

DISSERTATION  
THREE ESSAYS ON NON-MARKET VALUATION USING HEDONIC  
PROPERTY AND CONTINGENT VALUATION TECHNIQUES

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In partial fulfillment of the requirements  
For the Degree of Doctor of Philosophy  
Colorado State University  
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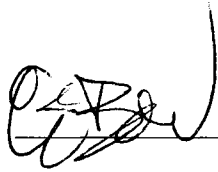
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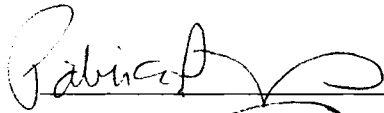
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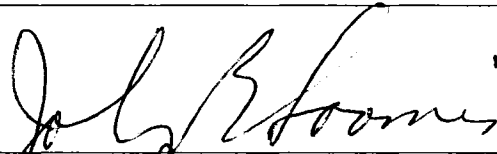
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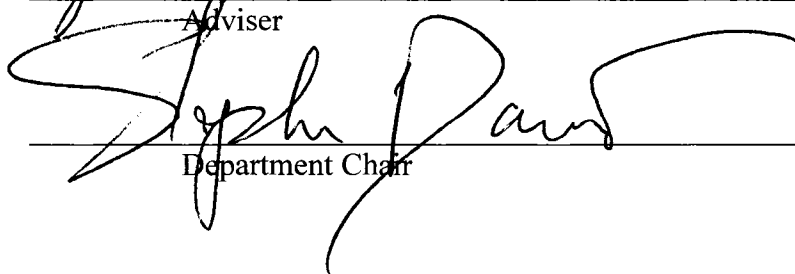


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ABSTRACT OF DISSERTATION  
THREE ESSAYS ON NON-MARKET VALUATION USING HEDONIC  
PROPERTY AND CONTINGENT VALUATION TECHNIQUES

Non-market valuation is commonly used to quantify the value of environmental amenities and hazards. The two main methods of non-market valuation are stated and revealed preference. The studies herein examine the non-market values of forest fires and wind power using stated and revealed preference methods.

The first essay investigates the construct validity of Ordinary Least Squares as a method for estimating hedonic price functions. The hedonic property method is based on the utility theoretic premise that house prices are a function of both structural and environmental attributes. Because environmental attributes are location specific, the estimated hedonic price function may have issues with spatial dependence. The first essay tests for spatial dependence and finds that estimates of implicit prices using OLS, while technically biased, do not exhibit an economically significant difference from spatially corrected estimates.

The second essay applies the hedonic property method to a larger dataset using OLS to quantify both the immediate and long-term effects of forest fires on house prices in Southern California. Forest fires have a statistically significant and negative immediate effect on house prices. After a first fire, house prices continue to decrease over time, while after a second fire, house prices begin to

recover. The results indicate that homebuyers in high-risk areas may not be fully aware of the effects of short and long term fire risks.

The final essay applies the contingent valuation technique to the results of a dichotomous-choice survey. The survey investigates Massachusetts residents' willingness to pay to forego and willingness to accept to allow a proposed wind park. Although the survey was formulated assuming that the majority of respondents would be willing to pay to forego the wind park, the WTP results indicate that respondents are willing to pay to \$193 a year to obtain the wind park, and the WTA results indicate that respondents are willing to pay \$35 a year to obtain the wind park.

Each essay applies a particular type of non-market valuation technique and investigates the methodology and the policy implications of the application.

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## 1. INTRODUCTION

## 1.1 INTRODUCTION

Non-market valuation began when economists first struggled with the idea of finding solutions to market failures in the presence of externalities. In the 1960s debate about natural resources began to move beyond finding the optimal levels of inter-temporal use to attempting to quantify the values of the amenities associated with natural environments. What was first coined *option demand* was referred to as people's willingness to pay to preserve natural environments that have few practical substitutes. Because environmental amenities have public good characteristics, without government intervention, they will be underprovided. Non-market valuation is a method of valuing these environmental amenities, so that policies can be enacted to ensure socially optimal allocations (Krutilla, 1967).

Two methods of non-market valuation are commonly applied in economic literature. Revealed preference methods are based on people's observable choices and behavior. Stated preference methods involve surveying people about their valuation for non-market goods. Both stated preference and revealed preference techniques are continually being updated and refined. Dramatic increases in computing capabilities have resulted in better data gathering capabilities and availability. Methods of estimation in non-market valuation continue to adapt to changes in theory and computing power.

Revealed preference methods of non-market valuation include the hedonic property model and the travel cost model. Hedonic property models are used to

estimate people's valuation of goods using information on the selling price of houses combined with house characteristics, neighborhood demographics, and nearby environmental attributes or hazards (Taylor, 2002). Travel cost models are used to estimate recreation values based on the cost of travel and distance traveled to recreation sites (Parsons, 2002). Thus, data for both hedonic property and travel cost models are spatial in nature. Homebuyers choose their homes based on location. Trip cost is directly related to distance and location. Recently, because of increased availability of spatial data and advancement of Geographical Information Systems in the U.S., an area of particular growth is in spatial analysis.

Contingent valuation (CV), a stated preference method of non-market valuation, asks consumers of a non-market good their willingness to pay to obtain that good or how much money they would be willing to accept to give up the good. CV was highly criticized in its early years. Since the NOAA Panel in 1993, however, it has been accepted as a method of measuring values of environmental amenities or hazards (Arrow, 1993). Unlike revealed preference methods, CV provides estimates of use and non-use values. Debate over the methodology, implementation, and practical application of CV continues, and resulting improvements have contributed to the robustness of CV results. CV research has "matured as a result of the spotlight that has been placed upon it" (Carson, Flores, and Meade, 2000). Because of the high publicity of debate over

CV, the methodology has advanced steadily and estimation techniques continue to improve.

Stated preference techniques combined with maximum likelihood estimation can be used to estimate willingness to pay functions. From estimated willingness to pay functions, policymakers can make inferences about the net benefits and the distributional effects of benefits and costs. Renewable, or “green” energy, in particular wind power, can have distributional effects in terms of its benefits and costs.

The objective of the following research is to use both stated preference and revealed preference methods to value non-market environmental goods with a focus on spatial dimensions and estimation techniques. The first essay investigates the methodology of estimation in hedonic property models, comparing the results from conventional Ordinary Least Squares estimation to the results from Maximum Likelihood estimation with spatial corrections. Based on the methodological conclusions from the first essay, the second essay estimates the non-market value of repeated forest fires over time. The third paper uses the contingent valuation method to investigate consumer preferences for a proposed wind park and estimates the distribution of willingness to pay for green energy.

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2. SPATIAL DEPENDENCE IN HEDONIC PROPERTY MODELS: DO  
DIFFERENT CORRECTIONS FOR SPATIAL DEPENDENCE RESULT IN  
ECONOMICALLY SIGNIFICANT DIFFERENCES IN ESTIMATED  
IMPLICIT PRICES?

## 2.1 INTRODUCTION

Spatial issues are receiving increased attention in environmental and natural resource economics, including the use of spatial hedonic property models to value environmental amenities and dis-amenities (Bateman, Yang, and Boxall, 2006). In hedonic property models, the estimated value of an environmental amenity is the marginal effect of the amenity on the observed house price. OLS has been the common empirical method for estimating the hedonic price function. However, the data used in hedonic property models are spatial in nature because they are based on house sales in a given area, and failure to correct for spatial dependence can result in biased and inefficient estimates of implicit prices. Correcting for spatial dependence requires that data are geo-coded. Because of recent advances in Geographical Information Systems, geo-coded data are becoming widely available, although such data are not universally available for all counties in the U.S. and are rarely available outside the U.S. and Europe.

If geo-coded data are unavailable, does OLS without spatial corrections give a ballpark estimate of the value of an environmental amenity, or conversely, should analysts use the hedonic property method only when geo-coded data are available? Of particular interest to analysts and policymakers is whether the difference in estimated implicit prices with and without corrections for spatial dependence is of economic significance. Specifically, do previous estimates of implicit prices from hedonic property models suffer from an economically significant bias because of failure to recognize spatial dependence? Many past

hedonic property studies did not have spatially coded data. If so, are past meta-analyses of hedonic property studies still useful for benefit transfer? These are some of the questions that I address with the results from this study.

## 2.2 LITERATURE REVIEW

The data used in hedonic models are spatial in nature, but many past studies do not account for spatial dependence. Failure to correct for spatial dependence can result in inefficient and biased coefficient estimates and associated effects on marginal implicit prices. When a spatially lagged dependent variable is ignored in a model specification, but present in the underlying data generating process, the resulting mis-specification is of the omitted variable type—i.e., OLS is biased and inconsistent. When the errors exhibit spatial correlation, the primary problem with OLS is inefficiency (Anselin and Bera, 1998). Therefore, failure to correct for spatial dependence in hedonic property models may result in inefficient or biased estimates of marginal implicit prices.

Some evidence for the importance of spatial effects in hedonic studies is presented in Brasington and Hite's (2005) analysis of the demand for environmental quality. They find relatively large differences in estimates of the implicit price of environmental quality for models with and without spatial effects and conclude that researchers should at least test for spatial effects in hedonic models. Hunt et al (2005) present a similar warning in the conclusion of their analysis on the impact of logging on the hedonic price of remote fishing trips in Alberta, Canada. In their case, including the spatial lag in the regression model

caused most of the OLS parameter estimates to deflate. They conclude that researchers should use considerable caution when estimating econometric models with inherently spatial data.

Several hedonic studies have incorporated spatial corrections. However, few studies analyze the effects of wildfires on house prices using spatially corrected models. In a study on the effect of wildfire risk on house prices, Donovan, Champ, and Butry (2007) find that accounting for spatial dependence is economically significant. They estimate the changes in the effects of wildfire risk variables on house prices after provision of fire risk information. Spatial dependence causes a large percent bias in their estimated coefficients (ranging from 37% to 167%). However, in another paper comparing spatial estimates to OLS estimates, Pattanayak and Butry (2007) find that failure to account for spatial effects leads to only a slight underestimation (e.g., a few percent) of the true benefits from ecosystem services. Kim, Phipps, and Anselin (2003) also find little difference in a hedonic estimation of willingness to pay per household for improvement in air quality for OLS estimates relative to spatially corrected estimates.

The objective of this paper is to extend the literature on spatial dependence by comparing estimated coefficients for relatively new general spatial models to OLS estimates to determine if spatial corrections result in economically significant differences in the estimated effects of wildfires on house prices. My comparison models go beyond Kim, Phipps and Anselin (2003) by including a

general spatial model that simultaneously incorporates both spatial lag and spatial error into one model. I also test for differences in spatial effects on marginal implicit prices using two different types of weighting matrices to examine the robustness of my results. The insights gained from my study may be valuable to analysts without spatial data.

### 2.3 MODEL SPECIFICATION

The hedonic property method was first proposed by Rosen (1974). It is based on the proposition that identical houses in similar neighborhoods will have different prices if the houses have different levels of an environmental amenity. Homebuyers are willing to pay more for a house with an environmental amenity such as a forested view or a house located on a lake. The resulting house price differential between houses with varying levels of an amenity is homebuyers' marginal willingness to pay for that amenity.

For the following hedonic property model, the dependent variable is the natural log of the real sale price, adjusted using the housing price index for Los Angeles, Riverside, and Orange Counties (1983 base year). A log-linear specification allows the marginal effect of each independent variable to vary with the level of the dependent variable. Thus, with my specification, the marginal effects of independent variables vary as house price varies.

To address the temporal effects of wildfires on house prices, a sale date for each house is required. The recorded sale date is not the date when the actual

purchase decision was made. Offers on house purchases are made one to two months in advance of the recorded sale date. Since homebuyers are locked into their contracts once an offer is made, the time element of my model is represented by a decision date, defined as 60 days prior to the recorded sale date. For example, if a sale date is April 30, 1998, the decision date is March 1, 1998.<sup>1</sup>

The independent variables of interest are wildfire indicator variables. Controls for housing structure and neighborhood demographics are included. The general model is as follows:

$$P_{it} = f(E_{it}, S_i, N_i, M_{it}) \quad (2.1)$$

$P_{it}$ : Sale amount at decision date  $t$ , with sale amount deflated using the annual housing price index for Los Angeles, Orange, and Riverside Counties (1983 Base Year).

The choice of included independent variables for my first stage hedonic property model was based on prior research, data availability, and data characteristics (i.e., correlations). Including irrelevant variables in an OLS regression results in large standard errors for the coefficient estimates, increasing the probability of type II errors (failing to reject the null hypothesis when the null is false). Furthermore, including several highly collinear explanatory variables in a regression may result in unreliable parameter estimates. Failure to include relevant variables, however, results in biased coefficient estimates (Taylor, 2002).

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<sup>1</sup> The timing adjustment is similar to the adjustment used in Loomis and Feldman (2003).

The following are the independent variables I chose to include in my empirical specification:

$E_{it}$ : Environmental and Location Variables:

- (i) **After One Fire:** An indicator variable that equals one if a house sold after and is located within 1.75 miles of at least one wildfire
- (ii) **After Two Fires:** An indicator variable that equals one if a house sold after and is located within 1.75 miles of at least two wildfires<sup>2</sup>
- (iii) **Days Since First Fire:** Number of days since the first wildfire, if the house sold after and is located within 1.75 miles of at least one wildfire
- (iv) **Days Since Second Fire:** Number of days since the second wildfire, if the house sold after and is located within 1.75 miles of at least two wildfires
- (v) **Distance to fire center:** Distance from house to the center of each wildfire (meters)
- (vi) **Distance to USDA Forest Service Land:** Distance from house to the edge of the nearest USDA Forest Service owned land (kilometers)

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<sup>2</sup> I include dummy variables that are equal to one if the house sold after one fire and after two fires. Therefore, the estimated coefficients on the After Fire dummy variables are relative to those houses that sold before any of the fires and those that sold after but were located more than 1.75 miles away from any fire.

- (vii) **Elevation:** Elevation of the house (meters)
- (viii) **Distance to Los Angeles:** Distance from house to Los Angeles city limits (kilometers)

Distance to USDA Forest Service owned land is a proxy for distance to open space or forested land. The elevation of a house lot serves as a proxy for vegetation type (higher elevations have more flammable vegetation). Houses located at higher elevations and nearer to forests have a higher risk of burning from a wildfire. The distance to downtown Los Angeles is included in the model because Los Angeles is the biggest employment center in the area and people commute to Los Angeles for work.

$S_i$ : Housing Structure Variables:

- (i) **Square feet:** The number of square feet in each house
- (ii) **New House:** An indicator that equals one if the house sells in the year it was built or one year after it was built

Several measures of housing characteristics were available. Square feet is the most commonly used approach in hedonic property models to control for housing structure, and therefore is the structural characteristic I decided to include. I also used new house as a structure quality control.

$N_i$ : Neighborhood Demographics Factors:

- (i) **Median Household Income:** Median household income in census tract (Year 2000 dollars)

- (ii) **Percent with No High School Degree:** Percent of residents in census tract above 18 years old with no high school degree

Neighborhood characteristics commonly included in hedonic models are school district quality and household income (Taylor, 2002). A direct measure of school district quality is unavailable within my data, so a measure of the percent with no high school degree in a neighborhood is used as a proxy for the relative level of educational attainment in a particular community. Neighborhoods with high percentages of educated people generally have higher quality schools. Median household income is also included as a proxy for neighborhood desirability.

$M_{it}$ : Market Variables

- (i) **Mortgage Rate:** 30 Year mortgage interest rates—US (base year—1983)
- (ii) **Unemployment Rate:** California annual unemployment rates

Macroeconomic fluctuations affect the housing market. Although my sale amounts are deflated by the housing price index, changes in employment levels and mortgage rates also cause changes in housing demand. Periods of high unemployment decrease demand for housing, lowering the equilibrium price of homes. Periods of high mortgage interest rates make it difficult for people to borrow and cause a decrease in the demand for housing, also lowering the

equilibrium price of homes. The California unemployment rate and the U.S. mortgage interest rate are included in my model to control for market fluctuations. The full empirical specification is as follows:

$$\begin{aligned}
 \text{Log (Real Sale Amount)} = & \beta_0 + \beta_1*(\text{After One Fire}) + \\
 & \beta_2*(\text{After Two Fires}) + \beta_3*(\text{Days Since First Fire}) + \\
 & \beta_4*(\text{Days Since Second Fire}) + \beta_5*(\text{Square Feet}) + \\
 & \beta_6*(\text{New House}) + \beta_7*(\% \text{ with no High School Degree})+ \\
 & \beta_8*(\text{Median Household Income}) + \beta_9*(\text{Distance to USFS Land}) + \\
 & \beta_{10}*(\text{Distance to Los Angeles}) + \beta_{11}*(\text{Unemployment Rate})+ \\
 & \beta_{12}*(\text{Mortgage Rate}) + \beta_{13}*(\text{Elevation})
 \end{aligned}
 \tag{2.2}$$

Estimating the full model posed problems, including high correlations between some of the independent variables. High correlation of independent variables leads to multi-collinearity in OLS models. Multi-collinearity is a data problem not related to the efficiency of estimators. Table 2.1 reports correlations between different variables. Not including the After Fire and Since Fire variables, the average of the absolute value of the correlations between variables is 0.29. The After Fire and Since Fire variables are highly correlated by definition. Specifically, Since First Fire is only positive when After One Fire equals one. The same concept applies to After Two Fires and Since Second Fire.

The final estimated model eliminates the Mortgage Rate because of its high correlation with the Unemployment Rate. I also eliminated the New House variable and Distance to Los Angeles because they did not affect the key results and were statistically insignificant. Distance to Los Angeles may not be

statistically significant because of directional heterogeneity (Cameron, 2006).

Some houses may be priced higher because they are located near highways, even if their distance to Los Angeles is further. Thus, both distance and direction may matter, and this could contribute to the lack of significance in the distance to Los Angeles variable. As will be seen in the results section, my parameter estimates for the highly correlated After Fire and Since Fire variables are statistically significant in numerous specifications despite having inflated standard errors.

The estimated model is as follows:

$$\begin{aligned} \text{Log (Real Sale Amount)} = & \beta_0 + \beta_1*(\text{After One Fire}) + \\ & \beta_2*(\text{After Two Fires}) + \beta_3*(\text{Days Since First Fire}) + \\ & \beta_4*(\text{Days Since Second Fire}) + \beta_5*(\text{Square Feet}) + \\ & \beta_6*(\% \text{ with no High School Degree}) + \beta_7*(\text{Median Household} \\ & \text{Income}) + \beta_8*(\text{Distance to USFS Land}) + \beta_9*(\text{Unemployment} \\ & \text{Rate}) + \beta_{10}*(\text{Elevation}) \end{aligned} \tag{2.3}$$

**Table 2.1: Correlations**

	After 1	After 2	Since 1 <sup>st</sup>	Since 2 <sup>nd</sup>	Sq Ft	New	% no HS	Inc	Dist USFS	Dist LA	Unem	Mort	Elev
After One Fire	1.00												
After Two Fires	0.62	1.00											
Days Since First Fire	0.68	0.80	1.00										
Days Since Second Fire	0.48	0.79	0.90	1.00									
Square Feet	0.01	0.06	-0.03	0.02	1.00								
New House	0.00	0.09	-0.05	0.04	0.33	1.00							
% With No H. School Degree	0.04	0.00	0.12	0.02	-0.47	-0.22	1.00						
Median Household Income	0.00	0.04	-0.04	0.03	0.42	0.23	-0.65	1.00					
Distance to U.S.F.S. Land	-0.24	-0.28	-0.28	-0.23	0.15	-0.06	-0.20	0.20	1.00				
Distance to Los Angeles	-0.09	-0.09	-0.10	-0.09	0.10	-0.05	-0.11	0.07	0.36	1.00			
Unemployment Rate	-0.19	-0.55	-0.42	-0.44	-0.04	-0.18	0.04	-0.10	0.06	0.01	1.00		
Mortgage Rate	-0.67	-0.57	-0.67	-0.61	-0.04	0.05	0.06	-0.02	0.04	0.02	-0.07	1.00	
Elevation (meters)	0.04	0.13	-0.01	0.07	0.11	0.25	-0.36	0.15	-0.42	-0.17	-0.06	-0.09	1.00

## 2.4 SPATIAL MODELS

I also estimate the three types of spatial models using Maximum Likelihood.

The first is a Spatial Auto-regressive model (SAR). A SAR model allows for spatial autocorrelation. Spatial autocorrelation occurs when the value of the dependent variable for an observation is correlated with that of nearby observations (Anselin and Bera, 1998). Spatial autocorrelation is likely to occur when one house's sale price depends upon the sale price of neighboring houses. This may occur in several ways, including the common practice of real estate agents and appraisers relying on nearby sales to set the initial selling price for a home. The SAR model is similar to the familiar time series lagged dependent variable model. With  $y$  as the dependent variable and  $X$  as a matrix of independent variables, the SAR model is as follows:

$$y = \rho(Wy) + X\beta + \varepsilon \tag{2.4}$$

$W$  is the  $n$  by  $n$  weighting matrix,  $\beta$  is a vector of estimated coefficients,  $\varepsilon_i \sim N(0, \sigma)$  and  $\rho$  is the spatial lag operator.

The second type of spatial model I estimate is a Spatial Error Model (SEM). It allows for spatially correlated error terms. Spatially correlated errors are likely to occur when measurement error is related to location (Anselin and Bera, 1998). For example, if neighborhood effects are not captured in the demographic characteristics, OLS will result in spatially correlated errors. The SEM is as follows:

$$\begin{aligned} y &= X\beta + \mu \\ \mu &= \lambda W\mu + \varepsilon \end{aligned} \tag{2.5}$$

$W$ ,  $y$ ,  $x$ ,  $\beta$  and  $\varepsilon$  are as defined above. Here,  $\lambda$  is a coefficient on the spatially correlated errors.

The final model I estimate is a General Spatial Model, or a Spatial Lag and Error model. A General Spatial Model incorporates both a first-order spatial lag and spatially correlated errors. It is appropriate when values of the dependent variable are spatially correlated and measurement error is related to location. The General Spatial Model is as follows:

$$\begin{aligned} y &= \rho W y + X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + \mu \end{aligned} \tag{2.6}$$

All parameters are as defined above. So that the models are comparable, I use the same independent and dependent variables in all specifications. When estimating the General Spatial Model, I used the same weighting matrix for both the spatial lag and spatial error process. Therefore, I am assuming that the underlying spatial relationship follows the same process for both types of spatial dependence.

The first step is estimating Equation (2.3) using OLS and testing for spatial dependence using Moran's I. Since spatial dependence exists, I estimate SAR and SEM models. Then, I test for correlation in the errors of my SAR, and since it exists, estimate the General Spatial Model. I repeat the estimation process for three different weighting matrices. Then, I compare the implicit price of the environmental hazard variable from OLS estimation to the three spatial models to investigate the possibility of a policy relevant difference in marginal values. My hypothesis is that in some cases, the difference will be policy relevant, and the researcher will need to use caution when reporting only OLS estimates. What this study contributes is an analysis of the difference in estimated coefficients given the nature of my data and environmental hazard.

## 2.5 SPATIAL WEIGHTS

If spatial dependence is present, the estimated coefficients on OLS models may be biased and inefficient. Testing for spatial dependence and estimating spatially corrected models requires the use of a spatial weights matrix. The spatial weights matrix is an n-by-n representation of the neighbors for each

observation. A neighbor is represented by a non-zero element in the spatial weights matrix. MATLAB was used to generate the spatial weights matrices.<sup>3</sup>

Weighting matrices can generally be categorized as those based on distances or contiguity. Those based on contiguity define neighbors as those observations sharing a common border or vertex. Weights based on distance define neighbors either as all parcels within a minimum cut-off distance or the k-nearest neighbors to each given observation. The benefit of k-nearest neighbors weighting matrices is that they eliminate the possibility of islands, or observations that have no neighbors (Anselin and Bera, 1998). Boxall, Chan, and McMillan (2005) use an inverse distance weights matrix with a cutoff of 4km in their hedonic analysis of the impact of oil and natural gas facilities on house prices. Hunt et al (2005) also use a distance-based weights matrix in their spatial hedonic analysis, while Kim, Phipps, and Anselin (2003) use a nearest-neighbors type distance matrix.

While the choice of the appropriate weighting matrix is determined by the researcher, it may also be influenced by the particulars of the dataset. By generating the weights matrix, the researcher makes assumptions about the spatial relationships within the data. In a spatial hedonic study comparing Generalized Moments estimators to Maximum Likelihood estimators, Bell and Bockstael (2000) find that the estimated coefficients are more sensitive to the choice of weighting matrix than the method of estimation. They used weighting matrices

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<sup>3</sup> The MATLAB code used for generating the spatial weights matrices and the spatial models is in the Spatial Econometrics Toolbox by James LeSage. The toolbox and all documentation are available for download at <http://www.spatial-econometrics.com>.

based on inverse distance and contiguity. To ensure that my estimates are robust to the choice of weighting matrix, I use three different spatial weights matrices for my estimations: four nearest neighbors, eight nearest neighbors, and an inverse distance matrix. The four nearest-neighbors weights matrices have non-zero elements for the specified number of nearest neighbors for each observation. Each weights matrix is then row-standardized so that the elements of each row sum to one. This facilitates the interpretation of the spatial weights as the averaging of neighboring values. MATLAB finds the nearest neighbors for each observation by finding those with the smallest Euclidean distance. The four nearest neighbors weights matrix has four non-zero elements in each row for the four nearest neighbors for each observation. The eight nearest neighbors weighting matrix has eight non-zero elements in each row for the eight nearest neighbors for each observation.

If spatial dependence exists in my data, it is likely that prices of houses clustered together are affected by wildfires in the same way, resulting in a loss of information. That is, prices of houses located further away from each other should exhibit less spatial dependence. In order to capture this effect in the spatial model, I generated an inverse-distance weighting matrix. To facilitate estimation, a weighting matrix should be sparse, i.e. have a large number of zero elements. For my distance matrix, I consider parcels “neighbors” if they are located within the minimum Euclidean distance such that every parcel has at least one neighbor. In contrast to the nearest neighbors weighting matrices, the number

of neighbors varies between parcels in this matrix. For example, parcels located in densely developed areas can have up to 112 neighbors, while some parcels have only a few neighbors. The non-zero elements of the inverse distance matrix are the inverse of the Euclidean distance between two parcels for parcels located within the minimum distance requirement. It is normalized so each row sums to one. This allows neighbors located closer to each other to have higher weights than neighbors located far away.

## 2.6 DATA AND SAMPLING METHODOLOGY

I obtained several datasets from various sources and merged them to form a database that includes housing parcel sale date, sale amount, location, demographic characteristics, fire distances, and distance to employment centers. Each housing parcel is a single-family residence located within 1.75 miles of a relevant wildfire. All parcels sold at least once between 1989 and 2003.<sup>4</sup>

Over 54,000 single-family residences were available to sample from. Outliers were removed from the sample if they were recorded as having less than 500 square feet, if the sale amount in dollars per square foot was less than \$50, and if the sale amount appeared to be a data entry error.<sup>5</sup> In addition, houses with zero bedrooms or zero bathrooms were eliminated from the sample. Because I linked housing data with demographic data using a zip code, houses with no recorded zip code were eliminated from the sample. After outliers were removed, the sample was stratified by distance to wildfire and sale date. Each wildfire was

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<sup>4</sup> I know only the most recent sale date of a house.

<sup>5</sup> For example, there were several observations with sale amounts of 0, 8 27, or 99999999.

mapped with a series of quarter mile rings from the fire center, until the last ring, which is 1.75 miles from the fire center. A target of 25 houses for each distance strata and each year was used. Houses were randomly sampled when there were more than 25 houses for a given distance and sale date.<sup>6</sup>

#### Fire Sampling Methodology:

Wildfires that occurred in the 1990s were chosen for analysis to ensure I have sufficient data after each wildfire to analyze long-term effects. Los Angeles County was selected because there were numerous wildfires within the wild-land urban interface in the county during the 1990s. The study area is composed of five fires and is approximately 5.25 miles across. See Figure 2.1 for a map of the fire area. The darkest areas are the fire perimeters. The gray shaded colored areas represent 0.25-mile rings mapped out from each fire perimeter. The tiny gray shapes represent housing parcels.

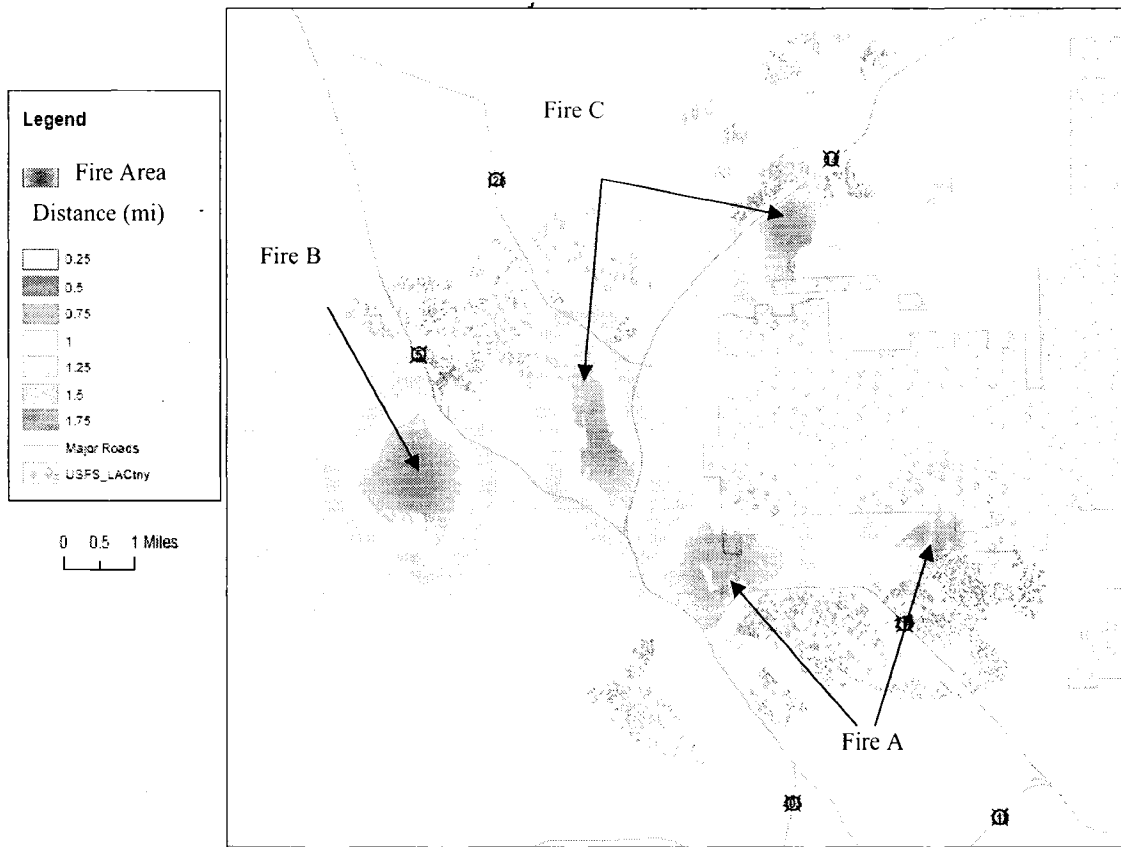
The Sylmar Fire occurred on November 25, 1991 and the Polk Fire occurred on November 28, 1991. Because the Sylmar and Polk fires occurred within three days of and just a few miles from each other and are considered one fire (Fire A) for purposes of this analysis. The Towseley fire occurred on December 4, 1995 and is treated as one fire (Fire B). The Placerita Fire occurred on July 3, 1997 and the Sierra Fire occurred on August 8, 1997. Because the Sierra fire occurred less than 60 days after the Placerita fire, also within miles of the Placerita fire, the Placerita and Sierra fires are also counted as one fire (Fire

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<sup>6</sup> No houses were lost to fire in our fire area.

C). All three wildfires are of comparable size—Fire A burned 937 acres, Fire B burned 818 acres, and Fire C burned 977 acres.

Figure 2.1: Map of Fire Area



Recall that I generated an After One Fire, After Two Fires, Days Since First Fire, and Days Since Second Fire variable for each house. Each house in the study area is located within 1.75 miles of at least one of the fires, but may have sold before the nearest fire. A house within my sample is considered to experience a wildfire if it sells after and is located within 1.75 miles of the wildfire. That is, my After First Fire variable is equal to one for the first wildfire that a particular house sold after and was located within 1.75 miles of. Alternatively, houses that sold before all fires located within 1.75 miles of the house are coded with After One Fire equal to zero and are treated as a control group.

The 1.75-mile cut-off is consistent with the distance cutoffs used in previous hedonic literature on environmental hazards and dis-amenities. For example, Loomis (2004) measured the effect of a forest fire on house prices in a town located about 2 miles from the fire. Gayer, Hamilton, and Viscusi (2000) use quarter mile distance cutoffs ranging from 0.25 mile to 1 mile in a hedonic study on Superfund sites. In another hedonic study on the impact of oil and natural gas facilities Boxall, Chan, and McMillan (2005) find that oil and sour gas facilities located within 4km (2.48 miles) significantly affect house prices. Nonetheless, because of my sampling design, my results apply only to houses located within 1.75 miles of a fire. There may be effects on prices of houses located further than 1.75 miles from fires. But in discussion with United States Forest Service specialists, the cut-off seemed reasonable based on fire risk and other concerns such as evacuation areas.

The Days Since First Fire variable equals the number of days since the first wildfire for houses with After First Fire equal to one. After Second Fire equals one for the second wildfire for houses that sell after and are located within 1.75 miles of two wildfires. The Days Since Second Fire variable equals the number of days since the second wildfire for houses with After Second Fire equal to one. Therefore, houses selling on different dates and located in different areas will have different values for the After Fire and Since Fire Variables. Some houses are located near only one of the three wildfires in my area, some houses are located near only two wildfires in my area, and some houses are located near three wildfires in my area.

Table 2.2 illustrates the sampling for each of my three wildfires. Fire A is a first wildfire for 1181 houses. Fire B is a first wildfire for 657 houses and a second wildfire for 807 houses. All 807 of the houses with Fire B as a second wildfire had Fire A as a first wildfire. Fire C is not a first wildfire for any houses, but it is a second wildfire for 465 houses and a third wildfire for 34 houses. 682 houses have After First Fire, Since First Fire, After Second Fire, and Days Since Second wildfire equal to zero because 411 sold before the nearest fires. By allowing different wildfires to be the “first” wildfire for different houses, I reduce the likelihood that my estimates are biased by spurious correlation with other events.<sup>7</sup>

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<sup>7</sup> Only 34 houses experienced a third fire, so I do not analyze the effect of a third fire.

**Table 2.2: Fire Sampling**

<b>Fire</b>	<b>Year</b>	<b>Sample Inclusions for each Fire</b>	<b>Acres Burned</b>
		682 houses sold before all fires within 1.75 miles	
A	1991	<i>1st</i> Fire for 1181 houses	937
B	1995	<i>1st</i> Fire for 657 houses	818
		<i>2nd</i> Fire for 807 houses	
C	1997	<i>1st</i> Fire for 0 houses	977
		<i>2nd</i> Fire for 465 houses	
		<i>3rd</i> Fire for 34 houses	
		2520 Houses Total	

**Structural and Demographic Characteristics:**

The parcel data were obtained from Los Angeles County through Nobel Systems.<sup>8</sup> The data contain the geographic location, sale date, sale price, and structural characteristics of housing parcels in Los Angeles County.

Demographic variables were attached to each parcel using Geolytics software. Sixty-six demographic characteristics from the 2000 Census were appended to each parcel at the tract block level including median household income, racial make-up, marital status, education, and age of households. I decided to include median household income (measured in year 2000 dollars) and percent with no high school degree in my models. Both demographic variables are proxies for overall neighborhood quality. Including demographic characteristics in the model will control for differences in house prices because of variation in

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<sup>8</sup> Thanks to Shil Niyogi of Nobel Systems for his assistance with the Los Angeles Country parcel data.

neighborhood quality, allowing a more accurate measure of the effects of wildfires on house prices.

#### Geographic Characteristics:

Geographical Information Systems was used to measure a series of different distances for each parcel.<sup>9</sup> The geographic data include:

- Distance to fire center for all wildfires (kilometers)
- Distance to edge of nearest USDA Forest Service owned land (kilometers)
- Distance to Los Angeles (kilometers)

#### Market Variables:

Sale price data is deflated using an annual Housing Price Index for Los Angeles, Orange, and Riverside Counties.<sup>10</sup> Annual unemployment rates for the state of California were also obtained from the Bureau of Labor Statistics website.<sup>11</sup> Table 2.3 shows summary statistics for the variables included in the final empirical model. The Housing Price index uses 1983 as a base year, so the mean real sale amount for each fire area is in 1983 dollars. The demographic variables are from the 2000 Census, so median household income is measured in year 2000 dollars. Seventy-three percent of the houses sampled are located within

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<sup>9</sup> I am very grateful to Nate Peterson, our GIS expert, for his valuable contributions to this project.

<sup>10</sup> The annual Housing Price Index was obtained from the Bureau of Labor Statistics website (<http://data.bls.gov/cgi-bin/srgate>) and typing in the series id CUURA421SAH.

<sup>11</sup> The website is <http://data.bls.gov/cgi-bin/srgate>, with the series id LAUST06000003.

1.75 miles of and sold after at least one wildfire. Fifty percent of the houses sampled are located within 1.75 miles of and sold after at least two wildfires.

**Table 2.3:** Summary Statistics

<b>Variable Name</b>	<b>Mean</b>	<b>Standard Error</b>
<i>Real Sale Amount (Year \$1983 )</i>	151,907.10	3,026.06
<i>Log of Real Sale Amount</i>	11.85	0.24
<i>After One Fire</i>	0.73	0.01
<i>After Two Fires</i>	0.50	0.01
<i>Days Since First Fire</i>	1,450	28.90
<i>Days Since Second Fire</i>	693	13.81
<i>Square Feet</i>	1,842	36.70
<i>% With No High School Degree</i>	21.76	0.43
<i>Median HH Inc. (Year \$ 2000, Th.)</i>	65.68	1.31
<i>Distance to U.S.F.S. Land (km)</i>	2.83	0.06
<i>Elevation (meters)</i>	1,426	28.40
<i>Unemployment Rate</i>	6.77	0.13

## 2.7 RESULTS

The OLS results are reported in Table 2.4. The coefficients on After First Fire and After Second Fire are negative and statistically significant. To test for spatial dependence, I perform the Moran's I Test. The null hypothesis of a Moran's I Test is of no spatial dependence. The alternative hypothesis is that spatial dependence exists. Moran's I-statistic is:

$$I = \frac{e'We}{e'e} \tag{2.7}$$

where W is the row-standardized weighting matrix, and e is a vector of OLS regression residuals. The asymptotic distribution of the Moran's I-statistic

corresponds to a standard normal distribution after subtracting the mean and dividing the I-statistic by its standard deviation.<sup>12</sup>

The Moran's I-statistic for all three weighting matrices is highly significant, indicating that I reject the null hypothesis of no spatial dependence. The Moran's I-statistic for each weighting matrix is reported in Table 2.5.

**Table 2.4: OLS Results**  
Dependent Variable: Log of Real House Price

Variable	Coefficient	t-statistic	t-probability
Constant	11.879204	130.94	<0.0001
After One Fire	-0.138185	-7.41	<0.0001
After Two Fires	-0.203071	-9.18	<0.0001
Days Since First Fire	-0.000004	-0.29	0.769784
Days Since Second Fire	0.000194	11.60	<0.0001
Square Feet	0.000344	40.70	<0.0001
No High School Degree	-0.006372	-10.44	<0.0001
Median Household Income	0.000000	1.34	0.179035
Unemployment Rate	-0.035247	-7.78	<0.0001
Elevation (meters)	-0.000196	-4.60	<0.0001
Distance to USFS Land	0.000009	2.68	0.007435
R-squared	0.66		
Rbar-squared	0.66		
Number of Observations	1762		

**Table 2.5: Moran's I Test Results**

	4 Nearest Neighbors	8 Nearest Neighbors	Inverse Distance
Moran I-statistic	7.68	11.01	9.10
Marginal Probability	<0.0001	<0.0001	<0.0001

The next step is to estimate a SAR model. The results for all three weighting matrices are reported in Table 2.6. The log likelihood is nearly the same for all

<sup>12</sup> Basic intuition derived from Lesage's Econometrics Toolbox Documentation. See Kelejian and Prucha (2001) for a detailed analysis of the asymptotic distribution of the Moran I-statistic.

three models, so the SAR results do not give a good indication of what weighting matrix to use. In addition, the estimated coefficients on the After Fire and Since Fire variables are similar for all three weighting matrices. The coefficient on  $\rho$  is statistically significant, providing evidence that the data follow a spatial autoregressive process. However, the statistically significant coefficient on  $\rho$  may also indicate mis-specification.

**Table 2.6: Spatial Auto-Regressive Model Results**

Dependent Variable: Log of Real House Price\*

Weighting Approach	4 NN*		8 NN*		Inverse Distance	
	Coefficient	z-probability	Coefficient	z-probability	Coefficient	z-probability
Constant	11.661471	<0.0001	11.642379	<0.0001	11.837075	<0.0001
After One Fire	-0.136772	<0.0001	-0.136667	<0.0001	-0.139052	<0.0001
After Two Fires	-0.201346	<0.0001	-0.201313	<0.0001	-0.205774	<0.0001
Days Since First Fire	-0.000005	0.681685	-0.000005	0.687343	-0.000002	0.862549
Days Since Second Fire	0.000196	<0.0001	0.000196	<0.0001	0.000192	<0.0001
Square Feet	0.000340	<0.0001	0.000340	<0.0001	0.000343	<0.0001
No High School Degree	-0.006251	<0.0001	-0.006242	<0.0001	-0.006275	<0.0001
Median Household Income	0.000000	<0.0001	0.000000	<0.0001	0.000000	<0.0001
Unemployment Rate	-0.034935	<0.0001	-0.034930	<0.0001	-0.035396	<0.0001
Elevation (meters)	-0.000190	<0.0001	-0.000189	<0.0001	-0.000202	<0.0001
Distance to USFS Land	0.000009	0.005594	0.000009	0.005438	0.000009	0.008981
$\rho$	<b>0.017986</b>	<b>0.001115</b>	<b>0.019524</b>	<b>&lt;0.0001</b>	<b>0.003813</b>	<b>0.040617</b>
R-bar squared	0.66		0.66		0.66	
Log-likelihood	752.40		752.87		752.51	

\* 4 NN and 8 NN are four and eight nearest neighbors respectively.

Because the Moran's I Test does not distinguish between different types of spatial dependence, I need to investigate the possibility of spatially correlated errors. Therefore, my next step is to estimate a SEM. Table 2.7 shows the results from the SEM estimation for all three weighting matrices. The log-likelihood is

1,058 for the inverse-distance weighting matrix, while it is only 771 and 779 for the SAR and SEM models respectively, suggesting that the inverse-distance weighting matrix has the best fit.  $\lambda$  is statistically significant in all three models, indicating the presence of spatially auto-correlated errors.

**Table 2.7: Spatial Error Model Results**  
Dependent Variable: Log of Real House Price

Weighting Approach	4 NN*		8 NN*		Inverse Distance	
	Coefficient	z-probability	Coefficient	z-probability	Coefficient	z-probability
Constant	11.914517	<0.0001	11.903375	<0.0001	11.882828	<0.0001
After One Fire	-0.127981	<0.0001	-0.124734	<0.0001	-0.137340	<0.0001
After Two Fires	-0.209221	<0.0001	-0.204751	<0.0001	-0.203962	<0.0001
Days Since First Fire	-0.000014	0.024382	-0.000019	<0.0001	-0.000005	<0.0001
Days Since Second Fire	0.000205	<0.0001	0.000209	<0.0001	0.000195	<0.0001
Square Feet	0.000328	<0.0001	0.000314	<0.0001	0.000343	<0.0001
No High School Degree	-0.006400	<0.0001	-0.006380	<0.0001	-0.006417	<0.0001
Median Household Income	0.000001	<0.0001	0.000001	<0.0001	0.000000	<0.0001
Unemployment Rate	-0.036975	<0.0001	-0.037256	<0.0001	-0.035485	<0.0001
Elevation (meters)	-0.000191	0.000149	-0.000165	0.006919	-0.000195	0.145653
Distance to USFS Land	0.000009	0.028507	0.000011	0.032384	0.000009	0.008152
$\lambda$	<b>0.210977</b>	<b>&lt;0.0001</b>	<b>0.369995</b>	<b>&lt;0.0001</b>	<b>0.179000</b>	<b>&lt;0.0001</b>
R-bar squared	0.67		0.68		0.77	
Log-likelihood	771.74		790.91		1058.52	

\* 4 NN and 8 NN are four and eight nearest neighbors respectively.

Since  $\rho$  is statistically significant in the SAR model, and  $\lambda$  is statistically significant in the SEM model, I perform an LM test on the SAR model to see if the errors in the SAR model are spatially auto-correlated. The results for the LM test on the SAR residuals are presented in Table 2.8. With each of the three weighting matrices, the test results suggest that the errors in the SAR model are

spatially correlated. Therefore, I estimate the General Spatial Model that allows for both a spatial lag process and spatially correlated errors.

**Table 2.8:** LM SAR Test Results

	<b>4 Nearest Neighbors</b>	<b>8 Nearest Neighbors</b>	<b>Inverse Distance</b>
LM value	56.53	112.16	921.00
Marginal Probability	<0.0001	<0.0001	<0.0001

The results for the General model for all three weighting matrices are presented in Table 2.9. The log-likelihood is significantly higher for all three models relative to both the SAR and SEM specifications. Therefore, I have strong evidence indicating the data follow a first-order spatial autoregressive process, and that the errors are also spatially correlated. The “best” model based on log-likelihood is the General Spatial Model using the inverse-distance weighting matrix.

**Table 2.9: General Spatial Model Results**  
 Dependent Variable: Log of Real House Price

	4 NN*		8 NN*		Inverse Distance	
	Coefficient	z-probability	Coefficient	z-probability	Coefficient	z-probability
Constant	11.856190	<0.0001	11.838221	<0.0001	10.935958	<0.0001
After One Fire	-0.127982	<0.0001	-0.124661	<0.0001	-0.129179	<0.0001
After Two Fires	-0.208603	0.000000	-0.204164	<0.0001	-0.186803	<0.0001
Days Since First Fire	-0.000014	0.082681	-0.000019	<0.0001	-0.000002	0.882499
Days Since Second Fire	0.000206	<0.0001	0.000210	<0.0001	0.000177	<0.0001
Square Feet	0.000328	<0.0001	0.000314	<0.0001	0.000319	<0.0001
No High School Degree	-0.006370	<0.0001	-0.006359	<0.0001	-0.005240	<0.0001
Median Household Income	0.000001	<0.0001	0.000000	<0.0001	0.000000	<0.0001
Unemployment Rate	-0.036851	<0.0001	-0.037133	<0.0001	-0.031223	<0.0001
Elevation (meters)	-0.000190	0.000180	-0.000164	0.006787	-0.000279	<0.0001
Distance to USFS Land	0.000009	0.026021	0.000011	0.028996	0.000011	0.000725
$\rho$	<b>0.004689</b>	<b>0.244010</b>	<b>0.005306</b>	<b>0.462843</b>	<b>0.081000</b>	<b>&lt;0.0001</b>
$\lambda$	<b>0.204000</b>	<b>&lt;0.0001</b>	<b>0.361000</b>	<b>&lt;0.0001</b>	<b>0.175000</b>	<b>&lt;0.0001</b>
R-bar squared	0.67		0.68		0.78	
Log-likelihood	1780.55		1799.47		2113.07	

\* 4NN and 8NN are four and eight nearest neighbors respectively.

My tests and results indicate that these data follow a general spatial process, with first-order spatial autocorrelation and spatially correlated errors. When a first-order spatial auto-regressive process exists, OLS results are both biased and inefficient. Given that the General Spatial Model, SAR, and SEM have improved fit over OLS, I investigate the size and nature of the bias in my OLS results. To look at the bias in my OLS results, I compare estimated implicit prices. In a spatial lag model, the marginal effect of an independent variable depends upon the estimated value for  $\rho$ . Following Kim, Phipps, and Anselin (2003), I use the spatial multiplier

$$\frac{1}{1-\rho}$$

(2.8)

to determine the implicit prices in the SAR and General Spatial Model. When finding the implicit price for the fire variables in my semi-log specification, I multiply the estimated coefficient times the mean house price, and then multiply this by the spatial multiplier. That is:

$$\text{Marginal Implicit Price} = \hat{\beta} \cdot \bar{x} \cdot \frac{1}{1-\rho}$$

(2.9)

where  $\hat{\beta}$  = the estimated coefficient on the After Fire variable, and  $\bar{x}$  = the average house price.

The estimated coefficients on After One Fire and After Two Fires are negative and statistically significant in every specification, indicating that house prices

drop following a first fire, and then drop again following a second fire. Table 2.10 shows the implicit price drop for an average house for all specifications. In all cases, the effect of a second fire is larger than the effect of a first fire. In addition, OLS and the three spatial models all give qualitatively similar results in Tables 2.4, 2.6, 2.7, and 2.9 with regard to signs and significance of other variables.

**Table 2.10:** Estimated Marginal Implicit Prices for OLS, SAR, SEM, and General Spatial Model Using 3 Different Weighting Matrices

Dependent Variable: Log of Real House Price

<b>OLS</b>				
	After First Fire	-\$22,803	-\$22,803	-\$22,803
	After Second Fire	-\$33,510	-\$33,510	-\$33,510
	Cumulative Effect	-\$56,313	-\$56,313	-\$56,313
<i>Weighting Approach</i>		<b>4 NN*</b>	<b>8 NN*</b>	<b>Inverse Distance</b>
<b>Spatial Lag</b>	$\rho$	0.0180	0.0195	0.0038
	<i>Spatial Multiplier</i>	1.0183	1.0199	1.0038
	After First Fire	-\$22,739	-\$23,001	-\$23,034
	After Second Fire	-\$35,363	-\$33,881	-\$34,086
	Cumulative Effect	-\$58,102	-\$56,882	-\$57,119
<b>Spatial Error</b>				
	After First Fire	-\$21,119	-\$20,583	-\$22,663
	After Second Fire	-\$34,525	-\$33,787	-\$33,657
	Cumulative Effect	-\$55,644	-\$54,370	-\$56,320
<b>General Spatial Model</b>				
	$\rho$	0.0047	0.0053	0.0810
	<i>Spatial Multiplier</i>	1.0047	1.0053	1.0881
	After First Fire	-\$21,218	-\$20,681	-\$23,195
	After Second Fire	-\$34,585	-\$33,870	-\$33,542
	Cumulative Effect	-\$55,803	-\$54,551	-\$56,738
Mean Sale Amount	\$165,015			

\* 4 NN and 8 NN are four and eight nearest neighbors respectively.

Table 2.11 shows the percent difference in the implicit prices relative to OLS. The largest percent difference relative to OLS is in the SEM using the 8 nearest neighbors weighting matrix, where the coefficient on After Second Fire is 9.73% less than the OLS estimate. Note that my “best” model, the General Spatial Model with the inverse distance matrix, has very little variation in implicit prices relative to OLS. Although these percentage changes look relatively small, I could use the Delta method to calculate standard errors on the percent changes to see if they are statistically different from zero. It is possible that some of the higher percent differences are statistically significant differences.

My results are similar to Kim, Phipps, and Anselin (2003) in the sense that I find little difference in implicit prices from spatially corrected models relative to OLS. However, my results differ from Kim, Phipps, and Anselin because my estimated coefficients are similar in my OLS and spatially corrected models, and my  $\rho$  is very small. In contrast, the estimated coefficients in the Kim, Phipps, and Anselin paper are much smaller in the spatially corrected models, but their estimate of  $\rho$  is much larger. The smaller coefficients are balanced by the large spatial multiplier, with the final result being little difference relative to OLS.

**Table 2.11: Percent Difference in Implicit Prices Relative to OLS**

<b>Weighting Approach</b>		<b>4 NN*</b>	<b>8 NN*</b>	<b>Inverse Distance</b>
<b>Spatial Lag</b>				
	After First Fire	-0.28%	0.87%	1.01%
	After Second Fire	5.53%	1.11%	1.72%
<b>Spatial Error</b>				
	After First Fire	-7.38%	-9.73%	-0.61%
	After Second Fire	3.03%	0.83%	0.44%
<b>Spatial Lag and Error</b>				
	After First Fire	-6.95%	-9.31%	1.72%
	After Second Fire	3.21%	1.07%	0.10%

\* 4 NN and 8 NN are four and eight nearest neighbors respectively.

Donovan, Champ, and Butry (2007) find large differences in their OLS estimates of implicit prices relative to the spatially corrected model. They do not report their OLS coefficients. However, they do have estimates of  $\rho$  that range from 0.142 to 0.334, with corresponding spatial multipliers of 1.16 and 1.49, respectively. I can conclude that the large percent differences in their implicit prices are because of both differences in the estimated coefficients and relatively large spatial multipliers.

## 2.8 CONCLUSIONS

Given that my data follow a first-order spatial auto-regressive process, my largest bias of 9% for OLS is relatively small, especially compared with the large percentage differences in estimated coefficients found in Donovan, Champ, and Butry (2007). The minimal bias in my OLS estimates supports the conclusion that using OLS in hedonic models to estimate implicit prices of environmental amenities may give reasonable estimates of these implicit prices even if spatial

dependence is present. From a theoretical standpoint, OLS will remain biased. However, from a practical standpoint, this bias may not be large enough to change a benefit-cost ratio in regulatory impact analyses.

My findings reflect the specific nature of my data. The area of study is a relatively small geographical area. If the neighborhood demographic characteristics that I include in my model accurately reflect differences in house prices relative to location, this may reduce the necessity for correcting for spatial effects. One way that I could investigate this issue further is to eliminate the demographic characteristics and analyze the significance of the  $\rho$  parameter. Including the demographics may be implicitly correcting for the spatial dependence.

Avenues for further research in this area include Monte Carlo type experiments to attempt to determine the exact nature and magnitude of spatial dependence required to cause significant bias in OLS estimates relative to spatially corrected estimates. In addition, a meta-analysis of hedonic property studies that have both OLS and spatially corrected coefficients would be informative. This study offers insight into the possibility that if spatial data are unavailable for a hedonic property model, reasonable estimates may be obtained by using OLS despite the inherent spatial nature of the data. In addition, older, non-spatial hedonic property models may still provide useful estimates of implicit prices.

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CHAPTER 3: DO REPEATED WILDFIRES CHANGE HOMEBUYERS'  
DEMAND FOR HOMES IN HIGH-RISK AREAS? A HEDONIC ANALYSIS  
OF THE SHORT AND LONG-TERM EFFECTS OF FOREST FIRES ON  
HOUSE PRICES IN SOUTHERN CALIFORNIA

### 3.1 INTRODUCTION

The occurrence of a natural disaster increases the public's perceived risk of such an event. Earthquakes, floods, tornadoes, hurricanes, and wildfires are covered in depth by local and national media. While all empathize with the victims of these disasters, residents of nearby communities feel particularly exposed to the risks of natural disasters. Destruction caused by natural hazards is often readily quantifiable. Much economic research has been conducted quantifying the non-market costs of natural hazards such as earthquakes (Bin and Polasky, 2004) and flooding (Beron et al., 1997). Despite the breadth of information and research on other types of natural disasters, little has been done researching the effects of wildfires. Wildfires capture the country's imagination and speak to homeowners' worst fears. Hundreds of years of fires suppression have left areas of the western United States at a particularly high risk for forest fires. Public pressure to control fires and keep homes safe has only exacerbated the problem. Because of past fire suppression and hesitancy to perform prescribed burns, fires are burning hotter, covering much larger areas, and endangering and destroying more property, often doing so in an unpredictable manner. Simultaneously, suburban expansion is leaking into the wild-land urban interface, resulting in an increase in the number of homes and occupants located in high risk areas.

Homeowners in high-risk areas expect that during a wildfire local, state, and federal firefighters will come to their rescue. The federal government provides millions of dollars of aid to fire victims each year. By providing aid and assistance, however, the government may be investing in a perverse subsidy because aid and rescue policies in effect reduce the cost of fire risk to homeowners. In addition, new homebuyers may not be fully aware of the risks associated with nearby fires. If potential homebuyers are aware of the financial costs of wildfire risk, it may affect their decision to purchase a home in the wild-land urban interface. This study investigates the short and long term effects of wildfires on house prices.

My study area is Southern California, a densely populated region whose occupants come from a wide range of socio-economic classes. The region is highly prone to wildfires because of decades of wildfire suppression. In 2003, the state of California suffered its worst wildfire season on record. From October 21 to November 3, 2003, 14 wildfires ravaged their way through five Southern California counties. Twenty-four lives were lost. Over 750,000 acres were burned and 3,710 homes were destroyed, causing billions of dollars worth of insured and uninsured losses and costing federal, state, and local governments millions for emergency assistance. When local, state, and federal policymakers design policies that correctly address issues surrounding wildfires such as prevention and disaster assistance, they should have an accurate measure of the damages caused by wildfires. Although the immediate effects of wildfires have been estimated in

previous studies (Loomis, 2004), few have investigated the effect of wildfires over time, and to the author's knowledge none have investigated the effect of multiple fires. In this study, I use the hedonic property method to analyze both the immediate and long-term effects of repeated wildfires on house prices in Los Angeles County.

The hedonic property method is often used to measure the value of environmental amenities or dis-amenities proximate to the home, including open space, (Irwin, 2002), water quality (Leggett and Bockstael, 2000), nuclear waste transport (Gawande and Jenkins-Smith, 2001), and maintaining adequate lake water levels (Loomis and Feldman, 2003).<sup>13</sup> In addition, several studies use hedonic property models to estimate the marginal implicit price of reduced risk of natural disasters. For example, Bin and Polasky (2004) use a hedonic model to estimate the effect of flooding on residential property values. Not surprisingly, they found that houses located within a floodplain have lower prices than houses located outside a floodplain. Furthermore, they found that the price differential increases after a major hurricane caused severe flooding. Bin and Polasky conclude that recent flooding causes an increase in perceived risk of flooding.

Previous studies have also found indications that homebuyers have inaccurate information on the risk of natural disasters. After failing to find significant evidence of a flood risk discount in a hedonic study, Chivers and

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<sup>13</sup> See Boyle and Kiel (2001) for a comprehensive survey of hedonic studies on environmental externalities.

Flores (2002) surveyed homeowners in an area that has high risk of flooding to investigate the possibility of market failures associated with lack of information. Their survey results indicate that most homebuyers were unaware of the actual flood risk of their homes until after they made an offer. In another hedonic study, Beron et al. (1997) found that the hedonic price of reduced earthquake risk decreased after a major earthquake in Northern California. They attributed the surprising decrease in the hedonic price of risk to inaccurate perception of earthquake risk. They contend that homebuyers over-estimated the risk of damage from earthquakes, and after experiencing an earthquake, re-evaluated their risk profiles. Even though the hedonic price of earthquake risk was reduced after an earthquake, Beron et al's study indicates the market failure was attributed to imperfect information.

Previous research on the effect of wildfires on house prices finds a negative initial impact on house prices. A recent study by Loomis (2004) found that house prices in an unburned community two miles from a Colorado wildfire decreased by 15% after the fire. In addition, a study by Price Waterhouse Coopers in New Mexico found that house prices in Los Alamos decreased by 3 to 11% after the Los Alamos wildfire (FEMA, 2004). Both of these wildfire studies investigate what happens to house prices immediately following a wildfire, but neither study analyzes the long-term effect of the wildfires. Performing a broad temporal analysis is one of the objectives of this study. Both wildfire studies also

assess the effect of a single wildfire on house prices. Another objective of this study is to assess the effect of repeated wildfires.

### 3.2 MODEL AND DATA

The estimated model is the same as the model presented in Chapter 2, Equation 3, with the variables that caused multi-collinearity problems eliminated:

$$\begin{aligned} \text{Log (Real Sale Amount)} = & \beta_0 + \beta_1*(\text{After One Fire}) + \\ & \beta_2*(\text{After Two Fires}) + \beta_3*(\text{Days Since First Fire}) + \beta_4*(\text{Days} \\ & \text{Since Second Fire}) + \beta_5*(\text{Square Feet}) + \beta_6*(\% \text{ with no High} \\ & \text{School Degree}) + \beta_8*(\text{Median Household Income}) + \beta_9*(\text{Distance} \\ & \text{to U.S.F.S. Land}) + \beta_{10}*(\text{Unemployment Rate}) + \beta_{11}*(\text{Elevation}) \end{aligned} \quad (3.1)$$

I analyze both initial and long-term effects of wildfires on house prices. The After One Fire and After Two Fires variables measure the initial effect of first and second wildfires on house prices, but the After Fire variables do not measure long-term effects of wildfires on house prices. Including the Days Since First and Second Fire variables allows house prices to change after an initial shock and also allows the rate of change of house prices to differ after first and second wildfires. This approach is linear in Days Since Fire. In the Appendix to this chapter I present results using a non-linear Days Since Fire specification.

In Chapter 2, I found strong evidence that the bias caused by spatial dependence within these data is minimal. When coding the data, 758 observations were not spatially coded. Because I tested these data for spatial dependence and found the bias to be minimal, I chose to include the lost

observations when analyzing the applications of my hedonic property model. Therefore, the model in this section is estimated using OLS and has 2,520 observations.

### 3.3 RESULTS

The estimation results are reported in Table 3.1. The coefficient on the After One Fire variable is negative and statistically significant. House prices dropped approximately 9.71% after one wildfire. The signs and significance of the After Fire variables are robust to different mileage cut-offs, but the relative magnitude of the coefficients does change as the distance cut-off varies (see Appendix Table 2.A1). The coefficient on the After Two Fires variable is also negative and statistically significant. House prices drop an additional 22.68% after a second wildfire. The coefficients on the Days Since First Fire and Days Since Second Fire are also statistically significant, but they have different signs, with the estimated coefficient on Days Since First Fire negative and the estimated coefficient on Days Since Second Fire positive. This means that house prices follow a declining trend after one fire, but after a second fire, they begin to increase.

**Table 3.1: Regression Results** <sup>a,b</sup>  
*Dependent Variable: Log of Deflated Sale Price*

	<b>Regression Results</b>	<b>Mean</b>
<i>After One Fire</i>	-0.09706 (5.53)**	0.73
<i>After Two Fires</i>	-0.22681 (11.88)**	0.50
<i>Days Since First Fire</i>	-0.00004 (3.70)**	1451
<i>Days Since Second Fire</i>	0.00024 (15.36)**	693
<i>Square Feet</i>	0.00035 (38.44)**	1,842
<i>Median Household Income</i>	0.000963 (2.78)**	65.68
<i>% With no High School Degree</i>	-0.00435 (7.75)**	21.76
<i>Distance to U.S.F.S. land</i>	0.00000565 (1.60)	2.83
<i>Elevation (meters)</i>	-0.00025 (5.72)**	1426
<i>Unemployment Rate</i>	-0.02691 (6.82)**	6.77
<i>Constant</i>	11.85281 (128.67)**	
<i>Observations</i>	2520	
<i>R-squared</i>	0.64	

<sup>a</sup> The absolute values of t-statistics are in parentheses. \* Indicates significance at the 5% level, \*\* indicates significance at the 1% level.

<sup>b</sup> Errors reported are robust standard errors.

The signs on Square Feet, Percent with no High School Degree, and Median Household Income are as expected. More square footage increases predicted sale price, and houses located in neighborhoods with relatively educated and wealthy residents have higher selling prices. The negative and statistically significant sign on the unemployment rate indicates that in times of high unemployment, house prices tend to be lower.

In addition, my results indicate that elevation and proximity to open space have negative effects on house prices. Both proximity to US Forest Service Land and living at higher elevations have positive amenity values (they are both proxies for forest views). The results indicate that houses located near open space have lower selling prices than houses located further away from open space, *ceteris paribus*. Also, houses at higher elevations have lower selling prices than houses located at lower elevations.<sup>14</sup> Since the majority of my house sales occur after at least one wildfire, the perceived loss in utility because of fire risk seems to dominate the amenity effect of proximity to public lands and living at high elevations.

Table 3.2 shows the marginal and cumulative effects of a wildfire for the average priced house in my sample. The mean deflated sale price over all years in my sample is \$151,907. The estimated marginal effect of the first wildfire within 1.75 miles is a decrease in house price of \$14,744. A second wildfire within 1.75

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<sup>14</sup> Donovan, Champ, and Butry (2007) find for some fire variables that risk effects dominate amenity effects after wildfire risk information is provided. One possible way I could investigate this in the future would be to add interaction effects between the After Fire variables and the elevation and proximity to open space variables.

miles will cause an additional decrease of \$34,453 in house price. The cumulative effect of two wildfires on the selling price of an average house is a \$49,198 drop.

**Table 3.2:** Marginal and Cumulative Effects of First and Second Fires\*

	Estimated Coefficient	Marginal Effect	Cumulative Effect
<i>One Fire</i>	-0.0971 (0.01756)	-\$14,744.59 (258.92)	-\$14,744.59 (258.92)
<i>Two Fires</i>	-0.2268 (0.10909)	-\$34,453.54 (657.72)	-\$49,198.13 (939.19)

\* Standard errors in parenthesis

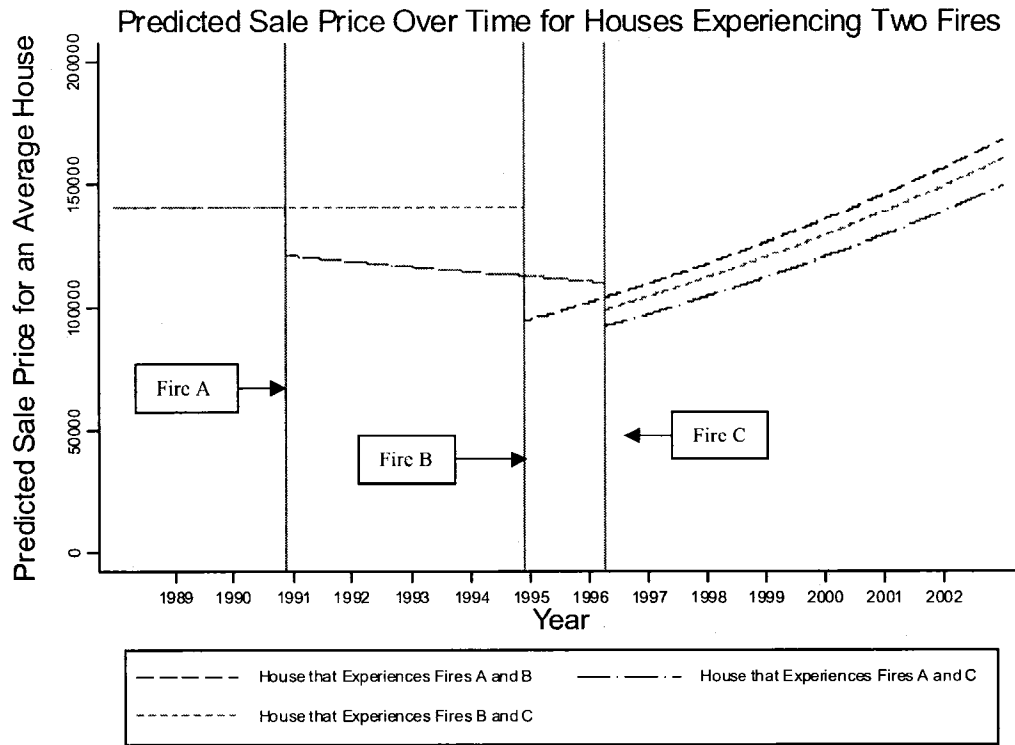
Since the coefficients on the After Fire variables are both statistically different from zero, I also tested the null hypothesis that the coefficients on the After Fire variables are equal to each other. The test had a p-value of 0.0001, indicating that I reject the null hypothesis and conclude that a second wildfire has a larger initial effect than the first wildfire.

In addition, the coefficients on the Days Since Fire variables are statistically different from zero in my regression. However, they have different signs. The first wildfire causes an initial drop followed by a continued decrease in house price, but the second wildfire causes an initial drop followed by a subsequent increase in house prices. This pattern of signs and significance was also found using the natural log of Days Since the First Fire and Days Since Second Fire. See Appendix Table 2.A2 for more details.

The exact length of time it takes for the house price to recover after the second fire depends upon the length of time between the first and second fires. Recall that different houses can experience different combinations of fires within

my area. Figure 3.1 illustrates the time path for a house with the mean values of all characteristics in three possible fire event combinations. Each house that experienced two fires could have experienced Fire A and Fire B, Fire A and Fire C, or Fire B and Fire C. The change in house price over time depends upon the particular fire combination a house experienced. As shown, house prices are constant before the first fire. After the first fire, house prices drop, and continue to decrease. After the second fire, house prices drop again, but begin to recover. It takes between 5 and 7 years for house prices to fully recover after a second fire. The time frame for recovery seems reasonable. Within a few years, the natural vegetation near the house will have regenerated. In addition, if several years pass without a fire, people may begin again to forget about the risk of fire.

Figure 3.1:



### 3.4 CONCLUSIONS

Wildfires differ from other natural disasters in that repeat events are not independent of one another. After an area burns from wildfire, it is not likely to burn again for a few years. Yet, areas recently burned are prone to other natural disasters, such as landslides and flooding. Wildfires burn vegetation, causing the winter rains in Southern California to loosen sediment. Areas burned by wildfires are prone to mudslides and debris flows. When debris flows occur, the sediment is collected in debris basins. A recent paper by Loomis et al (2003) found that sediment yield following wildfires is significantly more costly than the amount following prescribed burns. Following large wildfires, emergency clean up is often necessary to remove excessive amount of debris. Some of the observed decreases in house prices in this study are likely to be related to other risks associated with living in an area recently burned by wildfire. Unfortunately, separating these effects from the wildfire effects is not possible with these data.

A striking result from my estimation is that a second wildfire causes a larger initial decrease in house price than the first wildfire. One explanation of the observed difference in impacts is that a single wildfire may not be a sufficient stimulus to cause homeowners to move, while a second wildfire causes more risk-averse homeowners to move to areas less prone to wildfire. A homeowner may think that the first wildfire is going to be the only nearby wildfire for an extended period of time and hence remain living in a high-risk area after one wildfire. However, house prices continue to decrease after the first wildfire because of

diminished surrounding landscape amenities. Then, a second wildfire occurs, causing more devastation, and another update in perceived wildfire risk. Because homeowners did not expect another wildfire for a prolonged period of time, the second wildfire causes a more devastating initial shock than the first. As a result of the second wildfire, highly risk-averse homeowners may be replaced by less risk-averse homeowners. As new homeowners move in, house prices begin to recover, explaining the subsequent increase of house prices after a second wildfire. In other words, it takes more than one wildfire to induce a permanent reaction (in the form of moving) from current homebuyers.

One unique aspect of forest fires relative to other types of natural disasters is that the risk of a repeated event decreases after a fire. Flammable vegetation, and hence the likelihood of another wildfire, is greatly reduced after burning. Thus, with two nearby fires, residents may be accurately aware of the reduced risk and thus the recovery of house prices. The observed increase in prices after a second fire may be due to the belief that a third fire is highly unlikely.

Another reason for the observed pattern in house prices is that there may have been less fear of damage associated with the second fire because the first fire caused homeowners to invest in risk-reducing activities, such as vegetation thinning and safer building materials. These investments may reduce the amenity value of a home temporarily, but after a second fire, the risk issue prevails, and house prices begin to recover.

Yet another reason why house prices drop after a first fire, continue to decrease, drop again and then recover after a second fire may be homeowners' reluctance to go through the work of selling a home after one fire. The purchase of a home is an enormous investment, and moving is costly for both economic and social reasons. People may absorb a loss after a first fire, hoping there is not another fire so that they don't have to take their children to new schools, meet new neighbors, etc. In addition, the time between the decision to sell and the date of sale may be quite lengthy depending upon the type of house and market characteristics.

My results indicate that demand for houses located near wildfires decreases immediately following each wildfire, and that demand decreases more after repeated wildfires. This means that many homebuyers do not want to live in areas with repeated wildfires, and that perhaps homebuyers purchase homes in high risk areas without being fully aware of actual wildfire risk. Hence, policymakers could decrease losses associated with wildfires by increasing wildfire risk awareness through public information campaigns. For example, Donovan, Champ, and Butry (2007) found that public information provision had a statistically significant effect on the relationship between wildfire risk and house price. Because amenities that increase house price are often correlated with wildfire risk, Donovan, Champ, and Butry analyzed the difference between the wildfire risk ratings and house price before and after a public information campaign, and they found characteristics that affect wildfire risk outweighed

amenity values after an educational campaign on wildfires. What this study suggests, in conjunction with the findings of Donovan, Champ, and Butry, is that homeowners' risk perceptions may be inaccurate but a portion of the loss associated with fires may be mitigated by public education campaigns.

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### 3.6 APPENDIX

**Table 2.A1: Comparing Distance Cut-offs** <sup>a,b</sup>  
*Dependent Variable: Log of Deflated Sale Price*

	<b>1.5 Miles</b>	<b>1 Mile</b>	<b>0.5 Mile</b>
After One Fire	-0.21912122 (12.28)**	-0.26466565 (13.95)**	-0.19637733 (8.00)**
After Two Fires	-0.21858087 (9.91)**	-0.18939619 (7.12)**	-0.15465020 (4.70)**
Days Since 1 <sup>st</sup> Fire	0.00011411 (11.51)**	0.00014286 (12.74)**	0.00010458 (5.93)**
Days Since 2 <sup>nd</sup> Fire	0.00007270 (4.55)**	0.00003754 (1.97)*	0.00006416 (2.36)*
Square Feet	0.00034321 (36.83)**	0.00034300 (36.72)**	0.00033755 (33.44)**
% With no HS	-0.00493732 (8.59)**	-0.00476966 (8.02)**	-0.00451880 (7.48)**
Median HH Inc (th)	0.00109725 (3.03)**	0.00117612 (3.24)**	0.00119857 (3.18)**
Distance USFS (km)	0.00881049 (2.65)**	0.00754846 (2.08)*	0.01160199 (3.17)**
Elevation (meters)	-0.00012026 (2.82)**	-0.00007254 (1.66)	-0.00010720 (2.35)*
Unemployment Rate	-0.02515156 (6.37)**	-0.02784550 (7.33)**	-0.02655881 (7.26)**
Constant	11.61265788 (126.94)**	11.54947499 (125.50)**	11.56228632 (123.37)**
Observations	2520	2520	2520
R-squared	0.61	0.60	0.57

<sup>a</sup> The absolute values of t-statistics are in parentheses. \* Indicates significance at the 5% level, \*\* indicates significance at the 1% level.

<sup>b</sup> Errors reported are robust standard errors.

The signs and significance of key variables are robust to changes in the distance cut-off. Specifications using every quarter-mile distance cut-off were attempted, starting from 0.25 mile and ending at the largest cutoff available, 1.75 miles. Since the sign and significance of key variables is robust to the choice of

cut-off, I chose the furthest cut-off to have the largest sample of houses experiencing fires.

**Table 2.A2:** Comparing Linear, Quadratic, and Double-Log Specifications of the Days Since Fire Variables<sup>a,b</sup>

*Dependent Variable:* Log of Deflated Sale Price

	<b>Final Model</b>	<b>Quadratic</b>	<b>Double-Log</b>
After One Fire	-0.09706321 (5.53)**	-0.08767308 (3.83)**	0.00773351 (0.10)
After Two Fires	-0.22680664 (11.88)**	-0.10063791 (4.07)**	-1.15100444 (16.19)**
Days Since First Fire	-0.00004791 (3.70)**	-0.00003489 (1.29)	
Days Since Second Fire	0.00024268 (15.36)**	-0.00005714 (1.43)	
Days Since First Fire Squared		-0.00000001 (1.43)	
Days Since Second Fire Squared		0.00000012 (7.65)**	
Log of Days Since First Fire			-0.02381209 (1.96)*
Log of Days Since Second Fire			0.17596229 (16.21)**
Square Feet	0.00034755 (38.44)**	0.00034986 (38.71)**	0.00034386 (37.34)**
% With no High School Degree	-0.00435356 (7.75)**	-0.00414189 (7.42)**	-0.00455951 (7.93)**
Median Household Income (thousands)	0.00096283 (2.78)**	0.00111382 (3.27)**	0.00091220 (2.56)*
Distance to USFS Owned Land (km)	0.00564799 (1.60)	0.00443917 (1.24)	0.00644766 (1.87)
Elevation (meters)	-0.00025039 (5.72)**	-0.00024483 (5.58)**	-0.00025758 (5.97)**
Unemployment Rate	-0.02690644 (6.82)**	-0.04098826 (9.64)**	-0.01632917 (4.00)**
Constant	11.85280765 (128.67)**	11.93238834 (129.35)**	11.79811982 (128.24)**
Observations	2520	2520	2520
R-squared	0.64	0.65	0.62

<sup>a</sup> The absolute values of t-statistics are in parentheses. \* Indicates significance at the 5% level, \*\* indicates significance at the 1% level.

<sup>b</sup> Errors reported are robust standard errors.

The results are robust to different specifications in terms of sign and significance. In particular, the sign and significance of the After Fire variables are the same in the quadratic as in the linear models. Also, the sign and significance of the Since Fire variables are the same in the log as in the linear models. I chose the linear specification because all the After Fire and Since Fire variables were statistically significant.

CHAPTER 4: CONTINGENT VALUATION ANALYSIS OF CONSUMER  
PREFERENCES FOR AN OFFSHORE WIND PARK

## 4.1 INTRODUCTION

Wind power is the fastest growing renewable energy industry in the world. As oil prices hover at \$60 a barrel, renewable energy sources are receiving more media attention because of the opportunity to decrease dependence on foreign oil sources and increase environmental sustainability through their use. Although wind energy currently provides only 1% of the world's energy, this percentage will increase as more countries adopt wind energy technology. The global growth rate of wind power use in 2005 was 24%, indicating a significant increase in its popularity worldwide.<sup>15</sup> The United States lags far behind Europe in the percentage of renewable energy consumed, but it has the potential to be a close rival in the near future.

The focus of this study is the Cape Wind Proposal. The Cape Wind Proposal proposes the construction of an offshore wind park in Massachusetts. The wind park would consist of 130 wind turbines over 24 square miles in Nantucket Sound. It would generate enough energy to provide approximately 75% of the energy for the Cape area and surrounding islands. If constructed, Cape Wind will be the first offshore wind park in the United States and the largest offshore wind park in the world (Heerde, 2005).

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<sup>15</sup> World Wind Energy Association, "Worldwide Energy Boom in 2005." [www.wwindea.org](http://www.wwindea.org)

Debate about the Cape Wind Proposal began in 2001, but the discussion continues today with the wind park making headlines in the fall of 2006.<sup>16</sup> Proponents of the wind park believe the benefits of sustainable energy outweigh the costs of the wind park in terms of obstruction of views. Some proponents claim that the wind park will allow Massachusetts to be a world leader in green energy, resulting in a positive image and increased tourism for the area. Opponents worry about the detrimental change in ocean views and the effects the offshore wind turbines may have on boater recreation and avian safety. A final decision on the construction of the wind park will be made in 2008.

A Draft Environmental Impact Statement from the Army Corps of Engineers predicted minimal environmental effects of the wind park beyond obstruction of views. Although the construction of the wind park would temporarily disrupt the patterns of some fish and birds in the area, the Corps asserts that the high availability of substitute areas for breeding and feeding will greatly reduce the likelihood of any permanent impact. In addition, the impact statement outlines the potential for approximately 150 permanent jobs to be created in the area. The Environmental Impact Statement provides an in-depth analysis of the predicted environmental impacts of the wind park.<sup>17</sup>

The objective of this study is to obtain a measure of the change in economic welfare for local residents in terms of the non-market value of the wind park.

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<sup>16</sup> Daley, Beth, *Boston Globe* October 15, 2006, [www.boston.com/news/local/articles/2006/10/15/on\\_the\\_horizon/](http://www.boston.com/news/local/articles/2006/10/15/on_the_horizon/)

<sup>17</sup> See U.S. Army Corps of Engineers, "Cape Wind Energy Project Draft Environmental Impact Statement." [www.nae.usace.army.mil/projects/ma/ccwf/deis.htm](http://www.nae.usace.army.mil/projects/ma/ccwf/deis.htm)

Specifically, I measure resident's willingness to accept compensation in order to allow construction of the wind park and resident's willingness to pay to forego the wind park. The Cape Wind Proposal reflects a unique situation in which the provision of a public good may result in a decrease in utility for relevant participants. While most will agree that a shift to renewable, sustainable energy should be considered a "good" for society as a whole, this belief is challenged by the possibility of having a wind park within view of an individual's home. This is the "Not in My Backyard" (NIMBY) syndrome and is often referred to in the literature when discussing public services that have distributional aspects, such as hazardous waste disposal (Feinerman, Finkelshtain, and Kan, 2004). Measuring the non-market value of the Cape Wind Proposal therefore necessitates measuring net utility from the wind park. Building the wind park may have positive benefits overall, yet a portion of the population will suffer significant losses because of its construction. Because the Cape Wind Proposal is likely to have uneven distribution of benefits and costs, another objective of this study is to estimate the distribution of WTP and WTA and analyze how it affects relevant participants. To my knowledge, there has been no quantitative research on the economic valuation of the wind farm to current residents. Thus, the main contribution of this paper is to provide the first quantitative analysis of a highly controversial public issue, the Cape Wind Proposal.

## 4.2 METHOD

The method of contingent valuation is commonly used to measure consumers' willingness to pay for non-market goods. When property rights are implied by the status quo, contingent valuation techniques measure equivalent variation. When property rights are implied in the change, contingent valuation techniques measure compensating variation. In this case, the survey asks respondents one of two dichotomous-choice questions. The questions asked are: (1) what monetary compensation residents are willing to accept to change the status quo and support construction of the wind park and (2) what price increase in electricity residents are willing to pay to forego construction of the wind park. Thus the stance of the question is that the wind park will have a negative net effect. Because of the implied property rights, the WTP to forego question measures equivalent variation, and the WTA to allow question measures compensating variation (Flores, 2003).

Unlike other environmental amenities and natural resources, the debate over wind power divides environmentalists, making it difficult to predict those in favor and those opposed. Environmentalists who prioritize global concerns are likely to support wind parks, while those who favor local concerns may oppose wind parks because of preferences to keep the natural environment undisturbed. Prominent politicians own coastal property near the proposed wind park, and most are publicly opposed to the park. Asking members of the public their feelings

about the wind park using a contingent valuation survey is a direct method of finding out public values for the wind park.

While several contingent valuation studies in the United States examine preferences for green energy, few have specifically estimated willingness to pay for wind energy and none have valued offshore wind parks. The wind energy industry, as mentioned above, is growing quickly, and quantitative evidence regarding public opinion of wind farms is necessary to ensure socially efficient allocations of wind energy. In a study on inland wind farms in Ireland and Scotland, Warren et al (2005) test three counter-intuitive hypotheses on public perceptions of wind power. They find that local people become more favorable toward wind parks after construction and the closer people live to the wind parks, the higher the degree of acceptability. They also find evidence that the NIMBY syndrome is not adequate to explain heterogeneity in preferences for wind parks. The authors note that the media concentrates on the negative aspects of the wind parks, yet most people living in close proximity to the wind parks are either indifferent or moderately in support of them.

Although their results give valuable insight into people's attitudes toward wind power in Scotland and Ireland, Warren et al (2005) do not apply contingent valuation techniques or derive any willingness to pay measures for wind parks. A few studies in the United States have derived willingness to pay for green electricity programs. For example, a recent paper by Champ and Bishop (2005) uses dichotomous choice and payment card formats to elicit willingness to pay for

wind power. The lower bound estimates for per-year WTP for wind power were \$59 using the dichotomous choice format and \$28 using the payment card format. Another study by Byrnes, Jones, and Goodman (1999) found residents of Colorado and Wisconsin are WTP between \$0.84 and \$31.44 per year for their local utility company to switch to sustainable energy.

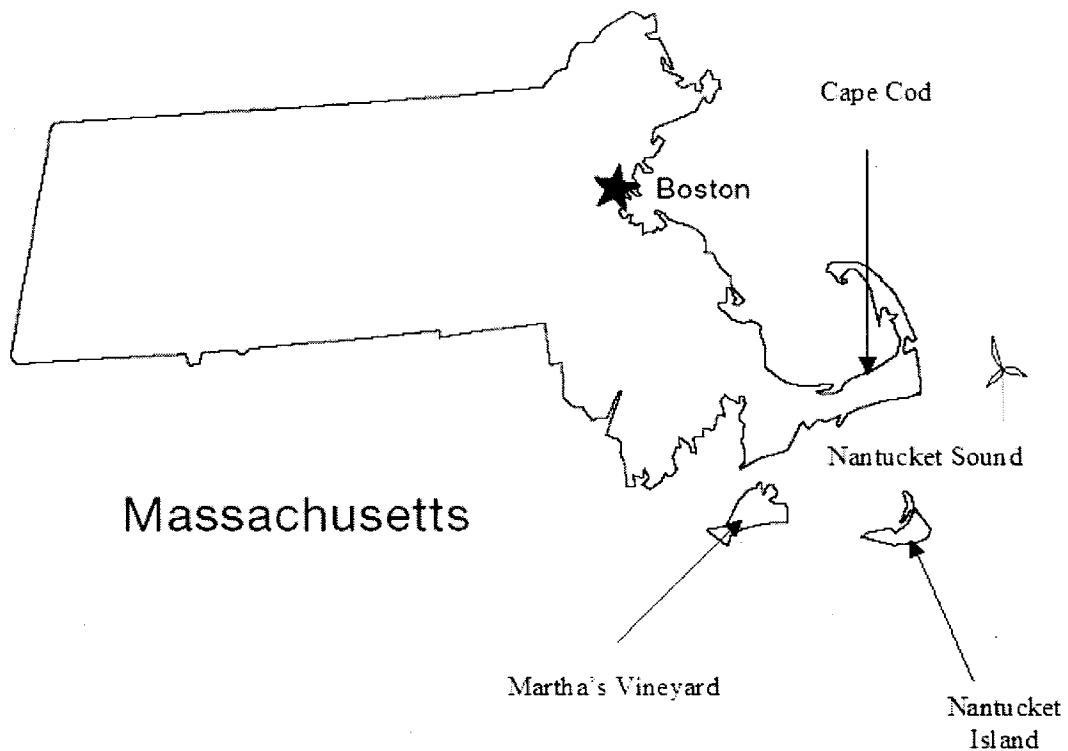
One difference between my study and previous contingent valuation studies on green energy in the United States is that the electricity generation will come from an offshore wind park that will hinder ocean views for many of the respondents. The survey explicitly addresses this issue. Because the effects of the wind park are not necessarily positive for all relevant recipients, I also investigate the distributional effect of the Cape Wind Proposal.

#### 4.3 SURVEY INSTRUMENT

One thousand surveys were sent to residents of Cape Cod, Martha's Vineyard, and Nantucket, and 1,000 surveys were sent to residents of all other areas in Massachusetts. A representative sample was purchased from Survey Sampling Inc., a company specializing in getting the most representative sample possible. The mailings were sent out using the Dillman Tailored Design Method. An announcement letter was sent, followed by a survey with a dollar gift. People who did not respond were sent a reminder postcard and then a second survey. With the undelivered surveys taken out of the total, the overall response rate was 51.2%. The Cape and Islands area had a higher response rate of 56.8%, while the rest of Massachusetts had a slightly lower response rate of 45.7%. Figure 4.1 shows a

map of Massachusetts, with Nantucket Sound, the area for the proposed wind park, and the Cape and Islands areas nearest the sound highlighted.

**Figure 4.1:** Map of Massachusetts



Respondents were given an overview of the Cape Wind Proposal, including a map with the area of the proposed wind park depicted. They were then asked preliminary questions about their level of familiarity with the proposal. After the preliminary questions, the respondents were given a list of arguments from proponents and opponents of the Cape Wind Proposal, with an equal number of arguments for each side. Then, respondents were informed that experts predict



opponents information. The bid amounts were 1, 5, 10, 25, 50, 75, 100, 200, and 350 dollars per year for both WTP and WTA. Table 4.1 illustrates the different versions of the survey. A complete copy of Version 1 of the survey is in the Appendix to this chapter.

**Table 4.1:** Survey Versions

	<b>WTP Question</b>	<b>WTA Question</b>
<b>Opponents First</b>	Version 1	Version 3
<b>Proponents First</b>	Version 2	Version 4

Both the willingness to accept and willingness to pay questions were followed by a question asking respondents how certain they are of their response, and the reasons for a yes or no response to help identify protest responses. Finally, respondents were asked demographic information, area of residence (zip code), and occupation information. They were also given a page for commenting on their feelings about the survey and the Cape Wind Proposal.

#### 4.4 THEORETICAL MODEL

Suppose that individuals derive utility from green energy and ocean views. The *net* utility of the wind park may be positive or negative depending upon the relative weight an individual gives to each of these choices. For this survey, the property right is implied in the change for the WTP question. That is, respondents are told that the wind park will be built unless they are WTP to avoid it. Because the implied property right is in the change, the estimates of WTP measure equivalent variation. Conversely, the WTA question is phrased such that the

property rights are implied in the status quo of no wind park. Therefore, estimates of WTA measure compensating variation (Flores, 2003).

### Theoretical Framework for WTP

Following Hanneman (1984), let  $V_i(I_i, S_i, G_i, X_i)$  represent indirect utility for individual  $i$  as a function of income ( $I$ ), ocean view ( $S$ ), green energy ( $G$ ), and other market goods ( $X$ ). Recall that for the WTP question, the status quo is with the wind park.  $V_i(I_i, S_{i0}, G_{i0}, X_i)$  represents indirect utility for individual  $i$  with the subscript 0 denoting levels of green energy and ocean views associated with having the wind park. Let  $A$  represent the bid amount in the WTP question and thus  $V_i(I_i - A, S_{i1}, G_{i1}, X_i)$  represents indirect utility with the subscript 1 denoting levels of green energy and ocean views associated with no wind park. Per the random utility hypothesis, the individual knows her utility function, but to the researcher, components of indirect utility are unobservable or unknown. Let  $\varepsilon_i$  represent the component of random utility unknown to the researcher. An individual will vote “yes” on the WTP question if

$$V_i(I_i - A, S_{i1}, G_{i1}, X_i) + \varepsilon_1 \geq V_i(I_i, S_{i0}, G_{i0}, X_i) + \varepsilon_0$$

and “no” otherwise. An individual’s decision to vote “yes” or “no” on the WTP question is a random variable. Therefore,

$$P_0 \equiv \Pr\{Vote = "yes"\} = \Pr\{V_i(I_i - A, S_{i1}, G_{i1}, X_i) \geq V_i(I_i, S_{i0}, G_{i0}, X_i)\}$$

and

$$P_1 \equiv \Pr\{Vote = "no"\} = 1 - P_0.$$

## Theoretical Framework for WTA

Recall that with the WTA question, the implied status quo is without the wind park. With parameters defined as above an individual will vote “yes” to the WTA question if

$$V_i(I_i + A, S_{i0}, G_{i0}, X_i) + \varepsilon_0 \geq V_i(I_i, S_{i1}, G_{i1}, X_i) + \varepsilon_1,$$

where consistent with the notation above, the subscript 1 denotes levels of green energy and ocean views without the wind park, and the subscript 0 denotes levels of green energy and ocean views with the wind park. For the WTP estimation

$$P_0 \equiv \Pr\{Vote = "yes"\} = \Pr\{V_i(I_i + A, S_{i0}, G_{i0}, X_i) \geq V_i(I_i, S_{i1}, G_{i1}, X_i)\},$$

and

$$P_1 \equiv \Pr\{Vote = "no"\} = 1 - P_0.$$

### 4.5 ESTIMATED MODEL

To estimate the distributions of WTP and WTA, I use a logit model with “vote” as the dependent variable and the bid amount as the independent variable. Let  $\alpha$  be the estimated constant from the logit estimation and  $\beta$  be the estimated coefficient on bid amount. Assuming a logistic distribution for WTP and WTA,

$$P_0 = \Pr\{vote = yes\} = \frac{1}{1 + e^{-(\alpha + \beta \cdot Bid)}}$$

$$P_1 = \Pr\{vote = no\} = \frac{1}{1 + e^{(\alpha + \beta \cdot Bid)}}.$$

Valuing the Cape Wind Proposal involves measuring the net utility from the proposal. Despite being a public good, the provision of green energy involves an

opportunity cost of obstructed ocean views. Therefore, it is possible that WTP to forego and WTA to allow could be positive or negative depending on the relative strength of the preferences for green energy versus ocean views. A logit model allows estimated WTP and WTA to be negative or positive.

Following Hanneman (1989) I let  $G(A)$  be the cumulative distribution function of an individual's true WTP or WTA. In this case,

$$G(A) = \frac{1}{1 + e^{-(\alpha + \beta \cdot Bid)}}.$$

The mean and median WTP or WTA (Hanneman's C+), considering both the positive and negative portions of the distribution is:

$$\int_0^{\infty} [1 - G(A)] dA - \int_{-\infty}^0 G(A) dA \tag{4.1}$$

so that

$$\text{Mean and Median WTP and WTA} = -\frac{\alpha}{\beta}, \tag{4.2}$$

where  $\alpha$  is the constant, and  $\beta$  is the coefficient on the bid amount in the WTP or WTA regression. This calculation can be considered the WTP or WTA for the net utility of the wind park. Basically, it calculates the area under the entire estimated WTP or WTA function. This basic model can be augmented by including covariates to account for inherent heterogeneity of respondents' preferences or even spatially related heterogeneity due to location. However,

adding such covariates will have little or no effect on mean and median WTP or WTA because when calculating mean and median WTP or WTA, the coefficients on these covariates are multiplied by their sample mean and added to the constant term. When not including these covariates separately in the model, the net effect of these covariates is captured in the estimated constant.

Debate exists over whether the mean or the median is the best measure of true WTP and WTA. Following Hanneman (1989) I calculate the mean WTP and WTA allowing the distribution to be negative. In the linear in bid logit model, the mean WTP and WTA correspond to the median. I also estimate the mean WTP and WTA focusing only on the positive portion of the distribution. Although, as Hanneman (1989) claims, this measure will overestimate the true mean WTP and WTA, it may provide useful information to policymakers about the Cape Wind Proposal. For completeness, I also calculate the mean WTP and WTA focusing only on the negative portion of the WTP or WTA distribution. This measure, while likely to underestimate the true WTP or WTA, also provides useful information to policymakers, especially those interested in the distributional effects of the proposed wind park.

A policymaker or politician may be interested in the value for only those who are in favor or opposed to the wind park. Thus, I separate those who are WTP to obtain versus those who are WTP to avoid the wind park, and separately determine their valuations. To do this, I only need to evaluate one part of the sum of integrals in Equation (4.1). For the positive side of the distribution, I evaluate:

$$\int_0^{\infty} [1 - G(A)] dA \tag{4.3}$$

Using a linear in bid logit model,

$$\text{Mean WTP and WTA (positive)} = \frac{\ln(1 + e^{\alpha})}{\beta} \tag{4.4}$$

For the negative side of the distribution, I evaluate:

$$- \int_{-\infty}^0 G(A) dA \tag{4.5}$$

Solving (4.1) and plugging in (4.2) and (4.3), (4.5),

$$\text{Mean WTP and WTP (negative)} = \frac{\ln(1 + e^{\alpha}) - \alpha}{\beta} \tag{4.6}$$

Equation (4.3) overstates mean WTP because it truncates the distribution below zero, and the WTP distribution spans both positive and negative values. Equation (4.5) calculates the mean WTP for all those who are WTP to obtain the wind park. All three measures are useful in determining the value for the gainers and losers if the wind park is built.

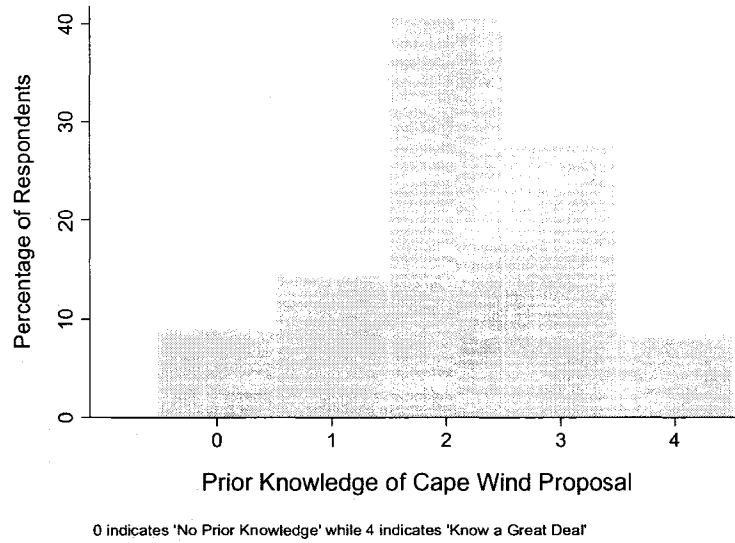
#### 4.4 RESPONDENT CHARACTERISTICS

Before providing information about the arguments of proponents and opponents of the wind park, respondents were asked their opinion of the Cape

Wind Proposal. From a total of 798 responses to the question “Based on what you know, are you in favor of building the wind turbines in Nantucket sound?” 218 (27%) were against, 156 people (20%) were undecided, and 424 (53%) were in favor of building the turbines. It was hypothesized that a much larger percentage of respondents would be against the Cape Wind Proposal based on the results from focus groups. Thus, the WTP and WTA questions assumed that the wind park would be viewed as a public “bad.” The high percentage of respondents voting “In Favor” of the wind park indicates some people may be willing to pay to obtain the wind park. Because of the surprising number of “In Favor” responses, I focus on the distribution of preferences for the wind park and not only point estimates of mean WTP and WTA.

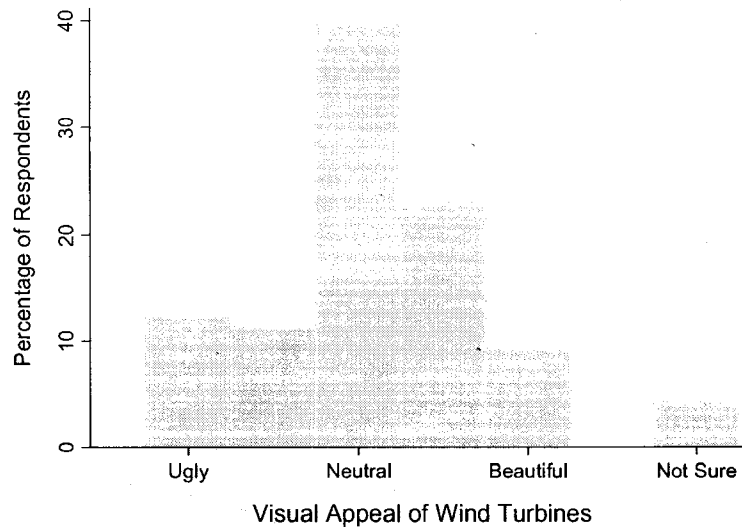
Before they were given the arguments of proponents and opponents, respondents were also asked about their familiarity with the Cape Wind Proposal. Most respondents had at least some prior knowledge of the Proposal. Figure 4.2 shows the percent of respondents choosing each level of knowledge, with zero representing no prior knowledge, and 4 corresponding to “I know a great deal about the proposal.” Less than 10% of respondents had no prior knowledge of the Cape Wind Proposal, reflecting the high publicity of the proposal.

**Figure 4.2: Respondents' Prior Knowledge**



Approximately 75% of respondents report having seen a wind turbine. On average, people report to be relatively ambivalent about the visual appeal of the wind turbines. Forty percent of people chose “neutral” when asked their opinion on the visual appeal of turbines. Figure 4.3 shows how respondents answered when asked about the visual appeal of wind turbines.

**Figure 4.3: Opinions on the Visual Appeal of Wind Turbines**



Sixty-five percent of respondents were male with a mean annual pre-tax income of \$81,000. It is common that a high percentage of respondents are male because surveys often go to heads of households. The median household income for the state of Massachusetts is \$71,655, so the survey respondents were slightly wealthier than the average Massachusetts resident.<sup>18</sup>

Participants were asked how far their Cape Cod residence is from Nantucket Sound. Twenty two percent of respondents have homes between 2 and 9.9 miles from the sound. About half the respondents live within 20 miles of Nantucket Sound. Table 4.2 shows the percentage of respondents in each distance category. Data on all survey questions along with frequency distributions of relevant responses are in the Appendix to this chapter

<sup>18</sup> Obtained from [www.factfinder.census.gov](http://www.factfinder.census.gov) for the state of Massachusetts.

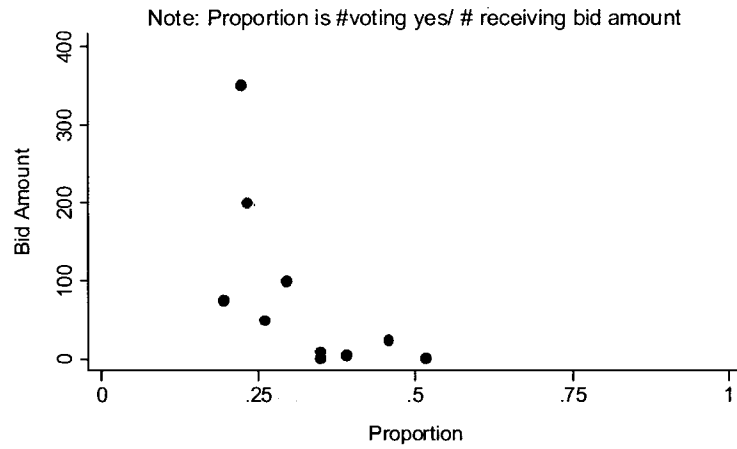
**Table 4.2:** Distance of Residence from Nantucket Sound

Variable	% Respondents
Between 0 and 1.9 Miles	18%
Between 2 and 9.9 Miles	22%
Between 10 and 19.9 Miles	11%
Between 20 and 39.9 Miles	8%
Between 40 and 59.9 Miles	13%
60 Miles or More	27%

Before I estimate WTP and WTA functions using a logit model, it is instructive to examine the proportion of respondents voting “yes” on the WTP and WTA questions for each bid amount. One would expect that as the bid amount increases, respondents will be more likely to vote “no” on the WTP question and more likely to vote “yes” on the WTA question. Figure 4.4 shows the proportion of respondents voting “yes” on the WTP question for each bid amount. Note that, as expected, the proportion of people voting “yes” generally decreases as the bid amount increases. A positive proportion of respondents voted “yes” to the WTP question even at a bid amount of \$350. Figure 4.5 shows the proportion of respondents answering “yes” to the WTA to allow question. As expected with a WTA question, as the bid increases, respondents are more likely to vote “yes” on the WTA question. Note also the non-zero proportions of “yes” votes for every WTA bid amount. Figures 4.4 and 4.5 indicate that the bid assignment may not have captured the full range of respondents’ true WTP and WTA. Even at the highest bid amount, approximately one quarter of respondents voted “yes” to the WTP question. At the lowest bid amount, approximately one third of respondents vote “yes” to the WTA question.

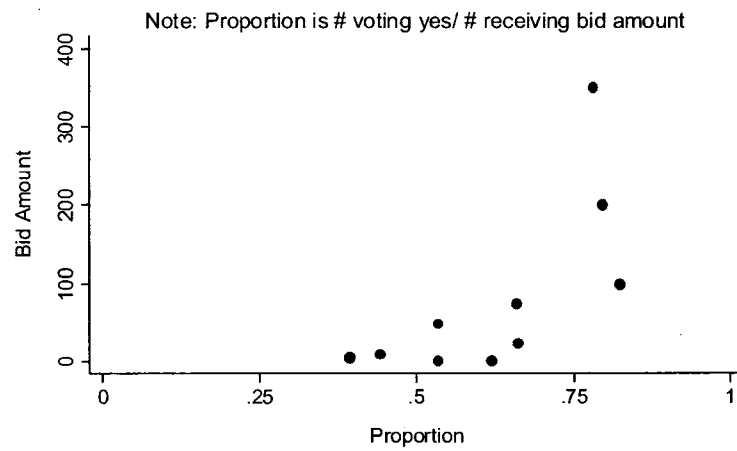
**Figure 4.4**

Proportion of People Voting Yes to WTP to forego Question



**Figure 4.5:**

Proportion of People Voting Yes to WTA to Allow Question



## 4.5 RESULTS

To examine the voting behavior of all the respondents, I estimate a logit regression with “In Favor” as the dependent variable. “In Favor” equals 1 if the respondent said they were in favor of the Cape Wind Proposal, and 0 if they are undecided or against it. Table 4.3 reports the regression results for the initial logit regression. The control distance category is for those residents living between 0 and 1.9 miles from Nantucket Sound. Almost all of the distance categories are statistically significant, and all are positive. They also show an increasing trend as distance increases. The results indicate that people living further away from Nantucket Sound are more likely to be in favor of the Cape Wind Proposal. Those with prior knowledge of the Proposal are more likely to be in favor of it. People who have seen a wind turbine are also more likely to be in favor of the proposal, although the coefficient on “Seen” is statistically significant only at the 10.5% level. Males are more likely to be in favor of the proposal than females. Income is not a statistically significant indicator of prior opinion for the wind park, perhaps because people who live near the coast may be relatively wealthy. Thus, the distance effect could be confounding the income effect.

**Table 4.3: Logit Regression Results**

Dependent Variable: “In Favor” (=1 if respondent is “in favor” of proposal at start of survey, 0 if “against” or “undecided”)

<b>Dependent Variable</b>	<b>Estimated Coeff.</b>	<b>Std. Error</b>	<b>z</b>	<b>P&gt; z </b>
<i>Prior Knowledge</i>	0.2567	0.0918	2.80	0.0050
<i>Seen</i>	0.3220	0.1954	1.62	0.1050
<i>Male</i>	0.5265	0.1815	2.96	0.0030
<i>Between 2 and 9.9 Miles</i>	-0.2294	0.2545	0.80	0.4210
<i>Between 10 and 19.9 Miles</i>	0.7200	0.2969	3.42	0.0010
<i>Between 20 and 39.9 Miles</i>	1.0966	0.3349	4.77	<0.0001
<i>Between 40 and 59.9 Miles</i>	1.2118	0.2938	5.76	<0.0001
<i>60 Miles or More</i>	1.0475	0.2429	5.33	<0.0001
<i>Household Income</i>	-0.0019	0.0017	-1.14	0.2530
<i>Constant</i>	-1.3976	0.3107		

Next, I separate the sample into WTP and WTA categories to get baseline values for WTP and WTA. I estimate two separate logit models using the bid amount as the independent variable. Recall that in this survey, the WTP question is WTP to forego the wind park and the WTA question is WTA to allow the wind park. Thus, when mean WTP to forego  $<0$ , it is interpreted as WTA to forego. Conversely, when mean WTA to allow  $<0$ , it is interpreted as WTP to allow.

Table 4.4 shows the results from the WTP estimation, and Table 4.5 shows the results from the WTA estimation. In the WTP regression, the estimated coefficient on Bid Amount is negative, indicating that the probability of the respondent voting “yes” on the WTP question decreases as the bid amount increases. Conversely, the estimated coefficient on Bid Amount is positive in the WTA regression, indicating that respondents are more likely to vote “yes” on the WTA question as the bid amount increases.

Using Equation (4.2) to calculate WTP, the mean and the median WTP to forego the wind park is -\$193.68. Therefore, these data predict that the average individual is willing to accept \$193 to forego the wind park. Using Equation (4.2) to calculate WTA, the mean and median WTA to allow the wind park is -\$35.49. Like the WTP results, the results from the WTA regression indicate that the net utility of the park is positive, or in other words, people are actually willing to pay \$35.49 to allow the wind park. The average annual utility bill for respondents is \$1,488. Therefore the WTP regression predicts that respondents would be willing to accept a 12% increase in their annual electricity bills forego the wind park, and the WTA regression predicts that respondents would be willing to pay about 2% more per year to allow the wind park.

As addressed earlier, WTP is estimating equivalent variation and WTA is estimating compensating variation. In this case, the estimated WTA is smaller than the estimated WTP. The common occurrence is the opposite effect. In a review of WTA and WTP studies, Horowitz and McConnell (2002) find that the average WTA/WTP ratio is about 7. This ratio has a statistically significant difference depending on the type of good being valued. They find that public and non-market goods tend to have the highest WTA/WTP ratios relative to ordinary market goods. In this case, respondents were asked WTP to forego and WTA to allow construction of a wind park that they, on average, were WTP to obtain.

Differences in WTP and WTA can be due to differences in the holder of the property right (Carson, Flores, and Meade, 2000). When valuing a public

good, WTP is bounded by income, while WTA can be infinite (Hanneman, 1991). Usually, surveys for non-market goods ask valuation for an improvement in a public good (i.e., air quality, water quality, land preservation). When asked a WTA question, respondents are essentially given the property right to the good in question, and their WTA is an estimation of what they would accept to give up the property right. For a WTP question, the property right does not belong to the respondent, and the WTP is an estimation of what the respondent would be willing to pay to obtain the property right. Once again, the survey in this study is unique because it values a good that may have a negative effect on some respondents. Because respondents are asked WTP to forego and WTA to allow, but the majority of respondents are actually in favor of the wind park, the WTA is smaller (in absolute value) than the WTP. WTA still assumes that the property right belongs to the respondent. My results essentially imply that if we give the development rights of Nantucket Sound over to public ownership, we would have to compensate the public *less* than if the rights were given to private ownership. Although this logic is opposite to that presented in Horowitz and McConnell (2002), it makes sense with the case of a public good that provides net benefits, but some private disutility.

**Table 4.4** Logit Results for WTP  
 Dependent Variable: "Vote" (1 if yes, 0 if no)

Number of observations	444			
LR chi2(1)	8.00			
Prob > chi2	0.0047			
Pseudo R2	0.0144			
Log likelihood	-274.27045			
	<b>Estimated Coefficient</b>	<b>Std. Error</b>	<b>Z</b>	<b>P&gt;z</b>
<i>Bid Amount</i>	-0.0027	0.0010	-2.70	0.0070
<i>Constant</i>	-0.5303	0.1276	-4.16	<0.0001

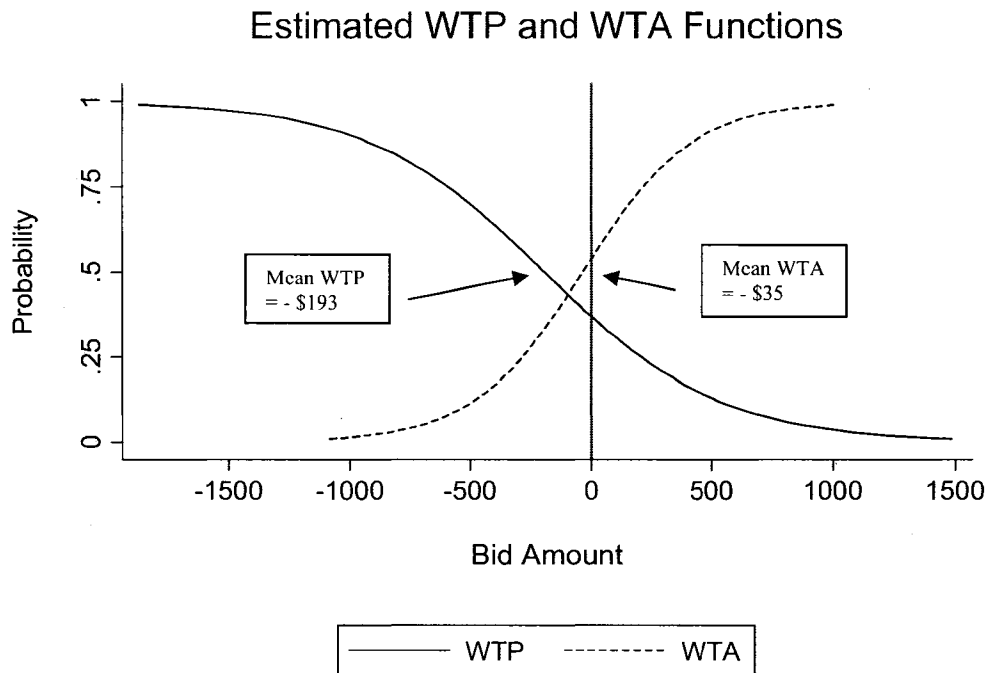
**Table 4.5** Logit Results for WTA  
 Dependent Variable: "Vote" (1 if yes, 0 if no)

Number of observations	437			
LR chi2(1)	20.0200			
Prob > chi2	<0.0001			
Pseudo R2	0.0345			
Log likelihood	-280.1554			
	<b>Estimated Coefficient</b>	<b>Std. Error</b>	<b>Z</b>	<b>P&gt;z</b>
<i>Bid Amount</i>	0.0044	0.0011	4.12	<0.0001
<i>Constant</i>	0.1560	0.1230	1.27	0.2050

Figure 4.6 shows the estimated WTP and WTA functions derived from the logit models. The solid line represents the WTP function, and the dashed line represents the WTA function. Both functions have probability values less than 1 at the zero bid. The mean WTP using the entire distribution deviates from that using only the positive distribution. The greater the deviation of the value of the estimated WTP function from 1 at a bid amount of zero, the more likely it is that the true WTP is in fact negative (Hanneman, 1989). As the bid for WTP

increases, the proportion of people WTP that amount decreases. The estimated WTP function predicts that no one will vote “yes” to the WTP question for bids higher than \$1,500. As the bid for WTA increases, the proportion of people WTA increases. The estimated WTA function predicts that everyone will vote “yes” to the WTA question for bids higher than \$1,000.

Figure 4.6:



Using equations (4.4) and (4.6), the estimated WTP to forego using only the positive portion of the WTP distribution is \$168.99. The estimated WTP to forego using only the negative portion of the distribution is -\$362.67. Table 4.6 shows the predicted WTP and WTA for different probabilities used to graph Figure 4.6. The estimated WTP function has a probability of approximately 0.6 at a bid amount of -\$362.67, meaning that approximately 40% of respondents would vote for the Cape Wind Proposal, even if it cost them an additional \$363 a year on their utility bill. The estimated WTP function has a probability of approximately 0.25 at a bid amount of \$163. This means that about 25% of people would vote

against the Cape Wind Proposal, even if it meant they would see a \$163 annual increase in their utility bill.

**Table 4.6:** Probabilities of Estimated WTP and WTA

<b>Probability</b>	<b>WTP to forego</b>	<b>WTA to allow</b>
0.10	\$608.75	-\$535.47
0.20	\$312.59	-\$350.95
0.30	\$115.75	-\$228.30
0.40	-\$45.61	-\$127.76
0.50	-\$193.68	-\$35.50
0.60	-\$341.76	\$56.77
0.70	-\$503.12	\$157.31
0.80	-\$699.96	\$279.95
0.90	-\$996.11	\$464.48

Using (4.4) and (4.6), the estimated mean WTA to allow for those who are against the wind park is \$176.16. The estimated WTA function has a probability of about 0.7 at the bid amount of \$176.16, indicating that 70% of people would vote against the Cape Wind Proposal, even if it meant a \$176 annual increase in their utility bills. The estimated WTA for those who are in favor of the wind park is -\$211.66 with a corresponding probability of approximately 0.3. This indicates that 30% of respondents would vote in favor of the Cape Wind Proposal, even if it resulted in a \$211 increase in their yearly utility bills.

The estimated WTP distribution predicts that at a bid amount of zero, 37% of people will vote “yes” on the WTP question. The data show 27% of people being “against” Cape Wind at the start of the survey. The estimated WTA distribution predicts that 53% of people will vote “yes” to the WTA question, while the data show 53% of people being “In Favor” of the proposal at the start of

the survey. Note that the predictions for the negative portion of the distribution are out of sample predictions. The highest bid amount asked was \$350, and I have no information about the negative portion of either distribution beyond what my logit model predicts. Yet, because so many people were “In Favor” of the proposal (53%), it is important to consider the predicted outcome for those who are WTP to obtain and WTA to forego the wind park, but with the awareness that these predictions are extrapolations.

#### 4.6 CONCLUSIONS

Previous studies have found the public mildly in favor of green energy, producing evidence that the net utility from wind parks is positive (Byrnes, Jones and Goodman, 1999 and Champ and Bishop, 2005). The results presented here similarly indicate that the net utility of the Cape Wind Proposal, if enacted, is positive. However, the estimated WTP and WTA functions indicate that some relevant participants will receive disutility if the proposal is enacted.

Unfortunately, focus groups for this survey provided strong evidence that a vast majority of the population was opposed to the Cape Wind Proposal, and the survey was formulated according to this supposition. Because of the apparent strong opposition to the Cape Wind Proposal based both on negative media coverage and focus groups, the survey was modeled assuming respondents would be WTP to forego or WTA to allow the wind park. These data, however, show that a majority of respondents are in favor or indifferent to the Proposal. The modeling, therefore, is challenging because of the lack of data for the negative

portion of the WTP distribution. That is, I have little information on the people who are WTP to obtain or WTA to reject the wind park.

If the responses from focus groups were more indicative of the general preferences of the survey respondents, I would have included WTP questions allowing for both positive and negative WTP. In addition, I would have also included questions to determine indifference for the wind park. Then, a spike model that allows both positive and negative WTP, with a spike at 0 to allow for indifference, could be estimated. For example, similar to Nahuelhual-Munoz et al (2004), I could initially ask:

1. Are you in favor or against the Cape Wind Proposal? (If In Favor, go to question 2, if against, skip to question 3).
2. If construction of the wind park were to cause your electricity bill to increase by \$\_\_\_\_ per year, would you still vote in favor of the proposal?  
If no, go to part a. If yes, skip to Question 4.
  - a. If construction of the wind park were to cause your electricity bill to increase by \$1 per year, would you still vote in favor of the proposal?
3. If construction of the wind park were to reduce your electricity bill by \$\_\_\_\_per year, would you vote **in favor** of the Proposal? If no, go to part a. If yes, skip to Question 4.
  - a. If construction of the wind part were to reduce your electricity bill by \$1, would you vote **in favor** of the Proposal?

In addition, information on certainty of responses and respondent's reasons for their vote are available. One extension of the research presented above is to use respondent's answers to the first question on their opinion of the wind park to estimate a spike model allowing zero willingness to pay. Another extension is to investigate the reasons behind the "no" votes on WTP and WTA to make inferences about respondents' preferences for green energy.

In addition, spatial coding is available for these data, and another area left for exploration is to examine the spatial effects of WTP and WTA. It is likely that the probability of voting "yes" on the WTP question increases as distance to the wind park decreases. That is, people who live near Nantucket Sound are more likely to be opposed to the proposal, while residents of western Massachusetts are more likely to be in favor of the proposal.

The results presented above do provide useful insight to policymakers. Despite a large volume of negative press and a vocally strong opposition to the wind park, the majority of Massachusetts residents are in favor of the Cape Wind Proposal, and would vote for the proposal even if it resulted in an increase in their annual utility bills. The results above also provide evidence to future researchers estimating WTP and WTA for highly public and controversial issues to exercise thoughtful caution and thorough pre-testing when formulating WTP and WTA questions because the loudest voices in focus groups and the media may be a small proportion of the population and may not accurately reflect the feelings of the majority.

#### 4.8 REFERENCES

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853-875.


4.9 APPENDIX

**The Cape Wind Proposal and Nantucket Sound...**



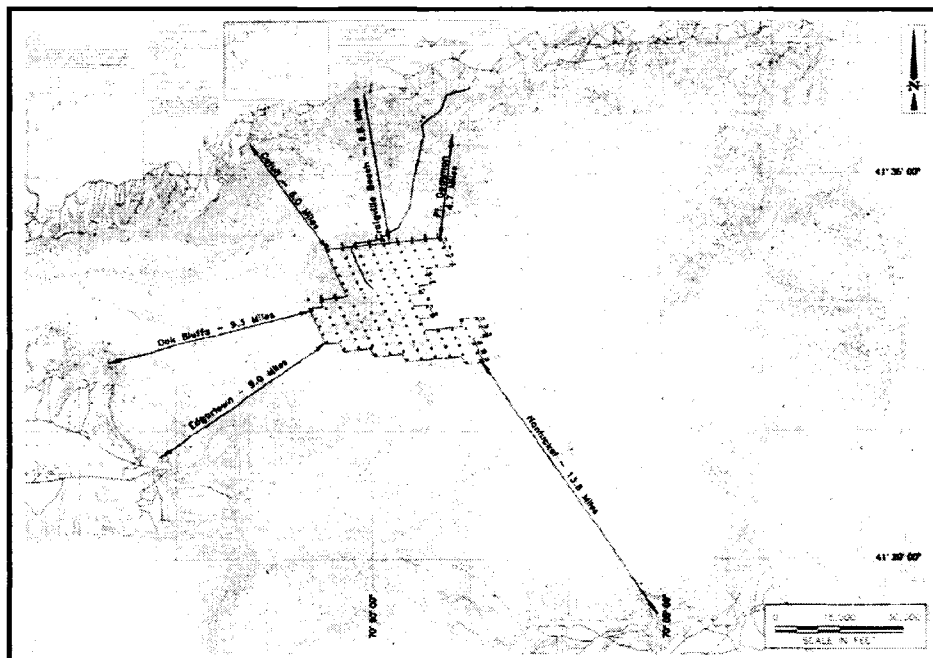
**How do you feel?**

 UNIVERSITY of NEW HAMPSHIRE  
Department of Resource Economics and Development  
James Hall  
Durham, NH 03824

 UMASS  
AMHERST  
Department of Resource Economics  
Stockbridge Hall  
Amherst, MA 01003

## Background Information

In 2001, Cape Wind LLC. applied for a permit to build 130 wind turbines (windmills) in federally managed waters in Nantucket Sound off the southern coast of Cape Cod. The wind turbines would be 250 feet tall to the center of the rotor and 417 feet tall at the tallest point of the windmill's blades. They would be spaced 1/3 to 1/2 a mile apart across a 24 square mile area. The wind turbines closest to shore would be 6 miles from the town of Cotuit on Cape Cod, 9.3 miles from Oak Bluffs on Martha's Vineyard and 13.8 miles from Nantucket. The illustration below shows the location.



Map courtesy of US Army Corps of Engineers, from Draft Environmental Impact Statement

Cape Wind LLC. proposes that the wind turbines could supply a peak of 454 Megawatt Hours (MWh) of electricity and an average of 170 MWh. This is about 75% of the electricity needs of Cape Cod, Martha's Vineyard and Nantucket. The energy produced by the wind turbines will be transferred by underwater cables to the power grid in Barnstable, MA. Once the electricity enters the New England power grid, it will first be distributed to homes and business within the region. If there is any extra electricity, it will be distributed to other regions of New England. The proposal is still under review by the US Army Corp of Engineers.

Cover photo courtesy of [www.freefoto.com](http://www.freefoto.com)  
Simulated photos courtesy of Cape Wind, edited by Eric Steltzer



## Section 2: Your Chance to Vote

The decision to place wind turbines in Nantucket Sound has been debated locally and nationally. The following pages are the opinions from both sides of the debate. Please read these pages and refer to the pictures inserted into the survey before moving on to Page 5.

### **Opponents-** NO to Wind Turbines in the Nantucket Sound

Opponents feel that Nantucket Sound is unique and too valuable to be spoiled by wind turbines. Key arguments against the development include:

- **Economic Impacts:** Cape Cod, Martha's Vineyard and Nantucket rely heavily on tourism to support the region's economy. One of the main draws to the Cape Cod area is the natural beauty. The wind turbines could alter the beauty of Nantucket Sound and result in a decline in tourists. Additionally, the jobs offered by the Cape Wind development require special experience that is not available within the region's workforce.
- **Environmental Impacts:** Nantucket Sound is home to thousands of different species of plants, fish and birds. The wind turbines could negatively affect the area by impacting the seabed, killing young fish and driving away adult fish. The turbines may also be an obstacle for migratory birds and a sizeable amount of them could be killed.
- **Oil Spill:** An Electrical Service Platform would be placed in the middle of the wind turbines, to gather the electricity produced from the turbines. This service platform contains 40,000 gallons of mineral oil, needed to operate the facility. If an accident occurred, this oil could cause environmental damage to marine life.
- **Navigation:** Recreational and commercial boaters use Nantucket Sound heavily. The wind turbines could create a hazard for boaters. Also, the turbines may make it difficult for the rescuers to reach boaters who are in trouble.
- **Regulatory Process:** Many people believe that poor policy is in place to properly review the benefits and the impacts of the proposed development. The review of the proposal is being led by the US Army Corp of Engineers and they do not have the experience needed to determine the effects of this development. There is already good policy in place for offshore oil and gas exploration and similar policy should be in place before any offshore wind turbines are developed in the ocean.
- **Takeover by Private Developer:** Cape Wind LLC. is a private company that would be occupying public waters. Plans are in place for private companies such as ranchers, miners, ski resorts and other companies who use federal areas to be charged a fee. However, there is currently no plan to charge Cape Wind for their use of the public waters. They would be using the public resources for free.
- **Visual Destruction:** The location of the wind turbines are too close to shore. They would be visible from shore and could turn Nantucket Sound into an industrialized landscape. It could ruin the natural beauty of Nantucket Sound for residents and tourists who visit the area.

## **Proponents-** YES to Wind Turbines in Nantucket Sound

Proponents feel that the environmental benefits of clean energy are an important step towards reducing the impacts from other sources of energy. Key arguments for the development include:

- **Economic Benefits:** As a resource, wind is free and does not go up and down in price like oil and natural gas. This could allow companies to create a long term fixed price on electricity, ultimately reducing electricity costs for residents in the area. In addition to reduced electric bills, over 1,000 skilled jobs could be created within the Cape Cod community.
- **European Success:** Countries along Northern Europe have been building offshore wind turbines along their coasts for the 10 years. The wind parks have been a welcomed addition to the communities and there have been no measurable negative effects on tourism, property values, or the environment.
- **Clean Energy:** Conventional sources of electricity such as coal and natural gas require the fuel to be extracted from the Earth, shipped to the power plant and then burned to produce electricity. Each of these stages has an impact to the environment by adding carbon dioxide, sulfur dioxide, and nitrogen oxides. Scientists believe these pollutants could be responsible for global warming and health related illnesses such as asthma. The Cape Wind proposal could reduce these harmful pollutants and improve air quality within the region.
- **Improved Technology:** Wind power has been around since the 1970's but it was too expensive to compete with conventional power plants. The technology of the wind turbines has improved over the past 15 years and it could compete with natural gas, coal and oil powered energy plants. Wind power could be the fastest growing energy source in the world.
- **Offshore Wind Resource:** Offshore winds have a higher wind speed and are more stable than onshore winds. These factors allow for more energy to be produced and since the winds are stable, less maintenance is required on the turbines. Nantucket Sound is an ideal location due to the location near the regional power grid and the shallow water protects the wind turbines from the large waves and currents of the open ocean.
- **State Law:** The Massachusetts Electric Utility Restructuring Act of 1997 ordered that a portion of all electricity used had to come from 'green' (cleaner) sources. This was done to slow the increase in electricity prices and to make power plants support electricity generated from renewable resources.
- **Visual Attraction:** Some people think that modern wind turbines are beautiful and hypnotic to watch as they turn slowly in the wind. From a distance of 6 miles, they will stand a 1/2 inch above the horizon and a 1/4 inch from 14 miles. The area is known for foggy conditions, so the wind turbines often would not be visible.

Experts expect the cost of electricity will go up as the population in the area increases. Building the wind turbines could affect the price of your electricity bill. Suppose that everyone on Cape Cod and the Islands were asked to vote in the next public ballot. How would you vote on the following question?

**Your Chance to Vote:**

If the wind turbines are **not** built, electricity prices are likely to go up.  
 Would you be willing to have your household's electricity bill go up by \$\_\_\_\_\_ per year so that the wind turbines would **not** be built?

\_\_\_ YES                      \_\_\_ NO

How certain are you of your answer to question? (Please circle a number on the scale below)

not sure
neutral
very sure  
 0    1    2    3    4    5    6    7    8    9    10

**We are interested in the reasons why you voted the way you did.**

If you voted **YES** (you would pay more to avoid the wind turbines) please check your top 3 reasons

- |  |   |
|--|---|
| <input type="checkbox"/> Access- fear of reduced access to the area<br><input type="checkbox"/> Natural Beauty- the view would be destroyed<br><input type="checkbox"/> Economic Impact- jobs and tourism decline<br><input type="checkbox"/> Environmental Impacts- marine life & birds<br><input type="checkbox"/> Navigational Concerns<br><input type="checkbox"/> Noise level of turbines | <input type="checkbox"/> Oil spill concerns from the Electric Service Platform<br><input type="checkbox"/> Personal- I'd pay to stop the development<br><input type="checkbox"/> Pollution reductions offered by the Wind Park are small<br><input type="checkbox"/> Private Developer profiting from public resource<br><input type="checkbox"/> Policy Problems- Regulatory process is not sufficient<br><input type="checkbox"/> Other: please specify _____ |
|--|---|

If you voted **NO** (you would **not** pay more to avoid the wind turbines) please check your top 3 reasons

- |  |  |
|--|--|
| <input type="checkbox"/> Natural Beauty- wind turbines will not impact the view<br><input type="checkbox"/> Air Quality improvement- reduce health illnesses<br><input type="checkbox"/> Economic Benefits: business, tourism, clean air<br><input type="checkbox"/> Electricity is needed and prices will be reduced<br><input type="checkbox"/> Foreign Oil- reduce dependency from overseas<br><input type="checkbox"/> Global Warming- reduce greenhouse gases | <input type="checkbox"/> Location is ideal for offshore wind power<br><input type="checkbox"/> Personal- I should not have to pay to stop the project<br><input type="checkbox"/> Personal- I'd pay more to have the development built<br><input type="checkbox"/> The increase in electricity price above is too high<br><input type="checkbox"/> Society's responsibility to future generations<br><input type="checkbox"/> Set precedence for future renewable energy development<br><input type="checkbox"/> Other: please specify _____ |
|--|--|

### Section 3: About You

The last few questions will help us to make sure our sample represents the actual population.  
**YOUR ANSWERS ARE STRICTLY CONFIDENTIAL AND WILL ONLY BE USED FOR THIS STUDY.**  
**YOU WILL NOT BE IDENTIFIED IN ANY WAY**

- 1) Are you:  Male  Female
- 2) What is your zip code? \_\_\_\_\_
- 3) What is your age? \_\_\_\_\_ years
- 4) What is your monthly household electricity bill on average? \$ \_\_\_\_\_
- 5) Are you a member of a conservation or preservation organization?  Yes  No
- 6) What is the highest **year** of formal schooling you have completed (circle one):  

1 2 3 4 5 6	7 8 9	10 11 12	13 14 15 16	17 18 19 20
(Elementary)	(Jr. High)	(High School)	(College or Technical School)	(Graduate or Professional School)
- 7) How long have you had a residence on Cape Cod? \_\_\_\_\_ years
- 8) What is your residency on Cape Cod?  Part-time resident  Full-time resident
- 9) How far away is your Cape Cod residence from Nantucket Sound?  
 0 - 1.9 miles  2 - 9.9 miles  10 - 19.9 miles  
 20 - 39.9 miles  40 - 59.9 miles  60 miles or more
- 10) Including yourself, how many members are in your household? \_\_\_\_\_ Person(s)  
How many members of your household are under 18? \_\_\_\_\_ Person(s)
- 11) Including yourself, what was your approximate total *household* income from all sources (before taxes) last year?  

<input type="checkbox"/> less than \$ 10,000	<input type="checkbox"/> \$ 40,001 to \$ 50,000	<input type="checkbox"/> \$ 80,001 to \$ 90,000
<input type="checkbox"/> \$ 10,000 to \$ 20,000	<input type="checkbox"/> \$ 50,001 to \$ 60,000	<input type="checkbox"/> \$ 90,001 to \$ 100,000
<input type="checkbox"/> \$ 20,001 to \$ 30,000	<input type="checkbox"/> \$ 60,001 to \$ 70,000	<input type="checkbox"/> \$ 100,001 to \$ 150,000
<input type="checkbox"/> \$ 30,001 to \$ 40,000	<input type="checkbox"/> \$ 70,001 to \$ 80,000	<input type="checkbox"/> over \$ 150,000
- 12) What is your occupation?  

<input type="checkbox"/> Agriculture	<input type="checkbox"/> Government	<input type="checkbox"/> Real Estate
<input type="checkbox"/> Construction	<input type="checkbox"/> Healthcare	<input type="checkbox"/> Sales
<input type="checkbox"/> Education	<input type="checkbox"/> Hospitality- Tourism	<input type="checkbox"/> Self Employed
<input type="checkbox"/> Finance	<input type="checkbox"/> Nonprofit	<input type="checkbox"/> Other: _____

**Thank You for Completing the Survey!**

If you have any additional thoughts on the Cape Wind proposal or energy planning in New England, feel free to write them down in the space provided below. When you are finished, please mail the survey in the enclosed stamped return envelope.

*Please return this survey to*  
**Department of Resource Economics and Development  
James Hall  
University of New Hampshire  
Durham, NH 03824**

**Table 4.A1: Summary Statistics for Survey Data**

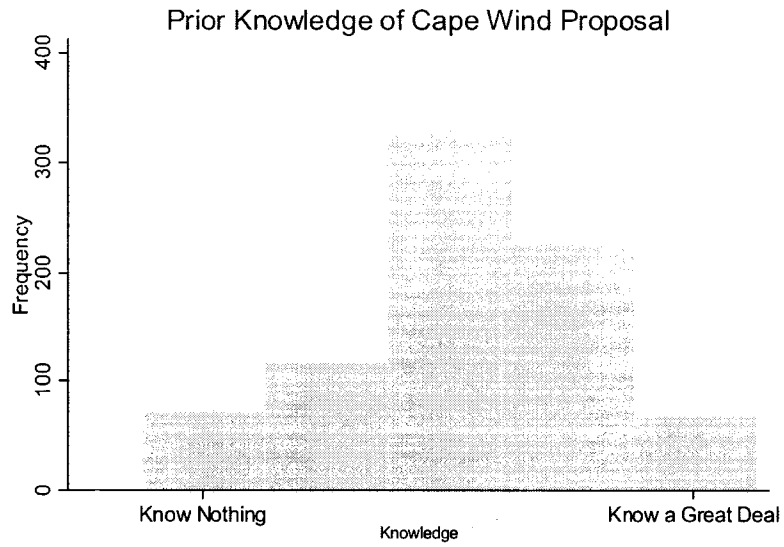
Variable	# Obs.	Mean	Std. Dev.	Min	Max
(for dichotomous variables 1= yes)					
Knowledge of Proposal	814	2.12	1.05	0	4
Where did you learn about Cape Wind?					
Local News	835	0.82	0.38	0	1
National News	834	0.23	0.42	0	1
Drafit EIS	835	0.06	0.23	0	1
Friends	835	0.32	0.47	0	1
TV	835	0.57	0.50	0	1
Army	835	0.05	0.22	0	1
Public Hearing	835	0.09	0.29	0	1
Academic Journal Articles	835	0.07	0.26	0	1
Websites	835	0.09	0.29	0	1
Other	835	0.16	0.36	0	1
Are you in favor of Cape Wind?	798	0.53	0.50	0	1
(undecided = 0)					
What fuel do you use to produce electricity?					
Biomass	855	0.03	0.18	0	1
Coal	855	0.14	0.35	0	1
Hydro--rivers	855	0.07	0.26	0	1
Natural Gas	855	0.42	0.49	0	1
Nuclear	855	0.17	0.38	0	1
Oil	855	0.43	0.50	0	1
Solar	855	0.02	0.13	0	1
Wind--land base	855	0.01	0.10	0	1
Wind--offshore	854	0.00	0.06	0	1
Other	855	0.03	0.17	0	1
Not Sure	855	0.23	0.42	0	1
Where would you like to see NE get energy?					
Biomass	855	0.03	0.17	0	1
Coal	855	0.06	0.24	0	1
Hydro--rivers	855	0.30	0.46	0	1
Natural Gas	855	0.22	0.41	0	1
Nuclear	855	0.27	0.44	0	1
Oil	855	0.08	0.27	0	1
Solar	855	0.50	0.50	0	1
Wind--land base	855	0.43	0.50	0	1
Wind--offshore	855	0.51	0.50	0	1
Other	855	0.04	0.19	0	1
Not Sure	855	0.13	0.34	0	1

Variable	# Obs.	Mean	Std. Dev.	Min	Max
Have you seen a wind turbine?	861	0.75	0.43	0	1
If yes, where?					
Media footage	648	0.11	0.32	0	1
Boston	648	0.22	0.42	0	1
California	648	0.27	0.44	0	1
New England	648	0.21	0.40	0	1
West	648	0.05	0.22	0	1
Foreign Lands	648	0.17	0.37	0	1
Other US Areas	648	0.08	0.28	0	1
Visual Appeal of Turbines	857	0.53	2.86	-4	9
Bid Amount	898	3.91	141.96	-350	350
Vote on WTP/WTA Question	881	0.47	0.50	0	1
How Certain are you?	850	8.11	2.37	0	10
If you voted no, what are you top 3 reasons?					
Turbines will not affect natural beauty	876	0.09	0.28	0	1
Air quality improvements	876	0.26	0.44	0	1
Economic benefits	876	0.09	0.28	0	1
Price of electricity will decrease	876	0.26	0.44	0	1
Reduce dependence on foreign oil	876	0.36	0.48	0	1
Reduce global warming	876	0.20	0.40	0	1
Location is ideal	876	0.12	0.33	0	1
Personal--should not have to pay to stop	876	0.04	0.20	0	1
Personal--would pay more	876	0.00	0.07	0	1
Price increase too high	876	0.05	0.22	0	1
Responsibility to future generations	876	0.19	0.39	0	1
To set precedence	876	0.22	0.42	0	1
Other	876	0.01	0.11	0	1

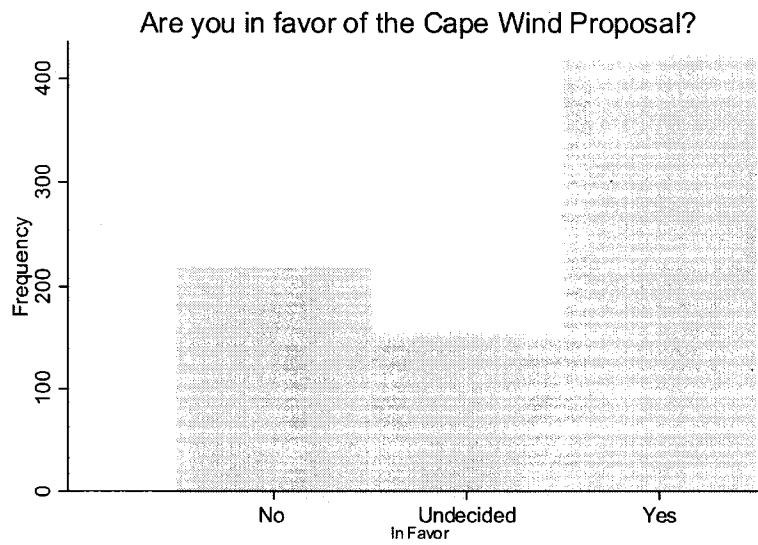
Variable	# Obs.	Mean	Std. Dev.	Min	Max
If you voted yes, what are your top 3 reasons?					
Access to area	876	0.04	0.18	0	1
Natural beauty destroyed	876	0.20	0.40	0	1
Economic--job loss	876	0.04	0.20	0	1
Environmental--marine life	876	0.19	0.39	0	1
Navigational	876	0.11	0.32	0	1
Noise from turbines	876	0.02	0.14	0	1
Oil spill risk	876	0.07	0.26	0	1
Personal	876	0.01	0.09	0	1
Pollution benefits small	876	0.03	0.17	0	1
Private developer benefits from public resource	876	0.17	0.38	0	1
Policy --regulatory process not sufficient	876	0.06	0.23	0	1
Other	876	0.05	0.23	0	1
Male	896	0.65	0.48	0	1
Age	888	56.63	14.79	16	95
Monthly electricity bill (dollars)	819	124.13	202.85	9	5000
Membership in Environmental Organization	871	0.15	0.36	0	1
Highest year of formal education	882	15.20	2.76	4	20
What is your residency on Cape Cod? (0 = Full Time, 1= Part time)	485	0.19	0.40	0	1
How long have you had a residence on Cape Cod?	481	22.54	16.92	0	93
How far is your residence from Nantucket Sound?					
Less than 2 Miles	862	0.18	0.38	0	1
Between 2 and 10 Miles	863	0.22	0.42	0	1
Between 10 and 20 Miles	863	0.11	0.31	0	1
Between 20 and 40 Miles	863	0.08	0.27	0	1
Between 40 and 60 Miles	863	0.13	0.34	0	1
More than 60 Miles	863	0.27	0.45	0	1
Members in household including self	880	2.54	1.38	1	11
Members in household under 18	876	0.52	0.94	0	5
Household Income (thousands of dollars)	819	80.97	49.77	7.5	175

<b>Variable</b>	<b># Obs.</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
What is your occupation?					
Agriculture	889	0.01	0.08	0	1
Construction	889	0.07	0.25	0	1
Education	889	0.06	0.23	0	1
Finance	889	0.03	0.17	0	1
Government	889	0.06	0.25	0	1
Health Care	889	0.06	0.25	0	1
Hospitality--tourism	889	0.01	0.10	0	1
Non-Profit	888	0.02	0.14	0	1
Real Estate	889	0.02	0.14	0	1
Sales	889	0.05	0.22	0	1
Self-Employed	889	0.12	0.32	0	1
Retired	889	0.27	0.44	0	1
Other	889	0.21	0.41	0	1

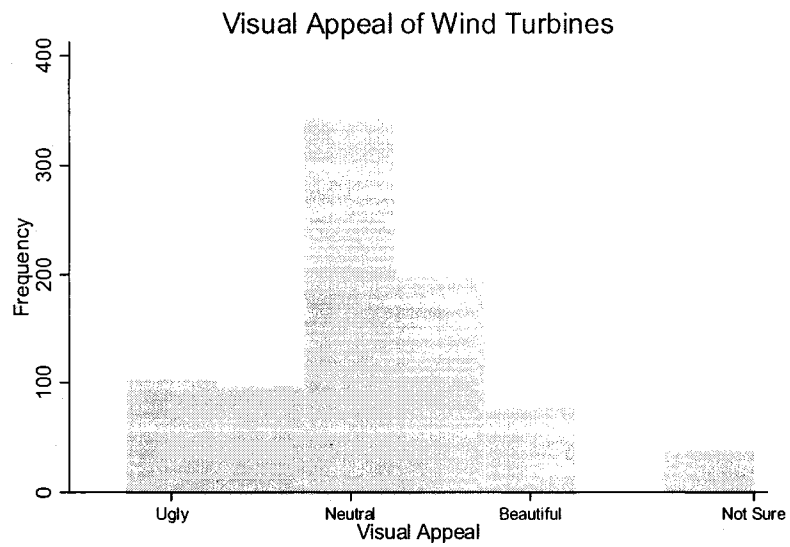
**Figure 4.A1: Summary Statistics for Survey Data**



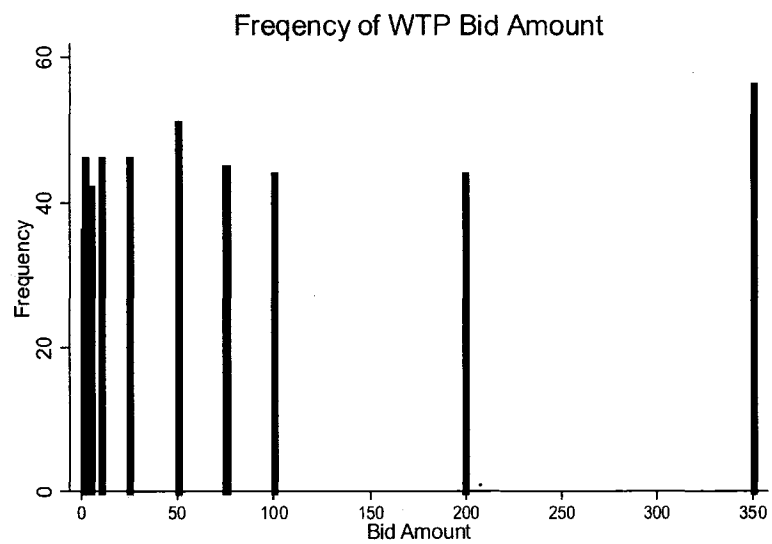
**Figure 4.A2: In Favor Frequency Distribution**



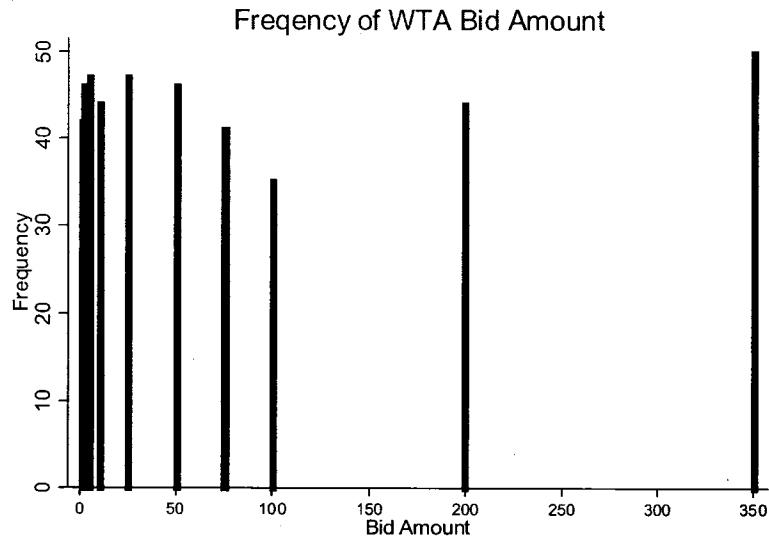
**Figure 4.A3: Visual Appeal Frequency Distribution**



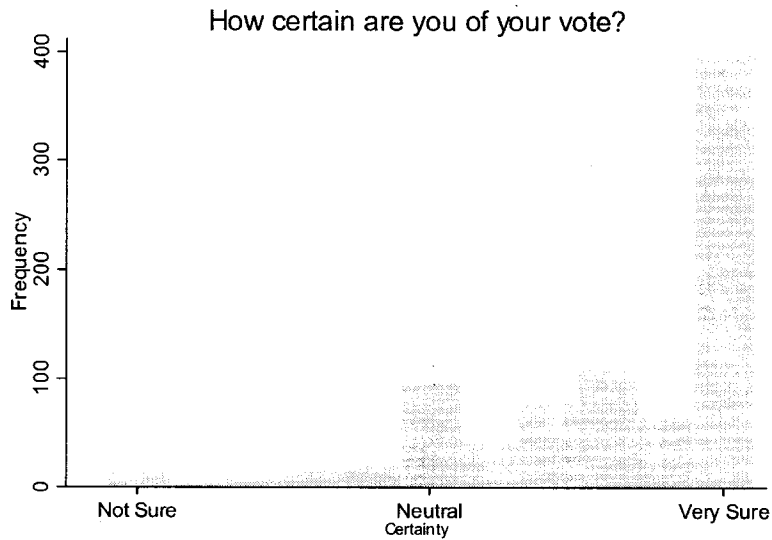
**Figure 4.A4: Frequency of WTP Bid Amount**



**Figure 4.A5: Frequency of WTA Bid Amount**



**Figure 4.A6: Certainty Frequency Distribution**



## CHAPTER 5: CONCLUSIONS

“Our greatest intellectual adventures often occur within us—not in the restless search for new facts and new objects on the earth or in the stars, but from a need to expunge old prejudices and build new conceptual structures. No hunt can have sweeter reward, a more admirable goal, than the excitement of thoroughly revised understanding—the inward journey that thrills real scholars and scares the bejesus out of the rest of us.”<sup>19</sup>

The three essays presented above share a common thread beyond their applications in non-market valuation. All results could be considered curious and unpredictable—the data analyses presented somewhat surprising results. Yet, let us not forget the basis of economics—it is the study of people’s choices. I started this journey believing all I needed to achieve the economic version of enlightenment was to acquire the skills needed to fully comprehend, apply, and dissect the most complicated of economic models. This struggle, like all that retain value, will continue indefinitely as economic models evolve and become seemingly more complex. However, my true economic enlightenment occurred with the realization that as long as truth is defined as a human reality, no economic model will ever fully represent this truth.

While certain aspects of economics are considered concrete and indisputable by most, economics is based on human decisions. The human dimension is what separates economics from the physical sciences. Yet we economists, with our affinity for mathematical and statistical models, often neglect to give credit to the essence of the imperfections within our methodology—no human being is 100% predictable. True, we model these

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<sup>19</sup> Gould, S.J. 1995. *Natural History*. 104 (6)

imperfections in minute detail, adding stochastic elements to every possible assumption. Yet economics as a science, like humanity, is inherently imperfect. My “thoroughly revised understanding” is the personal discovery that the quest for the researcher is not to train one’s self to comprehend each assumption and outcome of a previously accepted model of reality. The quest for the researcher is to question those models that have become conventions and to investigate the assumptions they are based upon, the applicability of the results obtained from them, and the implications of using them to make decisions that affect the well being of society.

The far-reaching goal of the research herein is to provide valuable insight into policy analyses with the hope that improved policy actions will also increase sustainable economic welfare. The essays presented above are the beginnings of a research portfolio increasing public awareness and use of non-market valuation as a tool for decisions that affect the livelihoods of present and future generations without neglecting the insight that models of human behavior are flawed by the very nature of what they attempt to mimic. Continual challenge of the basis of these models can and should ensue, for there are aspects of human behavior that will always remain a mystery. We can only hope that the hunger for knowledge, like the desire to increase utility, remains (at least locally) insatiable.