The Value of Preventing Cryptosporidium Contamination*

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Introduction

Most of us believe that modern technology and scientific knowledge provide safe drinking water from U.S. community water supplies. Yet, from 1992 to 1994, 30 disease outbreaks were reported for contaminated drinking water.[1] Giardia lamblia (*Giardia*) or Cryptosporidium parvum (*Crypto*) caused ten of the 25 outbreaks for which an etiologic (responsible) agent was identified. *Giardia* is a well known parasitic protozoan, found in drinking water around the world. *Crypto* is another widespread parasitic protozoan found in drinking water.[2] Both lead to acute diarrhea. *Crypto* has a more complex life cycle and is currently more difficult to remove. Cryptosporidiosis (crypto), the disease associated with *Crypto,* is also more difficult to cure. No medications are yet available for giardiasis.

Crypto was rarely reported before 1982. It was recognized most frequently in immunocompromised individuals (e.g., people having acquired immunodeficiency syndrome (AIDS), chemotherapy patients, people with congenital depressed immunity, recipients of organ

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1 Michael H. Kramer et al., *Waterborne Disease: 1993 and 1994*, 88(3) **J. Am. Water Works Ass'n** 66 (1996).

2 Richard L. Guerrant, *Cryptosporidiosis: An Emerging, Highly Infectious Threat*, 3(1) **Emerging Infectious Disease** 51 (1997).

transplants, and the malnourished). Such individuals are not always able to clear *Crypto* from their bodies and may die from severe dehydration and weight loss. In a sound immune system, the diarrhea ends without treatment after about two weeks, although symptoms can recur after a period of recovery.

In 1982, reported cases began to increase primarily because of the increase in AIDS cases. Meanwhile, outbreaks and sporadic infections in immunocompetent individuals began to be identified with the help of newly developed laboratory diagnostic techniques. Concern about this disease increased dramatically when large crypto outbreaks were identified in England (UK) and the U.S. In North America the largest outbreak occurred in April 1993, in Milwaukee, Wisconsin; about 400,000 people became ill, and 100 died.[3]

The *Crypto* life cycle includes an oocyst form (i.e., a tiny hard-shelled egg-like form) shed into the environment with the feces of infected people, livestock and wildlife. An infected cow can pass millions of oocysts each day. Runoff can wash oocysts into nearby streams and rivers or well fields used to supply drinking water. Oocysts may also be introduced directly into water resources by, e.g., infected deer, birds or livestock.

In this form, *Crypto* is encapsulated by a thick wall making it resistant to environmental stresses and to disinfectants, such as chlorine, typically used to treat drinking water. Oocysts survive and remain infectious to experimental animals even after two hours of exposure to full strength household bleach.[4] This characteristic makes traditional water disinfection unreliable for treating *Crypto* oocysts. Moreover, the extremely small size of these oocysts, 4-6μm, makes them difficult to remove by filtration unless the filter is properly monitored and managed. Good management of drinking water supply facilities, especially at the filtration stage, can prevent oocysts from passing through the treatment process. Proper maintenance of the filtration process requires modifying parameters such as backwash frequency when the incoming water quality changes. Yet, deficiencies in matching

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3 U.S. EPA, **Drinking Water Infrastructure Needs**, (1997).

4 Ronald Fayer, *Effect of Sodium Hypochlorite Exposure on Infectivity of Cryptosporidium parvum Oocysts for Neonatal BALB/c Mice,* 39 **Applied Envtl Microbiology** 1 (1995).

backwash frequencies to incoming water quality, coupled with the reuse of backwash water, can actually lead to large increases in the number of oocysts in the treated water.

Following the recent crypto outbreaks, public health officials have become increasingly concerned. Benefit-cost analysis provides decision makers with information on tradeoffs involved in managing the risk from *Crypto* contamination events. An increase in crypto or other pollution-induced disease risks reduces human welfare through medical expenses for treating the disease, lost time at work or in leisure activities, expenditures on disease-avoidance activities, pain and suffering, and change in life expectancy.[5] Accurately measured, a dollar estimate of the benefits from avoiding an increase in risk would capture all of these effects. Yet some of these components, such as the cost of pain and suffering or the value of a change in life expectancy, are not easily measured. Information on other components can, however, place bounds on the benefits.[6] As long as the lower bound is at least as great the costs of actions to avoid the increase in risk, decision makers can be sure that benefits exceed costs. An approach for estimating the value of a change in crypto risk is presented below. This value can be used to examine the impact of an increase or decrease in crypto risks resulting from changes in land uses or water treatment parameters. At the method's core is an event tree identifying key decision points that influence the severity of outbreaks and the resulting costs. This event tree also helps identify critical information issues in the management of *Crypto* risks.

Application of this approach using data from other studies provides a practical technique for determining a lower-bound value to one statistical individual[7] of preventing one *Crypto* contamination event.

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5 *See* Maureen L. Cropper & A. Myrick Freeman III, *Environmental Health Effects*, in **Measuring the Demand for Envtl. Quality** Ch. 6 (J.B. Braden & C.D. Kolstad eds. 1991).

6 Timothy J. Bartik, *Evaluating the Benefits of Non-marginal Reductions in Pollution Using Information on Defensive Expenditures*, 15 **J. Envtl. Econ. Mgmt.** 111 (1988); Winston Harrington and Paul R. Portney, *Valuing the Benefits of Health and Safety Regulation*, 22 **J. Urban Econ.**. 101 (1987) and John Quiggin, *Risk, Self-Protection and Ex Ante Economic Value-Some Positive Results*, 23(1) **J. Envtl. Econ. Mgmt.** 40 (1992).

7 A statistical individual is a figurative person who incurs all the types of costs related to one contamination event.

Lancaster County, Pennsylvania was used as a case study location. Its large urban population is served by water systems that are located in an agricultural watershed with intensive livestock enterprises. Moreover, that county has frequent heavy rain and flooding, making water supplies particularly sensitive to *Crypto* contamination.

The methodology for evaluating the costs of *Crypto* events is presented first. Next, for the case study location, a lower-bound estimate of a statistical individual's value of preventing one contamination event, and the societal value of preventing this individual's experience with such an event is determined. After evaluating the sensitivity of these results to uncertainty in the parameters, how the results could be used to evaluate a future increase in the risk of *Crypto* outbreaks is demonstrated, including sensitivity analysis for several key parameters in this estimation. Finally, the implications of these results are considered.

Methodology

The economic benefits of reducing (or avoiding increased) morbidity risk come from reducing (or avoiding): (1) defensive or averting expenditures associated with attempts to prevent disease; (2) medical expenses associated with treating disease, including the opportunity costs of time spent in obtaining treatment; (3) lost wages; (4) disutility associated with the symptoms and lost opportunities for leisure activities; and (5) changes in life expectancy or risk of premature death[8]. Society's willingness to pay (WTP) to reduce pollution (or some other cause) and thus pollution related morbidity is a measure of these benefits. Under most conditions, a lower bound on the WTP for reducing pollution is provided by a modified cost-of-illness (COI) analysis that includes averting behavior costs, medication and treatment costs, and lost time.[9]

Lost time is included because the opportunity cost of that time is what the individual could earn by working. Koopmanschap et al. argue that using the human capital approach for measuring lost production due to illness may overestimate actual lost production.[10] They propose

8 Cropper & Freeman, *supra* note 5.

9 Harrington, & Portney, *supra* note 6, *see also*, Quiggen, *supra* note 6.

10 Marc A. Koopmanschap et al., *The Friction Cost Method for Measuring*

using the friction cost method, in which the value of lost production depends on the amount of time it takes for firms to restore production to its level prior to disease and thus, is dependent on labor market conditions and unemployment. Using a macroeconomic model to estimate losses from illness, disability and mortality in the Netherlands, they find that the friction and human capital methods yield similar results for short-term illness, but the human capital method yields higher estimates for long-term disability and mortality.[11] Because crypto is typically a short-term illness and because we are focusing on the costs of a specific disease which would be difficult to do in a macroeconomic model, the traditional human capital approach used by many others is applied.

For people without paid sick leave, the Harrington and Portney COI model[12] leads to a lower-bound estimate of the WTP because some of the costs resulting from pollution are not taken into account. These include pain and suffering and costs associated with loss of life. A modified version of this result that includes loss-of-life costs is used to estimate a lower bound value of WTP to prevent *Crypto* contamination events in Lancaster County, Pennsylvania.

A potential exception to the lower bound property may occur when workers have a paid-sick-leave policy. The incentives to stay home differ for someone without paid sick leave compared with someone who has paid sick leave. For someone with paid sick leave, their value for work time lost is likely to be less than the wage rate. Such a person is more likely to stay home for faster recovery than an employee without paid sick leave, who, even when not feeling well, has a monetary incentive to return to work. Paid-sick-leave policies may, however, affect the productivity of the employer's business. The responsibilities of absent employees may not be done or done as well by coworkers.[13] If many people are absent, which becomes likely during a waterborne disease outbreak, a business may even have to close. Thus with paid sick leave, an individual's WTP to reduce his own morbidity risk will be less

Indirect Costs of Disease, 14 **J. Health Econ.** 171 (1995).

11 *Id.*

12 Harrington & Portney, *supra* note 6.

13 At the level of an individual business or work place, this is, of course, consistent with the perspective of Koopmanschap et al. *supra* note 10.

than the societal WTP for reducing the risk, especially when many people are affected simultaneously.

Figure 1
Event Tree for Contamination Event

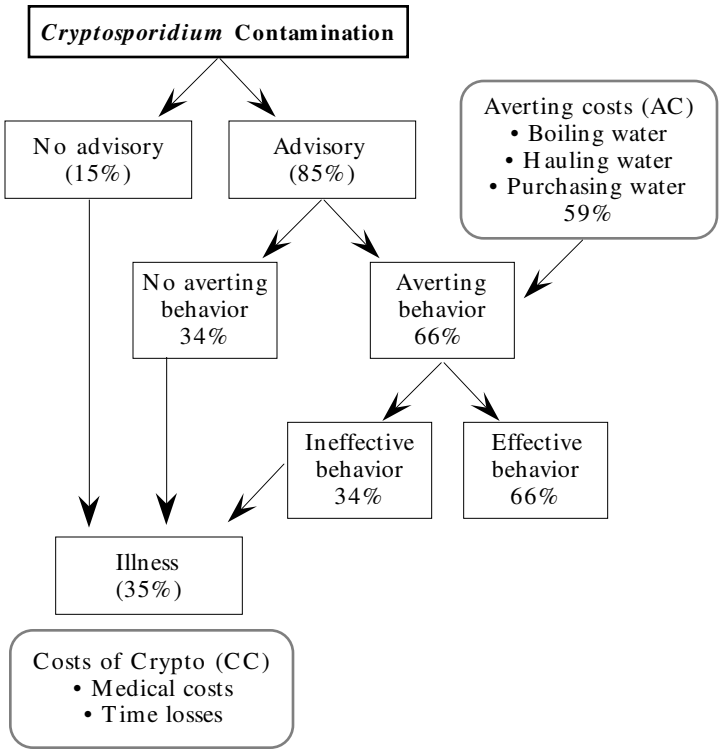


Figure 1 summarizes the methodology as a simplified event tree. Costs defined in the ovals relate to the share of the population incurring them. The arrows show the pathways through which one can prevent the infection, or become infected and then ill. This figure is interpreted in detail below.

When oocysts are detected by authorities, a boil-water advisory (BWA or advisory) is generally issued. Following this, averting actions should be undertaken by at-risk individuals. However, issuing an advisory does not eliminate risk for uninfected persons. In a survey after a BWA was issued during a waterborne salmonellosis outbreak in Missouri, Angulo et al. found that some people may not comply with a BWA or comply improperly because of misinformation, disbelief or simple negligence.[14] People who do not comply then have an

increased chance of illness. Infected individuals also can transmit crypto to others through a fecal-oral route (a secondary infection).

For *Crypto*, averting actions generally would involve obtaining uncontaminated water or deactivating the contaminant. These include boiling for at least three minutes, purchasing bottled water, and hauling water from any source outside the contaminated area. Home-use water filters are excluded; they tend to be ineffective in preventing crypto.[15] Moreover, Harrington et al. found that consumers rarely chose filters during a Giardia contamination outbreak.[16] *Giardia* is another protozoan that causes gastrointestinal illness, but it is larger than *Crypto* and easier to filter.

Daily costs for each averting behavior in Lancaster County are estimated for an average individual. Boiling costs include electricity and time. The cost of bottled water is its purchase price, assuming purchase occurs during usual shopping and thus does not require additional time or travel. Hauling costs include travel time. Different people may choose averting options according to, e.g., where they live, their social status, the structure and composition of the family, or their ages. For the community, the sum of these different costs, weighted by the percentage of people undertaking each of them, allows the estimation of the daily costs of averting behaviors for a statistical individual (AC).

For a statistical individual infected with crypto, costs of having crypto (CC) include medication and treatment as well as lost time. Although no current medication cures the disease, over-the-counter antidiarrheal medications or rehydration therapy may reduce symptoms.[17] Some seek a physician's assistance. The very ill require hospitalization for severe dehydration, and some may die. Medical costs used here include medication and treatment for one statistical individual having crypto, estimated for each of three illness categories,

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[14] Frederick J. Angulo et al., *A Community Waterborne Outbreak of Salmonellosis and the Effectiveness of a Boil Water Order*, 87 **Am. J. Pub. Health** 580 (1997).

[15] Dennis D. Juranek et al., *Cryptosporidiosis and Health: Workshop Report*, 87(9) **J. Am. Water Works Assoc**. 69 (1995).

[16] Winston Harrington, Alan J. Krupnick & Walter O. Spofford, Jr., *The Economic Losses of a Waterborne Disease Outbreak*, 25 **J. Urban Econ.** 116 (1989).

[17] Barbara J. Butler & Colin I. Mayfield, *Cryptosporidium spp. — A Review of the Organism, the Disease, and Implication for Managing Water Resources* (Working Paper, Dept. of Biology, University of Waterloo 1996).

mild, moderate and severe, respectively, and are weighted by the number of people in each to estimate the out-of-pocket costs to one statistical individual.

When illness prevents an individual from working or other activities, then the costs include opportunity costs. From an individual perspective, we value every hour at the after-tax wage to represent the real loss. To determine the societal costs of a statistical individual, we value work time at the average before-tax hourly rate. Leisure time lost to averting behaviors is valued at the average after-tax hourly wage rate. These figures represent the societal cost or lost productivity of this individual, which is what society loses when a person is sick or using time to prevent illness.[18] There is some question over whether the after-tax wage rate is an appropriate value of leisure time. Variations in both the value of leisure time and the allocation of time between work and leisure are allowed in the uncertainty analysis.

The cost of having crypto is estimated with and without mortality. The latter includes the medical expenditures and value of lost time, both weighted by illness category to estimate the costs of having crypto for one statistical individual (CC). The former adds the value of a statistical life weighted by the number of people who die. Estimates of the value of a statistical life are obtained by aggregating across individuals how much each individual is willing to pay for a small reduction in mortality risk.

TC represents the lower bound value for preventing a contamination event for a statistical resident in an at-risk population, and is the sum of AC and CC weighted by the percentages of the population incurring each of them. The weights (presented in Figure 1) also account for the effectiveness of the BWA issued by the water authorities, compliance of the population with the BWA, and sensitivity of the population to the disease.

There are inherent uncertainties in the parameters used in estimating the value of preventing a contamination event. A Monte Carlo analysis is performed to evaluate the sensitivity of TC to the

[18] Ideally, we should allocate non-working time between leisure and time spent in household production and perhaps value them differently. Because this is difficult to do, we refer to all non-working and non-sleeping time as leisure and value it at the after-tax wage rate.

assumptions made and parameter values used in the analysis. In a Monte Carlo analysis, distributions of the parameters in question are chosen, and sets of parameter values are randomly selected from these distributions. This allows examination of the impact on TC of multiple parameters varying simultaneously. TC is calculated for each randomly chosen set. When numerous simulations are performed, a distribution of TC values is obtained.

This methodology allows the estimation of a lower-bound value of preventing a *Crypto* contamination event. However, for policy purposes an estimate is needed for the value today of preventing potential *Crypto* contamination in the future. This is due to the lag time between when decisions are made and when the resulting environmental impacts occur. Therefore the modified COI estimates need to be discounted to account for costs now being more important to people than the same size costs delayed until sometime later.[19]

Assuming that for each year in an infinite time horizon there is a probability (P) of contamination, the expected present value (PVTC) of the cost of *Crypto* contamination events is shown in equation (1) where t indexes years, r is the discount rate allowing for time preferences, and TC_t is the total cost of one contamination event occurring in year t.

$$PV_{TC} = \sum_{t=1}^{\infty} \frac{P_t TC_t}{(1=r)_t} \tag{1}$$

A variety of factors may change the probability of a contamination event. The present value of an increase (or decrease) in the likelihood of *Crypto* contamination events is the difference between PVTC' and PVTC, where PVTC is the expected present value under existing conditions (at a given level of risk), and PVTC' is the expected present value under the changed conditions (at a new level of risk). Assuming that the probability is constant over time and that the change occurs in the current period, this cost, LBC, can be approximated as shown in equation (2).

$$LBC = \Delta P \frac{TC}{r} \tag{2}$$

19 Robert C. Lind, **Discounting for Time and Risk in Energy Policy** (1982).

ΔP is the difference between the probability of contamination under the new and existing conditions. LBC measures the marginal change in cost due to a change in risk of *Crypto* contamination events. It represents a lower bound measure of WTP to prevent an increase in such a risk.

Results and Discussion

The input values used for this analysis are from the COI literature[20], averting behavior literature[21] and waterborne diseases epidemiology literature[22] in addition to personal communication.[23] Cost figures for Lancaster County in 1996 are used when possible; when necessary, costs figures from the Laughland et al. study[24] are adjusted to 1996 dollars using the consumer price index of 124.0 and 156.9 for 1989 and 1996, respectively.[25]

Averting Costs

The costs of boiling water (C_B), hauling water (C_H) and purchasing water (C_P) as well as several combinations of these are presented in Table 1 for Lancaster County. The percentages of the population undertaking each of these action patterns, also presented in Table 1, are those found by Laughland et al. from a telephone survey about averting behavior during a Giardia contamination event in Milesburg, Pennsylvania.[26] Because the entire population is susceptible to waterborne *Crypto*, we use the average wage rate to measure time costs. The before-tax hourly wage rate in Lancaster County is $11.79 (1990 population census indexed to 1996). Using a tax rate of 21%, the after-tax wage rate is $9.31.[27] Only the after-tax wage rate is used for

20 Harrington et al., *supra* note 16.

21 Angulo et al., *supra* note 14, *see also*, Andrew S. Laughland et al., *The Opportunity Cost of Time and Averting Expenditures for Safe Drinking Water*, 29(2) **Water Resources Bull**. 291 (1993).

22 William R. MacKenzie et al., *A Massive Outbreak in Milwaukee of Cryptosporidium Infection Transmitted through Public Water*, 331(3) **New Eng. J. Med.** 161 (1994), *see also*, William R. Mac Kenzie et al., *Massive Outbreak of Waterborne Cryptosporidium Infection in Milwaukee, Wisconsin: Recurrence of Illness and Risk of Secondary Transmission*, 21 **Clin. Infectious Diseases** 57 (1995).

23 Anne Haddix, Centers for Disease Control, EPO, Personal communication (1997).

24 Laughland et al., *supra* note 21.

25 Economic Report of the President to Congress, Feb. 1997.

26 Laughland et al., *supra* note 21.

computing averting costs, assuming that all averting actions are undertaken after work. The most expensive averting behavior is boiling water because it is very time intensive; the least expensive is purchasing water because no time is involved given our assumption that individuals purchase bottled water on other trips rather than making special trips.

Table 1
Daily Averting Costs

Type of Averting Behavior	*Cost per Person ($)*	*Percentage of the Averting Population*
Boiling (B)	2.09	40
Hauling (H)	1.41	33
Purchasing (P)	0.38	9
B & P	1.23	7
B & H	1.75	10
P & H	0.89	0
All (B, H & P)	1.28	1

The daily average cost of averting behavior is:

$$.40\ C_B + .33\ C_H + .09\ C_P + .07\ C_{B+P} + .10\ C_{B+H} + .01\ C_{All} = \quad (3)$$

$$.40*2.09 + .33*1.41 + .09*.38 + .07*1.23 + .10*1.75 + .01*1.28 = \$1.61/day$$

Depending on the location of the *Crypto* contamination outbreak, the duration of the BWA may vary from one week as during the 1993 Milwaukee outbreak[28] to nine months as during a Giardia outbreak in Luzerne County, Pennsylvania.[29] It is assumed that 30 days is the time needed by water authorities to either improve the performance of the filter or switch to another water source. Therefore, the total averting behavior cost (AC) to one statistical individual is $48.30.

Cost of Having Cryptosporidiosis

The cost of having crypto (CC) is determined for three illness categories: mild illness involving over-the-counter medications, moderate illness involving physician or emergency room visits, and severe illness involving hospitalization. Table 2 presents estimates of the medical expenditures (E) and the costs of time lost (TL) associated

27 Harrington et al., *supra* note 16.

28 Robert. J. Griffin et al., *Public Reliance on Risk Communication Channels in the Wake of Cryptosporidium Outbreak*, Presented at the Society for Risk Analysis Annual Meeting, Baltimore, MD, Dec. 1994.

29 Harrington et al., *supra* note 16.

with the three illness categories. To compute the cost of time lost, it was assumed that people sleep for eight hours per day and spend the remaining sixteen hours per day at work and leisure in the proportions of 5/7 and 2/7, respectively. Thus, we assume that people spend five days per week working and performing associated personal maintenance activities and two days at leisure.[30]

Table 2
Costs of Cryptosporidiosis (CC) by Degree of Illness

	*Medical Expenditures ($) (**E**)*	*Lost Time ($) (**TL**)*		*Percentage of Sick Population*
		Individual	*Society*	
Mild	1.43	280	333	88
Moderate	173	1,670	1,986	11
Severe	10,894	2,964	3,525	1

Table 2 also presents the distribution of the Milwaukee population among the three illness categories during the 1993 outbreak.[31] The value of time lost includes the value of work hours and leisure hours lost both from an individual perspective (for which every hour is valued at the after-tax wage rate) and a societal perspective (for which working time is valued at the before-tax wage rate and the leisure time at the after-tax wage rate). The number of hours lost is based on Milwaukee residents' experiences during the 1993 crypto outbreak.[32]

The average cost of having crypto is:

$$.88\ (E_{mild}+TL_{mild}) + .11\ (E_{moderate}+TL_{moderate}) + .01\ (E_{severe}+TL_{severe}) \quad (4)$$

Hence, CC equals $589 from an individual perspective and $676 from a societal perspective.

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30 Alternatively, we assume that people work 40 hours per week and thus spend 0.36 of the sixteen non-sleeping hours at work and the remaining 0.64 at leisure. This yields societal costs of lost time of $307, $1,830, and $3,248 for the mild, moderate and severe illness levels respectively. Thus the societal CC (from equation 4) becomes $633. Alternate allocations of work and leisure are explored through the uncertainty analysis.

31 Rosemary Soave, *Editorial Response: Waterborne Cryptosporidiosis-Setting the Stage for Control of an Emerging Pathogen*, 21 **Clin. Infectious Diseases** 63 (1995).

32 Haddix, *supra* note 23.

Lower-bound Value for Preventing a Cryptosporidium Contamination Event

In their survey of an area experiencing waterborne salmonella, Angulo et al. found that 31% of the population did not take any averting actions.[33] Laughland et al. found that at least 34% did not follow recommendations properly even though they took some averting actions.[34] Previous epidemiologic studies determined that 53% of the people ingesting *Crypto* oocysts showed crypto symptoms. An additional 7% acquire the disease from a sick individual through the fecal-oral route.[35] Thus, as shown in Figure 1, the attack rate of 53% is multiplied by 1.07 when determining the percentage of people who become ill. It is assumed that a BWA is issued 85% of the time when contamination occurs. A 100% issuance is unlikely because existing techniques for detecting *Crypto* are very expensive for small facilities and not fully effective. Therefore, water may be tested infrequently, and tests may give false results.

Figure 1 shows the pathways by which an individual may become ill if a contamination event occurs, using the assumptions discussed above. To interpret this figure, it is assumed that water contamination by *Crypto* oocysts is detected and a boil water advisory issued for 85% of contamination events. For the 15% of such contamination events that are not detected, 1.07(53%) of the population will become ill. Given that a boil water advisory is issued, it is also assumed that 69% of the population will undertake averting behavior; 31% do not do so and thus have a 1.07(53%) chance of getting sick. Averting behavior undertaken will be effective 66% of the time, meaning that these people successfully remove oocysts from the water they ingest and do not become ill. However, 34% of such behavior is ineffective, meaning these people have a 1.07(53%) chance of getting sick. Thus, as the figures in parentheses show, when a water contamination event occurs, averting actions will be undertaken by 59% of the population and 35% will become ill with crypto.

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33 Angulo et al., *supra* note 14.

34 Laughland et al., *supra* note 21.

35 Guerrant, *supra* note 2, *see also*, MacKenzie et al., *supra* note 22.

The costs of a *Crypto* contamination event can be thought of as the sum of averting costs (AC) plus illness costs for those who do no averting behaviors plus illness costs for those who do some averting behaviors. Thus, the total cost to one statistical individual exposed to one *Crypto* contamination event (TC) weights these costs by the shares of the population incurring each cost (shown in Figure 1).

$$TC = .85(.69)AC + [(.85*.31)+.15](.53*1.07)CC + .85(.69)(.34)(.53*1.07)CC \quad (5)$$

Hence, one statistical Lancaster County resident's value of preventing one *Crypto* contamination event is at least $233, and the societal value for preventing an individual's experience with one contamination event is at least $263.

Uncertainty Analysis

Monte Carlo simulation analysis allows systematic evaluation of the sensitivity of estimated TC to parameter values and the underlying assumptions. The variables in question include: the probability of a BWA being issued, the length of a BWA, the proportion of the population taking averting actions, the proportion taking ineffective averting actions, daily averting costs, and costs of illness at both the individual and societal level. It is assumed that the parameters are independently distributed and follow the beta distribution function, Beta(α, β). The beta distribution is useful for variables that are constrained between two values, and it has a flexible functional form with a shape described by α and β.[36] We specify minimum, maximum and most likely (mode) values for each parameter, and these are used to calculate the shape parameters, *a* and ß. These parameters for the beta distribution are:

$$\alpha = \frac{(\mu\text{-min})(2*\text{mode-min-max})}{(\text{mode-}\mu)(\text{max-min})}; \beta = \alpha\frac{(\text{max-}\mu)}{(\mu\text{ -min})}; \text{ where } \mu = \frac{1}{6}(\text{min}+4*\text{mode}+\text{max})$$

Table 3 shows the bounding values chosen for each parameter (the minimum, maximum and mode) as well as the point estimate used in the earlier analysis. For each of the parameters, conservative bounds are selected so that the TC estimate will in turn be a lower bound estimate. For all but one of the parameters, the length of the BWA, the point estimate is assumed to be the most likely value. However, to allow for

[36] William H. Greene, **Econometric Analysis** (2d ed.1990).

the possibility of shorter time length for the BWA, the 30 day point estimate is used as the maximum allowed value and seven days is used as the most likely value. Using a range of $0.38 to $2.10 for daily averting costs per individual allows incorporation of a variety of values of time (assumed to be equal to the after tax wage rate in the point estimate) as well as variations in the percent of population undertaking each type of averting action. For instance, if all people purchased water, which is the least expensive averting behavior, each would pay $0.38 per day for averting actions, which is the lower bound. If all people boiled water, the most expensive averting behavior, each would pay $2.10 per day, the upper bound. The cost of having crypto (CC) per statistical individual, which includes medical treatment cost as well as the value of lost time, is allowed to vary from $300 to $750 for the individual and from $350 to $800 for society. These ranges allow incorporation of differing allocations of leisure and work time, lower values of leisure time as well as differing proportions of the severity in which the disease is experienced. For instance, assuming that the disease severity proportions remain the same as in the point estimates (88% mild, 11% moderate, 1% severe) but leisure time is valued at one-half of the after tax wage rate, $4.66, the societal CC would be $609. If the after-tax wage is used to value leisure but illness proportions change so that no severe illness cases occur and only 1% of the cases were moderate while the rest were mild, the societal CC would be $353.

Table 3
Bounds and Point Estimates for the Parameters

Parameter	Minimum	Maximum	Mode	Point Estimate
Probability of BWA	0.8	1.0	0.85	0.85
Length of BWA (days)	5	30	7	30
Averting Population	0.6	1.0	0.69	0.69
Ineffective Averting Population	0	0.35	0.34	0.34
Daily Averting Costs ($)	0.38	2.10	1.61	1.61
CC- individual ($)	300	750	589	589
CC- societal ($)	350	800	676	676

Five thousand sets of parameters are randomly drawn from the beta distributions, and TC is calculated for each. The means of the resulting distributions are $187 for TC from the individual's viewpoint and $211 for TC from society's viewpoint. Making use of the central limit

theorem, 95% confidence intervals were estimated for the means. These are [186, 187] for the individual's TC and [210, 212] for society's TC. These ranges are lower than our point estimates of $233 and $263 for the individual and societal viewpoints, respectively. For the remainder of this analysis, results will be presented using the estimates from our simulation analysis to ensure that our analysis produces lower bound estimates.

Mortality

The TC figures estimated so far represent the lower bound values for preventing a *Crypto* contamination event, assuming that no individual dies from crypto. However, death is a distinct possibility for immunocompromised individuals. The costs associated with mortality are estimated by weighting the value of a statistical life (V) by the mortality rate.

There is much debate over what is an appropriate value of a statistical life. There are three types of WTP studies from which V has been estimated; studies of the wage-risk tradeoff in the workplace, consumer market studies and contingent valuation studies. Fisher et al., in their review of the literature on this topic, report that $2.3 to $12.2 million (in 1996 dollars) is a plausible range.[37] Viscusi in his review of the literature argues that the $3.6 to $8.4 million (in 1996 dollars) range is most plausible.[38] Because the majority of the studies estimate the value for a healthy, adult working male, ideally the value of a statistical life should be adjusted downward to take into account the shorter life expectancy of immunocompromised individuals. Such people may be of any age and have a wide range of life expectancies. Hogg et al. found that life expectancy at age 20 for gay and bisexual men in Vancouver ranged from 34.0 to 46.3 years and that loss in life expectancy due to HIV/AIDS for such men ranged from nine to 21.3 years.[39] However, this is just one subgroup of immunocompromised

[37] Ann Fisher, Lauraine G. Chestnut & Daniel M. Violette, *The Value of Reducing Risk of Death: A Note on New Evidence*, 8(1) **J. Pol'y Analysis Mgmt.** 88 (1989).

[38] W. Kip Viscusi, *The Value of Risks to Life and Health*, 31(4) **J. Econ. Literature** 1912 (1993).

[39] Robert S. Hogg et al., *Modelling the Impact of HIV Disease on Mortality in Gay and Bisexual Men*, 26(3) **Int'l. J. Epidemiology** 657 (1997).

individuals. Johannesson and Johansson, in a contingent valuation study on how much adult Swedes would be willing to pay for an additional year of life conditional on living until age 75, find that the value of a statistical life ranges between $70,000 and $130,000 (in 1995 dollars).[40] Because of the uncertainty involved in determining V, we use three conservative values: $50,000, $1 million and $2.3 million. Obviously, the estimates of TC excluding mortality can be alternatively viewed as including mortality but assuming that the value of a statistical life is zero.

Rose reports that the mortality rate among AIDS patients in past outbreaks ranged from 52 to 68%.[41] Goldstein et al., in their investigation of a crypto outbreak in Las Vegas in 1994, found that 32 out of 61 (52%) of HIV infected adults died within six months of contracting crypto and 40 of 61 (66%) died within one year.[42] Vakil et al. found that 48 of 82 (59%) of HIV infected adults died within one year of becoming infected with crypto after the Milwaukee outbreak.[43] In order to ensure that our cost estimate is a lower bound, we assume that the mortality rate of the immunocompromised is 52%. We assume that this rate can be applied to those hospitalized (severely ill) with crypto. Estimates of TC including mortality are presented under three alternative assumptions concerning the proportion of those hospitalized who are immunocompromised and therefore at increased risk of dying: 100%, 50%, or 10% of those hospitalized are immunocompromised.

Table 4 presents estimates of the societal cost of a *Crypto* contamination event for a statistical individual including mortality under various assumptions about the value of a statistical life and the proportion of the severely ill who are immunocompromised. These TC figures, when compared with TC excluding mortality, vary from a

40 Magnus Johannesson & Per-Olov Johansson, *Quality of Life and the WTP for an Increased Life Expectancy at an Advanced Age*, 65 **J. Pub. Econ.** 219,228 (1997).

41 Joan B. Rose, *Environmental Ecology and Cryptosporidium and Public Health Implications*, 18 **Ann. Rev. Pub. Health** 135 (1997).

42 Susan T. Goldstein et al., *Cryptosporidiosis: An Outbreak Associated with Drinking Water Despite State-of-the-Art Water Treatment*, 124(5) **Annals Internal Med.** 459 (1996).

43 Nimish B. Vakil et al., *Biliary Cryptosporidiosis in HIV-Infected People After the Waterborne Outbreak of Cryptosporidiosis in Milwaukee*, 334(1) **New Eng. J. Med.** 19 (1996).

slight increase in TC in the most conservative case (V is $50,000 and only 10% of the severely ill are immunocompromised) to an increase in TC by a factor of almost nineteen (when V is $2.3 million and all of those hospitalized are immunocompromised).

Table 4
Estimates of TC Including Mortality ($)

Proportion of severely ill immunocompromised	*Value of a Statistical life ($)*		
	2,300,000	*500,000*	*50,000*
100%	3939	1022	292
50%	2075	616	252
10%	584	292	219
(Using simulation estimates: TC *excluding* mortality = $211)			

Lower -bound of the WTP to Prevent an Increase of Cryptosporidium Contamination Events

The probabilistic risk of *Crypto* contamination may change for a variety of reasons. These include changes in land use, watershed management, weather conditions and water treatment management. Changes in watershed management practices may reduce or increase the probability of contamination events. For instance, locating new water supply intakes closer to pastures may lead to more oocysts being flushed into water supplies, thus increasing the risk of contamination. In contrast, preventing cattle from having access to water supplies may decrease the risk of contamination. A change in land use may increase contamination risk by causing water to be routed through areas where it could be contaminated by *Crypto* oocysts. This might happen with urbanization of an area, e.g., paving more roads or new development, which may redirect water flow. Weather conditions, such as heavy rainfalls, could flush more oocysts from agricultural areas into streams and well fields increasing the contamination risk. This type of weather event can also increase turbidity of water supplies, making it more difficult for existing water treatment methods that remove oocysts to operate optimally, thereby augmenting the risk of contamination. Finally, practices at water treatment facilities themselves may affect contamination risk. If facilities are operating in a suboptimal manner, for instance due to improperly installed, monitored, maintained or

cleaned filters, contamination probability may rise. Conversely, if treatment facilities adopt new strategies to reduce the number of oocysts in treated water, as is the current practice in some facilities, contamination risk will fall.

Table 5
LBC Estimates (in 1996 dollars)

Discount rate (r)	Risk Increase (P) 0.01	0.001	0.0001
	TC=$211 (excludes mortality)		
3%	70.33	7.03	0.70
5%	42.20	4.22	0.42
7%	30.14	3.01	0.30
	TC=$1,022 (includes mortality)		
3%	340.67	34.07	3.41
5%	204.40	20.44	2.04
7%	146.00	14.60	1.46
	TC=$3,939 (includes mortality)		
3%	1313.00	131.30	13.13
5%	787.80	78.78	7.88
7%	562.71	56.27	5.63

Table 5 shows estimates of LBC, the lower bound value for preventing an increase in the risk of *Crypto* contamination. These estimates are based on the societal value for preventing an individual's experience with a given contamination event, TC. Estimates are presented using three TC values: $211, $1,022, and $3939. The first one excludes mortality while the second two include mortality and are taken from Table 4. These TC values are used to show the range of values that LBC may take under a variety of assumptions about TC.

Depending on which factor(s) cause the change in crypto risk, changes in the probability of contamination ΔP and the discount rate (r) may vary. Consequently, the LBC estimates may vary. For example, the first column of Table 5 shows the societal value of preventing a one percentage point increase in the probability of contamination. Accordingly, the value per individual for preventing such an occurrence is at least $70 ($42, $30) at a discount rate of 3% (5%, 7%), excluding mortality. Thus, if an event, such as suboptimal filtration at a water treatment facility or changes in land use in upstream watersheds, increases the contamination risk by one percentage point, society should be willing to pay at least $70 per individual to prevent this from

occurring at a discount rate of 3%. If mortality is included, this figure can become as high as $1,313.

The population of Lancaster County in 1996 was 450,834.[44] Conservatively assuming that only a portion of these people, the 202,007 people served by water supplies located in the 100-year floodplain in Lancaster County, are susceptible to *Crypto* contamination, the aggregate value of preventing contamination can be estimated. Thus, the public should be willing to pay at least $14.1 million to prevent a one percentage point increase in contamination risk using a 3% discount rate.

The large range of values in Table 5 for different discount rates and risk increases implies that the scenario studied must be clearly defined in order to determine a lower bound of the value of preventing an increase in *Crypto* contamination events. Parameters such as discount rate (r) and expected risk increase ΔP require careful investigation so that LBC estimates will be as close as possible to the real value of preventing the *Crypto* risk increase.

Conclusion

Contamination of water supplies with *Crypto* can be very harmful to human health, especially to immunocompromised individuals. Viewed in light of even conservative benefit-cost analyses, society has an interest in taking steps to prevent such contamination.

Using a modified COI approach and an event tree, a lower bound value to one resident for preventing a *Crypto* contamination event is estimated to be at least $187. The value to society of preventing this individual from experiencing a contamination event is estimated to be at least $211. When mortality is included in the analysis, the corresponding figures can become as high as $3,915 and $3,939, depending on the specific assumptions made about mortality. These lower bounds measure how costly such contamination would be for one statistical individual. Even though our analysis does not account for the share of the at-risk population that has paid sick leave, these represent a lower-bound of the WTP because our COI approach omits some important costs associated with a contamination outbreak. An

[44] U.S. Bureau of the Census, **Estimates of the Population of Counties** (1997).

individual affected by crypto will experience, for example, pain and suffering. In addition, a *Crypto* contamination outbreak may reduce the confidence people have in water authorities, leading them to modify their water usage routine beyond the end of the boil water advisory. The costs associated with this distress should be included to determine the "true value" of the WTP.

These estimates can be used to analyze the efficiency of future policies. Such a benefit-cost analysis requires a clear definition of the problem, including when the change leading to a *Crypto* risk increase will occur, how large the change will be and what discount rate should be used. Once these parameters are defined, a lower bound of the benefits of the policy that would reduce the likelihood of a *Crypto* contamination event can be estimated through the estimation of LBC (the discounted cost of illness associated with preventing the increase in *Crypto*).

This benefit estimate for preventing a *Crypto* increase is a first step to making a policy decision regarding, e.g., new drinking water treatment processes, land use changes or environmental changes (such as climate change) that could influence the number of oocysts flushed to water supplies. When comparing the estimated value to the costs of the available technology to prevent the increase, it should be kept in mind that this value is a lower-bound estimate, and that the cost figures presented are for one individual. When the discounted benefits clearly exceed (or are much less than) the discounted costs, the policy recommendation is obvious. Even if costs slightly exceed benefits, implementing the technology is likely to be efficient, and in society's or the individual's best interest (especially since the benefits are likely to be underestimated). Such policy changes may have multiple impacts such as reducing the risk of other waterborne illness in addition to crypto. It is important to isolate the costs associated with preventing crypto when comparing costs to benefits.

Aside from determining a lower-bound value of preventing crypto outbreaks in a timely and cost-efficient manner, this analysis allows one to determine the most sensitive aspect of a *Crypto* contamination event. For example, the event tree shows that 35% of the at-risk population can be expected to become ill. The failure to issue a BWA

accounts for 8.5% and the remaining 26.5% occurs because of inaction or inadequate action by at-risk individuals. Such information can be helpful when evaluating the cost-effectiveness of policies to improve water suppliers' issuance of BWAs compared with policies to improve the public's compliance with a BWA, once issued. Similarly, the analysis shows that most of the costs are associated with severe illness (and mortality). This indicates that policies, e.g., to provide information or improve averting behaviors, specifically directed toward people more likely to suffer severe illness that may lead to mortality, could be a cost-effective way to reduce the impact of *Crypto*.