulnerable and thus receive a smaller benefit from tagging; i.e., the marginal productivity of tagging is decreasing. The net effect is ambiguous. For the remainder of this paper, we allow for either sign possibility by treating each component separately.

The impacts of changes in the maximum permissible level of risk, the treatment plant efficiency and the cost of tagging are obtained through comparative static analysis. We provide the answers in proposition form, followed by some intuition. Proofs are provided in an appendix.

PROPOSITION 2.

(2a) $\frac{dT}{dk} \lesseqgtr 0$ *if* $\text{MRTS} \gtreqless \text{MRTS}_{D_{\max}}$;

(2b) $\frac{dT}{dc_2} > 0$;

(2c) $\frac{dT}{d\Theta} > 0$.

Expression (2a) demonstrates that the effect of the standard on water treatment levels depends upon relative marginal rates of technical substitution (MRTS) between treatment and tagging. When the average MRTS is greater than the MRTS at vulnerability $D_{\max}$, an increase in the stringency of the government standard leads to more water treatment. However, when the MRTS at vulnerability $D_{\max}$ is greater than the average MRTS, more stringent standards will lead to less water treatment. This counterintuitive result reflects the fact that at the margin, eliminating risk to a substantial high-risk group may have such a significant impact on overall health risk that it will reduce the residual risk constraint for the rest of the population. Thus, risk reduction for the vulnerable population may be substantial enough to more than offset a marginal increase in risk to the general population. Given that tagging and water treatment are substitutes in the health production function, expression (2b) confirms that price increases in tagging

[11] There is some evidence for thresholds, convexity, and linearity. If the dose–response is linear, the marginal productivity is linear and $M_{TT} = 0$. There is no evidence of a concave dose–response function in the health literature.

encourage the use of treatment. Expression (2c) presents the effect of treatment plant efficiency on water treatment levels. As plant efficiency increases, water treatment becomes relatively cheaper, leading to more water treatment.

PROPOSITION 3.

(3a)

$$\frac{dD_{\max}}{dk} \gtreqless 0 \qquad \textit{if } \frac{\lambda}{T}\frac{\partial M}{\partial T}\left[\xi_{\partial c_1/\partial T} + \xi_{\partial M/\partial T} - \xi_{(\partial M/\partial D_{\max})/\partial T}\cdot \mathrm{MRTS}\right] \gtreqless 0;$$

(3b) $dD_{\max}/dc_2 > 0$;

(3c) $dD_{\max}/d\Theta > 0$.

The change in tagging levels in response to a change in health standards depends on several elasticities, including the elasticity of the marginal cost of treatment, the elasticity of the marginal productivity of treatment, and the elasticity of a marginal treatment change on the marginal productivity of tagging. As demonstrated in (3a), more stringent standards (lower k) will lead to increases in tagging (lower $D_{\max}$) when additional water treatment is costly, additional water treatment is relatively unproductive, and tagging is moderately productive. When these conditions do not hold, the counterintuitive result obtains; i.e., tighter standards result in less tagging. Expression (3b) shows that the effect of tagging costs is the standard own-price effect for non-Giffen goods. The impact of treatment plant efficiency is presented in (3c). As water treatment facilities become more productive, treatment becomes relatively more attractive and tagging levels decline.

LEMMA 1. $dT/dk \gtreqless 0$ *if* $dD_{\max}/dk \lesseqgtr 0$.

Lemma 1 states that a more stringent standard can never lead to a decrease in both the water treatment levels and the tagging levels. This condition is a direct result of the second-order restrictions on the maximization problem (the sign of the bordered Hessian). This result is intuitive: a tighter standard could not be met if both health policies were simultaneously reduced.

PROPOSITION 4.

(4a) $\frac{d\lambda}{dk} \lesseqgtr 0$ *if* $\frac{dT}{dk} < 0$ *and* $dD_{\max}/dk \gtreqless 0$;[12]

(4b) $d\lambda/dc_2 \gtreqless 0$ *if* $dD_{\max}/dk \gtreqless 0$;

(4c) $\frac{d\lambda}{d\Theta} \lesseqgtr 0$ *if* $\frac{dT}{dk} \lesseqgtr 0$.

All of these results are driven by earlier conditions. Expression (4a) shows that a more stringent government health standard will result in a higher shadow value of health when both treatment and tagging levels increase in response to stricter health standards. The counterintuitive result (a lower shadow value for a higher health standard) occurs when the treatment effect from the health standard is as expected and the tagging effect is the special case described in Proposition 3. This occurs because the optimality of increased treatment and decreased tagging implies increasing returns to scale in water treatment productivity. In turn, the scale effect reduces the cost (value) of the marginal morbidity avoidance, λ. In the case where

[12] Note that the impact on the shadow value of health is ambiguous if the two subsequent derivatives are positive.

the tagging effect is as expected and the treatment effect is special, the effect of a tighter health standard on the shadow value of health is ambiguous. This will depend on the degree to which tagging exhibits increasing returns to scale, and thus on the shape of the vulnerability distribution.

Conditions (4b) and (4c) state that the impact of tagging costs and treatment plant efficiency on the level of tagging depend on the results previously described in Propositions 3 and 2, respectively. When the tagging effect described in (3a) is intuitive, higher tagging costs lead to higher shadow values. When the tagging effect is counterintuitive, tagging costs have a counterintuitive impact on the shadow value (higher tagging costs lead to lower shadow values). Similar logic can be applied to the effect of treatment plant efficiency described in (2a); i.e., when the treatment effect is as expected, decreased plant efficiency results in a higher shadow value of health.

IV. CASE STUDY: CRYPTOSPORIDIUM IN DRINKING WATER

This section presents an application of the conceptual model to a specific ailment caused by drinking water contamination: cryptosporidiosis. Cryptosporidiosis is a disease caused by the parasite *Cryptosporidium parvum*—crypto for short—a parasite that usually affects the gastrointestinal tract. The most common symptoms are diarrhea and abdominal cramping but may also include headaches, nausea, vomiting, and a low-grade fever. In immunocompetent persons, these symptoms usually last one to two weeks, after which the immune system is able to stop the infection. However, for persons with suppressed immune systems, such as people undergoing chemotherapy or people HIV-positive, the infection may persist and eventually become life threatening. There is no known cure for cryptosporidiosis (Current and Garcia [22], Navin and Juranek [23], and DuPont *et al*. [24]).

Cryptosporidiosis is spread by oral contact with an object that has been contaminated with the feces of an infected person or animal. Recent studies have shown that 50% of young calves shed crypto oocysts, an egglike form of the parasite (McClurg [25]). If those calves defecate in a stream, that water may become infected and cause illness in those who drink the water (Hayes *et al*. [26]). In addition to drinking water, cryptosporidiosis can be spread through contact with infected stool and eating raw or undercooked food contaminated with oocysts.

Since 1984, 11 outbreaks of cryptosporidiosis in the United States have been linked to local drinking water supplies. The worst of these cases occurred in 1993 when 403,000 residents in the Milwaukee metropolitan area became infected with the disease (MacKenzie *et al*. [27]). According to the Wisconsin Division of Health, this outbreak led to the premature deaths of at least 69 persons, most of whom were HIV-positive. A similar incident occurred in Las Vegas, Nevada in 1994 with 103 cases in total, 61 of which were with patients HIV-positive or that had AIDS. By 1995, 41 people had died, most of whom were HIV-positive.

Given the very small nature of the oocysts, which measure 2 to 4 microns, traditional water treatment filtration systems are not very effective in removing cryptosporidium.[13] Current research has revealed two potential water treatment

[13] The chlorine concentrations necessary to kill cryptosporidium oocysts are significantly higher than current practices. Given the recent evidence on chlorine carcinogenicity, increasing chlorine treatment is unlikely to become a feasible alternative.

options for the removal of cryptosporidium. The first is the construction of microfiltration plants which utilize membranes to remove particles as small as 0.2 microns. The other option is the use of ozone gas as a disinfectant. Ozone has proven to be very effective against microbial agents (including cryptosporidium) in Europe where its use is widespread. While these treatment options are quite effective, their costs are substantial.

The following analysis will examine treatment strategies for five municipal water districts in the state of California. These districts include the Alameda County Water District, Crestline–Lake Arrowhead, the city of Fairfield, the Metropolitan Water District of Southern California, and the Santa Clara Valley Water District. These particular sites were chosen in order to represent a wide range of district sizes, from 25,000 people to 16,000,000, as well as significant differences in the demographic composition of these populations, i.e., distinct vulnerability distributions. A summary of this information is presented in Table I.

TABLE I
Population Demographics, by Water District

	Number	Percentage
Alameda County WD		
immunocompetent	262,041	91.62%
children (< 5 years)	21,889	7.65%
chemotherapy	1038	0.36%
HIV/AIDS	1032	0.36%
total	*286,000*	
Crestline-Lake Arrowhead		
immunocompetent	23,433	93.73%
children (< 5 years)	1463	5.85%
chemotherapy	72	0.29%
HIV/AIDS	32	0.13%
total	*25,000*	
Fairfield, City of		
immunocompetent	67,095	89.46%
children (< 5 years)	7424	9.90%
chemotherapy	312	0.42%
HIV/AIDS	169	0.23%
total	*75,000*	
Metro WD of SoCal		
immunocompetent	14,684,647	91.78%
children (< 5 years)	1,218,083	7.61%
chemotherapy	54,650	0.34%
HIV/AIDS	42,620	0.27%
total	*16,000,000*	
Santa Clara Valley		
immunocompetent	1,480,037	92.50%
children (< 5 years)	111,821	6.99%
chemotherapy	5481	0.34%
HIV/AIDS	2661	0.17%
total	*1,600,000*	

Sources: Census of Population and Housing: California, 1990 [35], California Department of Health Services, Office of AIDS [36], and Northern California Cancer Center [37].

Municipal water district managers must choose water treatment strategies such that drinking water affiliated cases of cryptosporidiosis meet some prespecified government health standard. This goal can be met in one of two ways: (1) by adopting a technologically advanced treatment process that improves crypto removal or (2) by maintaining traditional treatment processes and "tagging" vulnerable populations with an alternative control. Based on its cost advantage in retrofitting existing treatment plants in California, ozone treatment was chosen as the technological innovation. Tagging involves the provision of home filtration kits. These treatment strategies will be discussed in more detail in a later section.

A. *The Dose–Response Relationship*

All citizens on a given water supply are assumed to be exposed to the same concentration of cryptosporidium oocysts.[14] The relationship between oocyst concentration and the probability of observing clinical symptoms of cryptosporidiosis, i.e., the dose–response relationship, is modeled using an exponential distribution (Eisenberg *et al.* [28]; Perz *et al.* [29]),

$$P_i = 1 - \exp\{-r_i \cdot w \cdot oc\},$$

where w is the drinking water ingestion rate, assumed to be 2.0 liters/day (EPA [30]), oc is the concentration of oocysts in finished drinking water (after water treatment), and r_i is a subpopulation specific response parameter.[15] The oocyst concentration in raw water, i.e., intake water at the treatment facility, is assumed to be 2.4 oocysts per liter based on mean values reported in LeChevallier and Norton [31].

The response parameters (r_i) are designed to capture the heterogeneity in susceptibility across specific subgroups in the population. The subgroups for this study, presented in ascending order of vulnerability, include the immunocompetent, children under the age of five, persons undergoing chemotherapy treatment, and persons with HIV/AIDS. Further, because each population differs in their intensity of symptoms from cryptosporidiosis (Goodgame *et al.* [32]; Goldstein *et al.* [33]), we use subpopulation specific parameters to convert the probability of illness (P_i) into number of sickness days. A list of the parameters and their values for each population are presented in Table II.

[14] While our assumption of uniform exposure is consistent with current EPA methods, in practice, municipal drinking water exposure and thus cryptosporidium exposure may not be identical for all citizens. Citizens may differ in their preintervention use of bottled water and home filtration systems. If this were the case, the model presented would need to be expanded to incorporate the distribution of baseline exposures for the population. If bottled water and filter use were motivated for health (rather than taste) reasons, the distributions of baseline exposures and vulnerabilities could be highly correlated. This would suggest that some of the costs of environmental protection are being shifted to private citizens. The desirability of this shift will depend on societal views about a "public" responsibility to ensure environmental protection.

[15] This exponential dose–response function is often referred to as a "single hit" model and is employed because it implies that each oocyst has an equal and independent probability of causing infection (Bogen [4]). This feature is consistent with clinical observations on the infectivity of crypto oocysts (DuPont *et al.* [24]).

TABLE II
Dose–Response Function Parameters

Parameter	Description	Value	References
w	Water ingestion rate	2.0 liters/day	EPA (average)
oc (raw)	Oocyst concentration pretreatment	2.4 oocysts/liter	LeChevallier and Norton
oc (finished)	Oocyst concentration post-treatment	xx oocysts/liter	
Immunocompetent			
$P1$	Probability of infection	—	
$r1$	Response parameter	0.0042	Perz *et al.*
$s1$	Duration of illness	5.625 days	MacKenzie *et al.*; Dupont *et al.* (average)
Children (< 5 years)			
$P2$	Probability of infection	—	
$r2$	Response parameter	0.0042	Perz *et al.*
$s2$	Duration of illness	15	
Chemotherapy			
$P3$	Probability of infection	—	
$r3$	Response parameter	0.0126	Assumed the same as HIV/AIDS
$s3$	Duration of illness	40	
HIV/AIDS			
$P4$	Probability of infection	—	
$r4$	Response parameter	0.0126	Perz *et al.*
$s4$	Duration of illness	47 days + prob. death	Goldstein *et al.* (extrapolation)

B. *The Effectiveness and Costs of Treatment and Tagging*

For our purposes, there are two types of treatment technologies: traditional filtration in conjunction with chlorine treatment and ozone gas. The effectiveness of the traditional technology varies according to levels of coagulation, flocculation, and sedimentation, with an average removal of 99.35% of oocysts (LeChevallier and Norton [31]). Further, the costs of traditional filtration vary significantly across water utilities. These differences can generally be attributed to increasing returns to scale, where larger districts tend to be better at cost spreading and are able to purchase more efficient equipment. One exception to this is the Alameda County Water District, which is able to provide its water at an average cost of approximately $21 per person per year. Treatment cost information, by district, is presented in Table III.

In contrast to conventional filtration, ozone gas treatment is assumed to be fully effective against cryptosporidium oocysts. However, this effectiveness does not come cheaply. Again, costs vary by district, ranging from $6.7 million to $1437 million per year. Districts, as well as average per person costs of ozone treatment, are also presented in Table III.

As mentioned earlier, the tagging policy refers to the government provision of end-point filtration equipment, which is installed in the home of the user. As with the ozone treatment, these microfilters are assumed to be fully effective against cryptosporidium. For simplicity, the costs of tagging are based solely on the cost of

TABLE III
Treatment Costs, by Municipal Water District

Water district	Traditional ($mil/year)	Ozone ($mil/year)	Population (persons)	Traditional ($/person)	Ozone ($/person)	Tagging ($/person)
Alameda County WD	6.07	6.71	286,000	$ 21.22	$ 23.46	$105.00
Crestline–Lake Arrowhead	6.44	6.87	25,000	$257.60	$274.80	$105.00
Fairfield, City of	16.8	18.14	75,000	$224.00	$241.87	$105.00
Metro WD of Socal	1369.11	1436.58	16,000,000	$ 85.57	$ 89.79	$105.00
Santa Clara Valley	62.6	70.33	1,600,000	$ 39.13	$ 43.96	$105.00

Sources: Association of California Water Agencies (ACWA) [38] and Bay-Delta Hearings: State Water Contractors Exhibit Number 204 [39].

crypto-certified home filtration kits.[16] The cost of filtration kits are based on observations at several retail stores in the San Francisco Bay Area, and are set at $45 each. These kits generally require filter replacements every four months at a cost of $20 per filter. Thus, annual filter costs are identical for all members of the population and are set at $105 per household.

In practice, the costs of tagging are more complicated. Identification of the immunocompromised population can be costly. To fully characterize these identification costs, a model of information discovery and diffusion must be developed. This, in turn, raises issues regarding the costs of "missing" vulnerable people, as well as the costs of privacy invasion. Further, the tagging solution, as we have discussed it, is tied to the home and therefore affords no protection for the immunocompromised when they are away from home. Protection away from home may add considerable costs or motivate a more portable tagging solution such as bottled water. In addition, there may be substantial political opposition to tagging programs. Environmental protection is generally thought of as providing a public good equally to all citizens. When citizens are heterogeneous in susceptibility and standards are based on population level outcomes, subgroups may differ in their level of protection. As more is learned about individual variation in susceptibility, these differences may become even more pronounced. If equal protection remains a social goal, standards may need to be subgroup specific, raising a new host of identification and implementation questions. These issues lie beyond the scope of this paper, but we raise them, as their incorporation is crucial for designing and evaluating practicable policy strategies in an environmental health context.

C. *The Results*

Cryptosporidium has only recently become a subject of regulation under the Enhanced Surface Water Treatment Rule of the EPA and health standards are still being determined. In order to cover the range of standards currently being suggested, we simulate results for three health standards such that cryptosporidium related sickness days from drinking water shall not exceed 1 sickness day per 500 people per year, 1 per 1250, and 1 per 2000.

[16] Point-of-use filters effective against cryptosporidium include reverse osmosis or "absolute" one micrometer filters. Generally, these and other crypto-effective filters are labeled Standard 53 for cyst removal by the National Sanitation Foundation International (Centers for Disease Control [34]).

TABLE IV
Optimal Intervention Strategies, Compliance Costs, and Savings, for Three Health Standards

Water district	Ozone adoption cost	Optimal strategy	Optimal strategy cost	Annual savings	Annual savings (%)	Shadow value of health
Alameda						
1/500	$640,000	tag HIV	$108,360	$531,640	83.1%	$53
1/1250	$640,000	ozone	$640,000	$000	0.0%	$1790
1/2000	$640,000	ozone	$640,000	$000	0.0%	$1790
Crestline–L.A.						
1/500	$430,000	tag HIV	$3,360	$426,640	99.2%	$53
1/1250	$430,000	tag HIV & chemo.	$10,920	$419,080	97.5%	$6679
1/2000	$430,000	ozone	$430,000	$000	0.0%	$15,370
Fairfield						
1/500	$1,340,000	tag HIV	$17,745	$1,322,255	98.7%	$53
1/1250	$1,340,000	tag all vulnerable	$830,025	$509,975	38.1%	$53,422
1/2000	$1,340,000	ozone	$1,340,000	$000	0.0%	$10,312
Met. of SoCal						
1/500	$67,470,000	tag HIV	$4,475,100	$62,994,900	93.4%	$53
1/1250	$67,470,000	ozone	$67,470,000	$000	0.0%	$4332
1/2000	$67,470,000	ozone	$67,470,000	$000	0.0%	$4332
Santa Clara						
1/500	$7,730,000	tag HIV	$279,405	$7,450,595	96.4%	$53
1/1250	$7,730,000	ozone	$7,730,000	$000	0.0%	$5246
1/2000	$7,730,000	ozone	$7,730,000	$000	0.0%	$5246

Table IV displays the results. When the government health standard is low, it is optimal for all water districts to tag individuals infected with HIV/AIDS, with annual compliance cost savings ranging from 83% to 99%. Due to the relatively low health standard, the implied shadow value for an avoided sickness day is $53. Conversely, when the health standard is high, it is optimal for all districts to adopt the ozone technology. This results in shadow values of health ranging from $1790 to $10,312 per day, where the larger shadow values reflect the inability of small municipalities to spread the significant capital costs of the ozone technology.

The case of the middle standard, 1 per 1250, demonstrates the importance of regional differences. In this case, the larger districts (Alameda County, the Metropolitan Water District of Southern California, and the Santa Clara Valley) still find the ozone technology optimal, with an average shadow value of health of $3790. This is consistent with theoretical results presented earlier. Recall that uniform treatment is increasing in treatment plant efficiency and a major component of plant efficiency is district size and the ability to cost spread.

In the two smaller districts (Crestline–Lake Arrowhead and Fairfield), returns to scale work in the opposite direction, with cost spreading difficult, making tagging policies an attractive alternative. For the Crestline–Lake Arrowhead Water District, this standard is met through a combination of conventional water treatment and the tagging of individuals infected with HIV/AIDS and those undergoing chemotherapy treatment. The employment of this discriminatory policy, as opposed to uniform ozone treatment, results in an annual savings of 97.5%, or $419,080, for

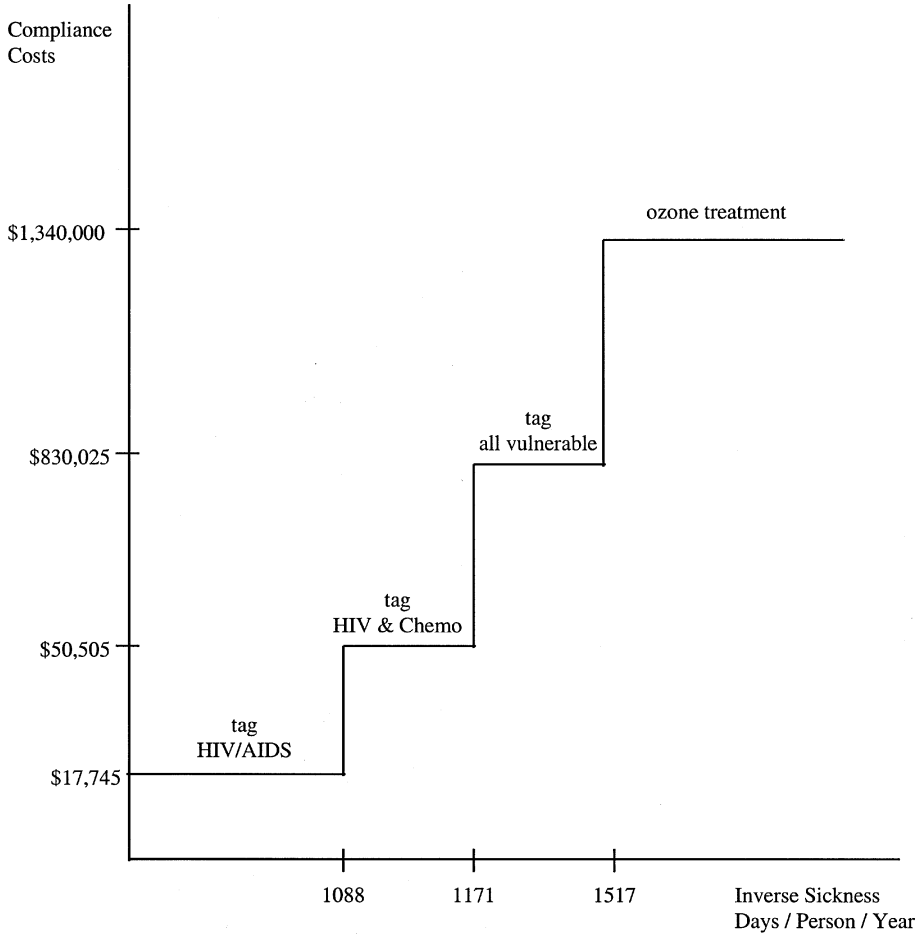

FIG. 1. Stepwise compliance cost function for the City of Fairfield.

the water district and implies a health value of $6679 per day. In the city of Fairfield, the standard is met by tagging all three vulnerable groups, with an annual compliance cost savings of 38.1%, or $509,975 and a health value of $53,422 per day.[17] To illustrate the impacts of a continuum of health standards on compliance strategies, a stepwise compliance cost function for the city of Fairfield is presented graphically in Fig. 1.

In addition to the scale effects discussed above, population demographics appear to have an effect on optimal policy decisions. A closer examination of Fairfield and Crestline–Lake Arrowhead reveals regional differences in the distribution of vulnerable populations (see Table I). In particular, the three vulnerable groups comprise roughly 6% of the total population in Crestline–Lake Arrowhead, while

[17] It is interesting to note that this shadow value is substantially higher that the shadow value associated with ozone treatment for this district. This occurs because the marginal cost of tagging small children is greater than the marginal cost of ozone treatment, but due to the capital costs associated with the ozone, the total cost of compliance is lower when all vulnerable groups are tagged.

in the city of Fairfield this group comprises approximately 11% of the population. This difference results in a larger amount of tagging in Fairfield, a result consistent with our theoretical discussion on the shape of the vulnerability distribution and its impacts on intervention strategies.

V. CONCLUSIONS

This paper develops and implements an economic model of environmental health risk regulation that is based on scientific constructs utilized in public health. This structural specification allows us to identify a menu of policy options, including the selection of optimal policies where vulnerable subgroups of the population are targeted with special exposure-reducing treatments. Our analytic results show that the potential economic gains from targeted policies will vary by location and depend critically on the quality of existing capital, the degree of returns to scale in treatment technologies, and the size and sensitivity of the vulnerable population.

An empirical study is conducted that analyzes policies to reduce the incidence of cryptosporidiosis from drinking water supplies for several municipal water districts in California. Results are simulated for several different government health standards.[18] Our analysis suggests that some tagging is optimal for all districts when the standard is low and that the ozone technology is optimal for all districts when the standard is high. The middle standard illustrates the importance of regional differences, where small districts employ tagging while large districts, due to returns to scale and the ability to cost spread capital costs among many users, adopt ozone. In cases where tagging is optimal, annual compliance cost savings can be substantial, ranging from 38% to 99%. Further, shadow values for an avoided day of sickness range from $53 per day for the low standard to as much as $15,000 per day for the high standard.

The framework developed here has been kept basic, both for analytical simplicity and due to gaps in existing data. Future research should examine issues of uncertainty at all stages in the risk generation process (contamination, exposure, and dose–response) and the impact these uncertainties may have on risk-averse regulators. Additional research should also analyze the role of information asymmetries on the regulation process, particularly with regard to individual vulnerability. It is likely that individuals know more about their condition than regulators, creating a need for models of information discovery and diffusion and policies that encourage self-revelation. Lastly, this research would benefit from the inclusion of monitoring issues, where monitoring could be used to reduce uncertainty about environmental quality or individual vulnerabilities. This uncertainty reduction could then be mapped to social welfare gains to provide a basis for investments in information-improving technologies. The incorporation of better data and a deeper understanding of underlying processes in the environmental health risk setting will allow policymakers to make more informed decisions based on sound economic principles.

[18] Cryptosporidium has only recently been added to the United States Environmental Protection Agency's list of concerns under the new Enhanced Surface Water Treatment rule and regulatory standards to meet this rule are still being suggested.

APPENDIX

A. *Treatment Only*

Totally differentiate Eqs. (1) and (2) and apply Cramer's Rule and the implicit function theorem to obtain the following:

PROPOSITION 1.

$$\begin{bmatrix} \dfrac{dT}{dk}; \dfrac{dT}{d\Theta} \\ \dfrac{d\lambda}{dk}; \dfrac{d\lambda}{d\Theta} \end{bmatrix} = \begin{bmatrix} \dfrac{-\dfrac{\partial M}{\partial T}}{|H|}; & 0 \\ \dfrac{\dfrac{\partial^2 c}{\partial T^2} + \lambda \dfrac{\partial^2 M}{\partial T^2}}{|H|}; & \dfrac{\dfrac{\partial M}{\partial T}\dfrac{\partial^2 c}{\partial T \partial \Theta}}{|H|} \end{bmatrix},$$

where the second derivative of the Hessian $|H|$ *is defined as* $-[\partial M/\partial T]^2 < 0$. *Given our assumptions regarding the properties of the morbidity production function and the treatment cost function, it follows that*: (1*a*) $\frac{dT}{dk} < 0$; (1*b*) $\frac{dT}{d\Theta} = 0$; (1*c*) $\frac{d\lambda}{dk} < 0$; *and* (1*d*) $\frac{d\lambda}{d\Theta} < 0$.

B. *Treatment and "Tagging"*

Totally differentiate Eqs. (3), (4) and (5) and apply Cramer's Rule and the implicit function theorem to obtain the following:

PROPOSITION 2.

$$\begin{bmatrix} \dfrac{dT}{dk} \\ \dfrac{dT}{dc_2} \\ \dfrac{dT}{d\Theta} \end{bmatrix} = \begin{bmatrix} \dfrac{-\lambda \dfrac{\partial^2 M}{\partial D_{\max}\, \partial T}\dfrac{\partial M}{\partial D_{\max}} - \dfrac{\partial M}{\partial T}\left[c_2 \dfrac{\partial g}{\partial D_{\max}} - \lambda \dfrac{\partial^2 M}{\partial D_{\max}^2}\right]}{|H|} \\ \dfrac{-\dfrac{\partial M}{\partial T} \cdot \dfrac{\partial M}{\partial D_{\max}} \cdot g(D_{\max})}{|H|} \\ \dfrac{-\dfrac{\partial^2 c_1}{\partial T \partial \Theta}\left[\dfrac{\partial M}{\partial D_{\max}}\right]^2}{|H|} \end{bmatrix}$$

where the second derivative of the bordered Hessian $|H|$ *is defined as*

$$\left(\frac{\partial^2 c_1}{\partial T^2} + \lambda \frac{\partial^2 M}{\partial T^2}\right)\left[\frac{\partial M}{\partial D_{\max}}\right]^2 - \left[\frac{\partial M}{\partial T}\right]^2 \left(c_2 \frac{\partial g}{\partial D_{\max}} - \lambda \frac{\partial^2 M}{\partial D_{\max}^2}\right)$$
$$- 2\lambda \frac{\partial^2 M}{\partial D_{\max}\, \partial T}\frac{\partial M}{\partial D_{\max}}\frac{\partial M}{\partial T}$$

and must be positive to ensure an interior solution to the maximization problem. In order to sign (2a), *it will prove useful to expand the expression above by selectively substituting in the morbidity production function, M. This yields the following expression*:

$$\frac{dT}{dk} = -\frac{\partial M}{\partial T}\left[\frac{\partial g}{\partial D_{\max}}\{c_2 - \lambda R(T, D_{\max})\} - \lambda g(D_{\max})\frac{\partial R(T, D_{\max})}{\partial D_{\max}}\right] - \lambda g(D_{\max})\frac{\partial R(T, D_{\max})}{\partial T}\frac{\partial M}{\partial D_{\max}}.$$

From the first-order condition in Eq. (4), *we know that the expression in braces* { } *is equal to zero. Algebraic manipulation suggests that* $\frac{dT}{dk} \gtreqless 0$ *when the following condition holds*:

$$\frac{\partial M}{\partial T}\bigg/\frac{\partial M}{\partial D_{\max}} \gtreqless \frac{\partial R(T, D_{\max})}{\partial T}\bigg/\frac{\partial R(T, D_{\max})}{\partial D_{\max}}.$$

Recognizing that the first term is the marginal rate of technical substitution (*MRTS*) *between the two technologies and that the second term is the MRTS evaluated at* D_{max}, *the proof of* (2a) *is complete,* $\frac{dT}{dk} \lesseqgtr 0$ *if* $MRTS \gtreqless MRTS_{D_{max}}$. *Given our assumptions regarding the properties of the morbidity production function and the treatment cost function, it follows that*: (2b) $dT/dc_2 > 0$ *and* (2*c*) $dT/d\Theta > 0$.

PROPOSITION 3.

$$\begin{bmatrix} \dfrac{dD_{\max}}{dk} \\ \dfrac{dD_{\max}}{dc_2} \\ \dfrac{dD_{\max}}{d\Theta} \end{bmatrix} = \begin{bmatrix} \dfrac{\dfrac{\partial M}{\partial D_{\max}}\left[\dfrac{\partial^2 c_1}{\partial T^2} + \lambda\dfrac{\partial^2 M}{\partial T^2}\right] - \lambda\dfrac{\partial M}{\partial T}\dfrac{\partial^2 M}{\partial D_{\max}\,\partial T}}{|H|} \\ \dfrac{\left[\dfrac{\partial M}{\partial T}\right]^2 \cdot g(D_{\max})}{|H|} \\ \dfrac{\dfrac{\partial^2 c_1}{\partial T\,\partial\Theta}\dfrac{\partial M}{\partial T}\dfrac{\partial M}{\partial D_{\max}}}{|H|} \end{bmatrix},$$

where the conditions on $|H|$ *are the same as above. Noting that from the first-order condition defined in Eq.* (3),

$$\frac{\partial M}{\partial T} = -\frac{\partial c_1}{\partial T}\frac{1}{\lambda},$$

and multiplying and dividing by $\frac{\lambda}{T}\frac{\partial M}{\partial T}$, *the expression that defines* (3a) *can be rewritten as*

$$\frac{dD_{\max}}{dk} = \frac{\lambda}{T}\frac{\partial M}{\partial T}\left[\frac{\partial^2 c_1}{\partial T^2}\frac{T}{\frac{\partial c_1}{\partial T}} + \frac{\partial^2 M}{\partial T^2}\frac{T}{\frac{\partial M}{\partial T}} - \frac{\partial^2 M}{\partial D_{\max}\,\partial T}\frac{T}{\frac{\partial M}{\partial T}}\cdot \mathrm{MRTS}\right].$$

Recognizing the first term in brackets as the elasticity of the marginal cost of treatment, the second term as the elasticity of the marginal productivity of treatment, and the third term as the elasticity of the marginal treatment change on the marginal productivity of tagging multiplied by the MRTS, the proof of (3*a*) *is complete,*

$$\frac{dD_{\max}}{dk} \gtreqless 0 \qquad \text{if } \frac{\lambda}{T}\frac{\partial M}{\partial T}\left[\xi_{\partial c_1/\partial T} + \xi_{\partial M/\partial T} - \xi_{(\partial M/\partial D_{\max})/\partial T}\cdot \mathrm{MRTS}\right] \gtreqless 0.$$

Given our assumptions regarding the properties of the morbidity production function and the treatment cost function, it follows that: (3b) $dD_{\max}/dc_2 > 0$ *and* (3*c*) $dD_{\max}/d\Theta > 0$.

LEMMA 1. *Substituting some of the comparative static results into the bordered Hessian condition above, we obtain*

$$|H| = \frac{\partial M}{\partial D_{\max}}\left[\frac{dD_{\max}}{dk}\right] + \frac{\partial M}{\partial T}\left[\frac{dT}{dk}\right] > 0.$$

By construction, $\partial M/\partial D_{\max} > 0$ *and* $\partial M/\partial T < 0$. *So the second-order condition for a maximum can never hold when* $dD_{\max}/dk < 0$ *and* $dT/dk > 0$.

PROPOSITION 4.

$$\begin{bmatrix} \frac{d\lambda}{dk} \\ \frac{d\lambda}{dc_2} \\ \frac{d\lambda}{d\Theta} \end{bmatrix} = \begin{bmatrix} \dfrac{-\left(\frac{\partial^2 c_1}{\partial T^2} + \lambda\frac{\partial^2 M}{\partial T^2}\right)\left(\lambda\frac{\partial^2 M}{\partial D_{\max}^2} - c_2\frac{\partial g}{\partial D_{\max}}\right) + \left(\lambda\frac{\partial^2 M}{\partial D_{\max}\,\partial T}\right)^2}{|H|} \\ \dfrac{\left(\frac{\partial^2 c_1}{\partial T^2} + \lambda\frac{\partial^2 M}{\partial T^2}\right)\frac{\partial M}{\partial D_{\max}}g(D_{\max}) - \lambda\frac{\partial^2 M}{\partial D_{\max}\,\partial T}\frac{\partial M}{\partial T}g(D_{\max})}{|H|} \\ \dfrac{\frac{\partial^2 c_1}{\partial T\,\partial\Theta}\left[\lambda\frac{\partial^2 M}{\partial D_{\max}\,\partial T}\frac{\partial M}{\partial D_{\max}} + \frac{\partial M}{\partial T}\left(c_2\frac{\partial g}{\partial D_{\max}} - \lambda\frac{\partial^2 M}{\partial D_{\max}^2}\right)\right]}{|H|} \end{bmatrix},$$

where the conditions on $|H|$ *are as defined above. In order to sign* (4a), *it will prove useful to expand the expression above by selectively substituting in the morbidity production function,* M. *This yields the following expression*:

$$\frac{d\lambda}{dk} = \left(\frac{\partial^2 c_1}{\partial T^2} + \lambda\frac{\partial^2 M}{\partial T^2}\right)\left[\frac{\partial g}{\partial D_{\max}}\{\lambda R(T, D_{\max} - c_2)\} + \lambda g(D_{\max})\frac{\partial R(T, D_{\max})}{\partial D_{\max}}\right]$$
$$+ \left[\lambda g(D_{\max})\frac{\partial R(T, D_{\max})}{\partial T}\right]^2.$$

From the first-order condition in Eq. (4), *we know that the expression in braces* { } *is equal to zero. Algebraic manipulation suggests that* $\frac{d\lambda}{dk} \lesseqgtr 0$ *when the following condition holds*:

$$\left(\frac{\partial^2 c_1}{\partial T^2} + \lambda \frac{\partial^2 M}{\partial T^2}\right) \gtreqless \lambda g(D_{\max}) \frac{\partial R(T, D_{\max})}{\partial T} \cdot \mathrm{MRTS}_{D_{\max}}.$$

As shown in Proposition 2, $\mathrm{MRTS} > \mathrm{MRTS}_{D_{\max}}$ when $dT/dk < 0$, implying that $\partial\lambda/dk \lesseqgtr 0$ if $dD_{\max}/dk \gtreqless 0$ (see the proof of Proposition 3). Combining these results yields Proposition (4a): $d\lambda/dk \lesseqgtr 0$ if $dT/dk < 0$ and $dD_{\max}/dk \gtreqless 0$. It should be noted that when $dT/dk > 0$ and $dD_{\max}/dk > 0$, the sign of (4a) is ambiguous. The expression for (4b) can be rewritten as

$$\frac{d\lambda}{dc_2} = g(D_{\max}) \frac{dD_{\max}}{dk},$$

which yields our Proposition (4b):

$$\frac{d\lambda}{dc_2} \gtreqless 0 \qquad \text{if } \frac{dD_{\max}}{dk} \gtreqless 0.$$

Similarly, the equation for (4c) can be rewritten as

$$\frac{d\lambda}{d\Theta} = \frac{\partial^2 c_1}{\partial T \partial \Theta} \frac{dT}{dk},$$

which yields Proposition (4c):

$$\frac{d\lambda}{d\Theta} \lesseqgtr 0 \qquad \text{if } \frac{dT}{dk} \lesseqgtr 0.$$

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