Cost-benefit Analysis of Rapid Microbial Detection for Improving Marine Swim Advisories

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A manuscript for the Policy Analysis section of
Environmental Science & Technology

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ABSTRACT

Using a transfer policy analysis, we evaluate the effectiveness of real-time detection of fecal indicator bacteria (FIB) at reducing gastrointestinal illness and improving the net benefit of marine beach advisories over the *status quo*. We compare hypothetical advisory scenarios that assume a different water quality monitoring technology (none, culture-based assay, or rapid detection). Illness estimates are made using two epidemiological models that relate enterococci densities to gastrointestinal illness (GI). The health costs associated with GI are compared to the recreational value of swimming to determine net economic benefit. We find that rapid detection results in significantly fewer swimming-related GI with only one of the two epidemiological models. Beachgoer compliance with advisories is important in determining net benefit, but monitoring costs are not. Notably, non-compliance with advisories has the highest expected net benefit regardless of the speed of reporting. This finding is somewhat sensitive to the values chosen for V_{health} and V_{rec} under one epidemiologic model but not the other. In general, beaches are more likely to benefit from implementation of rapid detection technologies for monitoring when over 4% or 15% of the water quality measurements result in a change in advisory status, depending on the epidemiology model used.

INTRODUCTION

Federal and state laws establish criteria based on fecal indicator bacteria (hereafter referred to as FIB) including total coliform (TC), fecal coliform (FC), and enterococci (ENT) to determine when water quality conditions at recreational marine beaches are unfit for human contact (*1*,*2*). The practice of using FIB to distinguish periods of unacceptably high risk is based on epidemiology studies (*3*-*5*) that show correlations between human health symptoms (including stomach pain, diarrhea, and respiratory ailments) and FIB concentrations in marine water known to receive human fecal waste.

According to state and federal FIB criteria, bacterial pollution is widespread at United States (US) coastal, river and lake beaches. In 2005, there were over 20,000 beach closures and advisories, compared to just 6,200 in 1999 (*6*), a consequence of more stringent water quality criteria and an increase in the number of beaches monitored. Several studies have questioned the efficacy of current methods of issuing closures and advisories because testing methods for the quantification of FIB are culture-based, requiring more than 1-day (herein referred to as 1-d) of incubation. The 1-d time lag between sample collection and data availability for coastal managers can result in mis-notification of the beach-going public (*7*,*8*). Beaches failing the health criteria may be placed under advisory 1-d late while beaches returning to acceptable standards can remain posted erroneously.

To overcome this problem, the US Environmental Protection Agency (US EPA) and others (*9*,*10*) are developing rapid detection methods for FIB. Exploration of expedited FIB detection technologies is mandated by the US Beaches Environmental Assessment and Coastal Health Act of 2000 (*11*). Quantitative polymerase chain reaction (QPCR), transcription mediated amplification, and dual-wavelength fluorimetry are promising rapid detection technologies that take as little as three hours to produce bacterial counts (*9*,*10*,*12*). QPCR measurements of ENT correlate with swimmer gastrointestinal illness (GI) in the Great Lakes (*13*), indicating the tool has potential for use in protecting human health. If beach managers were to switch from culture-based techniques to a rapid detection technology, then unintended management errors resulting from the 1-d lag would be eliminated. Rapid detection would also help in determining when to lift a closure or advisory triggered by a storm or sewage spill. One issue that would not be addressed by rapid detection, however, is the variability of FIB densities observed at time scales less than a day (*14*).

In the present study, we determine the extent to which using a rapid-detection technology in day-to-day beach management would reduce incidence of recreational waterborne illness and increase net benefits among swimmers compared to the *status quo*. This is accomplished using a transfer policy analysis (*15*) that retrospectively examines hypothetical monitoring scenarios at a popular beach in southern California (CA). We extend the approaches taken in Rabinovici et al. (*8*) and Hou et al. (*16*) by introducing a mechanism for testing how sensitive the policy analysis outcome is to the level of compliance potential swimmers exhibit toward advisories. We compare three scenarios: (1) the beach is placed under a swimming advisory 1-d after CA water quality criteria are exceeded (as currently occurs owing to the 1-d required for culturing FIB), (2) the beach is placed under advisory on the same day CA water quality criteria are exceeded (as would occur if a rapid detection method were used to determine FIB densities), and (3) the beach is never placed under advisory. Illness estimates under each scenario are obtained using two available epidemiological models for the relationship between ENT and excess gastrointestinal illness (GI). The health costs associated with excess GI (*17*) are compared to the recreational value of a southern CA beach visit involving swimming (*18-20*) to determine the net benefit of rapid detection to potential swimmers.

The results are used to address the following five questions: (1) Which monitoring technology scenario results in the lowest predicted incidence of GI? (2) Does rapid detection reduce illness rates significantly more than 1-d lagged advisories, compared to never placing the beach under advisory? (3) Which policy scenario results in the highest net benefit in aggregate for swimmers? (4) Does rapid detection result in significantly higher net benefit for swimmers than 1-d lagged advisories? (5) What are the key sensitivities and uncertainties involved in answering the above questions?

MATERIALS AND METHODS

Water Quality Data. Our analysis focuses on Huntington State Beach (HSB) in Orange County, CA (Figure 1). HSB was selected for analysis because of its rich water quality and attendance records and importance as one of the most visited beaches in the nation (approximately 1.9 million visits were made to HSB in 2000 (*21*)). We use publicly available TC, FC, and ENT data sampled at four monitoring stations within HSB during the summer of 2000 (defined as the 99 days between Memorial Day – 29 May and Labor Day – 4 September) (*22*). When an FIB density is reported as under or over the method’s detection limit, we assumed the FIB density was equal to the detection limit (*14*). Further details regarding the FIB data are found in Supporting Information (SI).

In CA, violation of any one of seven water quality criteria (given in SI) requires a beach be placed under a swimming advisory (also referred to as “posted”). An advisory is distinct from a closure in that it is not enforced—swimmers are allowed to decide whether or not to enter the water. Advisories are intended to provide a binary signal to potential swimmers about whether FIB levels are above or below state standards at a particular site. Note that if all visitors decide not to swim once they see an advisory is in place, an advisory could be behaviorally equivalent to a closure.

We use FIB data at each of the four monitoring stations to determine the management decision (posted or not posted) for each policy scenario for the region of beach closest in proximity to that monitoring station (Figure 1). In light of studies showing that temporal variation between ENT on consecutive days exhibits complex behavior (*23*), we choose to examine policy outcomes only for the 71 out of 99 days in the summer 2000 season when water quality was actually measured at HSB rather than attempt to estimate ENT on days when water quality is not available.

Visitor Data and Behavioral Assumptions. Daily attendance data for HSB in the summer of 2000 are derived from lifeguard records as reported by Morton and Pendleton (*24*). In a recent study by Wade et al. (*13*), 18.4% and 42.1% of beach-goers reported immersing their heads during visits to Lake Erie and Lake Michigan beaches, respectively, in 2003. Similarly, Hanemann et al. found that in the summer of 2000, 43.6% of beach goers in Los Angeles and

Orange Counties had substantial contact with the ocean water (*18*). Based on these estimates, we assume 43% of beach visitors intend to go swimming on any given day.

We define the number of visitors to the beach multiplied by the percentage of visitors who intend to swim as the maximum number of "potential swimmers" that are impacted by an advisory. Potential swimmers are the individuals who would swim at the beach if there were no advisory. We assume that potential swimmers at HSB distribute themselves evenly along the beach and are exposed to the ENT density and management decision associated with the closest monitoring station. S_k represents the number of potential swimmers within the region closest to station k on a given day (Figure 1). We use the term "swimmers" to specify the number of potential swimmers who actually swim, conditional on advisory status. For days when no advisory is in effect, all potential swimmers are swimmers. When an advisory is issued, the two populations can diverge depending on how many potential swimmers choose to comply with the advisory.

To our knowledge, the behavioral response of potential swimmers to beach advisories has not been investigated. Anecdotal evidence suggests that some potential swimmers ignore advisories and swim despite being informed by a sign on-site about heightened health risks. We introduce a hypothetical compliance variable c to explore how changes in compliance would affect illness incidence and net benefits in the management scenarios. Hereafter, c ($0 \le c \le 1$) denotes the fraction of potential swimmers that comply with a beach advisory. If $c = 1$ there is complete compliance with the advisory (all potential swimmers refrain from entering the water). If $c = 0$, all potential swimmers disregard the advisory.

Advisory Scenarios. We consider the following three hypothetical policy scenarios:

1. Standard Practice Scenario (SP): Advisories are instituted following receipt of a water sample result that exceeds any one of seven CA standards, with results available 1-d after sampling.

2. Rapid Detection Scenario (RD): Advisories are instituted following receipt of a water sample result that exceeds any one of seven CA standards, except sampling results are available for use by mid-morning of the same day.

3. No Intervention Scenario (NI): No advisories are issued.

The advisory status of each region of beach k, P_k, is set to 1 if an advisory is posted and 0 if not. Advisories at a monitoring station are assumed to affect only the region of beach closest to that monitoring station (Figure 1). In SP and RD, advisories remain in effect until a subsequent sample result returns the beach to compliance with all standards.

Incidence of Gastrointestinal Illness. Recreational exposure to waters with elevated FIB can cause many types and severities of illness. In the present study, we limit our assessment to GI because it is the most frequent health endpoint associated with exposure to impaired recreational waters (*4*,*5*), though the definition of GI varies between epidemiology studies.

Currently, two distinct epidemiology models inform FIB standards internationally and in the United States (US). Kay et al. (*25*), cited in World Health Organization (WHO) guidelines (*26*), studied multiple health outcomes in a randomized, case-controlled group of 548 volunteer subjects exposed to marine waters in four separate United Kingdom sites in the 1990s. In the US, federal and state criteria are informed by cohort studies done at four US sites in the 1970s by Cabelli et al. (*27*). The Cabelli et al. model is similar to a model obtained in a meta-analysis of 27 epidemiology studies that includes a mix of cohort (including the sites examined by Cabelli et al.), event, and randomized trial designs that related water exposure to GI (*5*).

In the present study, we compare predicted excess GI using the epidemiology equations for the relationship between ENT density and GI reported by Kay et al. (*25*) and Cabelli et al. (*27*). We use both because there is ongoing debate in the literature about the appropriate derivation and use of these models (*5*, *28*-*31*).

We adopt the following equation from Cabelli et al. (*27*) to describe excess risk for a GI episode involving vomiting, diarrhea, stomach ache or nausea as:

$$R_k = \left[24.2\log(\mathrm{ENT}_k) - 5.1\right]/1000 \tag{1}$$

where R_k is the excess risk of GI for individuals exposed to ENT at region k, and ENT_k is the ENT concentration in colony forming units (CFU) per 100 mL to which individuals are exposed when they immerse in the water at region k. Excess risk is measured relative to non-swimmers. We use Cabelli et al.'s (*27*) GI health endpoint, rather than highly credible GI, because it is a suitable match to the health outcomes described by Kay et al. (*25*). Hereafter, the relationship between excess risk and ENT described in equation 1 is referred to as model C.

We use the following equation based on Kay et al. (*25*):

$$R_k = \frac{e^z}{1+e^z} - b \tag{2a}$$

where

$$z = 0.20102\sqrt{ENT_k - 32} - 2.3561 \quad (2b)$$

b is the background incidence of GI, and ENT_k as previously defined. The dependent variable in the original form of model K is fecal streptococci (FS), not ENT. According to the WHO, FS and ENT represent the same bacterial groups, so our substitution of ENT for FS in equation (2b) is justified (*26*). The health end-points for this epidemiology model are vomiting, diarrhea, nausea with fever, or indigestion with fever. We set b= 0.0975, the background risk observed in the Kay et al. study for non-swimmers. Non-zero estimates of R_k are obtained only for ENT_k greater than 32 CFU/100 mL. Because Kay et al. did not observe ENT levels above 158 CFU/100mL, we assume R_k = 0.378 for all ENT densities above 158 CFU/100mL. Equations 2a and 2b are hereafter referred to as model K.

The excess risk predicted as a function of ENT density varies substantially between these two models (Figure 2). The discrepancy can be attributed to contrasting study designs and the fact that the studies were conducted at different locations. Together with results from a recent study that found no statistical association between FIB exposures and 14 different human health outcomes in marine water predominantly affected by non-point sources (*32*), these discrepancies suggest that the relationship between health outcomes and water quality is a major source of uncertainty for any beach water quality policy analysis. In any case, the analysis presented here includes the best estimates for GI based on currently available information. Limitations and justifications for using these two models to estimate excess GI risk at HSB are described by Given et al. (*21*).

Daily GI predicted to occur at HSB is:

$$G = \sum_k S_k R_k (c \mid P_k) \quad (3)$$

where all variables have been defined previously. When there is no advisory in place ($P_k = 0$), c = 1 (one). When there is an advisory ($P_k = 1$), we allow c to vary between 0 (zero) and 1 (one) to reflect the level of compliance. For ease of display, we report an average per day estimate of illnesses for each scenario by dividing the total number of predicted illnesses for that policy scenario by 71, the number of days included in our analysis.

Transfer Policy Analysis and Net Economic Impacts. We use transfer policy analysis as the general framework for integrating the existing epidemiologic models and health and recreation welfare estimates and applying them to the water quality and visitor population at the case study site (*15*,*33*). Two key factors in the reliability of transfer policy analysis are the quality of the methods and data used in the original studies and the degree of similarity between the original and transfer contexts (*34*). In the present study, we transfer mean point estimate economic values from contemporary local studies and adjust those values using the Consumer Price Index to year 2000 dollars. We focus on the population of potential swimmers and do not address economic benefits or costs to local businesses or agencies from concessions, parking fees, and so on. The economic values that we consider are the benefits of outdoor swimming recreation (which accrues whenever a beachgoer who intended to swim actually does so) and the health costs incurred (when an illness results from that swim exposure). This is reasonable because advisories do nothing to change water quality and can only address exposure risk.

The expected per day net economic impact to potential swimmers at HSB is calculated as:

$$NB = \sum_k S_k (c \mid P_k)\left[V_{rec} - R_k V_{health}\right] - M \tag{4}$$

where V_{rec} is the average value of outdoor swim recreation per visitor per day, V_{health} is the average economic cost of illness (COI) per GI, and M is the scenario-specific cost of monitoring. We estimate a typical per day cost for collecting monitoring data at \$120 for culture-based assays for the SP scenario and \$370 for the RD scenario's tests (based on professional judgment, discussed in more detail in SI). The NI scenario is cost-free.

Expected net benefit is an accepted method for assessing trade-offs in aggregate by weighting outcomes by their probabilities of occurrence and the number of people affected. For any given day, the average individual's net benefit for swimming is given by: $V_{rec} - R_k V_{health}$. Equation 4 thus expresses the trade-off (unique to each day at each station) between the value of recreation and the excess risk posed by the ENT densities weighted by the value per health event and multiplied by the number of swimmers exposed on that day. This formulation implies that potential swimmers who choose not to swim based on an advisory experience no benefits or costs. In other words, we consider only changes to the individual's baseline utility that are attributable to their beach-going activity. Compliance with advisories is equivalent to "staying home". We assume that society prefers the policy that delivers the highest possible positive net benefit. Results are presented as per day averages for each scenario to simplify comparison and presentation.

For this study, we set V_{rec} = \$16.15, a value specific to southern California beaches (*19, 20*). We set V_{health} = \$35.57 based on a study by Dwight et al. (*17*) that estimated lost income (wage) and direct medical costs of a GI episode of the type described in the Kay et al. paper (*25*) to an average adult in Orange County, CA. Additional discussion of the merits and limitations involved in benefit (economic value) transfer is presented in SI.

Statistical Confidence. We use a Wilcoxon signed rank test to compare daily excess GI predicted under each policy scenario. This test is applied to all possible pairings of the three scenarios at values of *c* from 0 (zero) to 1 (one) at 0.05 increments. The different outcomes are compared for each day, and the magnitude and direction of these differences are tested to determine if there are consistent relationships between the scenarios. The illness distributions predicted by the epidemiological models meet the assumption of symmetry required by the Wilcoxon signed rank test. The distributions of net benefit do not, so we test the significance of the net benefit differences between scenarios with the less restrictive sign test. The above tests are computed using non-parametric routines in SPSS 11.

RESULTS

Water Quality and Attendance. During the study period, HSB experienced a total of 30 ENT, 18 FC, and 13 TC single-sample standard (SSS) exceedances as well as 55 ENT geometric mean standard (GMS) exceedances. Consecutive SSS exceedances occurred 11 times for ENT, 5 times for FC, and 4 times for TC. In addition, 48 consecutive-day exceedances of the ENT GMS were observed (Table 1). The number of consecutive exceedances relative to single day exceedances is important because for advisories lasting two or more days, RD will only yield different results from SP on the first day of the exceedance sequence and the day following the sequence.

Attendance data from the summer of 2000 shows a median daily visitor count of 9,800 and an inter-quartile range of 11,800 visitors. These numbers are typical for HSB (data not shown).

Estimated Illness Incidence. Using model C, RD with full compliance results in an average of 77 GI d^{-1}, 48 fewer than under NI (Figure 3). Therefore, in the best case of full compliance, real time water quality information eliminates 38% of the illnesses that would have occurred if there were no advisories issued. The SP scenario with full compliance leads to 79 GI d^{-1}, a reduction of 37% compared to the NI scenario. RD provides no significant improvement in illness reduction over SP ($p>0.05$). This is attributable to the low level of excess risk predicted by model C across the inter-quartile range of observed ENT concentrations (6 – 44 CFU/100mL). If model C is the most appropriate epidemiologic model for this site, management based on RD does not produce any appreciable improvement in illness incidence compared to SP.

In contrast, when model K is used in the policy analysis, the differences between RD and SP are statistically distinguishable at all values of *c* above 0 (zero) ($p<0.05$) (Figure 3). RD with full compliance results in an average of 65 GI d^{-1}, a 83% reduction in the number of GI that would have occurred if there were no advisories at all (NI). The SP scenario with full compliance leads to 144 GI d^{-1}, a reduction of 63% compared to the NI scenario. RD results in significantly fewer ($p<0.05$) illnesses relative to both the SP and NI scenarios.

Under both the C and K models, the differences between NI and each of the two intervention scenarios are statistically significant ($p<0.05$) whenever $c > 0$ (zero). Therefore, either monitoring strategy significantly reduces illness relative to never issuing advisories. The magnitude of the reduction depends critically on the proportion of potential swimmers that comply with posted advisories. Compliance with posted warnings affects illness outcomes for more under model K than model C (Figure 3). Note that even full compliance with advisories cannot eliminate all GI because concentrations of ENT under the CA water quality standards are still associated with excess illness (Figure 2). As many as 4% (model C) or 24% (model K) of swimmers may experience GI as a result of water conditions in compliance with the CA ENT SSS.

Expected Net Benefits. The NI scenario creates a higher expected net benefit than either of the two monitoring scenarios (net benefits for NI are \$74,870d^{-1} and \$65,397d^{-1} using models C and K, respectively). Net benefits are highest for both RD and SP when compliance is lowest—in other words, when visitors “choose” to make these two scenarios as similar as possible to NI by ignoring the advisories (Figure 4). Thus, non-compliance with advisories has the highest expected net benefit regardless of the speed of reporting.

At $c = 0$, the net benefits of SP and RD differ from NI only because of the costs associated with monitoring. For RD at $c = 0$, net benefits are \$74,378 d^{-1} using model C and \$64,905 d^{-1} using model K. For SP at c = 0, net benefits are \$74,710 d^{-1} using model C and \$65,237 d^{-1} using model K. Net benefits are consistently lower when model K is used because it predicts significantly ($p<0.05$) more GI than does model C for the same ENT density (Figure 2).

When model C is used, the net benefit provided by RD exceeds that of SP whenever compliance is above 0.17. However, the null hypothesis that the RD and SP scenarios provide the same net benefits cannot be rejected at any level of c (p>0.05). This is largely because there is little difference in GI between the two scenarios under model C (Figure 3).

The policy analysis using model K gives contrasting results. There is a significant difference (p<0.05) between the net benefits provided by all three scenarios. Above c of 0.07, the net benefit provided by RD exceeds that of SP. In other words, 93% of swimmers would have to be ignoring advisories for SP scenario net benefits to be less than those predicted in the RD scenario. At that extreme, the SP scenario provides higher net benefit only because of its lower testing costs. With full compliance (c = 1), RD provides $4,309 more net benefit per day than SP.

DISCUSSION

RD does not necessarily reduce illness rates significantly relative to SP. Using water quality and visitor data from HSB in the summer of 2000 and the best available epidemiologic models, we find that both RD and SP reduce the number of GI predicted to occur compared to having no advisories. However, RD provides a statistically significant benefit over SP only if excess risk for GI at HSB is best-described with model K. While model K is used in standard-setting internationally, it is an "outlier" that predicts more illnesses for the same range of ENT than the majority of other studies (*4,5*). Thus, it might be viewed by some experts as providing an over-estimate of GI at HSB. Indeed, both models C and K may over-estimate illness rates if the finding that traditional FIB in waters near San Diego, CA predominantly affected by non-point pollution were not associated with health risks to swimmers (34) is replicated elsewhere. That would call into question the assumption that models of GI-FIB relationships are transferable between locations and their suitability for standard-setting. If FIB do not indicate an increased health risk at a particular site, testing for FIB more rapidly there will do little improve to public health.

Issuing no advisories—a practice not permitted under current law—results in the highest net benefit for potential swimmers. Our analysis assumes that a major purpose of beach advisories is to reduce the incidence of GI in swimmers while providing a reasonable level of recreational access. Expected net benefit is the best available mechanism for expressing the trade-offs between these two disparate objectives. We find that RD does not necessarily result in significantly higher net benefit than SP for the average swimmer. Also, regardless of the epidemiologic model used or whether beachgoers comply with advisories, both RD and SP reduce net benefits compared to NI. Thus, according to our analysis, advisories based on CA water quality criteria decrease the net benefit compared to issuing no advisories.

This somewhat surprising result is consistent with previous findings (*8,16*) that when the best available epidemiologic and economic assumptions are used, the benefits to the large number of swimmers outweighs the economic impacts associated with the few who suffer the excess GI. Our finding does not imply that there would be no value to reducing bacterial contamination, because total net benefit could still be improved by reducing ENT densities to reduce excess risk. Under the NI scenario, the estimated number and total cost of GI, respectively, for the 71 day period at HSB were 8,860 and $315,153 under model C and 27,769 and $987,737 under model K.

Our formula for expected net benefit does not address the degree to which advisories increase safety awareness, precaution, or indirectly educate beach goers about issues of coastal water quality. Nor do we address the benefits that arise from either regular FIB monitoring to establish a baseline understanding of local water quality or intensive sampling efforts designed to track pollutant sources so they can be remediated. However, these benefits are unlikely to be different whether FIB detection is rapid or 1-d delayed.

We reach different conclusions with regard to the potential benefits of using RD depending on the epidemiologic model used. Under model K, both illness counts and net benefit outcomes between RD and SP were significantly different, but neither was under model C. This suggests that in beach policy analyses, careful attention is required in choosing a epidemiologic model that accords with the specific conditions of the beach(es) under consideration. New epidemiology studies that focus on understanding health outcomes resulting from exposure to coastal waters receiving different types and sources of contamination or visited by different bather populations (e.g., surfers versus swimmers or tourists versus regular local beach users) will improve future benefit transfer policy analyses. It is possible that including the economic costs associated with other types of recreational water-borne illnesses, such as significant respiratory disease, or including health effects experienced by more susceptible swimmers (for example, children, elderly, and immuno-compromised) would alter our findings.

The policy preference ranking is only sensitive to the values chosen for V_{health} and V_{rec} when model K is used. We assign \$35.57 to V_{health}, which is in the middle range of reported values for mild to moderate multi-day health impairments in a recent meta-analysis of seven morbidity valuation studies (*35*). Pain and suffering and the value of lost leisure time are not addressed, which could make the Dwight et al. value we use an under-estimate. We conduct a “break-even analysis” to show how high the V_{health} parameter would need to be (holding all else constant) for SP and RD to exhibit higher net benefits than NI. Using model C with full compliance, COI would have to be 1270% higher ($489) to make the SP scenario more net beneficial than the NI scenario and about 1110% higher ($430) for the RD scenario. Thus, the delivery of higher expected net benefit under NI compared to RD and SP appears unchanged over a range of reasonable values for the COI parameter under model C. Using model K with full compliance, COI would have to be about 150% higher ($90) than the Dwight et al. estimate for SP to be more net beneficial than NI, and about 80% higher ($63) for RD to rank more beneficial than NI. Thus if model K is the most appropriate epidemiology model for HSB and COI is twice the value estimated by Dwight et al., then the two monitoring scenarios could have higher net benefits than NI.

Conceptually, V_{rec} varies across individuals and user populations, thus it is useful to consider a reasonable range of values (*36*). Holding all else constant and using model C with full compliance, V_{rec} would have to be less than $1 for the SP and RD scenario to have higher net benefits than the NI scenario, a value which is implausibly low (see SI for a discussion). Using model K with full compliance, V_{rec} would have to be less than half the $16.15 value we used ($6.30 and $8.90, respectively) for SP and RD to rank more beneficial than NI. If model K is appropriate for this beach and V_{rec} is less than about 50% of the estimate we use, which is unlikely given our understanding of recreational valuations, then the RD and SP scenarios could produce higher net benefit than NI.

Swimmer behavior is a critical factor that deserves more study. We find that compliance behavior of potential swimmers has an important impact on both number of predicted illnesses and the potential net economic benefit of rapid detection technologies. Compliance does not, however, impact the policy preference ranking. Across nearly all possible values of *c* using models K and C to estimate GI, RD provides greater illness reduction and greater net benefits than SP. The only exception is at very low levels of compliance ($c < 0.07$ or $c < 0.17$, depending on epidemiology model) where the greater cost of RD monitoring causes the cheaper standard monitoring practice to win out. A survey of beachgoer behavior collected during summer 2005 at HSB indicates a reported 51% compliance rate both local and at other southern CA beaches (data not shown), suggesting that such low compliance is unlikely.

Our analysis does not address the potential for endogeneity between advisory status and beachgoer attendance and compliance with advisories. Chapman and Hanemann (*20*) provide evidence that availability of regional substitutes is important to both attendance level and recreational value lost. Further research is needed to identify how the number of potential bathers per day changes in response to advisory on prior day(s) or at nearby locations.

Analysis of a hypothetical beach water quality data set indicates that advisory "volatility" is key to determining of the benefit RD can provide relative to SP. We conducted the same benefits transfer analysis using 500,000 simulated ENT data series constructed by randomly sampling cumulative density functions of 10,000 different beta distributions. The goal was to determine the characteristics of beach water quality distribution that are important in determining if RD can improve net benefits to society relative to *status quo* (SP) (see SI for details). Our analysis indicates that "advisory volatility" is a key attribute of a beach water quality data that determines the outcome of the analysis. We define advisory volatility as the percent of monitoring days that result in a change in advisory status and can range from 0 to 100%. When volatility is low (advisory status changes relatively infrequently), RD does not provide improved benefits to society over SP under the assumptions used in this paper. As volatility increases above 4% and 15% for models K and C, respectively, then RD provides improved benefits over SP. The difference in the volatility threshold for analyses performed with the two epidemiology models arises because model C suggests a weaker relationship between ENT and excess risk than model K.

Our analysis suggests that beach managers should be cautious in moving to rapid detection of FIB for routine water quality monitoring. Beach-specific circumstances, including visitor levels, swimmer populations and their behavioral responses to advisories (especially substitution behavior from one beach to another which we did not consider), and day to day FIB density patterns can all limit how much reduction in exposure beach advisories based on rapid detection would be able to achieve.

ACKNOWLEDGEMENTS

The authors acknowledge Michael Hanemann, Jack Colford, and Deyi Hou for their input on the project. ABB and SJMR are supported by NOAA Oceans and Human Health Grant NA04OAR4600195 to ABB. SJMR conducted a substantial portion of this research while employed by the USGS.

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TABLES & FIGURES

FIB group	# samples over SSS	# samples over GMS	# consecutive samples over SSS	# consecutive samples over GMS
ENT	30	55	11	48
FC	18	0	5	0
TC	13	0	4	0

Table 1. Summary of water quality exceedances at HSB for the 71 when water samples were taken between 29 May 2000 and 4 September 2000. Four stations were sampled on each day, leading to a total of 284 observations. SSS is single sample standard, GMS is 30-day geometric mean standard. For explanations of these CA beach water quality standards, see SI. Note that the TC SSS exceedances include those that occur when the FC/TC ratio is greater than 0.1.Consecutive samples are counted if there was an exceedance the previous time a sample was collected.

Figure Captions

1. The excess risk of GI as a function of ENT density using models C and K over the ENT ranges available at HSB.

2. Schematic map of field site. The assumed distributions of water quality (FIB_k) and potential swimmer (S_k) are shown for the region surrounding each monitoring station.

3. GI d^{-1} projected under each management scenario by epidemiology equation.

4. Estimated net economic benefit to potential swimmers per day under each management scenario by epidemiology equation.

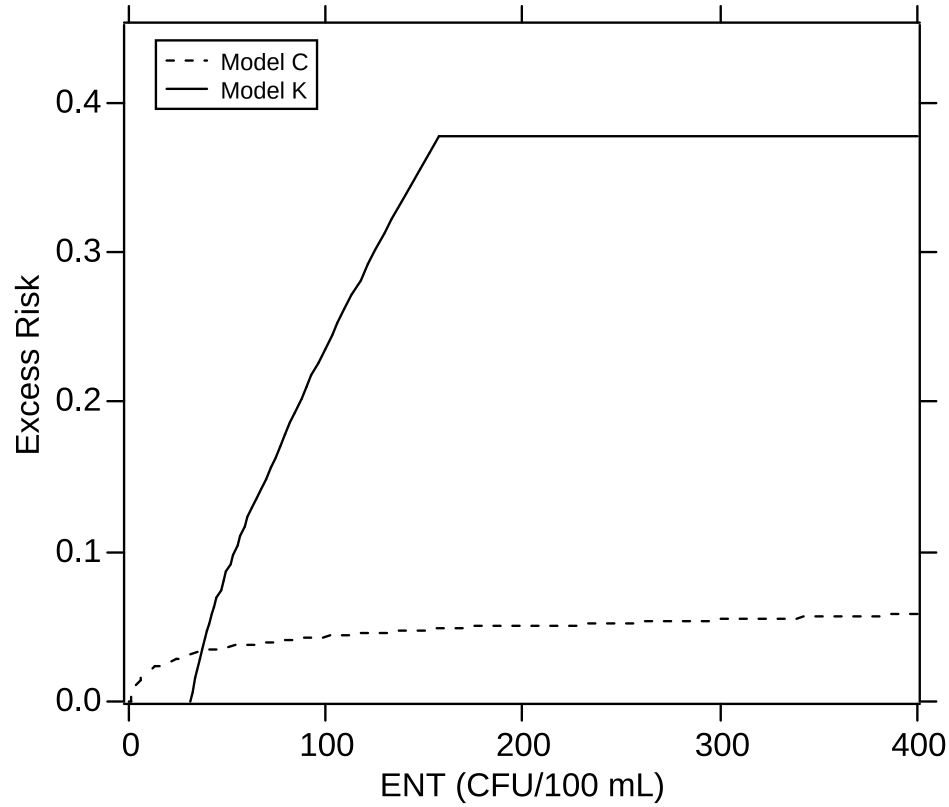

Figure 1.
Rabinovici et al.

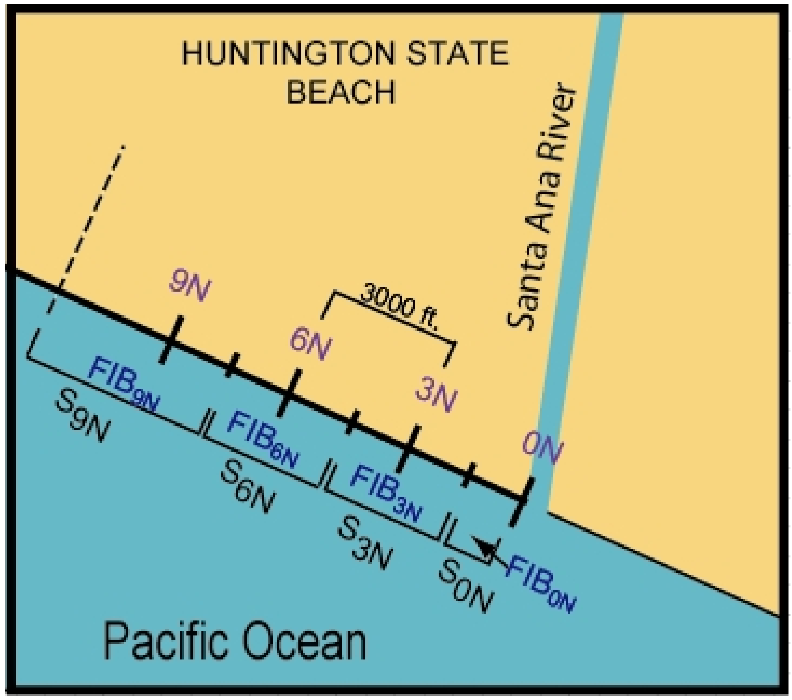

Figure 2.
Rabinovici et al.

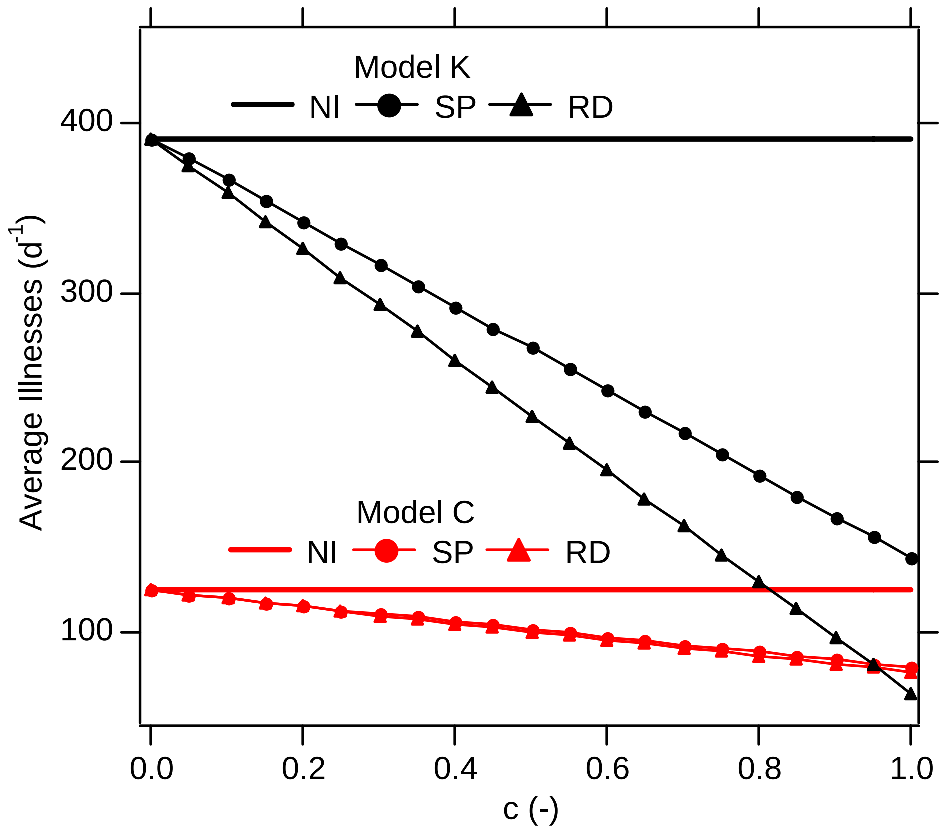

Figure 3.
Rabinovici et al.

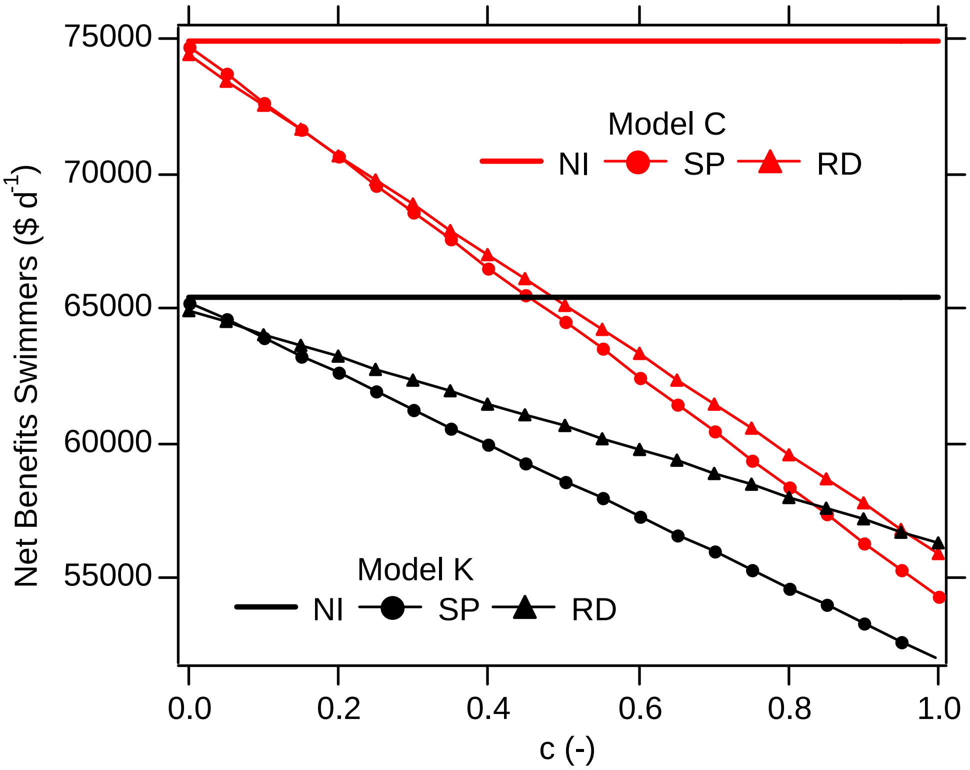

Figure 4.
Rabinovici et al.

Supporting Information

FIB Data

Samples for total coliform (TC), fecal coliform (FC), and enterococci (ENT) observations were collected in the morning five days per week (excluding Friday and Sunday) from four sampling stations at Huntington State Beach (0N, 3N, 6N, and 9N) (*1*). Water quality monitoring stations are located at 3,000 foot intervals along the shore and are named according to their distance from the Santa Ana River (e.g. station 6N is 6,000 feet north of the river).

The water samples were analyzed using standard methods for TC and FC published by the American Public Health Association and EPA method 1600 for ENT. TC and FC are reported within the range of 20 to 16,000 colony forming units (CFU) per 100 mL while ENT concentrations are reported between 2 and 400 CFU/100 mL. When the lower (upper) limit of detection was exceeded (as reported by the monitoring agency), it was replaced with the lower (upper) detection limit. High ENT pollution incidents were more frequent in 2000 than in 2001–2004, when HSB experienced lower median ENT levels and narrower inter-quartile ranges, but less frequent than in 1999 (data not shown).

California's Beach Water Quality Laws

Single sample (SS) standards require advisory the beach if a sample of beach water contains TC, FC, or ENT in excess of 10,000, 400, and 104 colony forming units (CFU)/100 mL, respectively (*2*). A more stringent SS standard for TC of 1000 CFU/100 mL is applicable if the FC to TC ratio is greater than 0.1. Geometric mean (GM) standards require the beach to be posted if the geometric mean of TC, FC, or ENT over five equally spaced samples taken within the previous 30 days, including the most recent sample, is in excess of 1000, 200, or 35 CFU/100 mL, respectively. California's guidelines are consistent with but slightly more stringent than current federal rules for recreational water quality (*3*). Even though there are multiple fecal indicators and rules used to trigger a advisory in the first two of our scenarios, each station day is assigned only one of the two possible values (0 or 1) using the indicator variable P_k.

Beach Visitor Swimming Behavior

In doing our comparative analysis of beach policies, we make a series of assumptions regarding the number and type of visitors exposed to ocean water at HSB. The lifeguard counting techniques in the Morton and Pendelton study we cite included estimating attendance from the lifeguard towers, parking, bike rack usage, and bus line capacity. We found the recent swimming percent value of Wade et al. to be reasonable, since Pendleton et al. found that in the summer season of 1999, 38.5% of beach goers in Orange County had significant contact with the water (includes bathing, swimming, surfing and body boarding) during their beach visit (*4*). In 1997, Pendleton counted a 35.9% average rate of head-immersion swimming at 15 beaches in Santa Monica Bay (*5*). In summer 2000, the number of visitors to HSB does not appear atypical in any way when compared to attendance from 1998 and 1999 (data not shown).

We assume that potential swimmers do not move to another region to swim or choose a different form of recreation if their region is under and advisory. Substitution behavior is not considered, despite some evidence that southern California beachgoers substitute at the regional scale (*6*). We also assume that the recreational benefit experienced by potential swimmers is not affected by advisories at regions other than their intended recreational site. These simplifying assumptions are made necessary by the fact that how potential swimmers respond to or change their behavior based on advisories at ocean beaches has not yet been modeled at the beach scale.

We acknowledge that the station-exposure assumptions produce an imprecise estimate, but deem it the best approach given the available data. The assumption that all swimmers for a particular day are exposed to the ENT concentration measured in the morning at the closest monitoring station reflects the approximation made in actual management practice. The effect of this assumption is ambiguous but probably conservative, since some studies have found FIB levels to be higher in the morning than mid-day (*7*).

Monitoring Costs

Monitoring costs are rough estimates based on the personal experience of the authors. We include labor costs for the collection and processing of three different FIB samples from four monitoring stations at HSB (for a total of twelve analyses), and the cost of supplies for each sample. These estimates do not take into account capital investment, equipment maintenance, and administrative costs of monitoring programs. We argue that these rough estimates are reasonable, especially since we later show that monitoring costs play a minor role in the policy preference ranking compared to the health and recreational trade-offs involved.

Non-Market Valuation and Transfer Policy Analysis

There is limited but consistent evidence that water quality affects the benefits that individuals derive from outdoor swim recreation (*8-12*). Relevant insights from this literature include the following: studies in the US and Europe show that people on average value each swim experience at about $4 to $50 (*12*); individual valuations vary based on income, gender, race, worldview, and other factors; valuations are sensitive to survey and modeling methods and specification; perception of water quality may matter as much as actual water quality; and willingness to pay for improvements in beach water quality are modest on a per person basis, adding about 30% of the total consumer surplus (*8*), but can become highly relevant to society if the beach is visited by many people.

In general, non-market valuation (NMV) has been a major area of research in environmental and health economics over the past thirty years (for a review of the development of NVM and its influence on environmental policy (see, e.g., (*13*)). The act of taking findings from NMV studies and using them to make a value estimate for some distinct place, time, and policy context is referred to as benefit transfer (BT) (*14*).

There is considerable debate in the small but growing BT literature about the conditions under which transfer methods are valid and justifiable. Repeated negative findings about the generalizability of environmental activity benefit estimates have led some to conclude that the transfer of unadjusted mean values (point transfer) or even value estimation models (function transfer) are not supported (*15*). Hypothesis tests of difference in means or difference in coefficients are often rejected. However, there is disagreement about whether the null hypothesis should really be *equality* of values across sites and circumstances, as is often assumed (*16*).

Benefit transfer experts urge analysts to consider the validity and accuracy of transfer results explicitly with regard to the policy objective at hand (*14*), a principle sometimes called the “importance test”. Point transfer of mean values is the simplest possible transfer procedure, but provides useful guidance regarding the general magnitude of the relevant welfare effects. To give a general idea of the level of accuracy documented in past tests of BT methodologies, a meta-analysis of seven BT point estimate studies found a maximum error of 56%, and errors were concentrated on the up- side (*17*). In other words, BT estimates tend to be under (not over) estimates. In one of the few examples specific to beach recreation and measurement of willingness to pay to avoid swimming-related health effects, Barton and Mourato (2003) found benefit function transfer errors to be on the order of 6 to 130 percent between beaches in a lesser developed (Costa Rica) versus a developed nation (Portugal) (*18*).

For this analysis, we assume a constant per person benefit of swim recreation to each and every adult that swims and treat the difference in utility of swimming in dirtier waters solely through the change in health state as a function of the indicator level. This is reasonable since the microbial pollution at issue here does nothing to change the immediate appearance or sensorial qualities of the water. We deem point transfers sufficient for this transfer policy analysis because we had values from contemporary local studies available for transfer. Importantly, the original recreation demand and cost of illness studies we cite can reasonably be assumed to cover an analogous population to the case study site.

Because this policy analysis is designed to produce a preference ranking of policies, accompanied by a sensitivity analyses that helps stakeholders judge whether even a worst case error in benefit estimation would reverse the conclusion, use of mean estimates is justified (*18*). We acknowledge the uncertainties created by using BT, and there are other uncertainties inherent to transfer policy analysis. However, by assembling a comparative analysis with the best available estimates for microbial, epidemiologic, behavioral, and economic parameters, our intent is to uncover the relative importance of the different sources of uncertainties in influencing the cost-effectiveness of an emerging technology and on outcomes of a beach management decision-making process.

Monte Carlo Simulations and Hypothetical Analysis

We used a Monte Carlo simulation to test the sensitivity of net benefit welfare outcomes to the distribution of water quality data. We did this to assess the generalizability of our findings to beaches with different water quality profiles and to determine whether particular water quality distributions favor RD over SP.

We simulated ENT densities using several different distributions (including beta, normal, gamma, and Weibull). A beta distribution was the best fit to the water quality data collected at Huntington State Beach (HSB), and thus was adopted to further explore how water quality distributions impacted the performance of RD over SP (data not shown). The beta distribution has two control parameters (α>0 and β>0) that together govern the skew and spread of the distribution. The absolute magnitude of the parameters determines the spread and the relative magnitude determines the skew (larger α skews to the left, larger β to the right). The probability distribution function (PDF) is governed by the following expression

$$PDF(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \qquad \text{(S1)}$$

where B is the beta function (or the Euler integral of the first kind) and x varies from 0 to 1. The cumulative distribution function (CDF) is given by

$$CDF(x) = I_x(\alpha, \beta) \tag{S2}$$

where I_x is the regularized incomplete beta function. Figure S1 shows a number of example CDFs for the beta distribution. The mean (μ) and variance (σ^2) of a beta distribution are defined as follows:

$$\mu = \frac{\alpha}{\alpha + \beta} \tag{S3a}$$

$$\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \tag{S3b}$$

Beta distributions with specific means (ranging from 1 to 100 CFU/100 mL in increments of 1) and variances (ranging from 100 to 10,000 $(\mathrm{CFU/100\ mL})^2$ in increments of 100) were sampled randomly to create fifty 71 day long data series of ENT densities. In total, 500,000 data series were generated. The volatility (V) of each hypothetical data series was determined as follows:

$$V = \frac{1}{N-1}\sum_{t=2}^{N}(P_t - P_{t-1})^2 \tag{S4}$$

where N is the number of data points (in our case N=71) and P_t is 1 or 0 if the ENT density of the randomly generated data series is greater than the single sample standard for ENT (104 CFU/100 mL). Volatility describes the percent of ENT measurements that give rise to a change in posting status. The average volatility of the fifty data series generated from a single beta distribution were averaged to obtain the expected volatility.

A benefits transfer analysis was used to determine if RD was net beneficial to society than SP for each of the 500,000 data series using the methods described in the main paper text with the following simplifying assumptions: (1) 2500 visitors per day were present at the beach with the generated water quality distribution – a similar number that is present at a single station within HSB, (2) only the ENT single-sample standard was used to determine the posting status at the beach, and (3) compliance was equal to 50%. In addition, a central assumption for this analysis is that water quality data is indeed random. No autocorrelation between measurements existed in the generated hypothetical distributions, whereas in actual data collected from southern California beaches, there is a significant autocorrelation that has a direct effect on the relative advantage of rapid detection versus 24-hour lagged testing methods. The percent of the fifty simulations for each beta distribution that indicated RD was more net beneficial than SP was recorded.

Figure S2 shows the relative likelihood of RD dominating SP as a color scale value for beta distributions with a designated mean and variance using models C (top) and K (bottom). Purple represents the highest probability of RD being more beneficial than SP and red represents the highest probability of SP being more beneficial than RD. The transition from green to light blue indicates where RD has a 50% chance of providing greater net benefits relative to SP. Figure S3 shows the average volatility (shown as a color scale) for the data series generated from beta distributions as a function of mean and variance.

A comparison of Figures S2 and S3 indicates that when ENT series have low volatility that SP is more likely to win over RD. For model C (top panel of Figure S2), when the volatility is more than about 0.20, RD wins over SP. For model K (bottom panel of Figure S2), RD wins over SP for volatility over 0.04. The differences in the threshold volatilities between the models arises because risk is a much weaker function of ENT density for model C than for model K. It should be noted that in our hypothetical simulation, we held attendance constant. If day-to-day attendance were variable, then this may change relative performance of RD and SP.

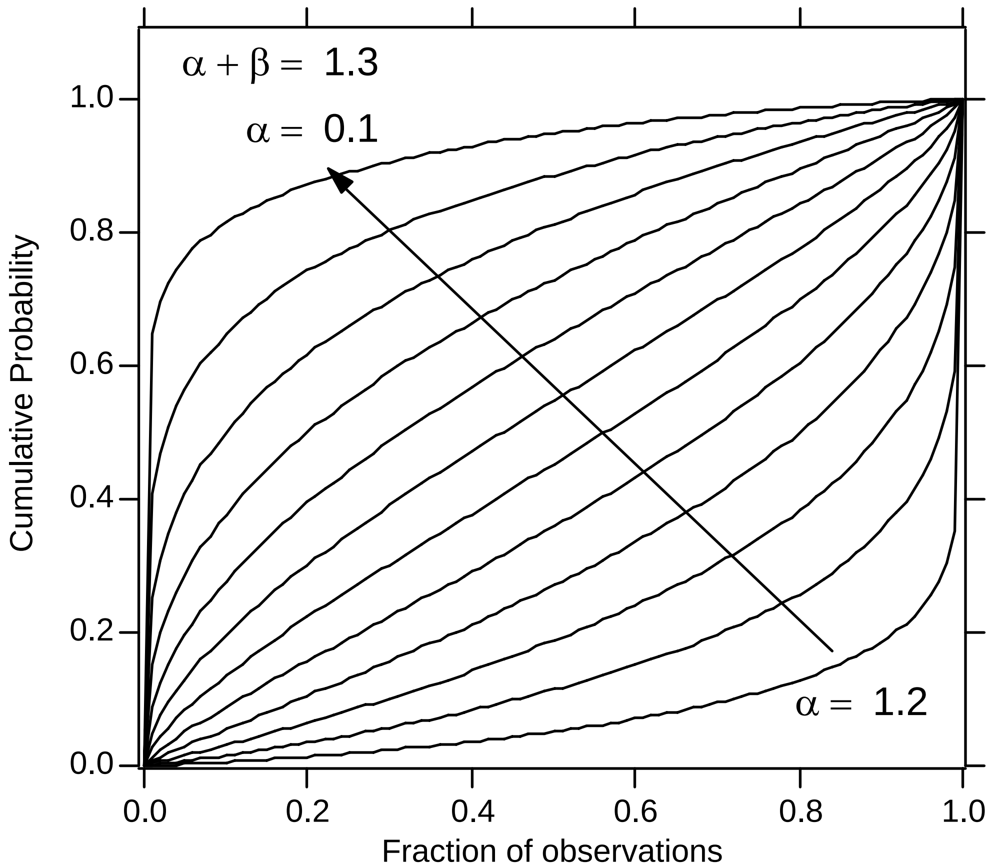

Figure S1. Example beta cumulative distribution functions (CDFs). Here, $\alpha+\beta=1.3$, and α is varied from 1.2 (right most curve) to 0.1 (left most curve) in 0.1 increments.

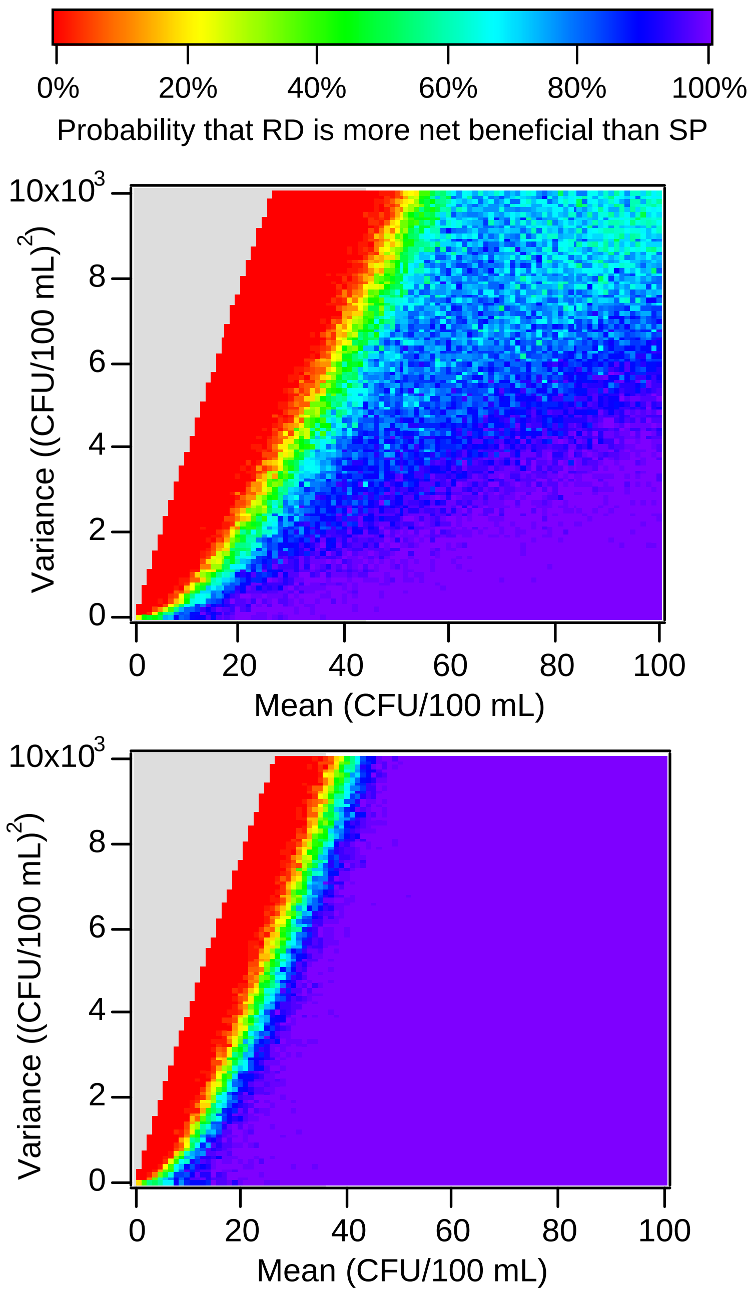

Figure S2. The probability of RD providing greater net benefit than SP for hypothetical beta ENT distributions. Top and bottom plot are results for models C and K, respectively. The grey background delineates combinations between means and variances for which beta distributions do not exist. Mathematically, this region is where α and β are less than or equal to 0.

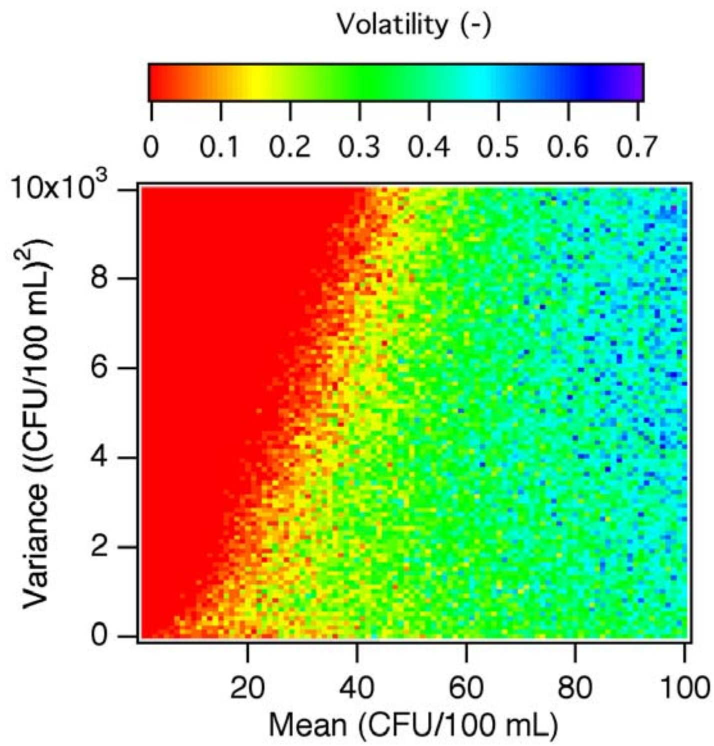

Figure S3. The volatility (V) for each of the beta distributions.

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