ESSAYS ON COMPUTATIONAL APPLICATIONS IN

LAND AND ENVIRONMENTAL ECONOMICS

by

Jacob R. Fooks

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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ABSTRACT

A New Approach to Elicit Continuous Attribute Values Using an Immersive Simulation Environment: Offshore Energy Production and Mid-Atlantic Beach Visitation

Abstract: This research proposes a new approach to measuring and estimating willingness-to-pay for the class of nonmarket amenities with spatially explicit components. The continuous variation of attributes present in many nonmarket goods is used to collect information on consumer choices related to land use at a higher resolution than is available through standard dichotomous choice questions. Our study gathers the information in an immersive simulation environment without directly asking participants to form explicit valuations, an unfamiliar and cognitively challenging task for most consumers. The resulting data can be estimated with a duration or survival model consistent with random utility theory, recovering an expression for willingness-to-pay as a function of the continuous attribute. We apply this approach to estimate beach visitors' visual disamenity associated with the presence of offshore wind turbine and oil platform installations.

Cost-Effective Conservation when Using Benefit Metrics

Abstract: There has been a recent push for conservation organizations adopt project selection approaches such as binary linear programming. The metrics used to measure the benefits of a project however, are poorly defined in that they do not directly compute a value. These scores represent normalized measurements of underlying values that are likely log-normally distributed. We propose the log-normal distribution of values as this is well recognized as the distribution underlying most of the natural processes that are relevant to conservation programs, such as nutrient and contaminant distribution and species abundance. This tendency towards log-normal distribution arises from basic thermodynamic properties of chemical and biophysical systems, when the maximum entropy principle is applied to a dynamic system of positive, conserved quantities. Applying such metrics in optimization will tend to undervalue high-benefit projects and select a suboptimal portfolio of projects relative to simpler approaches. This suboptimal performance can lead to losses in efficiency as high as 30 percent. We propose a hybrid optimization heuristic that can improve performance.

Protecting the Coastline—Optimal Coastal Inundation Adaptation Mechanisms

Abstract: People living in coastal areas are deeply concerned about the impact of rising sea levels along with the increase in extreme storms that could lead to more frequent coastal inundation events. In addition to physical damage from the initial storm surge, other consequences are likely, including contamination of drinking water,

alteration of soil and water chemistry in forest and wetland ecosystems, mobilization of previously stable chemical contaminants in industrial sites, and severe deterioration of agricultural soil quality. There are a number of coastal infrastructure options available to planners including dikes and levees, surge barriers, wetlands, and dune enhancement. Many landowners and communities have been reluctant to adopt these technologies because of expense or alteration of the landscape. This, along with spatial externalities can lead to an under provisioning of coastal infrastructure, and an opportunity for policy to improve infrastructure development.

This research uses laboratory experiments to test bed different policies in a public good context with payoff dynamics that are explicitly based on realistic hydrological transport dynamics. The experiments include three policy treatments – no mechanism, conditional fixed payment, or a Vickery-Clark-Groves based reverse auction – under both constant and uncertain inundation dynamics. They are designed to test the relative effectiveness of the two policy mechanisms in this context, how changes in the inundation dynamics consistent with sea level rise and increased extreme events affects the mechanisms, and how effective the mechanisms are at increasing coordination in investment decisions. Interestingly, the fixed payment is effective primarily in the constant inundation case, while the VCG mechanism is primarily effective in the random inundation case. Unfortunately, neither mechanism was very effective at increasing coordination.

Chapter 1

A NEW APPROACH TO ELICIT CONTINUOUS ATTRIBUTE VALUES USING AN IMMERSIVE SIMULATION ENVIRONMENT: OFFSHORE ENERGY PRODUCTION AND MID-ATLANTIC BEACH VISITATION

Introduction

Convention characterizes approaches to the valuation of non-market amenities and disamenities in terms of Stated Preference (SP) and Revealed Preference (RP). Historically, SP has been the primarily been the domain of survey-type instruments like contingent valuation and choice experiments, while RP approaches, like hedonic and travel cost studies have relied more on directly observed or calculated market data. Recently, both lab and field experiments have crept into both RP and SP literature both as a way of testing the validity of SP methodologies, and as using a high degree of control and precise value elicitation mechanisms to create preference revealing "markets" that would not otherwise exist. This research proposes a novel elicitation and estimation approach that draws from SP surveys, RP data, and lab experiment design. It uses a continuous variation in an attribute of a non-market amenity to generate a very data efficient estimate of the value of that attribute as a function of the variation. We apply this approach to estimate the effect of distance of offshore wind turbines and oil platforms from the beach on travelers' value for a beach vacation – an issue that has been of increasing interest, yet has received only modest attention (Landenburg, 2009; Landry et al., 2012). This approach integrates baseline RP travel cost data, and uses highly realistic, controlled and replicable, lab experiment style simulation that allows users to vary distance from shore of both wind turbines and oil platforms, in response to price signal. The data generated by this allows for estimation in a duration model context, from which WTP as a function of distance may be recovered.

Past efforts combining both SP and RP into a single analysis have taken many approaches, which are reviewed in Whitehead, et al. (2008a). Typical approaches to this include "stacking" RP and SP data with identical structures into a pooled dataset to extend sample size, or estimating separate models, often within subjects, to test for "convergent validity" or biases in methods. Recent approaches more directly integrate RP and SP by taking participants' observed behavior as a baseline, and then extending that with hypothetical variations of attributes (Train and Wilson, 2008; von Haefen and Phaneuf, 2008). This research is similar to this extended RP approach, but is has important differences in both the elicitation approach and the analysis. The elicitation instrument was designed to facilitate both an immersive decision environment, where participants controlled computer simulations involving an environment visually replicating the beach that they were visiting while they were taking the survey. The response data was structured as "spells", or adjacent spans of distance over which the offshore energy facilities would be acceptable at a given price, instead of the customary set of dichotomous choice, or referendum responses. This type of continuous variation is often a component of non-market goods. Other examples include proximity to amenities such as open space and farm land (Ready and Abdalla, 2005; Bergstrom and Ready, 2009), or protected habitat (Pate and Loomis, 1997; Loomis 2000; Neumann, Boyle, and Bell, 2009), or to disamenities, such as contaminated sites (Ihlanfeldt and Taylor, 2004; Messer et al, 2006), or the width of nourished beaches (Shivlani, Letson, and Theis, 2003; Whitehead, et al.; 2008b, Parsons, et al., 2013).

Dichotomous choice questions have been the de facto elicitation format for environmental valuation studies since Arrow et al.'s (1995) report to the National Oceanic and Atmospheric Administration (NOAA) on contingent valuation endorsed it as the standard for such work. This referendum-style choice format has persisted for two decades through the extensions of contingent valuation into the science of choice modeling. This contrasts with direct response formats such as open-ended -elicitation questions that seek responses in terms of willingness-to-pay (WTP) given a set of attributes. The upside of questions that directly measure WTP is precise observations, generally either points or small intervals. Dichotomous choice responses offer only yes/no responses at a few fixed prices so studies that use them typically require much larger samples to obtain a similar level of accuracy (Cameron and Quiggin, 1994). However, as consumers, research participants typically are much more familiar with posted-price decision-making. They are comfortable assessing whether they would be willing to accept an offered deal. The question of exactly how much they would be willing to pay for a hypothetical package of attributes is a far less familiar task and thus is more cognitively taxing. It is possible that studies of willingness-to-pay for a bundle of a large number of attributes are prone to bias (Balistreri et al., 2001). Exactly how substantial such bias may be is the subject of debate and likely depends on how familiar the situations presented and the design of the elicitation instrument are to participants.

Attempts have been made to improve the efficiency of dichotomous choice instruments. A notable example is the double bound (or interval) method, which poses a yes/no WTP question at a particular price level and then, depending on the response, presents a follow-up question involving a different price level (Albeini, 1995). Thus, the decision remains in the posted-price decision space, and the structure considerably improves the statistical efficiency of data collected (Hanemann, Loomis, and Kanninen, 1991). However, Cameron et al. (1996) observed a degree of inconsistency between the distributions of WTP for the initial and follow-up questions and speculated that introducing a new price-point may have caused participants to update their degree of WTP, which would be consistent with theories of value formation (Plott, 1996; Braga and Starmer, 2005; Kingsley and Brown, 2011).

In this research, we approach this using computer technology and drawing on approaches from lab experiment techniques, we developed a simulation related to offshore energy development off the Mid-Atlantic coast in the United Sates in which participants respond to the level of attribute provided at a given price. The simulation can be repeated using various price levels and attributes to obtain a series of observed intervals of attribute acceptance, which can be modeled with standard duration (or survival) models that estimate effects on the time required to achieve an event. When time is replaced by cost, duration models generate estimates of demand curves (Steinberg and Carson, 1989). Duration models are commonly used to estimate WTP from both payment-ladder valuation data (Wang and He, 2011) and medical treatment data (Luchini, Daoud, and Moatti, 2007). The approach recovers WTP as functions of attribute levels at the mean, at the median, or for a specific consumer when the model is specified in terms of attribute level with cost as a covariate.

Duration models offer new options in addressing issues like censoring and modeling unobserved heterogeneity. As shown below, they are consistent with the random utility model, the approach that motivates empirical analyses of dichotomous choice data, while also providing greater statistical power in the face of data collection constraints. We use a Monte Carlo experiment to compare estimates of WTP recovered from a duration model to WTP estimated from a simulation experiment involving multiple dichotomous choices using a logit model. We find a significant difference between the two sets of estimates. With small sample sizes, the difference is quite large, while even with "moderately" sized samples in the 50 to 100 respondent range, the magnitudes of the standard errors produced by the duration model are on the order of half of those of the dichotomous choice data. We then apply the two models to data collected from beach visitors to estimate the value of the visual disamenity generated by offshore energy production (wind turbines and drilling platforms).

Data were collected from an intercept survey of visitors at two popular Delaware beaches. Respondents reported information on their trip costs and then were asked to participate in a computer-simulation choice environment, involving a picture of the same beach on which they were standing with computer-generated wind turbines or oil platforms superimposed on the horizon. Participants were asked to adjust (i.e., enlarge or bring closer) the location of the turbines or platforms until they would no longer be willing to visit the beach despite several randomly assigned price discount. The distance choice data allowed estimation of a model of visitor attrition based on proximity to energy generation infrastructure using co-varying costs of the trip, type of energy generated, and demographic characteristics. Results show that beach visitors are relatively indifferent to wind turbines that are at least two to three miles offshore, are less accepting of oil platforms, and have a smaller price elasticity of demand for drilling platforms than for turbines.

Methods

As in a double-bound design, the model uses a dichotomous-choice referendum (accept or reject) for a fixed attribute bundle.1 In this study, however, participants may adjust their bundles after making an initial choice by decreasing the bundle to indifference, i.e., the point at which they would no longer make the same choice and thus equivalent to reducing their surplus to zero. Thus, instead of making decisions based on the price they are willing to pay, participants face a fixed price and instead "choose" by adjusting a continuously varying attribute to achieve a fixed

[1] An obvious extension of this work would be a multivariate choice model.

(reservation) level of utility. For concreteness, one can think of the "attribute" as distance of a group of wind turbines from shore, though this could be generalized to many other settings. Then, this process would be to fix the price at the cost of a vacation, and adjust the distance of the turbines from shore until the visual disamenity has absorbed the entire surplus. The exercise then repeats with different fixed prices.

By observing several price/distance pairs at the reservation utility level, we can trace the shape of an indifference curve through the reservation utility and locate it in the price/distance space. The survey instrument allowed participants to adjust the distance and gave them a realistic visual depiction of the results of their choices. As a result, the decision environment was more concrete than decisions made in terms of hypothetical monetary values.

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Estimation Approach

Consider individual i's choice of an outcome from a set of several options. According to the random utility model, individuals choose an outcome of interest, $j = 1$, when they believe that the utility associated with outcome $j = 1$ exceeds the utility of all other outcomes and the outcome of their next best option, $j = -1$, in particular.

$$U_{i,1} \geq U_{i,-1}$$

The indirect utility functions for both $j = 1$ and $j = -1$ are a function of the price associated with the outcome, $p_{i,j}$, and a vector of other individual, outcome-specific attributes, $z_{i,j}$. Suppose that outcome $j = 1$ includes turbine distance, which can take a value within a set range, $w_d \in [\underline{w}, \overline{w}]$, that has an effect on the utility of the outcome but not on utility of the other alternatives.[2] In our case, if we assume that the utility of the beach visit is linear in w_d, then

$$U_{i,1} = V(p_{i,1}, z_{i,1}) - \alpha w_d + \varepsilon_{i,1},$$

$$U_{i,-1} = T(p_{i,-1}, z_{i,-1}) + \varepsilon_{i,-i}.$$

The probability of an individual choosing option $j = 1$ can be expressed as:

$$\Pr[U_{i,1}(w) > U_{i,-1} | p_i, z_i] = \Pr[V(p_i, z_i) - \alpha w_d + \varepsilon_{i,1} > T(p_i, z_i) + \varepsilon_{i,-i} | p_i, z_i]$$

$$= \Pr\left[\frac{1}{\alpha}\left[V(p_i, z_i) - T(p_i, z_i) + \varepsilon_{i,1} - \varepsilon_{i,-i} > w_d\right] \middle| p_i, z_i\right]$$

$$= \Pr[U^* > w_d | p_i, z_i]$$

$$= S(w_d)$$

conditional on the alternatives' prices and the attributes.

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[2] In this case, we assume that decreasing values of attribute w have a negative effect on utility. The opposite could be easily accommodated by switching signs in the derivation of WTP from the hazard functions specified.

$U_{i,-1}$ thus acts as a reservation utility with the distribution $U_{i,-1} | p_i,z_i$ inherited from $\varepsilon_{i,-1}$. U^* is a random variable representing a scaled premium in utility for $j = 1$ when w_d is at the furthest bound of its range, $\overline{w}$. This U^* will be a random variable with a cumulative distribution of $F(w_d) = \int_0^w f(s)ds$. The function $S(w_d)$ is nearly identical to the survival function used in duration analysis except that in this case it is a function of w_d instead of time. An instrument that can solicit participant decisions in terms of a "withdrawal point" can be used to estimate the random utility model under a duration approach using standard econometric software. It is also useful to consider the hazard function: $\lambda(w_d) = f(w_d) / S(w_d)$. The survival function, $S(w_d)$, indicates the probability that an individual will continue to choose outcome $j = 1$ for $w < (w_d)$ while $\lambda(w_d)$ indicates an instantaneous likelihood of switching to the next best option at w_d.

The distribution of $U^* | p_i,z_i$—and hence the parametric specification of the duration model—depends on the distributions of $\varepsilon_{i,1}$ and $\varepsilon_{i,-1}$. Under the common assumption that these are both extreme value type I (EVI) distributions, $U^* | p_i,z_i$ will be logistic and the estimated duration model will be log-logistic. If we assume that both are normal distributions, $U^* | p_i,z_i$ will be normal, and the estimated duration model will be log-normal. If we assume that the disturbance on the utility of outcome $j = 1$ is EVI while the reservation utility is normal, then the difference will be an extreme value distribution, and the duration model can be specified as a Weibull model.[3] In practice, the choice between these models is often guided by the data, either through parameter significance tests for nested distributions (several of the distributions used in duration analysis are exponential and nested through restrictions on estimated parameters) or, more generally, through comparisons of Akaike information criteria (AICs).

A hazard model generally can be easily recovered from an estimated duration model. When the results are specified in hazard form, WTP is calculated from the estimation by calculating the payment required to maintain the hazard level for a change in attributes, as follows. With payment included as a covariate in the model, the fully augmented hazard function is $\lambda(w_{d;}\, p_{i,} z_i)$. At which point the compensation required to maintain the probability of a switch to the alternative—and hence the same level of utility–solves $\lambda(\underline{w};\ p_i, z_i) = \lambda(w_d;\ (p_i + C), z_i)$. A solution for C as a function of w_d will depend on the distribution assumptions. Notably, if we consider $\boldsymbol{X}$ to be the full covariate vector, β to be the vector of the regression coefficients, β_p to be the price coefficient, ρ to be the shape parameter of the Weibull distribution, and γ to be the shape parameter of the log-logistic distribution, then

for a Weibull model, the hazard ratio is

$$\lambda(w; X) = \rho e^{X\beta} w^{\rho-1}$$

and WTP will satisfy

[3] A Weibull specification is a more commonly used formulations in duration analysis and has the advantage of a relatively clean hazard function, and a resulting WTP function that depends only on p and w.

$$C(w_d;\beta_p,\rho,\underline{w}) = \left[\frac{\rho-1}{-\beta_p}\right]\ln\left[\frac{w_d}{\underline{w}}\right].$$

for a log-logistic model, the hazard ratio is

$$\lambda(w;X) = \frac{e^{X\beta}w^{(1/\gamma-1)}}{\gamma[1+e^{\left(-X\beta/\gamma\right)}w^{\left(\frac{1}{\gamma}\right)}]}$$

and WTP will satisfy

$$C(w_d;X,\beta,\gamma,\underline{w}) = \frac{\gamma}{\beta_p}\ln\left\{\left[\frac{w_d}{\underline{w}}\right]^{\left(\frac{1}{\gamma}-1\right)}\left[1+e^{-\frac{X\beta}{\gamma}}\underline{w}^{\frac{1}{\gamma}}\right]-\left[w_d{}^{\frac{1}{\gamma}}\right]\left[\mathrm{e}^{-X\beta}\right]\right\}.$$

Note that C in the case of the Weibull distribution is a function only of the price parameter and will be constant across the population; for the log-logistic distribution, C is a function of the full parameter vector and individual attributes so it will vary across individuals. Therefore, we must consider C functions for a given, mean, or median individual. The functions will describe iso-payment lines that maintain a given level of utility. Based on the WTP function for a particular (or average) participant, one can add a constant to satisfy a cost/distance point, again using a mean, median, or particular individual.

Estimator Efficiency

This approach is an alternative to dichotomous-choice/mixed-logit estimations because the data per observation have a higher resolution and thus should provide greater efficiency in terms of the ratio of sampling effort to statistical power. We test this hypothesis using a Monte Carlo experiment using realistic data generated based on data from beach visitors, described in the next section, similar to the approach in Kumioff, Parmeter and Pope (2010).

In this study, true parameters are assumed to represent individual participants' price and attribute parameters in the indirect utility function for the outcome of interest and for distributions for individuals' costs, disturbances on the utility function, and reservation utilities (see Table 1). The values were chosen reflect a distribution of costs, and a proportion of decisions that was similar to the data collected from on-site experiments with Delaware beach visitors, as described in the next section. The utility parameters and trip costs are used to describe the particular individual and the cost factors and attribute levels describe the points used in sampling.

Using these values, a sample of *n* participants is drawn. For each participant, we calculate a reservation utility, $\overline{U_i} \sim N(0, 1)$, and a utility level for each combination of sampling D_j and W_k:

$$U_{i,j,k} = \alpha + \beta C_i D_j + \gamma W_k + \varepsilon_i$$

where $U_{i,j,k}$ is the level of utility associated with the cost for the participant, C_i. C_i is a multiple of the cost for observation, D_j, and a value for the continuous attribute for the observation, which is represented by W_k. We then calculate nine responses from a dichotomous choice experiment using a response variable of $Y_{DC;i,j,k} = 1$ if

$U_{i,j,k} > \overline{U}_\iota$ and $Y_{DC;i,j,k} = 0$ otherwise. Using the response variable, the cost, and sampling variables, we estimate a fixed effects logit model and WTP_{DC}, which represents the marginal WTP for the attribute under the dichotomous model. We then calculate the 95% confidence interval and standard error using a parametric bootstrap method (Krinsky-Robb, 1986).

After estimating WTP_{DC}, we calculate the continuous response that will be modeled with a Weibull specification $Y_{W;\,i,\,j}$) by solving for the value of W_k that satisfies $U_{i,j,k} = \overline{U}_\iota$for each value of D_j:

$$Y_{W;i,j} = \frac{1}{\gamma}[\overline{U}_\iota - \alpha - \beta C_i D_j - \varepsilon_i].$$

This calculation generates three observations whereas the dichotomous choice experiment generated nine. We use these three observations to estimate a Weibull duration model and WTP under that model, designated as $\mathrm{WTP_W}$, using the same system as for $\mathrm{WTP_{DC}}$. Standard errors for the Weibull estimate are calculated using the delta method. This procedure repeats 10,000 times for each value of *n*.

Figure 1 displays the results of our calculations in terms of standard errors as a function of sample size for the dichotomous choice (WTP_{DC}) and continuous response (WTP_W) estimates. Based on the parameterization, the true WTP is 120. Consequently, WTP_W consistently generates smaller standard errors but the standard errors appear to converge as sample size increases.[4] At $n = 20$, WTP_W is significantly greater than zero at a 95% significance level. WTP_{DC} does not achieve that level of significance until $40 < n < 50$. If we consider a "moderate" sample size of $n = 100$, WTP_W has a standard error of about 9.5. WTP_{DC} does not achieve that standard error until $n > 150$. Thus, if we consider a typical sample range for this case, WTP_W requires a sample size one-half to two-thirds of the sample size required by WTP_{DC} to achieve a given level of precision.

Application: Offshore Energy Production and Beach Tourism in the Mid-Atlantic

To reduce dependence on fossil fuels, agencies in many coastal areas have proposed offshore wind projects as alternative sources of energy. An issue that arises for virtually all wind projects is whether wind turbines disfigure the natural seascape, thereby reducing residents' utility and tourism. A typical offshore wind project can include more than 100 turbines, each more than 400 feet tall, within sight of the shore. Similarly, oil platforms generate domestic fossil fuel, such as those established about one mile off the Gulf of Mexico's coast, and are visible from the shore. The potential disamenity impact of both structures drives some opposition to offshore energy projects. Perhaps the best-known conflict involves the Cape Wind project in Nantucket Sound off Cape Cod in Massachusetts. It was delayed for more than a

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[4] In general, the ratio of standard errors, r_s, will converge to some $c \leq 1$. In this case, $c = 0.75$. It achieves $r_s > 0.74$ at around $n = 200$.

decade because of objections from local residents whose ocean views would be interrupted. Similar objections to the appearance of wind turbines have recently been raised for by resort developers off the coast of Scotland, and as a potential keystone campaign issue by UK prime minister David Cameron and the conservative party.

One proposed solution is to locate such projects far enough away to alleviate the visual disamenity. The visibility driver of the conflict can be resolved entirely if the structures can be placed beyond the view of the horizon. Unfortunately, constructing turbines farther away increases capital and maintenance costs because the depth to the ocean floor increases. In addition, the cost of delivering the energy generated rises farther from the coast.

We estimate visual externalities associated with wind turbines and drilling platforms and investigate how such costs are affected by placing the structures farther from the shore. In the Mid-Atlantic, opening the state's coastline to offshore oil exploration also has been given consideration, and a recently proposed offshore wind projects has generated controversy. Thus the problem setting is rooted in live, recent debates.

Ladenburg (2009) provides an overview of the literature on amenity valuation related to wind projects, with more recent contributions from Gee (2010) and Landry et al. (2012). Less work has focused on the visual impacts of offshore oil and natural gas production (Nassuaer and Benner, 1984 being a notable counterexample), even though many of the same coastal areas that have considered adapting wind energy have been also considered for fossil fuel exploration (US MMS, 2010). Of particular interest, Krueger, Parsons, and Firestone (2011) studied offshore wind projects and the effect of how distant they would be from the coast in Delaware using a stated preference choice experiment involving projects situated 0.9, 3.6, 6.0, and 9.0 miles offshore for inland, bay, and ocean projects. Their results showed a disamenity value for beach residents of $19, $9, $1, and $0, respectively. Given that the value of a beach visit varies continuously with respect to the distance of such structures from shore and that the marginal social cost of moving a project back is of direct interest in determining optimal siting, this setting provides a useful application of our methodology.

Design

Iterative survey design occurred over two years, first, with semi-structured testing with a focus group composed of administrative staff members at a large public university in the Mid-Atlantic and, second, with an on-site pilot survey conducted with beachgoers at Rehoboth Beach, Delaware. These efforts produced feedback that led to refinements of instrument format and wording, but also allowed for testing the usability of the computer interface to ensure that subjects found the interface usable and unbiased. On-site beach intercept sessions with a four mobile computer interfaces produced many practical challenges (especially, sun, heat, and dust), which required significant time and effort to overcome.

The final version of the survey consisted of a computer exercise and a written survey instrument. The computer portion of the session elicited travel cost information and presented images of the beach that participants were at with realistic wind turbines or oil platforms on the horizon. Participants were able to adjust the distance of these objects from shore, in response to variations in price, implemented as a discount on the cost of their trip. Participants first responded to onscreen questions about the various costs associated with their vacation at the beach, including travel, food, lodging, retail spending, and amusements. This was similar in design to a revealed preference travel cost study. For each category of costs, respondents were provided with a pull-down list of values ranging between $0 and $5,000 in $50 increments. The sum of the cost responses (using midpoints of the $50 increments) from each category was calculated. Respondents were shown this total on their computer screen and could either accept it as reasonably accurate or adjust it to better represent the trip's total cost.

Final enumeration occurred with visitors to two popular Delaware beaches, Rehoboth Beach and Cape Henlopen (Figure 2), on July 12 through 15 and July 29 through August 1, 2012. Rehoboth Beach is a resort town with a beach and boardwalk while Cape Henlopen is a less developed, more natural beach in a state park. Rehoboth Beach is highly developed with hotels fronting on a boardwalk, restaurants, and other attractions. It mainly draws visitors from Delaware, Maryland, and the Washington DC metro area. A fenced-off dune area punctuated by intermittent access walkways separates the boardwalk from the beach. A large public parking lot serves as the primary spot for beach access to at Cape Henlopen as foot traffic is funneled on a single boardwalk a public bathhouse and small concession stand.

In both settings, enumerators approached the lead adult individual in every third group of visitors entering the beach on an access path and asked this individual to participate in a twenty-minute survey about his or her beach experiences. Pilot experiments showed a high refusal rate because of the high time commitment. So, in the final survey, those who declined were offered the opportunity to participate in a short two-minute survey about their opinions regarding a series of images of wind turbines and platforms offshore at various distances. The data from the short survey were used to test for any indication of nonresponse bias (see further discussion in the section below). Individuals who agreed to take the full survey proceeded to a tent containing four survey stations and were offered a bottle of water. To ensure privacy, the stations were placed several feet apart and had privacy screens, which also helped mitigate glare.

Participants were seated and instructed to put on headphones. They then watched a two-minute video demonstrating the interface and showing the full range of possible placements for offshore turbines and oil platforms on their computer screen. Respondents then answered onscreen questions about the costs associated with their beach visit. The final computerized section of the survey showed each participant a photo of the beach they were visiting with either 100 wind turbines or two oil platforms (thus providing equivalent amounts of energy) on the horizon. Figure 3 shows examples of images used in the research.

Using cursor keys, participants could scroll to change the size of the energy structures in intervals small enough to be essentially continuous (on the order of several feet). The program allowed participants to locate the turbines/platforms anywhere between ten miles (the farthest distance at which they can still be seen from the beach on an average day) and one-quarter mile (a function of the image of the structures remaining mostly contained within the computer screen). The starting spot for the turbines/platforms observed by the participants was varied randomly to avoid potential anchoring effects. The administrator asked each participant to use the computer interface to relocate the turbines/platforms to the point at which they would not have visited the beach.

Respondents were then asked to consider a scenario in which the local chamber of commerce offered travel discounts to increase tourism after construction of the energy project, thus reducing the cost of their trips, and were asked to move the turbines/platforms to make their proximity consistent with the discounted trip cost. Finally, participants repeated the exercise in response to a second discount, generating three price-level observations per object per participant. The potential discounts (25%, 37%, 48%, 58%, 67%, 75%, 82%, 88%, 93%, and 97%) were drawn at random without replacement, and the higher of the two discounts selected was offered first. Participants completed the process for one type of project and then repeated it for the other installation type. The type of installation (wind turbines or oil platforms) shown first was alternated each day. The same two discounts applied to both wind turbines and oil platforms. Once they finished the computer survey, participants filled out a written survey (see the Appendix) that requested demographic and attitude information measured.

Results

The full survey results were compared to those of the abridged survey to test sample response validity. In both, participants were shown wind turbines and oil platforms at random distances from the shoreline and asked if those structures would have enhanced, detracted, or made no difference to their beach experiences. Figure 4 displays the results of this comparison. The distributions of attitudes for the two samples are similar and are not statistically different.

Table 2 offers some basic summary statistics of participants that completed the full exercise. On average participants were slightly older and wealthier than national medians, which is not surprising for a sample of beach visitors. The general impressions of the initial images shown to participants were surprisingly similar for wind turbines and oil platforms. For both structures, around of participants 50% report that it would not make a difference to their beach experience, and about 25% say that while it would detract it would not cause them to alter their vacation plans. Only about 15% said it would have caused them not to have visited that beach. In spite of the similarity in stated attitude, when asked to move the structure to the point at which they would not have been willing to visit at their current trip price (before any discount was offered), the average placement for wind turbines was between 2.5 and 3 miles from shore, while the average initial placement for oil platforms was about 5.9 miles from shore. Figure 5 shows the distribution of participants' initial (pre-discount) placement of the turbines/platforms relative to the cost of their trips. Note that placement of both turbines and platforms spikes at ten miles. This indicates censoring because respondents were not allowed to place the structures more than ten miles from the shore. The spike is significant for both structures but was much larger for oil platforms (22.3% of all responses) than wind turbines (8.9% of all responses). For the uncensored observations, oil platforms are fairly uniformly distributed throughout the distance range while turbines are generally clustered within three miles of the shore, a result that is consistent with Krueger, Parsons, and Firestone's (2011) finding that disamenity values for offshore ocean wind turbines decreased drastically between 4 and 6 miles from the beach.

Figure 6 depicts keneral-smoothed hazard curves that represent the relative probability of a visitor choosing an alternate travel destination at a given distance of the structures from the shore. Figure 7 shows Kaplan-Meier survival curves that represent the share of visitors who would continue to visit the beach at a given distance for the structures. The curves show a greater hazard and a smaller beachgoer population for oil platforms than for wind turbines. Again, the results illustrate the dramatic increase in attrition of visitors in response to structures placed within two to three miles of the shore.

We estimate the full duration model as a multi-sequential event model (Andersen-Gill, 1982). Duration models represent data as "spells", or logged distance between (possibly censored) staring points and events. Sequential event models control for endogenous starting points when there are a series of events, such that each spell begins when the proceeding one ends (i.e. after the initial placement of wind turbines or oil platforms by participants, the distance spell for each price level begins at the end of the prior price spell). Table 3 shows the results of the estimates, with coefficients reported in standard, instead of exponentiated (or hazard ratio) form. The coefficients represent the effect of the covariates on the acceptable placement of the structure relative to the horizon, with negative numbers indicating movement closer to the beach. The significant negative constant for wind turbines indicate a baseline acceptance significantly closer than the horizon, while the coefficient on oil platforms is not significant, indicating a baseline placement at the horizon line. The coefficients can be interpreted as marginal movements toward the shore and away from the horizon. So, for instance those who do not own beach property will be willing to have oil platforms closer than individuals that do own beach properties. Age, trip cost, and visitors to the less developed destination tend to push oil platforms towards the horizon, while there is a small and borderline significant marginal increase in acceptance of platforms for males. Individuals with higher incomes are generally more willing to allow wind turbines closer to shore. The estimated shape parameter, rho, is important in recovering WTP estimates, and serves as a test of specification versus an exponential model when rho equals 1 (or ln(rho) equals 0). The primary parameter of interest from is model is the elasticity of distance with respect to trip cost. This is very significant for both wind turbines and oil platforms. It is also negative for both, indicating a percentage movement closer per percentage point trip discount.

Figure 8 shows our estimates of the total surplus of a beach trip with either wind turbines or oil platforms on the horizon for the mean beach visitor. Note that the distance intersections at about three and six miles denote the point at which such a visitor would choose an alternate destination over visiting the beach. As miles from shore increases, each curve approaches the "over the horizon" value for each installation type. The difference between the two curves at around 10 miles would indicate the baseline difference in disamenity value for each type being off-shore, capturing thing like concern for a relatively higher environmental risk from the oil platforms.

Conclusions

This research proposes a new approach to valuing some kinds of nonmarket goods by taking advantage of continuous variation in attributes of those goods. Observations from a continuous variation model typically are more precise than observations from dichotomous choice surveys and avoid some cognitive challenges associated with approaches that ask consumers how much they are willing to pay for a good. Our approach provides a series of "spell" data over the continuous attribute for different price levels that can be estimated using a duration model. A Monte-Carlo simulation demonstrates that the approach can reduce standard errors by 50% for small to moderate sample sizes relative to dichotomous choice questions with a gap in efficiency persisting asymptotically.

We applied our approach to a survey of visitors to Mid-Atlantic beaches to value the visual disamenity of potential offshore wind turbine and oil drilling projects. In the study, a computer simulation allowed beachgoers to adjust the distance between the beach and turbines/platforms based on the disamenity of the structures for several trip costs. The majority of the beach visitors were generally indifferent to the appearance of wind turbines that were at least two miles from shore and were more resistant to oil platforms. The disamenity associated with the oil platforms is also less price-elastic.

This simulation based continuous attribute acceptance elicitation approach could potentially be applied to any number of non-market valuation scenarios. Possibilities include physical distance related attributes like beach width and proximity to hazardous sites; however the approach can also be extended to other amenities or disamenities that could be presented and adjusted in a simulation environment, like water turbidity, traffic or recreational congestion, view impediments like haze or development, or even noise pollution.

Table 1.Monte Carlo Parameters

Variable	Description	Value
Α	U Intercept	15
Β	U Cost Parameter	-1.2
Γ	U Attribute Parameter	-0.01
C_i	Individual's Trip Cost	Normal(500, 1000)
D_j	Price Factor	{0.5, 0.75, 1}
W_k	Sampling Values for the Continuous Attribute	{6, 12, 18}

Table 2. Descriptive Statistics

Sample Means of Participant Characteristics		
	Rehoboth	Cape Henlopen
Sample Size	126	98
Age	43	49
Income (Median)	$55,001-$65,000	$55,001-$65,000
Percent Male	50.8	44.9
Total Trip Cost	996	416
Initial Impression (at random distance from shore)		
Wind Turbines		
Enhance	0.143	0.143
No difference	0.508	0.408
Detract - Would still visit	0.206	0.265
Detract - Would not still visit	0.143	0.184
Initial placement (miles from shore)	2.52	3.06
Oil Platforms		
Enhance	0.063	0.102
No difference	0.525	0.470
Detract - Would still visit	0.254	0.265
Detract - Would not visit	0.158	0.163
Initial placement (miles from shore)	5.87	5.89

Table 3. Sequential Event Weibull Regressions

Miles from horizon (β < 0 => closer to shore)	Wind Turbines	Oil Platforms
Constant	-6.825*** (1.652)	-2.435 (1.587)
Percent Trip Discount	-0.0227*** (0.0048)	-0.0178*** (0.0056)
Primarily Water Activities	0.137 (0.245)	-0.061 (0.280)
Primarily Sand Activities	0.225 (0.255)	0.362 (0.303)
Own Property at DE Beaches	0.242 (0.325)	1.356*** (0.387)
Income ($10,000)	-0.019** (0.009)	0.008 (0.009)
Years of Education	0.008 (0.029)	-0.029 (0.046)
Age	0.008 (0.006)	0.014** (0.007)
Male	0.125 (0.174)	-0.287* (0.204)
Trip Cost ($100)	-0.003 (0.006)	0.017** (0.007)
Turbines First	0.179 (0.163)	0.109 (0.227)
Henlopen	-0.005 (0.176)	0.378** (0.171)
Ln(Rho)	1.065*** (0.258)	0.599** (0.301)
N	112	112

Note: *, **, and *** represent significance at a 10%, 5%, and 1% level. Standard errors are clustered by participants. Controls for survey recruiter and day were included but are not reported.

Figure 1 Results of Monte-Carlo Experiment

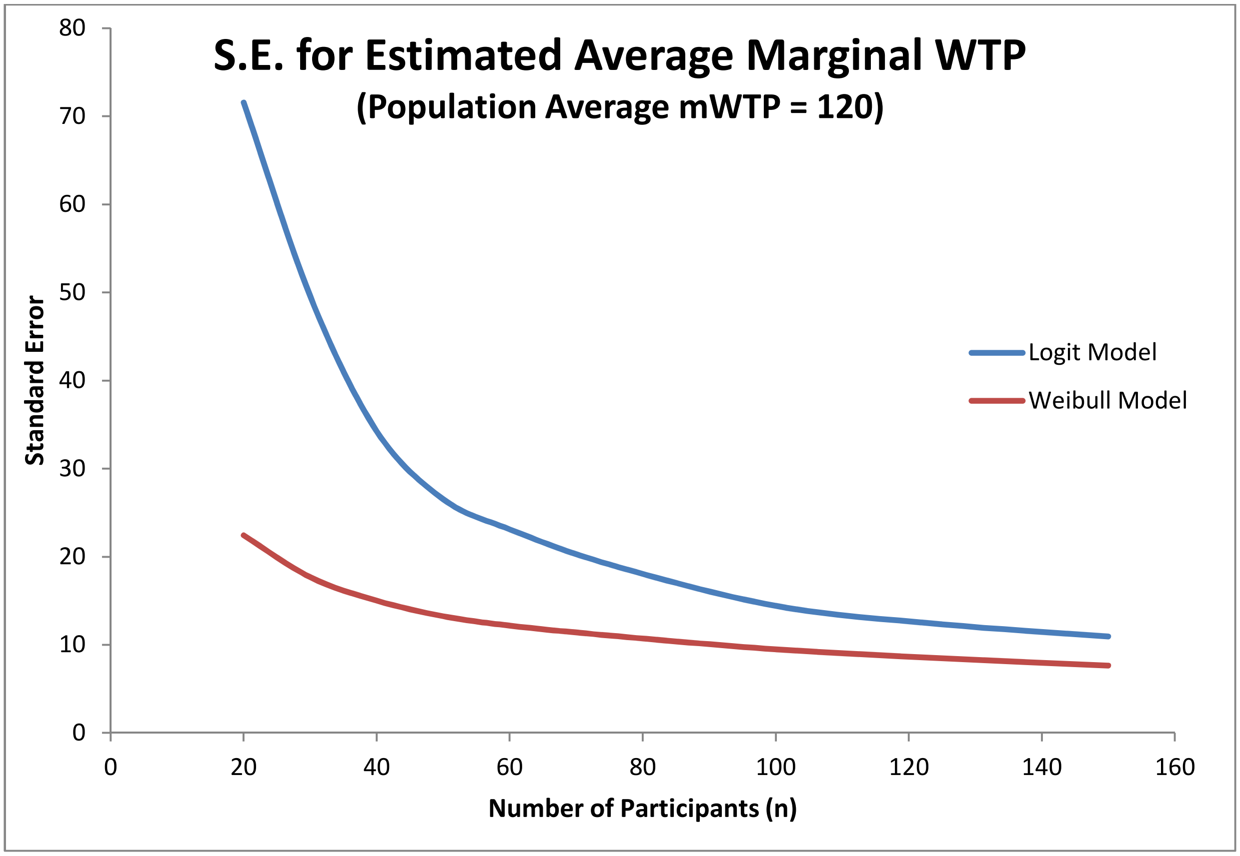


Figure 2 Map of Survey Sites

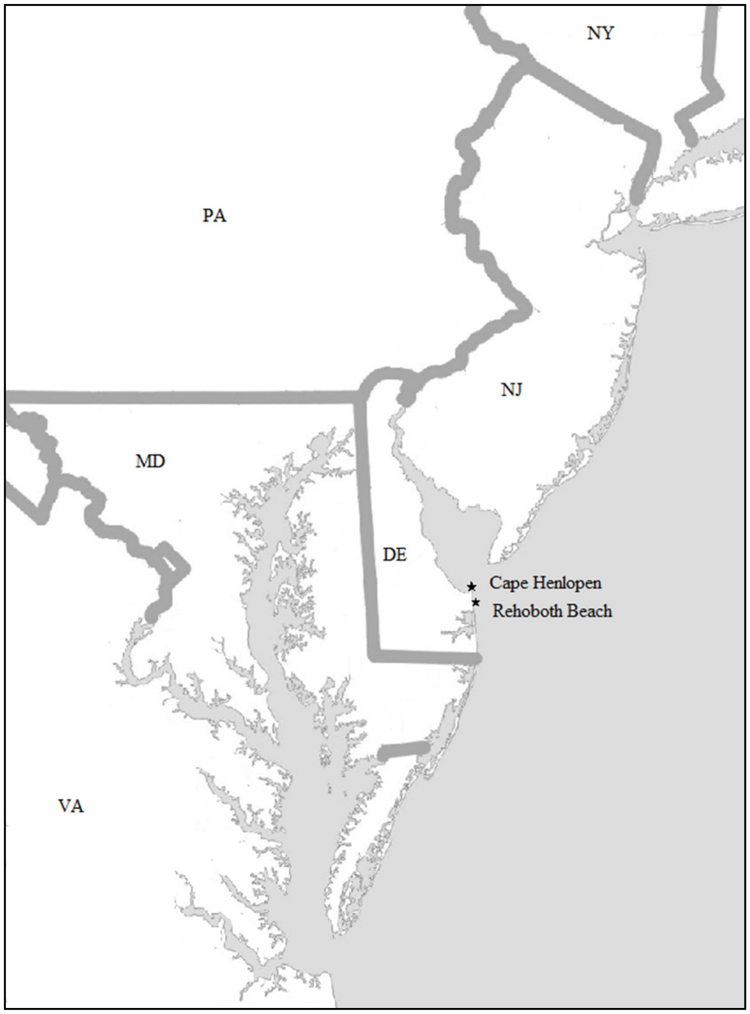


Figure 3 Images of Wind Turbines and Oil Platforms at 5 miles used in the Interface

Figure 4 Basic Attitudes in Survey and Validation Samples

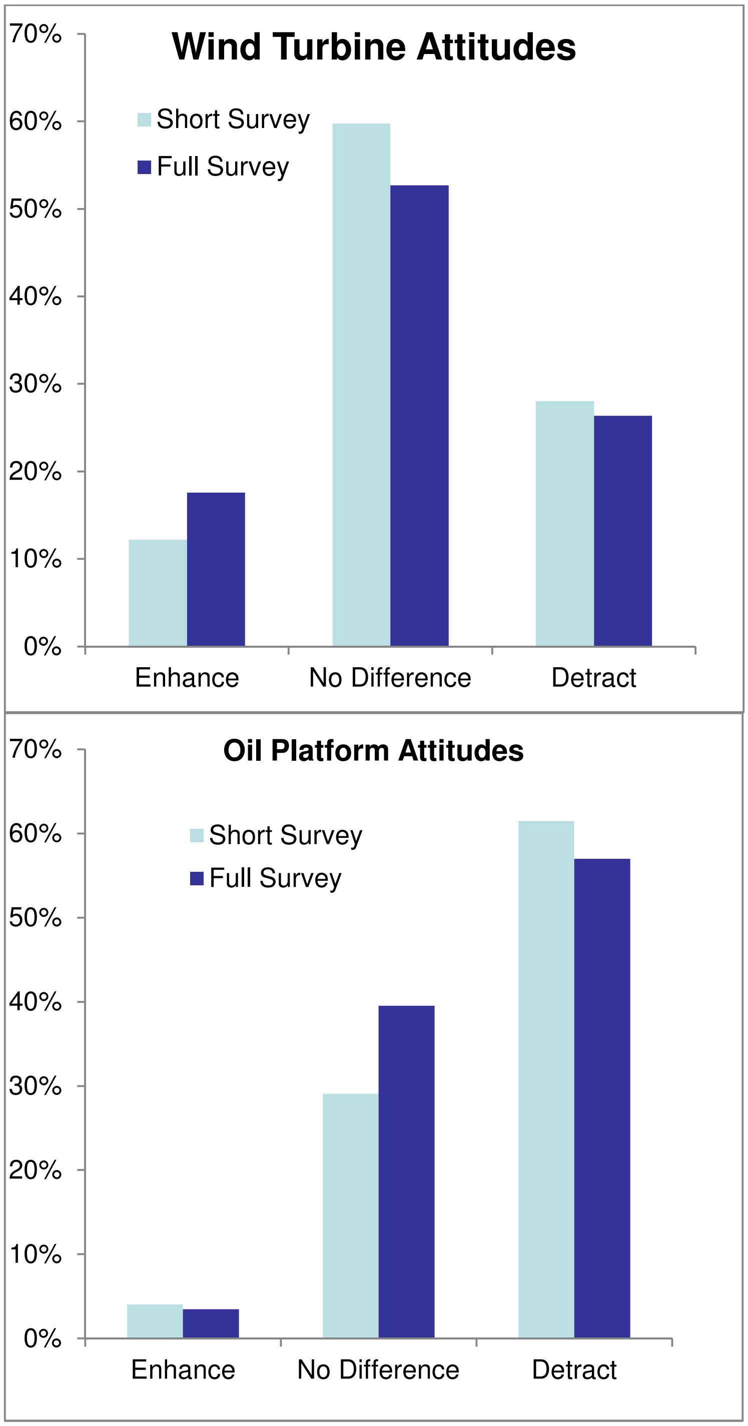
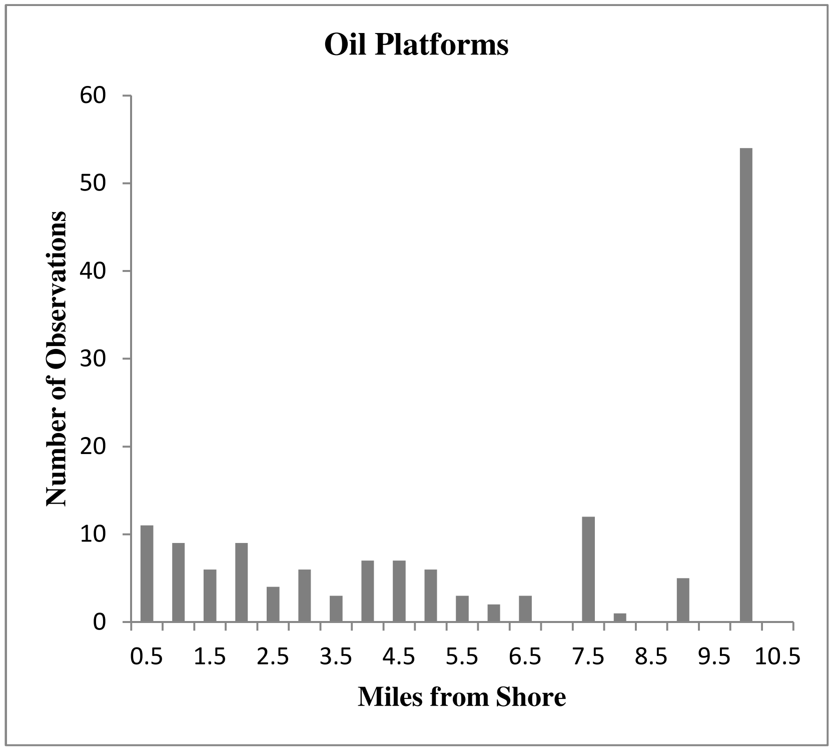


Figure 5 Histogram of Participants' Initial Placement at Reported Trip Costs



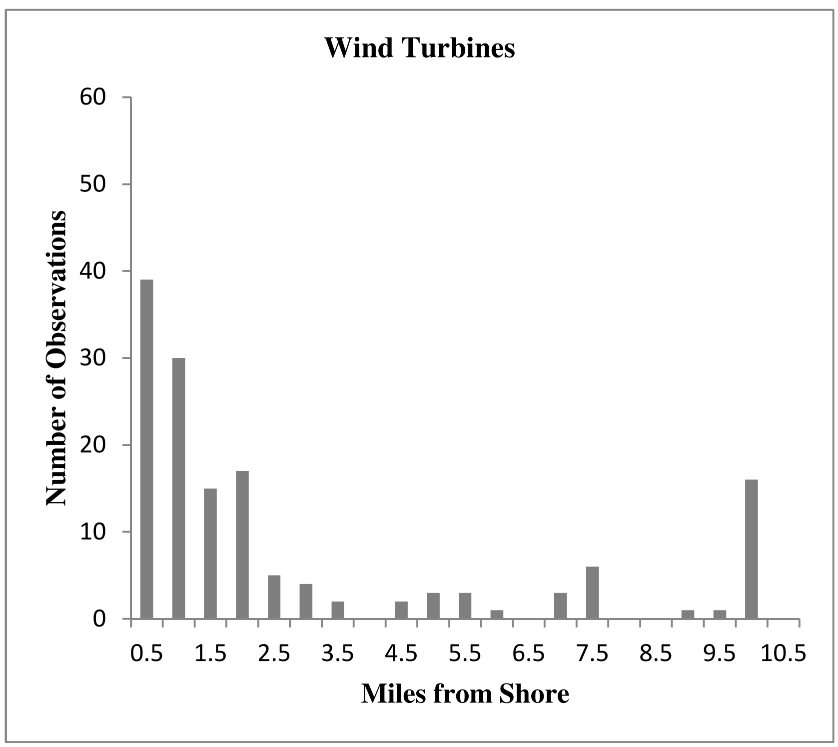


Figure 6 Average Smoothed Hazard Functions at Reported Trip Cost

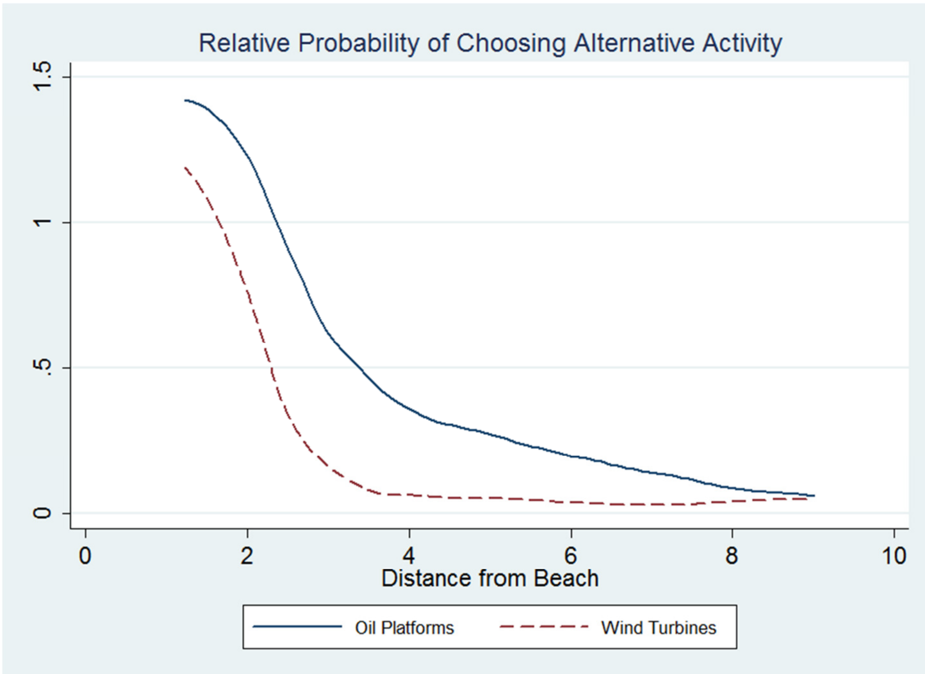


Figure 7 Kaplan-Meier Survival Curves at Reported Trip Cost

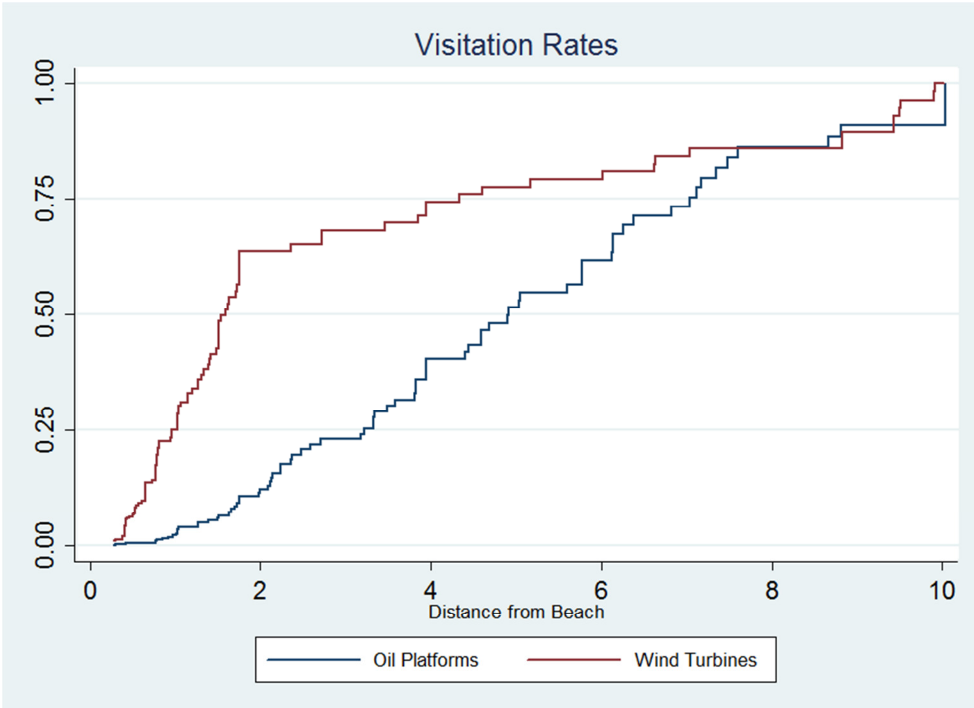
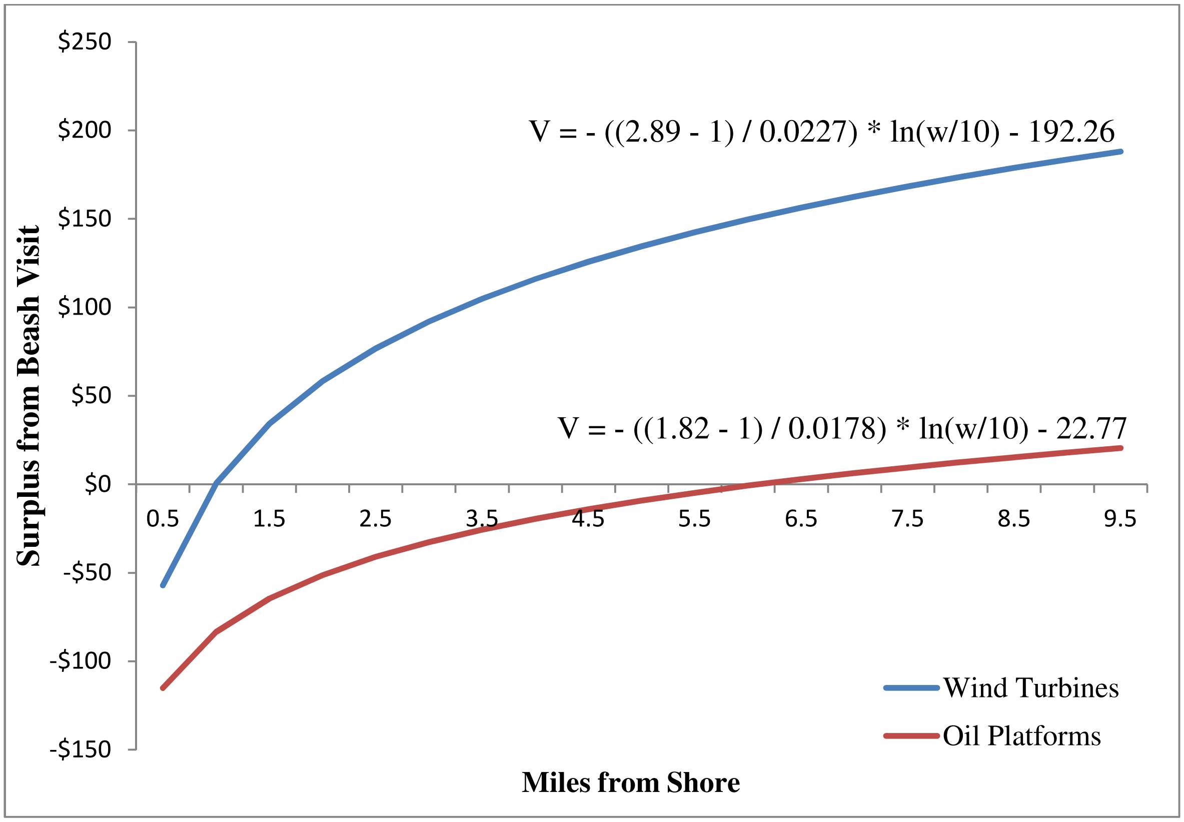


Figure 8 WTP as a Function of Distance



Chapter 2

COST-EFFECTIVE CONSERVATION WHEN USING BENEFIT METRICS

Introduction

This study considers measurement of benefits of conservation projects in the context of the broad literature associated with applying optimization to the process of targeting conservation efforts. Typically, measurements of project quality available to conservation programs do not represent the true value of a project; instead, they are indexes or other proxies for a difficult-to-measure objective. In the best case, they may be thought of as an apparently benign transformation of the underlying distribution of available benefits. However, we show that applying mathematical programming techniques to such proxy measurements can result in selection of a portfolio that falls substantially short of the total benefits available for a given budget. This outcome seems to be inconsistent with the intuition that the solution of an optimization problem would be invariant to monotonic transformations of the objective function. The problem in this case arises from the discrete nature of the solution set combined with a typically log-normal or otherwise skewed distribution of the biological, geological, and other environmental attributes across the landscape. Many standard measures of conservation value and environmental impairment, which include the U.S. Department of Agriculture's (USDA's) environmental benefit index (EBI), the U.S. Environmental Protection Agency's (EPA's) index of biotic integrity (IBI), and a host of state- or program-specific project-ranking tools, tend to normalize the benefits, which leads to over-selection of relatively low-value projects.

The tendency for environmental scoring systems to normalize measured benefits of conservation can be illustrated by drawing from the literatures on both economics and natural sciences. Additionally, we explore the implications of this tendency using a Monte Carlo simulation and find that ill-applied mathematical programming can decrease the overall conservation benefit achieved by as much as 30 percent. There are several ways to potentially solve this problem. We propose a hybrid optimization (HO) heuristic that would select a user-defined number of projects that score highest in a conservation-benefit ranking before applying optimization to select the rest of the portfolio of projects. This system would intentionally over-select otherwise-underrepresented high-benefit parcels and could recapture up to two-thirds of the lost conservation value. This novel approach is robust to positive correlations between benefits and costs. In addition, HO is likely to be more attractive to conservation professionals because it offers them the best of both worlds. They can pre-select several high-profile "signature" projects that offer exceptional benefits and then take a cost-effective approach with the funds that remain.[5]

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[5] One of the few conservation programs that has adopted binary linear programming, Baltimore County's Agricultural Protection Program (as documented in Kaiser and

Conservation Optimization and Environmental Benefits

Over the last three decades, a vast sum of both public and private funds has been devoted to environmental conservation. In 2010, for example, USDA's Conservation Reserve Program alone budgeted $1.8 billion for payments for retirement of farm land (USDA, 2009), and between 1998 and 2003, states and counties spent $31 billion on agricultural land protection (American Farmland Trust, 2010). In spite of this massive spending, most organizations do not have enough funds to take advantage of all of the conservation opportunities available and must carefully choose a handful of projects that they expect will maximize the amount of conservation achieved within the limits of their budget. A rigorous approach to this problem grew out of work using cost-efficiency measures (Babcock, et al., 1997) for policy decision-making and mathematical programming models to formulate and solve biological reserve selection as minimal-set and maximum-covering problems (Underhill, 1994; Ando, et al., 1998; Polasky, Camm, and Garber-Yonts, 2001; Wu, Adams, and Boggess, 2000; Azzaino, Conrad, and Ferraro, 2002; Messer and Allen, 2010). The strategic approach advocated in the literature uses "conservation optimization" approaches that explicitly acknowledge programs' budgetary constraints—binary linear programming (BLP) or benefit-cost-ratio prioritization (Babcock, et al., 1997).

Messer, 2011), has at times selected one or two of the highest scoring projects before turning to the optimization results to select parcels.

However, most conservation programs continue to use a benefit-targeting (BT) (also referred to as rank-based) approach that ignores costs and focuses solely on conservation benefits. We can formally express the BT approach with the following model. Suppose there are N proposed conservation projects in the form of parcels submitted to a funding organization. We represent the value of the benefits available from conservation of parcel n as v_n and the cost of conservation of that parcel as c_n. When the organization has a conservation budget of G and x_n is a binary variable with value of 1 if a parcel is chosen for funding and 0 otherwise, the BT algorithm can be expressed as

Declare array of structures (v_n, c_n, x_n) sorted such that $b_0 > b_1 > \ldots > b_{N-1}$.

For i from 0 to $N - 1$:

If $c_i \leq G - \sum_{j=0}^{i} x_j c_j$, then $x_i := 1$

Else, $x_i := 0$

End

The BLP problem is commonly stated as

(P-1)

$$\max_{x} \sum_{i=1}^{n} x_i v_i$$

$$st. \sum_{i=1}^{n} x_i c_i \leq G$$

$$x_i \in \{0,1\}.$$

Solving this problem would typically be approached with a branch-and-bound algorithm (Land and Doig, 1960) or one of a number of heuristics developed to approximate this problem.

An issue with both formulations is the assumption that we have good measures—a well-defined "conservation value"—of the benefits provided by conservation of each parcel. Ideally, conservation programs would have a way of measuring such benefits that perfectly captures the social value of each parcel under consideration (Duke, Dundas, and Messer, 2013). However, agencies and conservation organizations often do not collect this information, in part due to its expense and lack of staff economists that can do this work. Consequently, conservation programs typically adopt scoring systems that may not adequately capture variability in each parcel's underlying value for conservation. A study by Master (1991) considered conservation prioritization ranking schemes used by biodiversity programs in a number of states and found that many of them were "semi-quantitative rankings" that were largely "subjective" and "misleading" from a scientific perspective. Metrick and Weitzman (1996) found that government land-conservation selections tended to be driven more by "visceral" subjective factors such as the number of acres and habitats provided for "higher life forms" than by any "relevant and measurable" component.

There are many examples of the scoring/ranking systems used by conservationists in recent case studies. Two such studies involved conservation in Costa Rica. Wünscher, Engel, and Wunder (2006) offered a caveat of "coarse data and arbitrary assumptions" in developing a benefit score based on five normalized index scores, and Barton et al. (2003) acknowledged a dearth of biodiversity data and thus used a composite index of "surrogate indicators." Alix-García et al. (2005) recommended optimization of Mexico's program of payment for hydrological environmental services of forests; however, Muñoz-Piña et al. (2008) described the program's ranking system as based on simple grades assigned informally by program administrators. The scoring system used by the USDA Forest Service's Forest Legacy Program, which was incorporated into a multiple-objective optimization problem by Fooks and Messer (2012) employs an average of percentage grades (from 0% to 100% with an average in the 80% range) assigned by state forestry officers. Even USDA's EBI, which is used to rank Conservation Reserve Program applicants, involves the sum of six attribute scores that do not appear to give a true objective measure of the benefits achieved by preservation of a parcel (Farm Services Agency, 2011).

Beyond the question of the quality of the measures used to value projects, there is a more subtle issue. Even if we assume that the conservation organization has a calculated metric that is based on easily observed characteristics and is a good proxy (i.e., the metric is highly correlated with the underlying value), the tendency for scoring systems to normalize the data remains. Normalization here refers to a scoring system which translates difficult to quantify value into a familiar frame of reference, such as percent grades or ranking scales, which try to approximate the ordinal relation of the data. This normalization will tend to compress variability and decrease skew and occurs for a variety of reasons, including limited variability within the grading scale, a tendency of programs to "curve" when assessing a subjective, and numerical transformation that is implicit in the measurement process. When the underlying conservation values are relatively normally distributed, the difference between solutions obtained by optimizing over quality and over value will be small. However, it becomes a more important issue when the underlying distribution is skewed and it is most problematic when there are a few high-cost, signature (also sometimes referred to as “crown jewel”) projects and a larger number of less valuable projects that are close substitutes. A rank- or grade-based quality measure tends to reduce or eliminate this skewness (Solomon, 2008), and an optimization algorithm applied to such a set of parcels will under-weight the high-value parcels and identify a suboptimal portfolio of conservation projects.

Existing theory and prior empirical studies suggest that biological and environmental data are typically log-normally distributed while human willingness-to-pay values for ecosystem services are typically log-logistic. These two distributions present similar densities and behaviors for typical parameterizations (Ashkar and Aucoin, 2012) so we focus on the log-normal distribution since it is the de facto distribution for modeling natural attributes relevant to conservation (Limpert, et al., 2001).

A random variable, X, is log-normally distributed if $\ln(X)$ is normally distributed. A normal distribution is generated from the *sum* of independent random variables and has a confidence interval in a plus-or-minus form: $x \pm c$. A log-normal distribution arises from the *product* of independent random variables and the confidence interval takes a multiplied or divided form: $x \times/\div c$. These distributions typically have a large degree of skewness. Log-normal distributions arise in settings that include either a constant growth rate or some other multiplicative process combined with other random variation. Such settings are common in biological (Koch, 1966) and geological (Krieg, 1966) processes. Well-documented examples of quantities that occur in log-normal distributions include concentrations of elements in soil (Ahrens, 1954; Krieg, 1966), quantities of rainfall (Biondini, 1976), levels of environmental contaminants (Ott, 1978), and abundance of species (Magurran, 1988).

In general, if we believe that the value that conservation secures is generated as the result of some quantifiable property of parcels that has a non-negative value that results from a physical process, this property will be distributed as (Koch, 1966) or well approximated by (Koch, 1969) a log-normal distribution. Basic chemical process, as well as the more complex compound processes that underlie biophysical systems such as proliferation, differentiation, expansion, energy intake, adaptation and maturation can be formulated in thermodynamic terms using the statistics of open systems (Sharma and Annila, 2007). This generates a probability distribution over possible states of the system, and according the principle of maximum entropy, the process will evolve towards more probable states over time. When the system is representative of conserved, non-negative values (i.e. matter and energy), the distribution of this system will approach log-normal (Grönholm and Annila, 2007). Therefore, any case in which the conservation benefits in question are represented by the abundance of some physical quantity such as minerals, nutrients, or species, the benefits will tend to be log-normally distributed.

There are many examples of the tendency of scoring mechanisms to decrease skew and variation in data. EBI scores from applicants in recent rounds of selection for the Conservation Reserve Program have displayed a skewness of less than 0.5 (USDA, 2014) while many components of soil quality exhibit skewness that is significantly greater than 1.5. According to Good, Harms, and Ruckelshaus (2003) (see Figure 1), misuse of checklist assessments in targeting endangered species for recovery efforts "seriously compromises" the adequacy of such efforts. Note in Figure 1 that the composite values (which were based on careful quality assessments of the sites for salmon habitat) reflect the long right tail associated with a log-normal value distribution while the index scores normally used for targeting conservation efforts are much more symmetrical. A similar result is seen in Duke et al. (*forthcoming*), which compares values for multiple parcels of agricultural land in Sussex County, Delaware. Dundas (2011) compared conservation values calculated from geographic characteristics, economic data, and information on the degree of development threat (see Figure 2) with two scoring metrics, land evaluation and site assessment (LESA) and natural resource scores. Once again, the computed conservation values show a large skew while the scoring metrics commonly used by conservation programs are much more symmetric.

Methodology

In this study, we use Monte Carlo simulations to investigate the implications of a transformed, observed conservation benefit measure of the unobserved value of the conservation benefit in BLP and HO contexts. Note that we refer to “value” as the unobserved value of conservation and “measurement” as the observed, transformed conservation value.

We draw a sample of prospective parcels for funding from specified population distributions. From that sample, three subsets are selected: (i) the potential optimal set generated by applying BLP using the (unobserved) benefit values as the objective function; (ii) the BLP-achieved set generated by applying BLP to the observed benefit measure; and (iii) the HO-achieved set generated by applying BLP to the observed benefit measure. The potential optimal set serves as an unachievable (under benefit information constraints) benchmark against which to compare the sets selected by the BLP-achieved and HO-achieved algorithms. This process is repeated 10,000 times for each parameterization, and we then compare the distributions of total achieved benefit values for the two approaches to the benchmark and to each other.

To generate a set of parcels, we assume that parcel n has an unobserved conservation value, vn, that is randomly drawn from a log-normal distribution with scale and shape parameters (μ, σ). The unobserved conservation value is the actual benefits that accrue to society from conservation of parcel n. The observed benefit measure, mn, is generated through an observation function:

mn(vn) = B0 + B1evn. (1)

The exponential function transforms the log-distributed values to a linear scale and a symmetrical distribution while the parameters (B0, B1) allow for shifting and scaling of the distribution of the observed benefit measure. We parameterize the distribution of values so that it always generates a mean of 30.[6] We consider several levels of σ with μ calculated as

$$\mu(\sigma) = ln\left(\frac{30}{e^{\sigma^2/2}}\right) \qquad (2)$$

to maintain a mean of 30 for any given value of σ. The observation function is parameterized with B0 = 50 and B1 = 50, which establishes a range for the scores of 0 to 300, which is similar to the range in the EBI.

The shape parameter (σ) of the value distribution is varied to take on values of 0.25, 0.50, 0.75, 1.00, 1.25, and 1.50. The corresponding scale parameters (μ) generated from equation 2 are 3.3699, 3.2762, 3.1199, 2.9012, 2.6199, and 2.2762. Figure 3 displays the density of each distribution. A value of σ = 0.25 corresponds with a nearly symmetrical distribution of values that has a mean of 30.0, a median of 29.1, a mode of 27.3, and skewness of 1.92. Skewness increases with σ, and the distribution corresponding to σ = 1.50 has a mean of 30.0, a median of 9.7, a mode of

[6] The selection of the value of 30 is just for demonstration purposes and could be thought of as pounds of nitrogen per acre per year. In this example, this level is consistent with reductions in pounds of nitrogen per acre per year achieved by establishing riparian buffers on agricultural land in the Mid-Atlantic coastal plain (Dosskey, 2001).

1.0, and skewness of 21.5. Figure 4 compares each distribution of value with the corresponding distribution of the benefit measurements generated by equation 1. Note that all of the distributions maintain their means across all of the parameterizations. However, while the skewness of the value distribution increases and the medians and modes shift to the left as the value of the shape parameter increases, the skewness, medians, and modes of the measurement distribution remain symmetric; only the degree of variance increases.

We generate per-parcel conservation costs from random draws from a uniform distribution and initially assume that the conservation cost is independent of the benefit value and of the benefit measurement. However, prior studies have suggested that owners of parcels that have significant conservation value can inflate the price of the offer and extract surplus rent (Kirwan, Lubowski, and Roberts, 2005; Arnold, Duke, and Messer, 2013). Thus, to allow the cost of procuring environmental services from landowners to be arbitrarily correlated with the parcels' observable quality, we calculate the cost of protecting parcel n, cn, as

$$c_n(b_n) = C_0 + C_1[\rho \times \frac{m_n}{\bar{m}} + z_n\sqrt{1-\rho^2}].$$

In this expression, zi is a random draw from a uniform [0,1] distribution, C = (C0, C1) represents the lower bound and total range of costs, ρ is the level of correlation between the parcel's quality and the cost to enroll it, and $\bar{m}$ is the mean benefit measurement. For the initial estimates, we use values of C = (200, 800) and $\rho = 0.7$

A set of 30 realizations of (vi, zi) generates a sample of realized benefit values and costs. Using that sample, we consider the problem of a conservation professional who knows the true conservation value of each potential parcel and aims to optimize the provision of benefits by the portfolio of parcels selected subject to a budget constraint. We assume that the budget, G, is half of the sum of all of the offers: G = [(C0 + C1) × N] / 4. When the actual benefit values are known, the conservationist can select the optimal set of projects using BLP as stated in P-1. The vector that solves this problem, xP, is the potential optimal set. This solution would procure a total benefit of VP = Σ(vi × xiP): the benchmark potential total benefit.

When actual benefit values, vi, are not known but the benefit measurements, mi, are observed, the conservation organization can still apply BLP but must optimize over mi:

$$\max_{x} \sum_{i=1}^{n} x_i m_i$$

$$st. \sum_{i=1}^{n} x_i c_i \leq G$$

$$x_i \in \{0,1\}.$$

[7] These values roughly represent an average per-acre cost to implement a riparian buffer best management practice contract in the Mid-Atlantic coastal plain (Lynch and Tjaden, 2000).

The solution to this problem, xBLP, is the BLP-achieved solution and the total benefit achieved by this set of parcels, VBLP = Σ(vi × xi,BLP) is the achieved total benefit by BLP. Note that the solution is calculated using the observed measure, mi, while VBLP is calculated using the unobserved values, vi. Thus, VBLP measures the value that actually accrues to society from applying BLP to the observed measure. Both VP and VBLP are calculated using the same vi while VP is calculated using the vector xP, which maximizes vi; thus, VP ≥ VBLP. We compare the difference in total benefit produced by comparing distributions of BLP's benefit shortfall—the percent of the total (optimal) potential benefit that is achieved by the BLP solution: SBLP = (VP – VBLP) / VP.

For small values of σ, the distribution of the actual values is approximately symmetric. Thus the measurements will be an approximately linear transformation of the values, VBLP will be close to VP, and SBLP will be small. As σ gets larger, most of the mass of parcels will be clustered around the mode and the parcels become perfect substitutes. In that case, xP will select a set of parcels that is similar to the set selected solely by a cost-minimizing criterion. And while VP will always be smaller than VBLP, the difference may be minor. However, the difference becomes problematic as σ increases and marginal differences in the benefits dominate marginal differences in the costs. In that case, the set selected by xP will approach the set selected by a BT mechanism, VBLP can grow arbitrarily larger than VP, and SBLP can be very large.

Since determining the true value of conservation of a parcel is often difficult, expensive, and/or technically infeasible, a heuristic approach to parcel selection is desirable when there is likely to be a large skew in the underlying benefit distribution. In general, any solution aimed at improving the benefit achieved given a particular budget will tend to shift selection into the right tail of the benefit distribution. One imprecise but intuitive way to tackle this problem is to combine the BT selection approach with BLP. That would, in short, force the parcels with the highest observable quality ratings into the selection set, after which BLP could be used to optimize selection of the rest of the parcels from the remaining budget. This hybrid process would combine the most attractive elements of each procedure to "protect the best and optimize the rest." The BT/BLP hybrid model is intuitive and relatively easy to implement and explain, and it will be the most effective selection method when there is a poorly measured distribution of benefits with a long upper tail.

We can include this approach as a constraint by defining a hybrid variable:

$$h_i(m_i) = \begin{cases} 1 \; if \; m \; \geq \; m^{(k)} \\ 0 \; if \; m_i < m^{(k)} \end{cases}$$

where m(k) is the measured quality of the kth-highest-measured parcel. Then, the HO problem can be expressed as

$$\max_x \sum_{i=1}^{n} x_i q_i$$

$$st. \sum_{i=1}^{n} x_i c_i \leq G$$

$$\sum_{i=1}^{n} x_i h_i = k$$

$$x_i \in \{0,1\}.$$

The HO-achieved solution to this problem is indicated by the vector xHO, and the total benefit achieved by this set, VHO = Σ(vi × xiHO), is the achieved total benefit by HO. As in the VBLP case, VP is always equal to or greater than VHO. We similarly define the shortfall of HO relative to the optimal ideal solution as SHO = (VP – VHO) / VP. Of specific interest are the relative magnitudes of VBLP and VHO.8 Next, we specifically explore the relative performance of the BLP and HO approaches. We vary the distribution of the underlying values and allow for correlation between a parcel's quality and the cost to protect it as in Ferraro (2003).9

Using the preceding definitions, we generate 10,000 pseudo-random samples to construct distributions of VP, VBLP, VHO, SBLP, and SHO. We also consider percentage-point differences in the benefit achieved by BLP (BA,BLP) or HO (BA,HO) relative to the first best solution (BP): SBLP – SHO. A positive difference

[8] One might also be interested in considering the benefit achieved by a selection based on benefit-cost ratios (BCRs). Note, however, that the BCR benefit will always be less than or equal to BLP benefit, so conclusions on relative differences versus the HO benefit will be similar.

[9] We also considered measurement error in the benefit-observation function, which would lead to noise in the specification of the optimization as in Jansson (2007) and to variations in parameterization of the observation function. This alternative model did not yield any significant insights and thus the results are not reported. However, the code for all of those simulations is available from the authors.

indicates the amount (in percentage points) by which BLP outperforms HO. A negative difference describes the amount by which HO outperforms BLP in percentage points.

Results

We begin by documenting the BLP shortfall, SBLP = (VP – VBLP) / VP, when only the benefit measure is available. Table 1 reports average potential benefits achieved by BLP when optimizing over (1) the (unobserved) value of benefits (VP) and (2) the (observed) benefit measure (VBLP) plus the percent shortfall (SBLP) for every value of σ. When σ is small, the shortfall is extremely small, less than 1%. As σ gets larger, the difference increases, reaching a maximum of about 12% when $\sigma = 1$. Figure 5 illustrates the distributions of the shortfall for each value of σ. Note how the figures have a heavy right tail that tends to increase as the skew of the underlying benefit distribution increases, which indicates that the amount of benefit achieved using observed measurements quickly degrades relative to the potential benefits available under full value information.

Since BLP leaves a substantial number of potential benefits on the table when applied to observed quality measures, we want to know if the proposed HO heuristic can do better. Table 1 reports the average benefit (VHO) achieved and the shortfall (SHO) that results when the HO approach is applied to observed benefit measures. The shortfall under HO is markedly smaller than the shortfall under BLP; it never exceeds 1.5%. The percentage-point difference between the two is maximized when σ = 1; HO recovers 10.87 points of the 12.10% shortfall that results from BLP.

A key issue in the implementation of HO to conservation optimization is the choice of k, the degree of quality that defines signature parcels. To some extent, the choice is a function of the skew in the underlying distribution. In Table 2, we illustrate HO for each shape parameter (σ) for values of k from 0 to 12, which represents between 0% and 40% of the 30 available parcels. In this case, k = 0 represents a standard BLP approach. And since the available conservation budget is half of the cost to preserve all 30 parcels, values of k of 12 through 15 would generally represent a full BT approach. Values of k greater than 13 or 14 typically are not feasible because the budget is not sufficient to preserve that number of parcels. Higher values of k represent greater percentage-point differences in the shortfall—in how much improvement HO offers over BLP. When σ is small, there generally is a relatively small difference between the results achieved by the two techniques, and the performance of HO relative to BLP is maximized when k represents 10% to 30% of the total project pool. As σ increases, the optimal level of k stabilizes at about 30% of the project pool. Of course, in an actual application, the true level of σ would not be known. However, HO offers decision-makers the ability to parametrically vary k to provide a "menu" of possible conservation sets that can inform them about the choices and tradeoffs they face.

A natural extension in this context is the effect of ρ—the correlation between a parcel's quality and the cost of preserving that parcel (Ferraro, 2003). Table 3 shows average BLP shortfalls for $\rho = 0, 0.3, 0.6$, and 0.9 and Table 4 shows the percentage-point differences in the shortfalls between BLP and HO. We find that high levels of correlation between costs and benefits tend to further decrease the effectiveness of BLP when applied to measurements rather than to true values. Since settings in which benefits and costs are positively correlated are relatively common, this result raises a concern about the ability of BLP alone to make the most cost-effective selection. It appears that the shortfall recovered by HO increases as the effectiveness of HO declines, which increases the advantage of HO over BLP to some extent. It is not clear, however, whether the benefits recovered by HO are increasing or decreasing relative to the shortfall from BLP.

Conclusion

We consider a previously overlooked issue that is critical to the efficiency of applying selection techniques such as BLP and benefit-cost-ratio prioritization to conservation settings: implications of the imperfect quality metrics used by conservation groups to measure the value of benefits delivered by potential projects. We demonstrate that the portfolios selected by both approaches can fall short of the maximum possible benefit by as much as 30% if the grading metric tends to normalize scores from a skewed distribution of underlying value. The problem is most acute when some of the potential projects offer a large, signature-level of benefit but also are expensive.

To address this challenge, we introduce a new hybrid optimization heuristic that is intuitive, is easy to implement, and recovers a substantial amount of conservation value relative to standard approaches. Monte Carlo simulations demonstrate reasonable situations in which the HO recovers 20 percentage points or more of the shortfall by BLP relative to a full-information benchmark. We consider several variations of the assumptions underlying the HO approach, including correlation between the cost and benefit of preserving a parcel. HO typically performs as well as or better than BLP under relaxations of our initial assumptions.

As the state of the art of cost-effective conservation selection progresses and conservation professionals explore various optimization tools, effective communication and implementation of such tools will be essential to their becoming effective and enduring practices. Thus, it is important to recognize that mathematical optimization will not perform well, perhaps not as well as older approaches, when applied to ill-posed benefit metrics. Techniques such as hybrid optimization potentially offer methods for parcel selection that are both attractive to conservation professionals because of their flexibility and effective in procuring the best possible conservation outcomes from limited budgets.

Table 4. Average Achieved Total Benefits by BLP and HO Given Different Levels of σ.

		Binary Linear Programming		Hybrid Optimization		
σ	Potential Benefits (V^P)	Achieved Benefits (V^{BLP})	Shortfall (S^{BLP})	Achieved Benefits (V^{HO})	Shortfall (S^{HO})	Percentage Point Difference in Shortfall
0.25	538.22	534.97	0.60%	535.81	0.44%	0.16
0.50	588.95	559.52	5.01%	580.88	1.41%	3.59
0.75	662.29	600.01	9.34%	653.15	1.42%	7.92
1.00	709.86	624.07	12.10%	701.53	1.23%	10.87
1.25	761.13	689.25	9.64%	753.58	1.05%	8.59
1.50	828.66	772.15	7.23%	823.11	0.81%	6.43

Table 5. Percentage Point Difference in Shortfall Given Different Selections of k for Hybrid Optimization.

Top *k*	Top %	σ = 0.25	σ = 0.50	σ = 0.75	σ = 1.00	σ = 1.25	σ = 1.50
0	0%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	3%	0.0025	0.0119	0.0286	0.0303	0.0197	0.0086
2	7%	0.0036	0.0221	0.0439	0.0531	0.0323	0.0175
3	10%	**0.0063**	0.0324	0.0612	0.0702	0.0539	0.0290
4	13%	0.0010	0.0356	0.0782	0.0856	0.0636	0.0356
5	17%	–0.0017	0.0422	0.0833	0.0976	0.0756	0.0485
6	20%	–0.0086	0.0416	0.0913	0.1123	0.0908	0.0544
7	23%	–0.0153	0.0424	0.0985	0.1146	0.0963	0.0596
8	27%	–0.0271	**0.0430**	0.0986	0.1278	0.1076	0.0690
9	30%	–0.0432	0.0354	**0.1000**	0.1269	0.1073	0.0665
10	33%	–0.0615	0.0215	0.0989	**0.1283**	**0.1141**	**0.0709**
11	37%	–0.0764	0.0104	0.0766	0.1214	0.1086	0.0653
12	40%	–0.0828	0.0008	0.0701	0.0995	0.0985	0.0591

Table 6. Average Benefit Shortfall from BLP with Cost/Benefit Correlation ρ.

	σ = 0.25	σ = 0.50	σ = 0.75	σ = 1.00	σ = 1.25	σ = 1.50
ρ = 0	0.0072	0.0477	0.0934	0.1164	0.1027	0.0700
ρ = 0.3	0.0145	0.0934	0.1766	0.2169	0.2181	0.1886
ρ = 0.6	0.0229	0.1227	0.2206	0.2908	0.3012	0.2625
ρ = 0.9	0.0113	0.1166	0.2180	0.2856	0.3081	0.2534

Table 7. Average Percentage Point Difference between V^{BLP} and V^{HO} in Benefit Shortfall with Cost/Benefit Correlation ρ.

	σ = 0.25	σ = 0.50	σ = 0.75	σ = 1.00	σ = 1.25	σ = 1.50
ρ = 0	0.16	3.58	7.92	10.87	8.59	6.43
ρ = 0.3	0.31	4.18	10.53	10.82	10.31	12.38
ρ = 0.6	0.98	5.64	10.84	13.39	19.64	15.08
ρ = 0.9	0.28	9.97	18.51	21.52	21.38	17.90

Figure 9 Good, et al. 2003).

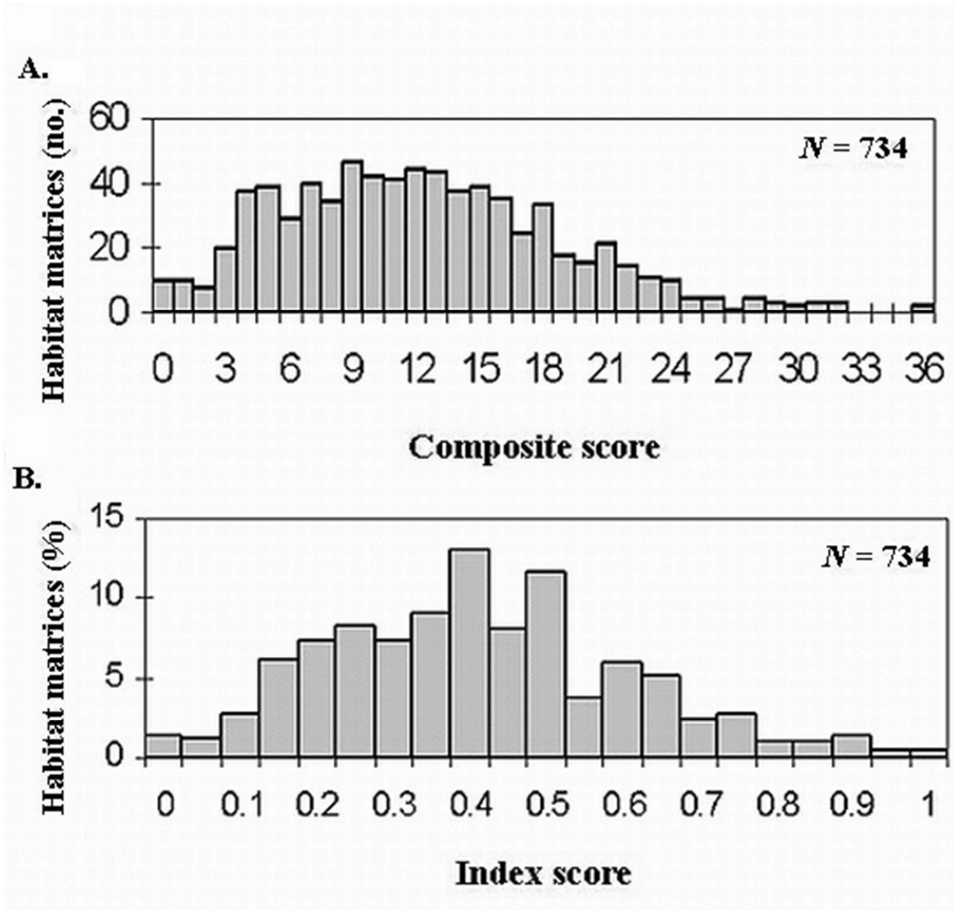
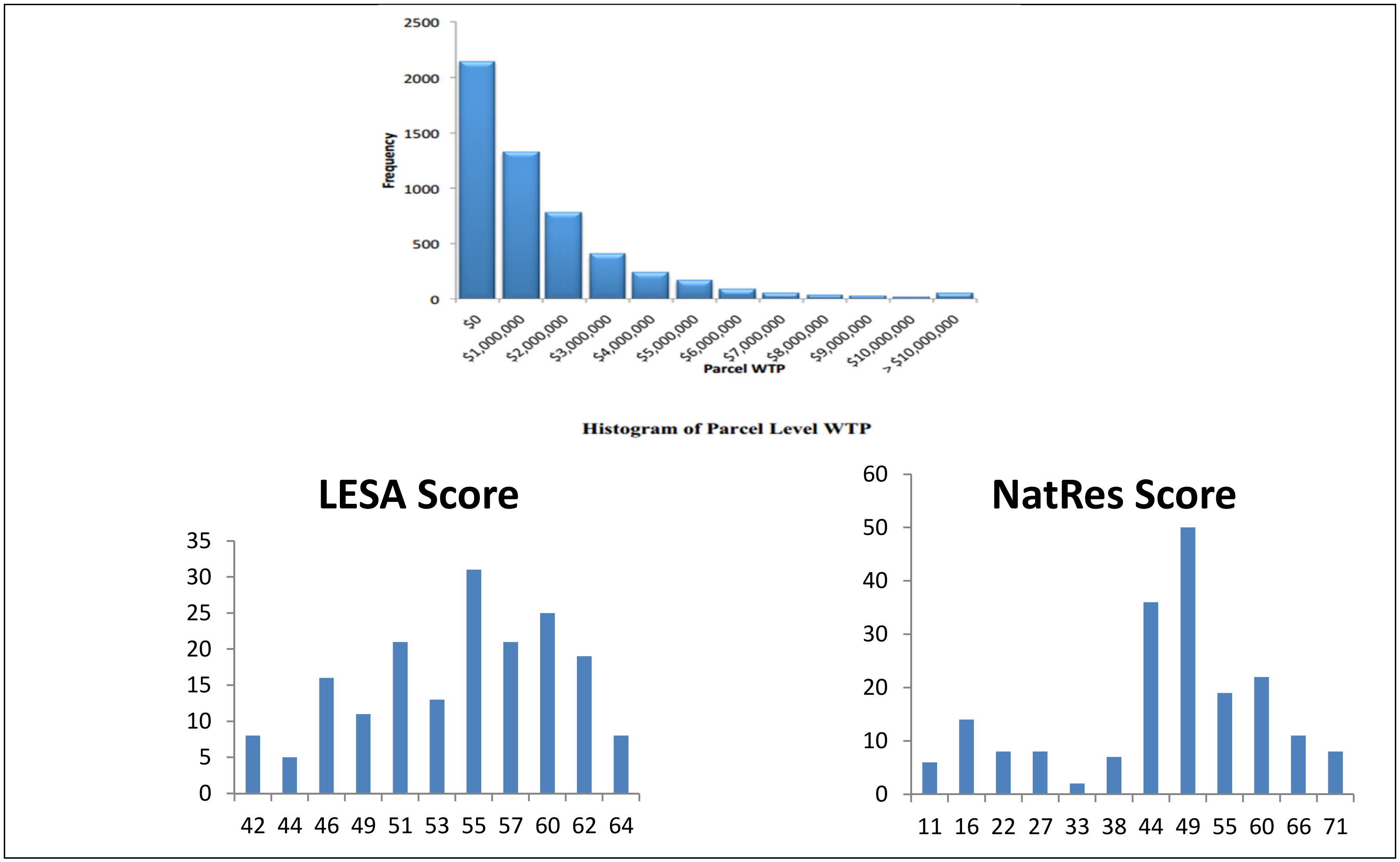


Figure reproduced from (Good, Harms, and Ruckelshaus 2003).

Figure 10 Histograms of Farm Land Conservation Value vs. Score Assessments in Sussex County, Delaware



Histogram of Parcel WTP Reproduced from Dundas (2011).

Figure 11 Density of Value Distributions of Conservation Benefits

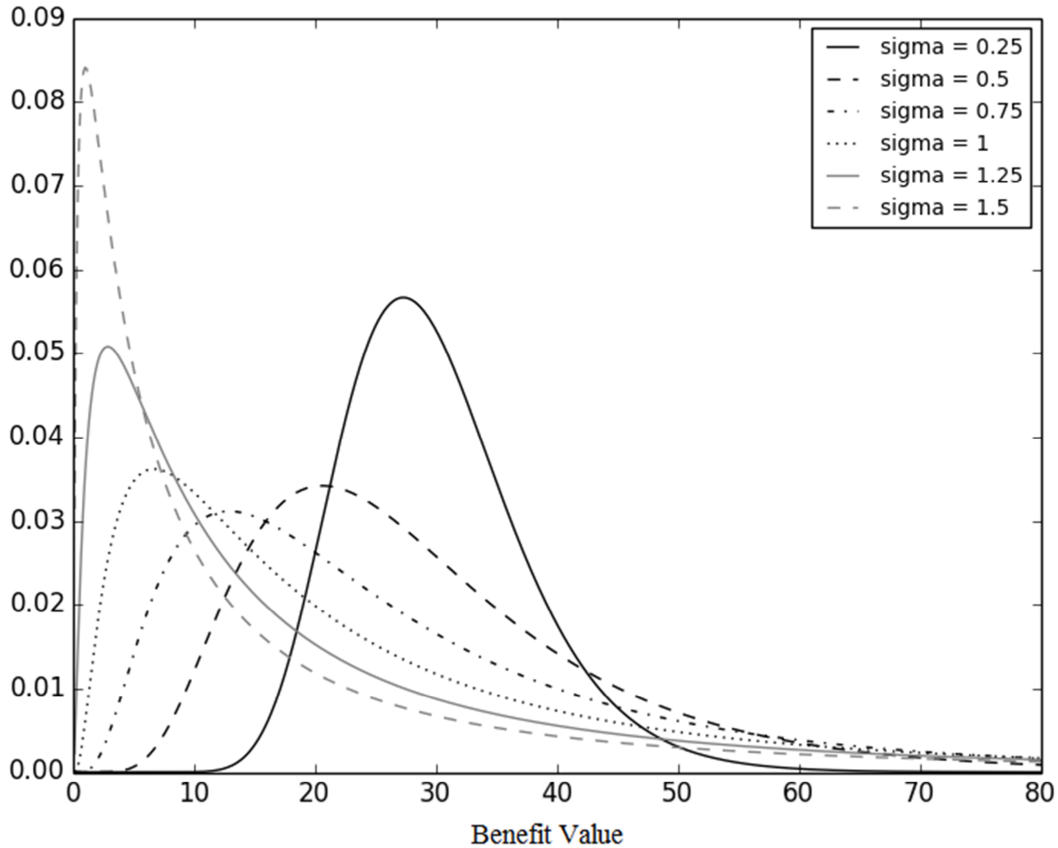


Figure 12 Density of Value Distributions of Conservation Benefits

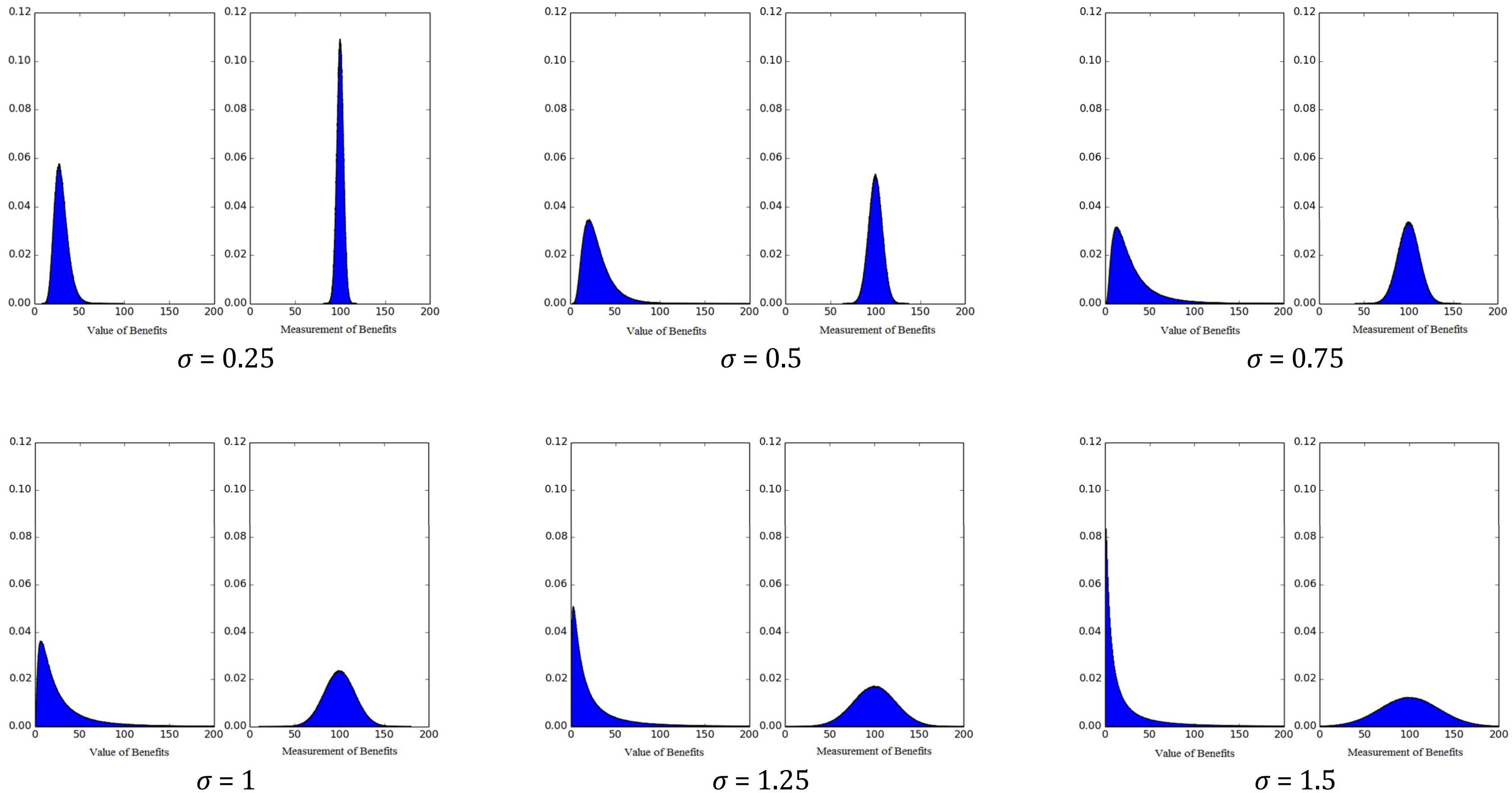
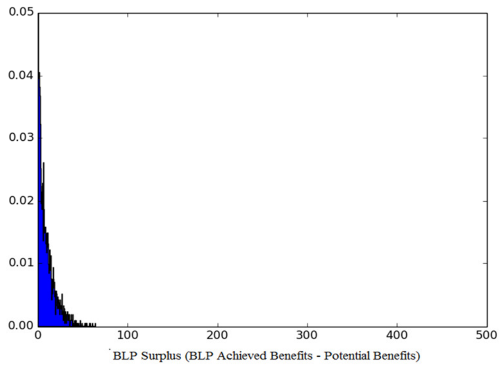
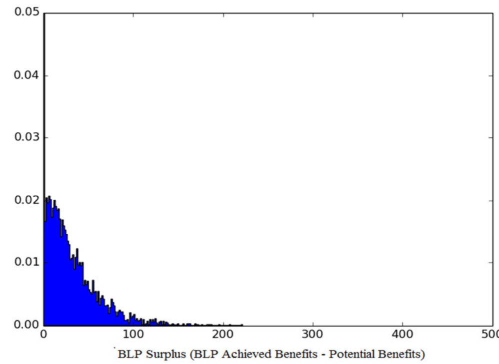


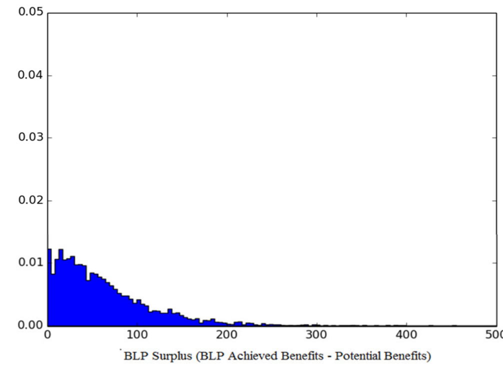
Figure 13 Histograms of Benefit Shortfall of BLP



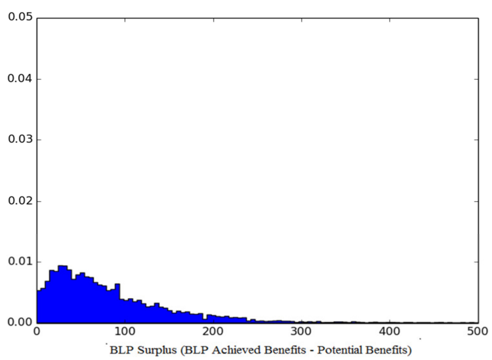
$\sigma = 0.25$



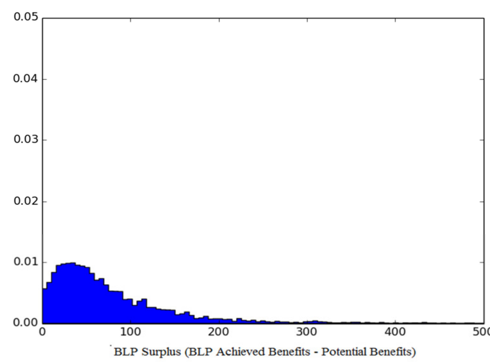
$\sigma = 0.5$



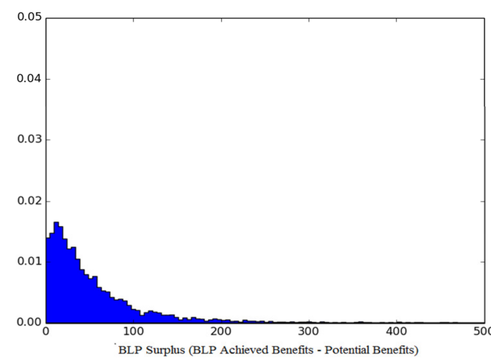
$\sigma = 0.75$



$\sigma = 1$



$\sigma = 1.25$



$\sigma = 1.25$

Chapter 3

PROTECTING THE COASTLINE—OPTIMAL COASTAL INUNDATION ADAPTATION MECHANISMS

Introduction

More than half of the people in the United States in 2010 lived in coastal areas. It is expected that this number will increase by 8% by 2020 (Woods & Poole and NOAA, 2011). The US mid-Atlantic coastal zone area is emblematic of issues that arise in these areas, being comprised of low-lying, densely populated coastal plain with a broad mix of land uses. This region is subject to the effects of climate change, which include sea level rise and more frequent and extreme weather events that have the potential for devastating economic impacts. The "isotactic rebound" effect, or a seesawing of tectonic plates from the retreat of inland glaciers after the last ice age, exacerbates this, effectively doubling the rate of sea level rise in some areas (Leorri, et al. 2011). Beach tourism, industrial production, and agriculture are all important industries in the region that are located in areas predicted to be subject to increased flooding as a result of climate change. Flooding generates not only local property damage caused by storm surges but also contamination of drinking water, alteration of soil and water chemistry in forest and wetland ecosystems, mobilization of previously stable chemical contaminants like arsenic and chromium, and increased salinity in productive agricultural soils.

Coastal infrastructure can ameliorate the effects of coastal inundation. Landowners and local authorities can choose from a variety of built structures, like levees and breakwaters, and natural protective systems, like marsh and beach nourishment, to offer protection to their property. In spite of this, there has been a historical reluctance to invest in such protections. After the devastating effects of Hurricane Sandy, many residents of New Jersey's beach communities objected to development of coastal barriers because they would interrupt their views of the beach. In their eyes, it seems, the scenic cost of such infrastructure improvements exceeds their perception of the risk of future damage. The cost of this damage, however, is borne in large part by taxpayers who subsidize flood insurance and pay for recovery expenses. The losses can also spill over to neighboring communities that are willing to develop infrastructure barriers for themselves but are exposed to overflow from less risk-averse communities.

Due to the public good nature of coastal protection, recent policy efforts have explored subsidizing investments in protective infrastructure. Notable examples of these, including New Jersey's Blue Acres Program, and Maryland's Shore Erosion Control program, model their implementation after conservation easement and Best Management Practice cost share programs traditionally applied in the context of ecosystem service provisioning. As such, they demonstrate issues similar to those studied in the land conservation context, including private landowner information about heterogeneous costs, as well as spatially non-linear externalities. This research explores the spatial complexity of policy design in the coastal infrastructure environment. Specifically, models of water flow and energy transport suggest that the damage minimizing infrastructure design would be symmetric development levels for all landowners, and that a deviation from symmetric development by one or more landowners could lead to potentially large external damages. The heterogeneity of landowner costs, on the other hand, would lead to non-symmetric private production decisions. Therefore, a social planner is in the position of trading off between increasing total damages from heterogeneous production, and pushing additional costs onto private landowners. Lab experiments implement no policy, fixed payment, and reverse auction based mechanisms in a public goods game with the payoff function based on a realistic coastal wave flow model with both constant and stochastic inundation dynamics. Results show that there is evidence of strategic play in the reverse auction setting; however, it is effective in increasing total welfare in the stochastic sea level rise setting. Fixed payments on the other hand, are effective in in increasing welfare under constant sea level rise dynamics, but lead to a net negative effect under stochastic dynamics. Interestingly, even though these policies are at least somewhat productive in increasing protective infrastructure development, they are not effective at increasing coordination of investment at a symmetric level.

Background

There is a growing literature on the optimal provision of ecosystem services in a spatially explicit ecosystem benefit functions. Experiments with both students and farmers/landowners as subjects have tested the effectiveness of various policy mechanisms discussed in the literature on land conservation policies and economics. This includes work on network optimization and reserve topology targeting (Williams, ReVelle, and Levin, 2005; Malcolm and ReVelle, 2002) and on targeted bonus structures to induce coordination among landowners (Parkhurst et al., 2002; Parkhurst and Shogren, 2007). Fooks, et al. (2014) includes treatments that offer conservation contracts through a reverse combinatorial auction with a spatially weighted benefit function and a reverse auction with bonus payments for spatially valuable parcels. One of the key insights of this work focused attention of the interaction between targeting and bonus payments in coordinating behavior and exploiting this coordination through proper targeting. In retrospect, this scheme is very much in the spirit (if not a technically precise implementation) of a reverse generalized Vickery-Clark-Groves (VCG) mechanism in which public goods are optimally procured and the agents who successfully execute contracts receive an additional subsidy based on the marginal value of their participation. This research specifically extends those experiments by formulating a realistic spatial objective functions, and precisely implemented policy mechanisms.

In terms of policy application, this research falls within the field of "conservation optimization," which involves applying mathematical programming and optimization to problems faced by environmental and conservation planners, especially studies that have investigated realistic and spatially explicit environmental or ecosystem dynamics. Works that have considered how to target and select projects in a conservation effort include Wu and Boggess (1999), which considered the impact of ecological nonlinearities in benefits. That study showed that, under variations in information, funding, and benefit structures, the distribution of funds can be highly inefficient under targeting mechanisms that are theoretically optimal. Wu and Skelton-Groth (2002) applied this idea to trout habitat conservation in Oregon and showed that targeting schemes that consider threshold effects are far more productive than those that do not. Considerable effort has been devoted to establishing mathematical programming as a tool for spatially targeted conservation efforts (for example, Babcock, Camm and Garber-Yonts, 1997; Polasky, et al., 2001; Wu, Adams and Boggess, 2000). Zabel and Roe (2009) is one of several works that considered how results for targeted efforts and flat rate conservation payments compare and the tradeoff between performance and moral hazard that results. It discusses several ways to address the problem, including bonuses, threshold payments, and relative performance payments. Messer and Allen (2010) compared the discount auction format used in Delaware to alternate selection approaches and found that selection methods that emphasized cost-effectiveness performed best under budget constraints.

Recent experiments that have focused on behavioral dynamics in conservation auctions include Cason and Gangadharan (2004), which focused on the benefits generated by information effects for discriminative and non-discriminative pricing schemes. Those results indicated that participants' strategic behavior increased with the information available to them, expanding the rents they were able to extract. Schilizzi and Latacz-Lohmann (2007) compared fixed price schemes and auctions over several repeated rounds that were independent and in which parcel endowments were shuffled between rounds. Auctions initially performed better but decreased in effectiveness over time. Rolfe et al. (2009) considered experiments involving multi-round auctions for conservation contracts; with a primary focus on learning. In that case, there was a substantial learning effect over the first three rounds but little evidence of strategizing.

Agglomeration bonuses have been proposed to improve coordination of landowners' acre-retirement selections across parcel borders to target optimal spatial distributions. Those studies were subsequently extended in an effort to improve the spatial distribution of habitat in wildlife conservation programs by inducing coordination of landowner entry over time. This approach was first developed by Smith and Shogren (2002) to offer landowners with adjacent parcels an incentive to coordinate the retirement of acres across fences. The bonus structure offers incentives to landowners who retired parcels adjacent to their neighbor's property. This approach has been the subject of several experiments that assessed its feasibility and concluded that it showed promise (Parkhurst et al., 2002; Parkhurst and Shogren, 2007).

Research Design

The Decision Environment

Participants representing coastal landowners or townships arranged in a linear array of parcels (Figure 1) are the decisions makers in this framework. Their decision is similar to the classic public good game, where they have an initial balance, out of which they must choose to allocate some amount to a public protection fund. After funds are allocated, each parcel receives damage as determined by a level of inundation, the amount of public investment by each parcel, and a coastal water-flooding model. They receive a total profit from each round based on their initial balance, minus their contribution to protection, minus their damage. The agents have heterogeneous privately known infrastructure development functions, which determine the amount of protection they get for their contribution to the public protection fund. The level of inundation can be thought of as either literal floodwater depth, or, if the rounds are thought of in terms of expected values of decisions made over time, time until the next extreme flooding event. In each round, the level of flooding was either constant, or a known distribution of values.

This setting is a variation on the canonical linear public good experiment setting has been well studied in the literature. Surveys of this literature (Ledyard, 1995; Zelmer, 2003) characterize common themes in the design of such experiments to include group size, round length and learning, nature of subjects, heterogeneity in marginal per capita return (or payout rate) and endowment, punishment, communication, and framing. Results that have consistently emerged include the positive effect of increases in marginal per capita return, communication, and endowment heterogeneity, and framing in determining the level of contribution to the public good, while increasing group size tends to have a negative effect, though only to a point (Zelmer, 2003). The role of learning, repetition, and dynamics are acknowledged as important, but a clear consensus has yet to emerge on the precise implications of these factors (Zelmer, 2003; Duffy, et al., 2007). Generally, however, the belief is that with reputation contribution rates tend to deteriorate, either because of learning effects, strategic issues, or punishment (Ledyard, 1995).

A ground-water flow model served as the basis for transport of damage from flooding between parcels and offshore. Since there is transport between parcels, there is the potential for a spatial externality. Consequently, landowners may under-develop protective infrastructures relative to the efficient level, and there may be a place for policy to improve the social outcome. We assume that there is a policymaker with a fixed budget. The planner may offer subsidies for the improvement of coastal protection, analogous to many of the existing coastal infrastructure development programs.

Groundwater flow dynamics will be based on KINEROS2, the "Kinematic Runoff and Erosion Model," which is a kinematic routing model developed by the U.S. Department of Agriculture (USDA) that is widely used in flood and runoff modeling. It is based on a one dimensional simplification of de Saint Venant shallow wave partial differential equations:

$$\frac{\partial h}{\partial t} + \alpha m h^{m-1} \frac{\partial h}{\partial x} = q(x,t)$$
$$h(0,t) = c$$

where *h* is the volume of water, *x* is linear distance, *t* is time, *q* is the lateral transport rate, *c* is a constant rate of drainage, and α and *m* are parameters related to the land surface. This has a first-order approximation in finite differences:

$$h_{t+1}^{i+1} - h_{t+1}^{i} + h_{t}^{i+1} - h_{t}^{i} + \tfrac{2*\Delta t}{\Delta x}\{\theta_w[\alpha_{t+1}^{i+1}(h_{t+1}^{i+1})^{m_{i+1}} - \alpha_{t}^{i+1}(h_{t}^{i+1})^{m_{i+1}}] +$$

$$(1-\theta_w)[\alpha_{t+1}^{i}(h_{t+1}^{i})^{m_i} - \alpha_{t}^{i}(h_{t}^{i})^{m_i}]\} - \Delta t(\bar{q}_{t+1} + \bar{q}_t) = 0.$$

The initial condition for *h* is based on the floodwater depth, minus flooding prevented through protective infrastructure:

$$h_0^i = f - v^i$$

Where *f* is the floodwater depth, and v^i is the allocation to public protection by parcel i.

This process is approximated using the classical Runge-Kutta method, and allowed to run until the total volume of floodwater drains below a small fraction of the initial amount, so that the final period, *T* satisfies: $\sum_i h_T^i \leq 0.0001 * \sum_i h_0^i$. The total damage to each parcel is defined as the sum of volume in that parcel over the total process: $D^i = \sum_{t=0}^{T} h_t^i$, while total overall damage is the sum of damages to each parcel: $D = \sum_i D^i$. A notable result in this context is the effect of "coastal profile", or structural variability on the coast on the flow of an inundation event. Coastal engineering studies (Lynett, et al, 2012; Park, et al, 2013) have found that a structural variability in coastal infrastructure can create sheltering and funneling effect that can amplify the forces from inundation water traveling through gaps in coastal infrastructure by 80 to 100 times. To test for this effect in this model, specify a representation of protection investment in terms of deviation from the mean: $v^i = \bar{v} + \widehat{v^i}$. Then, the "roughness" of a given investment set is the sum of absolute deviations: $V = \sum_i \left|\widehat{v^i}\right|$. We can test the effect of roughness on damage in this model by simulating a sample of investment/damage sets, and estimating:

$$\ln(D_k) = \beta_0 + \beta_1 \ln(\bar{v}_k) + \beta_2 \ln(V_k) + \varepsilon_k.$$

Table 1 reports results for this for a sample of 10,000 simulated observations. In general, increasing the average level of infrastructure by 1% decreases damage by 1.48%, however increasing roughness, or variation in levels of investment, by 1% increases damage by 0.26%. Ideally, a policy subsidizing infrastructure development should aim to increase the overall level of investment, while at the same time decreasing the level of variation between parcels' investment development.

This research considers three policy arrangements under both constant and random inundation level treatments. The first policy is a No Policy baseline case in which agents independently choose their investments in infrastructure to maximize their personal outputs. The second is a Fixed Payment Provision Point Mechanism, which offers a fixed subsidy as long as protection meets a minimum investment threshold. Here, damage is specifically targeted for the payment threshold instead of a metric of infrastructure production. There are a couple of reasons for this. The first is a matter of practicality of implementation; given the damage dynamics, it is not obvious if a minimum protection level, average protection level, roughness, some combination of these, or some other target would best achieve an efficient level of protection, while targeting damage allows landowners to figure out the optimal approach to reduce damage to the target level. Secondly, this approach of tying payment to damage reduction is increasingly the approach that the National Flood Insurance Program is taking with programs like the Community Rating System, Hazard Mitigation Assistance Program, and Construction Best Practices Manuals tying payments and premium subsidies to effective implementation of damage reduction measures (FEMA, 2011).

The third policy is a Reverse Combinatorial Vickery-Clarke-Groves (VCG) Mechanism (Varian and MacKie-Mason, 1995). First, funding agency observes the landowners' initial level of protection built. Then, the landowners may submit proposals consisting of an additional level of protection and a minimum payment amount. If a proposal is selected for funding, the landowner must construct the additional level of protection at their private cost. They receive a payment equal to their reported minimum payment, plus a bonus equal to the external value of their participation. For a potential set of projects, with parcel i offering a minimum payment of p_i. Call the damage achieved if all projects are funded D^*, and the damage if all parcels besides i are funded D^i. The bonus for parcel i is calculated by finding the damage to all other parcels if the full set of projects is funded: $D^*_{-i} = \sum_{j \neq i} D^{*,j}$, and the damage to all other parcels if all projects except for i's are funded: $D^i_{-i} = \sum_{j \neq i} D^{i,j}$.

Then the total payment for parcel i, if that set is selected is $p_i^* = p_i + \left(D_{-i}^* - D_{-i}^i\right)$. The funding agency solves the combinatorial selection problem to choose a subset of parcels which maximizes damage reduction, subject to the total payments (minimum payment plus bonus for all selected projects) being less than their budget. Since the calculation of the payment for each parcel depends upon the other parcels selected, and the full inundation dynamics must be simulated for each possible combination considered, this is extremely computationally intensive. In the context of the experiment, this was solved using a branch and bound algorithm that could be efficiently run on a computer with the capacity to execute several thousand simulations in parallel.

Experimental Design

Table 2 provides an outline of the experimental design. Six sessions were conducted, with twelve participants in each session, making 40 decisions each. Participants were recruited from University of Delaware undergraduate business majors. Session took about two hours, about 40 minutes of which were instructions and practice. Subjects averaged $35 in compensation, based on their performance in the experiment. The sessions took place at the Laboratory for Applied and Experimental Economics at the University of Delaware. The subject interface was programed with the software zTree (Fischbacher, 2007), with the background calculations being done in NumPy, a numerical analysis extension to the programing language Python.

The experiment was designed to test several hypotheses, listed in Table 10. The design is a two-by-three within subject design which incorporates two types of inundation settings along one dimension, and three policy arrangements along the other. The two inundation settings are constant inundation, in which there is a certain inundation level of 50 in every round, and random inundation, in which there will be inundation of 50 with probability of .5, inundation of 75 with probability of .3, and inundation of 100 with probability of .2. Note that the random inundation differs from the constant inundation in expected value. This is meant to specifically evoke the scenario of increasing strength or frequency of extreme events, and to see if this specific effect causes behavior changes in strategic responses to the policy mechanisms. However, it must be kept in mind when interpreting the effects of this treatment that there is both an increase in expected value, and the introduction of uncertainty, and that these two cannot be disentangles when attributing any effect of the treatment.

The three policy treatments are no policy, a fixed payment mechanism, and an auction like VCG mechanism. In the no policy setting each participant's problem is simply to optimize their own profit, given their own, privately known cost. Given the external damage that each parcel imposes on its neighbors when it receives inundation, the expectation is that this will be below the socially optimal level. The provision point mechanism pays each participant $13 conditional on the total damage across all parcels being less than \$75. A well-structured provision point mechanism can offer incentive compatible implementation of the public optimum, however has been shown to lead to over-contribution to the public good (Cadsby and Maynes, 1999). The third mechanism is an auction for provisioning contracts based on the VCG mechanism. Participants first announce the amount of infrastructure they will develop without subsidization. They then submit proposals for the development of additional infrastructure, along with a reservation price. The proposals are chosen for funding based on maximizing the total damage reduction of a set of funded proposals, subject to the total cost of funding the proposals being less than \$80. If a proposal is funded, the participant implementing the proposal receives a payment equal to their reservation price, plus the value of the external damage their additional infrastructure prevented. This type of funding mechanism is also incentive compatible, however is more complex than the provision point, which can lead to more mistakes on the part of participants (Varian and MacKie-Mason, 1995). Additionally, the "auction" format could lead to additional rent seeking by participants.

The first set of hypothesis listed in Table 10 considers the total welfare effect of the program settings within and across inundation dynamics. It is expected that the constant inundation setting will generally achieve higher welfare than the random inundation, and that the policy mechanisms will achieve greater welfare then the no policy setting. I suspect that the VCG mechanism will perform better than the provision point mechanism, though this is uncertain. The second set of hypotheses considers protection built my mechanism. Due to the tendency of provision point mechanisms to lead to over provision, it is expected that the provision point will lead to the highest (perhaps higher then efficient) level of investment, with the VCG being the intermediate and no policy having the lowest level of investment. The last two sets of hypotheses consider protection investment across inundation types, and the differential effect of inundation types on the mechanisms. It is expected that generally the random inundation setting will lead to higher levels of infrastructure development, both on average and across mechanisms as the random inundation setting has an increase in uncertainty, as well as the expected level of inundation.

Participants were assigned to parcels in one of two groups of six. The parcels will be adjacent to other participants' parcels, although the adjacency relationships were not known and subjects. Communications between participants was not allowed. Participants received written instructions (Appendix), and then were shown a brief recorded presentation explaining the main points of their decisions. They were then allowed to ask questions, and given several practice rounds to familiarize themselves with the software. To aid them in forming strategies, they also had an inundation calculator which allowed them to calculate the damage for different hypothetical production sets.

These parcel assignments rotated between treatments. Participants could have one of three costs of protection: High, Medium, or Low. They submitted their decisions in terms of the amount of their $100 initial balance they would invest in protection. This achieved a level or protection based on their cost, as shown in Figure 2.

After each session, subjects received payment based on the total amount of output they produced plus any transfers from the mechanism. This was be multiplied by a factor to convert from experimental outcome units to real US dollars.

Results

Data from the experiments was collected at two levels: for the individual parcel choices (including levels of productive and infrastructure investment, offers made to the funding agency, the timing and results of those offers) and at aggregate group level, including the amount of total damage and payments from the agency. Table 10 reviews the specific design hypothesis, and presents conclusions based on the results. The welfare results are mixed, and indeed present some interesting puzzles. In terms of the effectiveness of mechanisms in increasing provision, there is evidence that the mechanisms perform as expected in the random inundation treatment, but not in the constant inundation treatments. There is an increase in overall protection levels and in differential protection investment in random inundation (recall that the random inundation represents not only the introduction of uncertainty, but also an increase in expected value of damages. Of particular interest, we see that the mechanisms do not appear to perform as expected in the constant inundation case, and that the provision point mechanism decreases net welfare in the random inundation case. In analyzing the results, we will pay particular attention to possible explanations for these quandaries.

We will focus first on the bottom line – the total welfare effectiveness of the two policy settings as defined as decrease in damage relative to no policy, minus payments from the program. Then we will look more closely at individual investment and bidding behavior to understand how differences in behavior between treatments affect outcomes.

Figure 3 shows the average profit achieved per parcel between the treatments. In comparing the no mechanism cases between the two inundation settings, we see a slight decrease in profit obtained, which is expected given the increase in expected inundation. The effect on the treatments between the two settings is much larger, with the effects going in opposite directions between the mechanisms. It is not obvious that that should be the case. Some much of the remained of this section explores possible reasons for this. Table 3 tests the net welfare effect, defined here as the average increase in landowner profit from the program, minus program expenditures. We see a similar split pattern between policy and inundation treatments. The fixed payment mechanism has a significant positive effect in the constant inundation setting, but a marginal negative effect in the random inundation setting. On the other hand, the VCG mechanism did not have a significant welfare effect in the constant setting, but did have a significant effect in the random setting.

Table 4 compares the effectiveness of the mechanisms in terms increasing investment protection level, average protection level and increasing coordination in terms of average absolute deviation of individual protection from the average. We do see in the second column that the VCG mechanism is significantly effective at increasing the production of protective infrastructure, in both the constant case, and even more so in the random inundation case. The fixed payment mechanism, on the other hand, has a borderline negative effect in the constant case, but a significant positive effect in the random case. Interestingly, considering the first column, the fixed payment seems to be responding directly to changes in investment, while the VCG is demonstrating an increase in protection produced without a significant increase in the amount of money invested. This suggests that the increase in the level or protective infrastructure is coming from increased efficiency in the distribution of investment spending among cost types. In examining the third column it was hoped that there would be some negative effects, suggesting a decrease the deviation from average production, and hence an increase in coordination as a result of the mechanisms. Unfortunately, exactly the opposite seems to be happening, with the mechanisms leading to larger dispersion of infrastructure production from the mean.

Table 5 specifically examines bidding and rent extraction behavior across inundation treatment and parcel cost type in the VCG setting. Looking at the rent demanded in the first column, we do see evidence consistent with strategic rent extraction in the constant inundation setting, with low cost parcels seeking the highest levels of rent. This appears to be less systematic in the random inundation setting, with rent demanded decreasing for all cost types, with the exception of high cost parcels. Why they would be the exception is not clear, though some may be seeing it as offering them increased market power. These effects largely vanish for successful bids, indicating that the strategic rent seekers are largely off margin. The exception is that medium cost parcels were quite successful at demanding additional rent in their bids in the random inundation case, perhaps because they tended to be most strongly on the margin. In terms of total rent extracted, including both the requested minimum payment bid as well as the bonus paid in addition to the bid, it appears that the high cost parcels were successful at extracting rent in the constant inundation setting. This is likely because they would have the lowest baseline level of development, so would tend to receive high bonuses if their proposals were selected.

Conclusion

This paper considered the problem of optimally allocating funds to incentivize the development of infrastructure to prevent damages from storm surges, tsunamis, and other coastal inundation events. This problem is interesting because of both asymmetric cost information on the part of landowners, and because of the natural dynamic underlying the externality, which tends to localize damages, and to increase damages if there are large differences in levels if infrastructure development. Using lab experiments, we tested a conditional fixed payment mechanism, and well as a Vickery-Clark-Groves reverse auction mechanism in settings with both constant, and random inundation dynamics. The particular questions of interest were the relative effectiveness of these two mechanisms in this context, how changes in the inundation dynamics consistent with sea level rise and increased extreme events affects the efficacy of these two mechanisms, and how effective the mechanisms are at increasing coordination in investment decisions.

Fixed payment has a positive effect on welfare in the constant inundation case, but a substantial negative effect in the random inundation case, largely due to overinvestment in protective infrastructure. The VCG mechanism, on the other hand did not have a significant effect in the constant inundation case, but had a large positive effect in the random inundation case. This difference in performance apparently stems from a reduction in rent seeking behavior under random inundation. Unhappily, none of these instruments was effective in increasing coordination towards symmetric investment. This could partially be because of the relatively low cost of coordination failure, relative to the benefits of increased overall investment.

There are several interesting aspects to this problem left unexplored. An obvious extension is varying the parameters of the water flow dynamics to see if changing the balance of the effect of average infrastructure level versus deviation from the average level on damages impacts the ability of these mechanisms to incentivize coordination. Also, this experiment was framed as a static experiment, in that the rounds are independent. Coastal development tends to be a much more dynamic process. Relevant issues like infrastructure accumulation and deterioration, as well as irreversible decisions like strategic retreat lead to dynamics that are obscured in the static, independent round setting (Fooks, et al., forthcoming). Additionally, the dynamic environment offers the ability to explore several recent trends in the mechanism design literature, including robust and Bayesian mechanism design

(Bergemann and Morris,2005; Hartline and Lucier, 2010) and adaptive mechanism design (Pardoe et al., 2006).

Table 8. Average Effect of Non-symmetric Infrastructure Investment on Damage

ln(Total Damage)	
Constant	4.68*** (0.029)
ln(Average Protective Infrastructure)	-1.48*** (0.006)
ln(Total Absolute Deviation from Average)	0.26*** (0.005)
N	10,000
R^2	0.85

Note: *, **, and *** represent significance at a 10%, 5%, and 1% level.

Table 9: Experimental Design Summary

6 Sessions, 12 participants per session, 40 decision rounds per session
Average time: 2 hrs (~40 mins instructions)
Average earnings $35
Public Good Game Variation:
Groups of 6 parcels
Initial balance of $100, choose how much to invest in protection
After investment there is a flood event
Heterogeneous private investment costs
Payoff = $100 – Protection Investment – Damage
Damage is calculated based on 1D shallow wave propagation:

$$\frac{\partial h}{\partial t} + \alpha m h^{m-1} \frac{\partial h}{\partial x} = q(x, t)$$

$$h(0,\ t) = c$$

Within subject treatments:
Mechanism: None, Provision Point, Reverse Subsidy VGC
Storm Surge: Constant, Random
"Provision point"/Conditional Insurance: Payment of $13 to all in the group if
damage is below threshold
Reverse VCG: Submit proposal for additional investment at minimum payment
– if chosen receive payment + "bonus"
Constant surge: 50 units w/ prob = 1
Random Surge: 50 w/ P = .5, 75 w/ P = .3, 100 w/ P = .2.
Order varied between sessions in block Latin squares

	No Mechanism	Provision Point	Reverse VCG
Constant Surge	A	B	C
Random Surge	D	E	F

Table 10. Hypothesis Table

Topic	Hypothesis	Result
Welfare	H_0: 1. $\text{Welfare}_A = \text{Welfare}_B = \text{Welfare}_C$ 2. $\text{Welfare}_D = \text{Welfare}_E = \text{Welfare}_F$ 3. $\text{Welfare}_A = \text{Welfare}_D$ 4. $\text{Welfare}_B = \text{Welfare}_E$ 5. $\text{Welfare}_C = \text{Welfare}_F$	1.Fail to Reject H_0 2.Reject H_0 3. Reject H_0 4. Fail to Reject H_0 5. Reject H_0
	H_A: 1. $\text{Welfare}_C > \text{Welface}_B > \text{Welfare}_A$ 2. $\text{Welfare}_F > \text{Welfare}_E > \text{Welfare}_D$ 3. $\text{Welfare}_A > \text{Welfare}_D$ 4. $\text{Welfare}_B > \text{Welfare}_E$ 5. $\text{Welfare}_C > \text{Welfare}_F$	
Cross-Mechanism Development Effects	H_0: 1.$\text{Protection}_A = \text{Protection}_B = \text{Protection}_C$ 2. $\text{Protection}_D = \text{Protection}_E = \text{Protectiont}_F$	1. Fail to Reject H_0 2. Reject H_0
	H_A: 1. $\text{Protection}_B > \text{Protection}_C > \text{Protection}_A$ 2. $\text{Protection}_E > \text{Protection}_D > \text{Protection}_F$	
Cross-Dynamics Investment	H_0: $\text{Protection}_{A,B,C} = \text{Protection}_{D,E,F}$	Reject H_0
	H_A: $\text{Protection}_{D,E,F} = \text{Protection}_{A,B,C}$	
Differential Dynamic Effect	H_0: 1. $\text{Protection}_A = \text{Protection}_D$ 2. $\text{Protection}_B = \text{Protection}_E$ 3. $\text{Protection}_C = \text{Protection}_F$	1.Reject H_0 2.Reject H_0 3. Reject H_0
	H_A: 1. $\text{Protection}_A < \text{Protection}_D$ 2. $\text{Protection}_B < \text{Protection}_E$ 3. $\text{Protection}_C < \text{Protection}_F$	

Subscripts indicate treatment as listed in Table 9.

Table 11. T-Tests for Net Welfare Effects

	Fixed Payment	VCG
Constant Inundation	Positive***	None
Random Inundation	Negative*	Positive ***

Note: *, **, and *** represent significance at a 10%, 5%, and 1% level.

Table 12. Increased Protection vs. Coordination of Protection

	Average Investment in Protection	Average Protection Built	Absolute Deviation from Average Protection
Constant	27.86***	49.02***	35.69***
	(0.791)	(1.888)	(4.020)
Fixed Payment	-5.31***	-6.14*	1.55
	(1.407)	(3.191)	(6.795)
VCG	-0.596	7.24**	25.45***
	(1.408)	(3.360)	(7.154)
Random Inundation	-0.544	7.46**	3.92
	(1.251)	(2.985)	(6.356)
Random Inundation * Fixed Payment	10.09***	22.09***	16.03***
	(1.924)	(4.593)	(10.268)
Random Inundation * VCG	1.923	82.60***	56.04***
	(0.791)	(4.822)	(10.966)
N	9600	240	240
R^2	0.07	0.39	0.10

Note: *, **, and *** represent significance at a 10%, 5%, and 1% level. Standard errors are clustered by session.

Table 13. Bidding Behavior and Rent Extraction

	Rent Demanded	Rent Demanded – Successful Bids	Rent Extracted
Constant	12.38***	-2.45***	5.40
	(1.647)	(3.692)	(6.872)
High Cost	-13.47***	8.39*	19.10**
	(2.329)	(4.686)	(8.928)
Medium Cost	-5.34**	5.54	1.91
	(2.329)	(4.686)	(8.723)
Random Inundation	-11.95***	0.08	12.57
	(2.197)	(4.459)	(8.299)
Random Inundation * High Cost	19.73***	-5.02	-22.44**
	(3.190)	(6.032)	(11.229)
Random Inundation * Medium Cost	12.54	16.43***	-15.52
	(3.128)	(5.975)	(11.123)
N	864	203	203
R^2	0.10	0.39	0.09

Note: *, **, and *** represent significance at a 10%, 5%, and 1% level. Standard errors are clustered by session.

Figure 14 Layout of parcels in experiment.

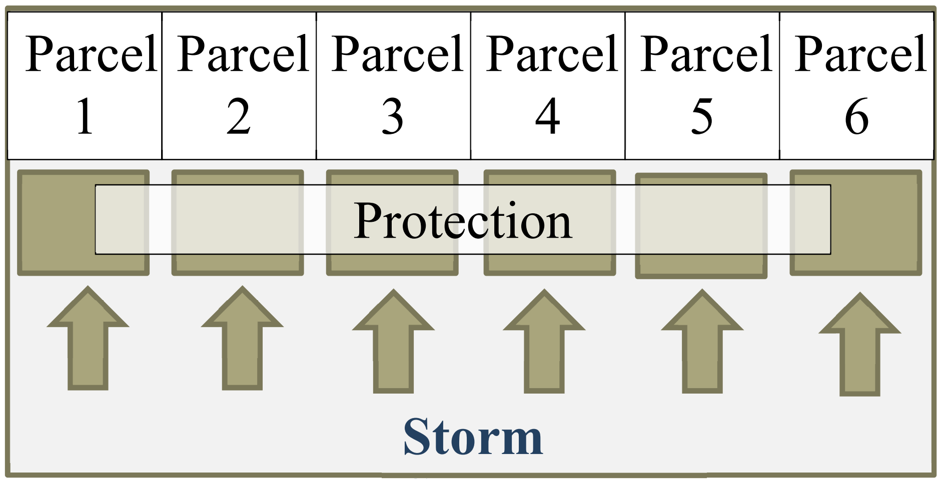


Figure 15 Heterogeneous Costs of Protection

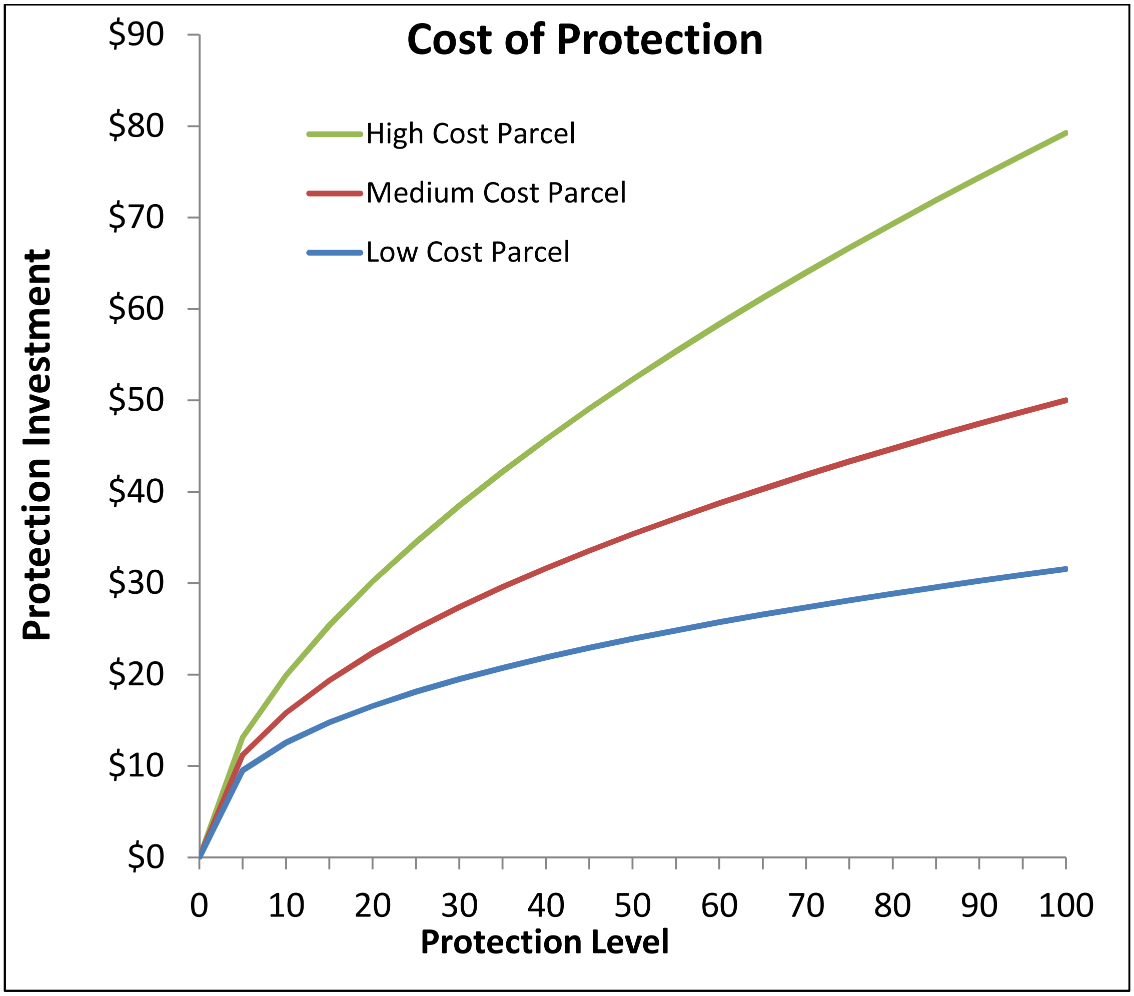
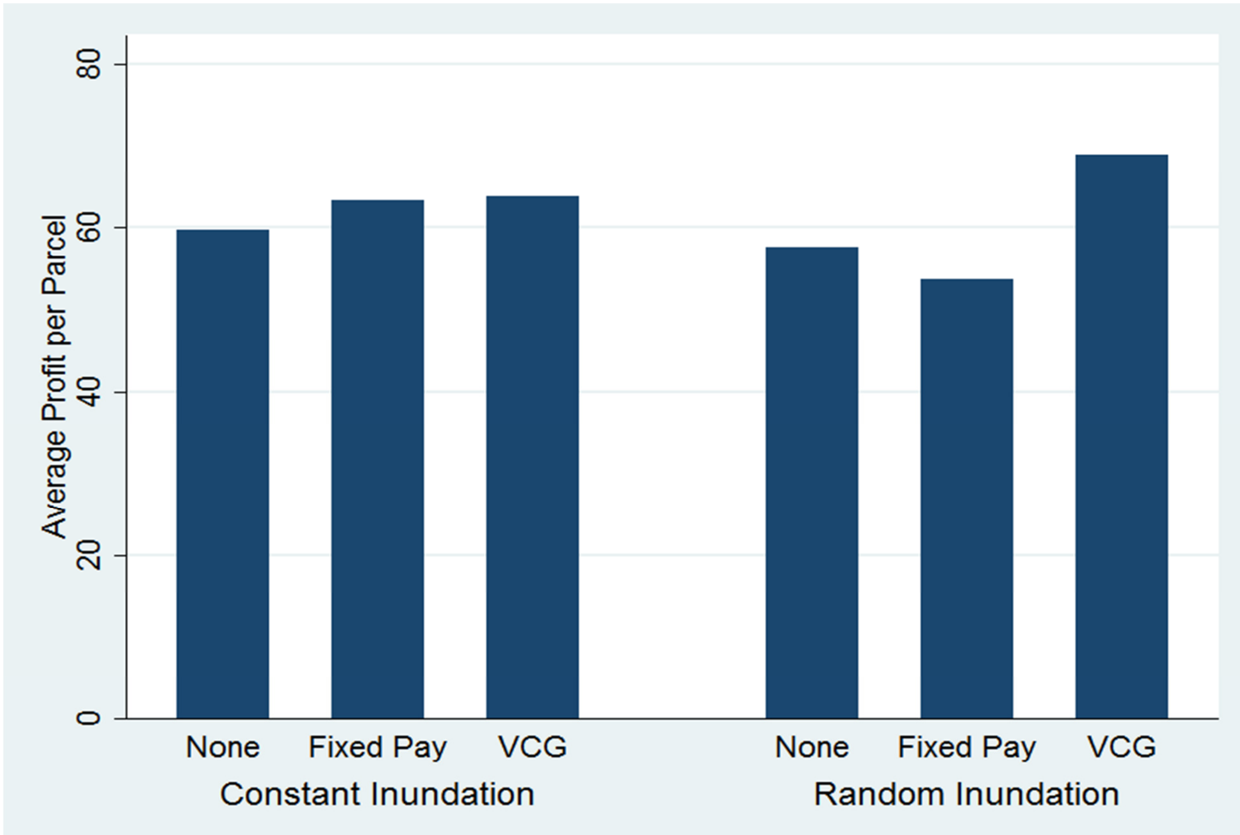


Figure 16 Total Profit between Treatments



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Appendix A

PAPER SURVEY OF BEACH VISITORS

Please answer the following questions. Your responses will be kept confidential. Please do not put your name on any of the materials. Any questions may be addressed to the study administrator.

1. Please indicate your sex.

   ________M ________F

2. In what year were you born?________________

3. What is the zip code at your primary residence? __________

4. How would you describe your area of residence?

   ________Urban _________ Suburban_________Rural

5. How years of formal schooling do you have? (Completed high school = 12 years)?___________

6. Are you currently…?

_______Employed Full Time ________Employed Part Time

_______Self Employed

_______ Student ________ Homemaker _______ Retired

_______ Unemployed

7. What is your total household gross annualincome?

_______ Less than$25,000 _______ $95,001-$105,000 _______ $175,001-$185,000

_______ $25,001-$35,000 _______ $105,001-$115,000 _______ $185,001-$195,000

_______ $35,001-$45,000 _______ $115,001-$125,000 _______ $195,001-$205,000

_______ $45,001-$55,000 _______ $125,001-$135,000 _______ $205,001-$215,000

_______ $55,001-$65,000 _______ $135,001-$145,000 _______ $215,001-$225,000

_______ $65,001-$75,000 _______ $145,001-$155,000 _______ $225,001-$235,000

_______ $75,001-$85,000 _______ $155,001-$165,000 _______ Greater than $235,000

_______ $85,001-$95,000 _______ $165,001-$175,000 _______ Prefer not to say

8. Do you own property in a Delaware beach community (within 5 miles of an ocean beach)? (Exclude investment properties)

_______Yes, my primary residence

Yes, my secondary residence

________No

9. Which activities are most important to you when visiting anocean beach or beach community in Delaware? (If you engage or more than one, pick the one that is most important.)

_______Activities in or on the water

_______Activities on the sand

_______Activities at the boardwalk or in town

10. Are you staying here for more than one night on your current trip? (Please skip if your primary residence in a Delaware beach community)

_______Yes ________No

If yes, for how many nights are you staying? _______

11. How many hours do you expect to spend on the beach and boardwalk today? ________

12. Including yourself how many people are you traveling with? ________

- How many children under age 18? _______

13. How many days have you spent on Delaware's ocean beaches (including time on the beach as well as in the community) since Memorial Day? (Please skip if your primary residence in a Delaware beach community)

(Days on the beach since May 28th)? _______

14. How many more days do you expect to spend on Delaware's ocean beaches before Labor Day

(Day on the beach between now and Sept. 3th)? _______

15. Are these primarily day trips or overnight trips?

_______ Day _______ Overnight

16. How many years have you been coming to Delaware's ocean beaches? _______

17. What would you most likely do with your time if the beach you were visiting on your current trip was closed for some reason for an extended period of time?

_______ Visit another beach in Delaware

_______ Visit the same beach community in Delaware but not go on the beach

________ Visit a beach in Maryland

________ Visit a beach in Virginia

________ Visit a beach in New Jersey

________ Visit a beach outside the mid-Atlantic (not MD, VA, NJ pr DE)

________ Visit a bay beach in Delaware

________ Engage in some other non-beach recreation

________ Stay home

________Other: ________________________________

18. On a scale of 1 to 5, how favorable are you toward the development offshore wind power in the Mid-Atlantic region?

On a scale of 1 to 5, how favorable are you toward the development of offshore oil production in the Mid-Atlantic region?

Rank your level of agreement with each of the following statements based on the this scale:		STRONGLY AGREE	MILDLY AGREE	UNSURE	MILDLY DISAGREE	STRONGLY DISAGREE
19.	How aware are you of the proposed wind farms off the coast of Delaware?	1	2	3	4	5
20.	How aware are you of oil drilling regulations on the Atlantic Outer Continental Shelf?	1	2	3	4	5
21.	Wind power is a financially viable energy source for our country.	1	2	3	4	5
22.	Offshore oil is a financially viable energy source for our country.	1	2	3	4	5
23.	Wind turbines have a negative impact on the landscape.	1	2	3	4	5
24.	Offshore oil platforms have a negative impact on the landscape.	1	2	3	4	5
25.	When humans interfere with nature it often produces disastrous consequences.	1	2	3	4	5
26.	Human ingenuity will insure that we do NOT make the earth unlivable.	1	2	3	4	5
27.	Humans are severely abusing the environment.	1	2	3	4	5
28.	The earth has plenty of natural resources if we just learn how to develop them.	1	2	3	4	5
29.	Plants and animals have as much right as humans to exist.	1	2	3	4	5
30.	The balance of nature is strong enough to cope with the impacts of modern industrial nations.	1	2	3	4	5
31.	Despite our special abilities humans are still subject to the laws of nature.	1	2	3	4	5
32.	The so-called "ecological crisis" facing humankind has been greatly exaggerated.	1	2	3	4	5
33.	The earth is like a spaceship with very limited room and resources.	1	2	3	4	5
34.	Humans were meant to rule over the rest of nature.	1	2	3	4	5
35.	The balance of nature is very delicate and easily upset.	1	2	3	4	5
36.	Humans will eventually learn enough about how nature works to be able to control it.	1	2	3	4	5
37.	If things continue on their present course,	1	2	3	4	5

we will soon experience a major ecological catastrophe.	

Appendix B

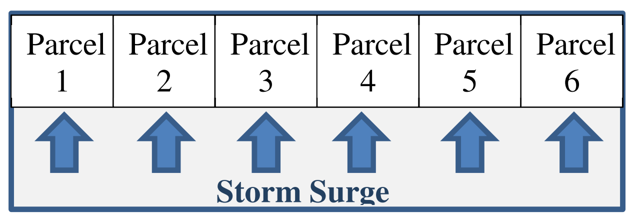
INSTRUTIONS FOR COASTAL INNUNDATION EXPERIMENT

<u>Experiment Instructions – Introduction</u>

Welcome to an experiment in the economics of decision making. In the course of the experiment you will have opportunities to earn money. Any money earned during this experiment will initially be recorded as **experimental dollars** which will be later converted into actual **US dollars** that will be yours to keep. Thus, the more experimental dollars you earn, the more US dollars you will receive. At the end of the experiment your earnings will be converted at a rate of $100 Experimental = $1 US. Please read these instructions carefully and do not communicate with any other participants during the experiment.

Protection and Profit

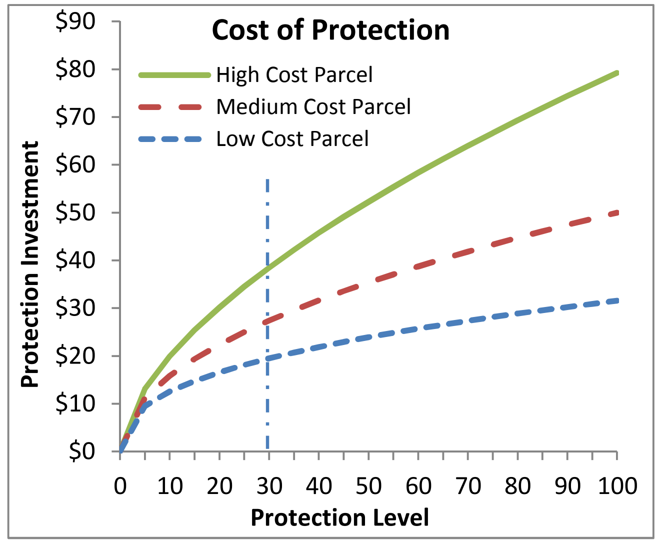
In today's experiment, you will participate in a number of **parts**. Each part will have 10 **rounds**. Each round is independent; decisions during a round <u>do not</u> affect future rounds, and each round starts off with zero for all values, except for your total profit. Throughout the experiment, you will be in a group of six participants. You and everyone else in your group will be managing a piece of oceanfront land. We will call this your **parcel**. Parcels will be labeled number one through six, and are arranged as shown in the image to the right. Which group you are in, and which parcel you have may change from part to part.



In each round you and everyone else in your group will have an initial balance of $100**.** You must decide how much of these funds to invest in **protection** from flood damage from storm surges, such as those that come from hurricanes or tsunamis, which can **damage** your parcels. In each round, you will receive **profit** equal to your initial balance, minus the amount you invest in protection, minus the flood damage to your parcel:

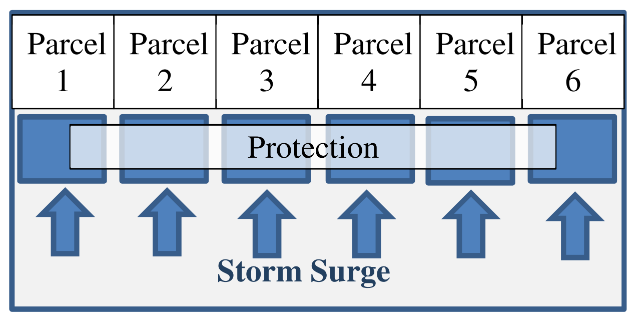
Profit = $100 – Protection Investment – Damage.

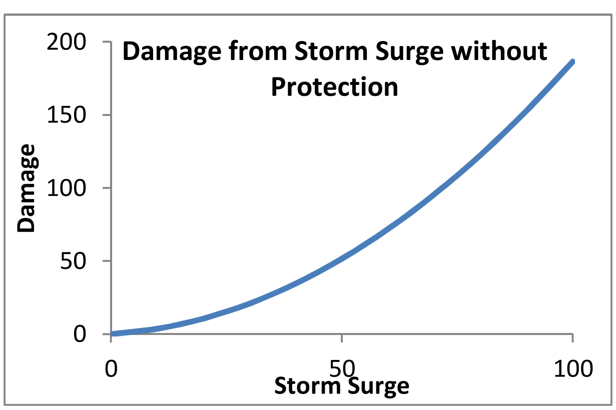
How much protection you receive from your investment depends on the condition of the shore of your parcel. You will invest some amount of dollars in protection, for which you will receive some units of protection, called you **level of protection.** Your parcel may have a **low cost** of protection, a **medium cost** of protection, or a **high cost** of protection. The graph to the right shows how much it will cost for each type of parcel to receive a certain level of protection. For instance, if you wanted a level of protection of 30 units (at the dashed vertical line), you would need to invest about $20 in protection if your parcel was low cost, $27 in protection if your parcel was medium cost, and $38 in protection if your parcel was high cost.



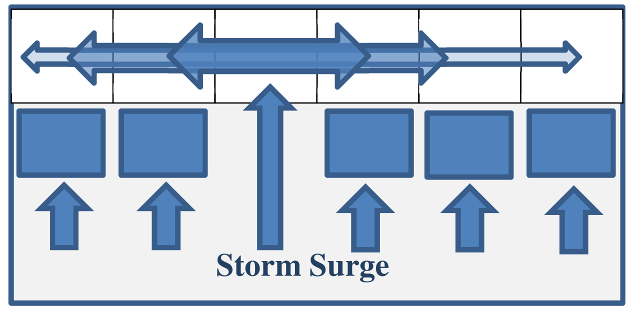
Storm Surges and Damage

In each round, you will be subject to a storm surge which may cause flooding on your parcel. Once a parcel is flooded, this flood water will continue to flood neighboring parcels causing damage to these parcels. The storm surges will be of different **sizes**. The figure below displays the damage on each parcel from different levels of storm surge if all parcels have zero units of protection. With a storm surge of 50 units, if there is no protection, each parcel will face damage of just over $50. This rate also rises such that a storm surge of 100 units with zero units of protection will cause $200 in damages

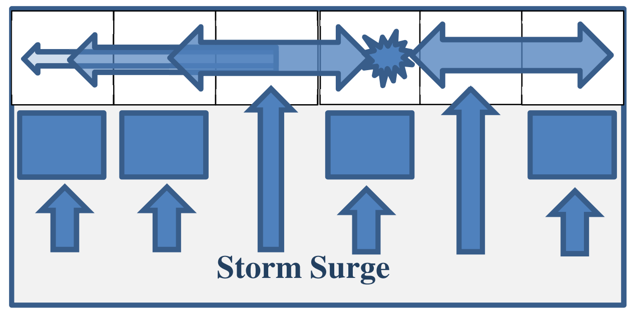




Your protection can absorb some or all of the storm surge at your parcel. If you have a protection level less than the size of the storm surge, your parcel will be flooded by the excess amount. For instance, if there is a storm surge of size 50 units, and you have a protection level of 30 units, you will be flooded by 20 units. If your protection level is equal to or exceeds the size of the storm surge you will not have any amount of flooding from the surge. Throughout the parts in today's session, the storm surge will be **a minimum of 50 units**, though it may be more in some parts. For each part you will be told what kind of storm surge to expect.



Since the flood water moves across neighboring parcels, the damage to your parcel depends on both the amount of flooding on your parcel as well as the amount of flooding on all of the other parcels. For instance, suppose all of the parcels had protection levels of 50 units or more except for parcel 3, which invested in zeros units of protection. Parcel 3 will flood with 50 units, and then the flood water will flow from parcel 3 to parcel 2 and parcel 4, which will then flow to parcel 1 and parcel 5, and so forth. The corresponding damage is listed under Example 1 in the table below.

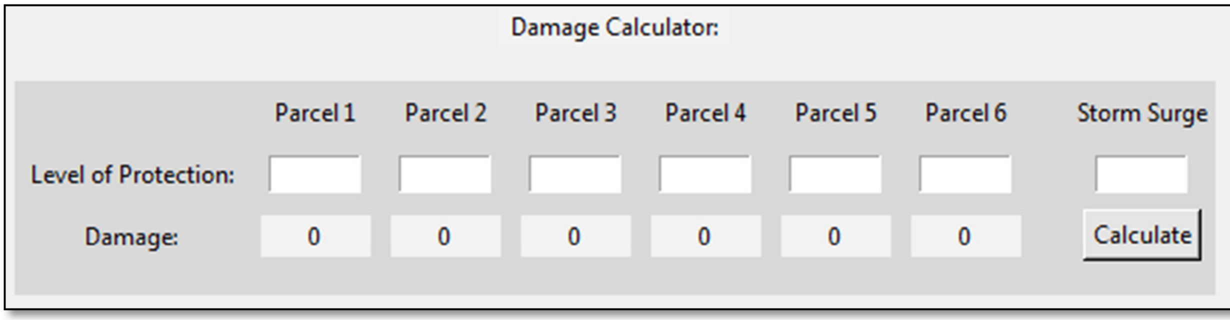


If there is flooding on multiple parcels, the pattern of damage may be more complex as water spreads from multiple points in wave patterns. For instance, if parcel 3 and parcel 5 invest in zero units of protection while all other structures have a protection level of 50 or more units, the flood waters will both run towards parcel 4, and combine dealing parcel 4 *more damage* than either parcel 3 or parcel 5. Some of that water will be reflected back over parcel 3, then parcel 2 and parcel 1, causing more damage to them then in the prior case. The corresponding damage is listed under Example 2 on the table below.

	Example 1		Example 2	
Parcel	**Protection**	**Damage**	**Protection**	**Damage**
1	50 Units	\$2	50 Units	\$2
2	50 Units	\$4	50 Units	\$4
3	0 Units	\$11	0 Units	\$13
4	50 Units	\$4	50 Units	\$15
5	50 Units	\$2	0 Units	\$13
6	50 Units	\$1	50 Units	\$4

The experiment software also includes a calculator to help you figure out the damage that will be caused by different sets of production decisions. You must put in protection level values for each parcel, and the water level, and then click the

Calculate button. This will calculate the damage that will be received by each parcel for you.



After everyone has had a chance to read these instructions, an administrator will provide additional explanations and you may ask questions.

Experiment Instructions

The storm surge will be 50 units in every round of this part.

This part of the experiment will be exactly as described in the introduction. Your profit will be calculated as:

Profit = \$100 – Protection – Damage

Experiment Instructions

The storm surge will be 50 units in every round of this part.

In this part of the experiment there will be a **development agency** that is offering **payments** to everyone in your group for investing in protection. This payment will be \$13 for each parcel; however it will only be paid if the **total damage** to all parcels is less than \$75. For example, if all of the parcels had protection levels so that each had damage of \$10, the total damage would be \$60, which is less than \$75. In this case, each parcel owner would receive a payment of \$13. If each parcel had total damage of \$15, the total damage would be \$90, which is greater than \$75. Thus, in this case, there would be no payment.

Profit if total damage is less than \$75:

Profit = \$100 – Protection– Damage + \$13

Profit if total damage is greater than \$75:

Profit = \$100 – Protection– Damage

Experiment Instructions

The storm surge will be 50 units in every round of this part.

In this part of the experiment there will be a **development agency** that is offering grants for developing protection. To receive a grant, you must submit a **proposal**. A proposal made up of two parts, (1) an amount of **additional investment** in protection, and (2) the **minimum payment** you would need to receive to make that additional investment. By submitting a proposal, you are offering to increase your investment in protection by the additional investment, in exchange for being paid at least the minimum payment.

The development agency has a limited **budget** of $80 in each round, so may not be able to fund all proposals. The agency will accept proposals to achieve the maximum amount of damage reduction that they can afford given their budget.

If your proposal is accepted:

-You will have to make that additional investment in protection at your parcel's cost level.
-You will receive a **total payment** as additional profit. This total payment will be equal to the **minimum payment** from your proposal, plus a **bonus**, based on the amount of **damage reduction** from the additional investment**.**
-The damage reduction is the amount of damage that other parcels would have received in this round, that is prevented by you additional protective investment.

Profit = $100 – Protection – Damage – Additional Investment + Total Payment

Profit if your proposal is not accepted:

-You will not make the additional investment
-You will only receive your normal profit.

Profit = $100 – Protection – Damage

.

Experiment Instructions

The storm surge in this part will have one of three randomly determined possible values: 50% of the time (or about 1 out of every 2 rounds) the storm surge will be 50 units, 30% of the time (or about 3 out of 10 rounds) the storm surge will be 75 units, and 20% of the time (or about 1 out of 5 rounds) the storm surge will be 100 units.

This part of the experiment will be exactly as described in the introduction. Your profit will be calculated as:

Profit = 100 – Protection– Damage.

Experiment Instructions

The storm surge in this part will have one of three randomly determined possible values: 50% of the time (or about 1 out of every 2 rounds) the storm surge will be 50 units, 30% of the time (or about 3 out of 10 rounds) the storm surge will be 75 units, and 20% of the time (or about 1 out of 5 rounds) the storm surge will be 100 units.

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Profit if total damage is less than \$75:

Profit = \$100 – Protection– Damage + \$13

Profit if total damage is greater than \$75:

Profit = \$100 – Protection– Damage

Experiment Instructions

The storm surge in this part will have one of three randomly determined possible values: 50% of the time (or about 1 out of every 2 rounds) the storm surge will be 50 units, 30% of the time (or about 3 out of 10 rounds) the storm surge will be 75 units, and 20% of the time (or about 1 out of 5 rounds) the storm surge will be 100 units.

In this part of the experiment there will be a **development agency** that is offering grants for developing protection. To receive a grant, you must submit a **proposal**. A proposal made up of two parts, (1) an amount of **additional investment** in protection, and (2) the **minimum payment** you would need to receive to make that additional investment. By submitting a proposal, you are offering to increase your investment in protection by the additional investment, in exchange for being paid at least the minimum payment.

The development agency has a limited **budget** of $80 in each round, so may not be able to fund all proposals. The agency will accept proposals to achieve the maximum amount of damage reduction that they can afford given their budget.

If your proposal is accepted:

-You will have to make that additional investment in protection at your parcel's cost level.
-You will receive a **total payment** as additional profit. This total payment will be equal to the **minimum payment** from your proposal, plus a **bonus**, based on the amount of **damage reduction** from the additional investment**.**
-The damage reduction is the amount of damage that other parcels would have received in this round, that is prevented by you additional protective investment.

Profit = $100 – Protection – Damage – Additional Investment + Total Payment

Profit if your proposal is not accepted:

-You will not make the additional investment
-You will only receive your normal profit.

Profit = $100 – Protection – Damage

Appendix C

IRB LETTER OF EXEMPTION FOR OFFSHORE ENERGY EXPERIMENT

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	August 5, 2011
TO:	Kent Messer, PhD
FROM:	University of Delaware IRB
STUDY TITLE:	[262188-1] Analysis of the Visual Effects of Offshore Wind Projects
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	August 5, 2011
REVIEW CATEGORY:	Exemption category # 2

Thank you for your submission of New Project materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Jody-Lynn Berg at (302) 831-1119 or jlberg@udel.edu. Please include your study title and reference number in all correspondence with this office.

Appendix D

IRB APPROVAL LETTER FOR COASTAL INUNDATION EXPERIMENT

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	April 29, 2014
TO:	Kent Messer
FROM:	University of Delaware IRB
STUDY TITLE:	[464373-2] Protecting the Coastline—Optimal Coastal Inundation Adaptation Mechanisms
SUBMISSION TYPE:	Amendment/Modification
ACTION:	APPROVED
APPROVAL DATE:	April 29, 2014
EXPIRATION DATE:	May 6, 2015
REVIEW TYPE:	Expedited Review
REVIEW CATEGORY:	Expedited review category # *(7)*

Thank you for your submission of Amendment/Modification materials for this research study. The University of Delaware IRB has APPROVED your submission. This approval is based on an appropriate risk/benefit ratio and a study design wherein the risks have been minimized. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on the applicable federal regulation.

Please remember that informed consent is a process beginning with a description of the study and insurance of participant understanding followed by a signed consent form. Informed consent must continue throughout the study via a dialogue between the researcher and research participant. Federal regulations require each participant receive a copy of the signed consent document.

Please note that any revision to previously approved materials must be approved by this office prior to initiation. Please use the appropriate revision forms for this procedure.

All SERIOUS and UNEXPECTED adverse events must be reported to this office. Please use the appropriate adverse event forms for this procedure. All sponsor reporting requirements should also be followed.

Please report all NON-COMPLIANCE issues or COMPLAINTS regarding this study to this office.

Please note that all research records must be retained for a minimum of three years.