Journal of Environmental and Resource Economics at Colby

Volume 01
Issue 01 *Spring 2014*

Article 9

2014

A Choice Experiment Survey Analysis of Public Preferences for Renewable Energy in the United States

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Cover Page Footnote
I would like to thank Professor Sahan Dissanayake and Research Assistants Max Pollinger and Pengyu Ren.

1. Introduction

In the context of increasing public awareness and attention on global climate change, there have been growing efforts in the Unites States directed at expanding our domestic renewable energy capacity. Energy is a heavily policy driven economic sector with state and federal regulatory activities influencing the ability of renewable energy technologies to compete in the electricity market. Renewable portfolio standards are the primary policy mechanism that establishes renewable energy capacity requirements and timelines for a specific state and for the nation as whole. Given the high start-up costs associated with renewable energy development, the federal government provides investment tax credits (ITCs) and production tax credits (PTCs) as an economic incentive for renewable energy development firms. Renewable energy currently accounts for 13% of the renewable energy supply with hydropower comprising 52% of total capacity. Additionally, 32% of our renewable energy supply comes from wind, 12% is from biomass, and 3% is from geothermal, and 2% is from solar.

As the U.S. seeks to diversify its energy portfolio and increase investments in renewable energy, the external costs and benefits associated with these investments must be examined. When designing policies for a more sustainable energy future, an important goal is to generate the lowest possible adverse socio-economic and environmental impacts for a given quantity of power output (Bergmann et al., 2006). Although renewable energy is inherently sustainable and has a significantly lower impact in comparison to burning fossil fuels, there are still real impacts associated with these new investments that must be taken into account. The major effects of renewable energy development include impacts on landscape, wildlife, air pollution, electricity prices and employment.

The primary objective of this study is to determine what attributes significantly impact individuals' willingness to pay (WTP) for a new renewable energy project. In turn, the results of this research may help to understand the environmental and economic aspects of renewable energy that most influence public acceptance of renewable energy development. Choice experiment analysis plays a critical role in building an understanding of public preferences and information produced from this research can be leveraged to achieve optimal public policy outcomes.

2. Literature Review

The economic literature on renewable energy is expanding. Non-market valuation studies have applied econometric methods to understand the value of renewable energy from both an environmental and social welfare perspective. Of relevance to this paper is the application of choice modeling to analyze the implicit trade-offs individuals make in choosing between alternative renewable energy project options. One of the major benefits of using this type of methodology is that it can be used to evaluate for heterogeneous preferences across different stakeholder groups.

In general, previous literature has found WTP for renewable energy is higher among young people, those who are more liberal, homeowners, women, and more environmentally conscious and highly educated individuals (Menegaki, 2008). Recent studies on this topic also suggest that people in higher income groups are WTP more for renewable energy (Menegaki, 2008).

One particular study by Bergmann et al. (2006) attempts to estimates the external costs and benefits in the case of renewable energy technologies in Scotland. The attributes that they consider in their choice experiment survey are landscape quality, habitat quality, and air quality. This particular study also considers welfare applications in terms of the effect of a renewable energy project on employment and electricity prices. The renewable energy types included in their model are hydropower, wind energy, and biomass. In their analysis they test for differences in preferences for urban versus rural communities, and for different interest groups. Their results revealed that all of the environmental attributes were significant determinants of utility at some level; however, employment effects were not found to be significant determinants of choices or utility (Bergmann et al., 2006). Also, when the sample population was divided into two groups (urban and rural), jobs remained insignificant for the urban sample, but became strongly significant for the rural model. Consistent with general consumer theory, expected increases in electricity prices reduced consumer utility.

Another study by Bergmann et al. (2008) applies a random parameter logit model to further analyze heterogeneity in preferences for urban and rural community residents. They are specifically interested in considering the relative weight of environmental and landscape effects associated with renewable energy as reflected in the WTP values for these two sub-groups. Anecdotal evidence suggests that urban and rural residents are impacted differently by renewable energy projects. For example, while the urban sub-group may place more value in reducing the direct impact on the environment and wildlife of a large-scale wind project, rural residents may place more value on the creation of new job opportunities. The urban and rural sub-sample models find that preferences, in fact, differ between these two groups. They also find that rural residents have greater support for renewable energy projects because they have more significant and positive attribute coefficients, and the coefficients on the cost attribute is less negative. Their results further underscore the importance of considering the preferences of both of these groups from a policy perspective, as they are certainly relevant stakeholders in the current debate.

This paper extends the work of these two studies by considering public preferences towards renewable energy in the U.S. In addition to accounting for heterogeneity across urban and rural population groups, this study also considers the relative importance of being affected by extreme weather events in determining the WTP for different attributes associated with renewable energy development.

3. Methodology

a. Survey Design and Implementation

Choice experiment surveys are a stated preference valuation tool to find WTP for environmental goods and services. This methodology is based on two fundamental building blocks: Lancaster's characteristics theory of value and random utility theory. Lancaster's theory states that consumers' derive utility not from goods themselves but rather from the attributes or characteristics that the goods possess. The value of a good, therefore, is the sum of the value of its individual characteristics (Lancaster, 1966). Random utility theory states that not all of the determinants to individuals' value for an environmental good or resource are observable to the researcher, so only an indirect determination of preferences can be made. The utility function of a particular individual can be divided into observable and stochastic components (McFadden, 1974).

In a choice experiment survey respondents are asked to make decisions amongst bundles containing different levels of the same attributes. The survey instrument that was designed for this study was based on a defined set of critical attributes associated with renewable energy projects in general. These attributes were selected based on an extensive review of non-market valuation studies evaluating public perception of renewable energy. The attributes included in this survey and their levels are outlined in table 1. Some of the guidelines considered in choosing the attributes to evaluate include relevance, credibility, and applicability to policy analysis.

Prior to administering the survey we conducted a focus group with eight members of the Colby College community. Feedback obtained through this process was used to refine our attributes and to identify questions in the survey that were ambiguous or needed to be clarified. The survey design is based on blocks of 6 choice profiles (see figure 1 for sample survey question). There were 6 unique surveys that were posted on Amazon Turk, an online survey platform that allows researchers to pay respondents for survey responses. The survey a respondent receive was determined based on his or her month of birth. Each survey contained 6 sets of unique binary choice questions. In addition to the choice experiment section, a demographic questionnaire was included to collect information related to peoples' environmental and climate change views, risk thresholds, and whether or not they currently live near a renewable energy facility.

Table 1. Attributes and Attribute Levels

Attribute	Description	Levels
Type of energy source	The type of energy source responsible for electricity generation	• Wind, solar, hydropower, geothermal, tidal, biomass
Distance and visibility	The distance to the energy source from your home	• <10 miles away and visible from house • <10 miles away and not visible from house • Between 10 and 20 miles away and not visible from house
Action to reduce environmental impact	Measures are taken to reduce environmental and ecosystem impact	• No measures are taken • Measures are taken
Local economic benefits	Renewable energy projects support local economies with higher tax revenue for local communities. This additional revenue stream can lower tax burden for homeowners and/or provide local communities funds for community development	• 1/3rd to private property tax breaks, 2/3rd to community development • ½ to private property tax breaks, ½ community development • 2/3rd to private property tax breaks,1/3rd to community development
Community job creation	The amount of jobs created by the energy source	• This feature ranges from 10 to 30 permanent jobs
Effect on electricity prices	The potential increase in residential electricity prices because of increased electricity generation from renewable energy sources	• This features ranges from \$0 to \$50 in the average monthly electricity bill in your household

Figure 1. Sample Choice Question

Question 1

Suppose Option A and Option B were the **only** renewable energy projects you could choose. Which **one** would you choose? Please read **all** the features of **each** option and then **check the box that represents your choice**. If you do not like either option A or option B, then please choose the box marked "No renewable energy development" which is Option C.

Attribute	Type of Energy Source	Distance and Visibility	Acton to Reduce Environmental Impact	Local Economic Benefit	Community Job Creation	Effect on Electricity Bill
Option A	Solar	Not Visible from home Less than 10 miles	No Measures taken	1/3rd to private property tax breaks 2/3rd to community development	10 permanent jobs	Bill increases by $10 (per month)
Option B	Geothermal	Not Visible from home Between 10-20 miles	Measures taken	1/3rd to private property tax breaks 2/3rd to community development	30 permanent jobs	No increase in bill
Option C	No Renewable Energy Development					No increase in bill

Survey Ver 5 Question No 1 1

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4. *Analysis Method*

In order to model the information collected in the choice experiment survey, data had to be converted into a spreadsheet where each option is a row and the sheet has the attribute levels corresponding to each choice situation. A conditional logit (CL) and mixed multinomial logit (MMNL) model were used to find estimates for the attributes as well as respondent's WTP. The CL model includes attributes as a linear summation in the following form:

$$V_j = \sum_{K=1}^{K} \beta_k \mathrm{X}_{kj} + \beta_p \mathrm{P}_j + \varepsilon_j$$

A main effects model estimates that coefficients of each parameter, and the marginal value of attribute k is equal to the ratio between the beta values of the parameters of the attributes divided by the parameter of the cost attribute:

$$MWTP_k = -\frac{\beta_k}{\beta_p}$$

The CL model assumes that respondents all have homogenous preferences and thus it provides a limited analysis of unobserved heterogeneity.

In order to account for preference heterogeneity, a MMNL model was also used to analyze the discrete choice data. The standard multinomial logit model assumes that the respondents are homogeneous with regard to their preferences (the βs are identical for all respondents). This strong assumption is not typically valid and recent literature has started using the mixed multinomial logit model (MMNL)[1] as one of the standard methods to analyze discrete choice data. The MMNL incorporates heterogeneity of preferences (Hensher and Greene. 2003, Carlsson, et al. 2003). The following is a summary of the derivation of the MMNL estimator and the calculation of the WTP. Assuming a linear utility, the utility gained by person *q* from alternative *i* in choice situation *t* is given by

$$U_{qit} = \alpha_{qi} + \beta_q X_{qit} + \varepsilon_{qit}$$

where X_{qit} is a vector of non-stochastic explanatory variables. The parameter α_{qi} represents an intrinsic preference for the alternative (also called the alternative specific constant). Following standard practice for logit models we assume that ε_{qit} is independently and identically distributed extreme value type I.

[1]This approach is also referred to as the mixed logit, hybrid logit, random parameter logit, and random coefficient logit model.

We assume the density of β_q is given by $f(\beta \mid \Omega)$ where the true parameter of the distribution is given by Ω. The conditional choice probability of alternative *i* for individual *q* in choice situation *t* is logit[2] and given by

$$L_q(\beta_q) = \prod_t \frac{\exp(\alpha_{qi} + \beta_q X_{qitq})}{\sum_{j \in J} \exp(\alpha_{qj} + \beta_q X_{qjt})}.$$

The unconditional choice probability for individual *q* is given by

$$P_q(\Omega) = \int L_q(\beta) f(\beta \mid \Omega) d\beta.$$

The above form allows for the utility coefficients to vary among individuals while remaining constant among the choice situations for each individual (Hensher, et al. 2005, Carlsson, et al. 2003, Train. 2003). There is no closed form for the above integral; therefore P_q needs to be simulated. The unconditional choice probability can be simulated by drawing R random drawings of β, β_r, from $f(\beta \mid \Omega)$[3] and then averaging the results to get

$$\tilde{P}_q(\Omega) = \frac{1}{R} \sum_{r \in R} L_q(\beta_r).$$

In the choice experiment questions, option A and option B are both restoration options that can be viewed as being closer substitutes with each other than with option C, the status quo option (Haaijer, *et al.* 2001; Blaeij et al. 2007). One method to incorporate this difference in substitution between options is to use an econometric specification for the mixed multinomial logit model that contains an alternative specific constant (ASC) that differentiates between the status quo option and choices that represent deviations from the status quo. This can be achieved by using a constant that is equal to one for alternative A or alternative B.

The coefficient estimates for the mixed multinomial logit model cannot be interpreted directly. Therefore, we calculate average marginal WTA for a change in each attribute *i* by dividing the coefficient estimate for each attribute with the coefficient estimate for the payment term, as given below (Dissanayake, 2014).

$$MWTA_i = \frac{\beta_i}{\beta_{cost}}$$

[2] The remaining error term is iid extreme value.

[3] Typically $f(\beta \mid \Omega)$ is assumed to be either normal or log-normal but it needs to be noted that the results are sensitive to the choice of the distribution.

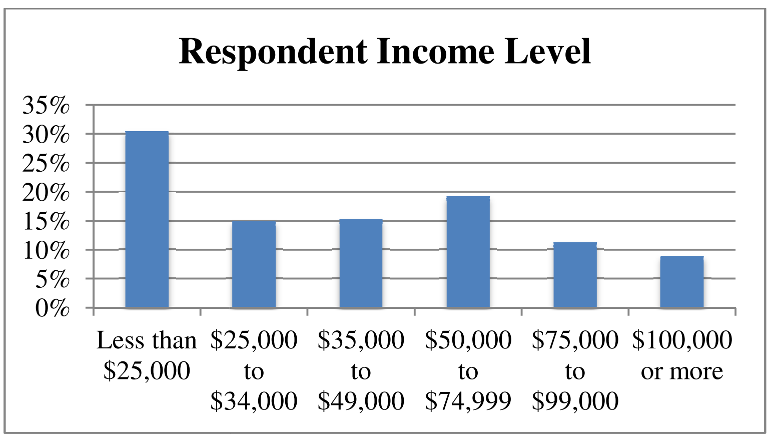
In this mixlogit model, cost was not includes as random variable, but rather as a standalone independent variable. To estimate the WTP, the coefficients for each attribute were divided by the coefficient for the cost term, which is this cases was the increase in monthly electricity bill.

5. Results

b. Descriptive Statistics

We received 304 usable surveys that captured information from across the United States. The median age of respondents was approximately 39 years old. The gender distribution of respondents was 53% male and 47% female. The average number of years of education achieved by respondents was 15 years and the average monthly income of respondents was below $50,000 (see figure 2). The average monthly electricity bill of respondents was approximately $131. In terms of the distribution of urban and rural respondents, 70% were from an urban or suburban area (70%) and the remaining 30% of the sample was from a rural area (see figure 3). Because I was interested in comparing the differences in preferences and WTP between urban and rural residents, I divided the sample population into two sub-groups in one of my models.

Figure 2. Distribution of Income Levels



Interestingly, of the 301 respondents who answered the question on climate change, 89% of respondents indicated that they believe that we are currently experiencing climate change. The question on climate change further revealed the distribution of beliefs as to the causes of climate change (see figure 4). Based on the 279 individuals that responded to this question, 41% believe that climate change is partly caused by natural processes and partly caused by human activity, while only 8% of respondents believe that climate change is entirely due to human activity. The survey questionnaire additionally asked whether or not a respondent has ever experienced an extreme weather event that they attribute to climate change. The survey captured a total of 301 answers to this question, with 208 (69%) individuals indicating that they have experienced an extreme weather event and 93 (31%) that have not. The second model I create in this paper segregates respondents based on whether or not they have experiences an extreme weather event.

Figure 3. Distribution of Respondents from Urban and Rural Locations

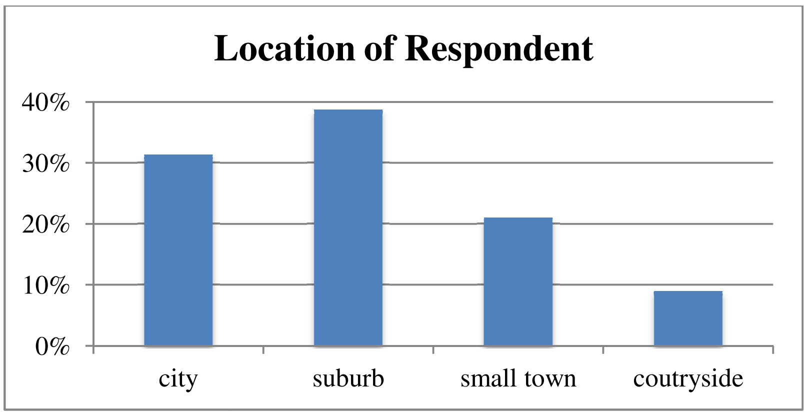
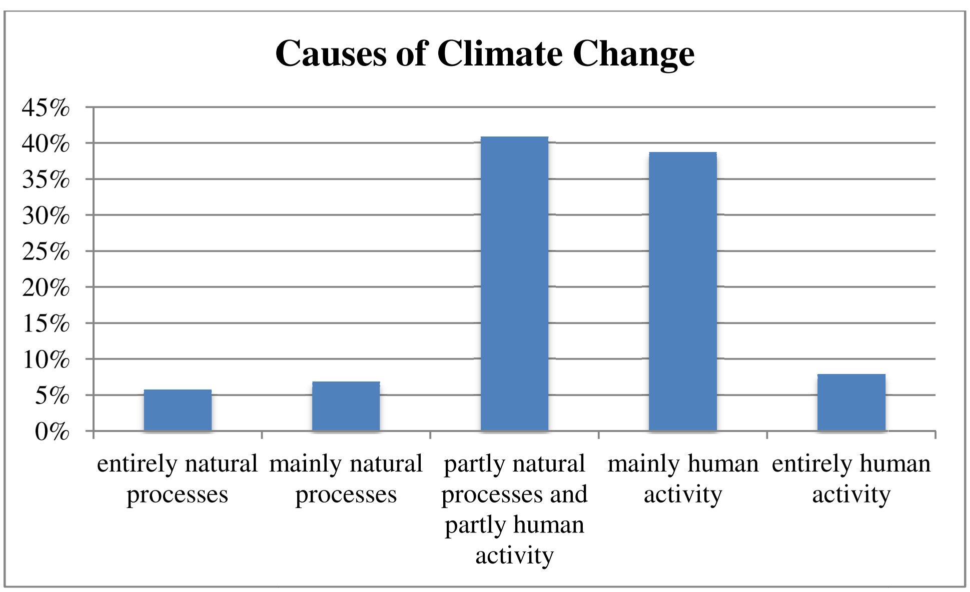


Figure 4. Beliefs Relating to Climate Change



c. Main Effects

The results for all 304 respondents from the CL and MMNL model are shown in table 2. The coefficients are interpreted as the parameters of the indirect utility function, although the fact that they are confounded with a scale parameter means that one cannot directly interpret the numerical value. Coefficient signs show the influence of attributes on choice probabilities: here almost all of the attributes have the expected signs except for the visible attribute. The signs of the econ and job attributes are both positive and significant, as consumer preference theory would predict, since these attributes are coded to show that an increase in local economic benefits and permanent job creation should lead to an increase in the utility that an individual receives from a particular project. The types of energy sources were all positive, however only the coefficients for wind, tidal and solar were significant at the 1% level. This implies that people are more likely to choose options where solar, wind, or tidal power are the energy type (geothermal is significant in the MMNL model). The sign of the environment attribute is positive and significant at the .1% level, an indication that whether or not actions to reduce the environmental impact of project highly influences a person's decision in choosing that project. The coefficient on distance is positive and significant, implying that people are more likely to choose a project that is cited further away from where they live. However, the fact that the sign of the visible term is positive brings conflict to the intuitive prediction that people prefer projects that are less visible. The main effect model results actually indicate that people are more likely to choose a project that they can see from where they live. The distance and visible attributes are both significant at the 1% level in the CL model and are significant at the 5% level in the MMNL model.

The MMNL model also provides information about the heterogeneity of preferences. In the basic model, the standard deviations of geothermal, wind, solar, distance, environment, econ, job and cost attributes are all significant, which means that there was significant variation among responses, or heterogeneity within the sample. The standard deviations for biomass, tidal and visible were not significant, which explains why the estimated coefficients for these attributes were not significant or less significant in this model.

Table 2. Results of Main Effect of Model

	Conditional Logit	Mixed Multinomial Logit	
	Coeff(SE)	Coeff(SE)	Significant SD
Geothermal	0.207 (0.126)	0.708** (0.257)	Yes
Biomass	0.135 (0.140)	0.328 (0.231)	No
Wind	0.527** (0.203)	1.555*** (0.381)	Yes
Tidal	0.381** (0.124)	0.486* (0.204)	No
Solar	0.647*** (0.118)	1.461*** (0.234)	Yes
Distance	0.280** (0.0997)	0.346* (0.172)	Yes
Visible	0.248** (0.0846)	0.284* (0.143)	No
Environment	0.907*** (0.0860)	1.697*** (0.198)	Yes
Econ	0.0915** (0.0344)	0.0497 (0.0602)	Yes
Job	0.0548*** (0.00426)	0.124*** (0.0121)	Yes
Cost	-0.0695*** (0.00303)	-0.144*** (0.0107)	Yes
Observations	5430	5430	

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

d. WTP Results (Model 1)

For my first model, I estimated the WTP values using the entire population sample and the results are shown in table 3. The estimated WTP coefficients are positive for all of the attributes. In particular, the results of the general model reveal that wind, tidal, solar, distance, visible, environment, and job are statistically significant for both the CL and MMNL. Also, Geothermal is statistically significant for the MMNL model and likewise Econ is only significant for the CL model. The Environmental and Solar attributes are significant at the .1% level and have the highest estimated WTP values, implying that individuals are willing to pay more to pay more for a solar energy project and they are also place higher value on projects where actions are taken to reduce the environmental impact. Another notable finding is that respondents highly value community job creation in choosing a project, as this is significant at the 1% level in both models.

Table 3. Model 1 WTP Estimates for Each Attribute in CL and MMNL Models

	CL	MMNL
Geothermal	2.974	4.927**
	(1.810)	(1.773)
Biomass	1.943	2.284
	(2.017)	(1.631)
Wind	7.580*	10.82***
	(2.950)	(2.586)
Tidal	5.482**	3.383*
	(1.772)	(1.433)
Solar	9.307***	10.17***
	(1.696)	(1.584)
distance	4.025**	2.408*
	(1.437)	(1.200)
visible	3.563**	1.977*
	(1.219)	(1.008)
Environment	13.05***	11.81***
	(1.172)	(1.194)
Econ	1.316**	0.346
	(0.494)	(0.421)
Job	0.789***	0.862***
	(0.0569)	(0.0633)
Observations	5430	5430

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

WTP Results (Model 2)

Table 4 shows WTP estimates for both the CL and MMNL models when the survey sample is divided into urban and rural subgroups. The WTP values were all positive for each of the attributes except for biomass, which was negative for the CL model. With respect to the urban subgroup, solar, environment, and job were consistently significant at the .1% level. It is also notable that environment and solar have the highest estimated WTP values. Similar to the results of model 1, members of the urban subgroup are willing to pay more more for solar energy project and more for a project where environmental precautions are taken. In fact, these results indicate that urban residents are, on average, willing to pay more than the population as a whole is for a project that includes these attributes.

Consistent with the WTP findings from model 1 and to that of the urban subgroup, solar, environment and job were the most significant attributes in determining an individual's WTP for a renewable energy project. All three of these attributes are positive and significant at the .1% level. Interestingly, wind was the most valuable attribute in the MMNL model for the rural group, and environment was highest in the CL model. This means that, in comparison to urban residents, rural residents value wind energy more highly and are willing to pay more for a project with this energy type. Wind is significant at the 1% level in this model. Environment and solar are also highly valued, which is consistent with the urban model results.

Based on the results of model 2, there are some interesting comparisons that can be made between these two subgroups. First, these results reveal that WTP values are indeed different between urban and rural residents. Specifically, urban residents are WTP more, on average, than rural residents mitigate environmental impacts and to have higher levels of local job creation. On the other hand, rural residents are WTP higher amounts for a solar or wind energy project. Another interesting result is that the WTP value for the distance attributes is higher and actually significant for the urban residents. This implies that distance to the renewable energy project significantly affects their utility, and so they are WTP more than a rural resident for a project that is cited further away from where they live.

Table 4. Model 2 WTP Estimates for Each Attribute in CL and MMNL Models

	Urban		Rural	
	CL	MMNL	CL	MMNL
Geothermal	2.525	3.922	3.049	5.365
	(2.146)	(2.196)	(3.297)	(3.024)
Biomass	2.137	3.898*	-0.00793	1.284
	(2.399)	(1.978)	(3.605)	(2.875)
Wind	6.244	9.891**	10.93*	12.79**
	(3.591)	(3.056)	(5.102)	(4.052)
Tidal	4.249*	1.839	7.989*	4.806
	(2.109)	(1.726)	(3.172)	(2.504)
Solar	8.180***	10.26***	11.08***	10.27***
	(2.022)	(2.054)	(3.023)	(2.767)
Distance	4.804**	3.192*	2.077	0.719
	(1.719)	(1.429)	(2.548)	(1.992)
Visible	3.553*	2.757*	2.494	0.0776
	(1.436)	(1.235)	(2.229)	(1.914)
Environment	13.66***	12.57***	11.87***	10.76***
	(1.389)	(1.502)	(2.128)	(2.020)
Econ	1.035	0.151	1.930*	1.359
	(0.593)	(0.552)	(0.864)	(0.721)
Job	0.835***	0.916***	0.700***	0.808***
	(0.0682)	(0.0792)	(0.0998)	(0.116)
Observations	3774	3774	1620	1620

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

WTP Results (Model 3)

Table 5 shows WTP estimates for both the CL and MMNL models when you divide the survey sample based on respondents that have experienced an extreme weather event and those that have not (extreme weather and no extreme weather). For the extreme weather group, the WTP estimates for all of the attributes were positive. With respect to the CL model's WTP estimates, wind, tidal, solar, environment and job are all significant a the .1% level. The most valuable attribute in terms of WTP for the CL model was environment, followed by wind and solar. In the MMNL model, all of the same attributes were significant. The most valuable attribute for the MMNL model, reflected in highest WTP was also the environment attribute, implying that people who have experienced an extreme weather event are willing to pay more for a project where the environmental impacts are reduced.

For the no extreme weather group, all of the estimated WTP coefficients for the CL and MMNL models were positive, except for wind, which was negative in both cases. Geothermal, distance, visible, environment, econ, and job were all significant for the CL model. For the MMNL model, geothermal, distance, environment, econ and job were all significant. The environmental and job attributes were significant at the .1% level. The most valuable attribute in terms of WTP for both models was also environment, consistent with the results for the extreme weather group.

In comparing these two groups, the results indicate that respondents who have experienced an extreme weather event that they attribute to climate change are willing to pay more than those that have not experienced an extreme weather event in taking actions to reduce the environmental impact of a renewable energy project. If respondents attribute experiencing extreme weather to a changing climate, then they may perhaps be more environmentally conscious to begin with, explaining the higher value they place on the environment attribute. Also, while wind, tidal and solar are all highly valued and significant attributes for the extreme weather group, there are much less valued by no extreme weather group. In fact, the estimated WTP value for wind and solar are negative for the no extreme weather group. However, since these results are statistically significant we cannot draw any major conclusions from these results. Another interesting finding is that the WTP value for econ is higher and significant for the no extreme weather group, but it is not significant attribute in determining WTP for the extreme weather group. In addition, people that have not experienced an extreme weather event place more value on projects that are further away from where they live. In contrast, distance to a renewable energy project does significantly impact respondents WTP if they have experienced an extreme weather event. People who have experienced extreme weather place more value on the energy source and this environmental impact of the project.

Table 5. Model 3 WTP Estimates for Each Attribute in CL And MMNL Models

	Extreme Weather		No Extreme Weather	
	CL	MMNL	CL	MMNL
Geothermal	1.627	4.938*	5.790*	6.833*
	(2.279)	(2.110)	(2.829)	(2.749)
Biomass	2.213	3.244	1.093	0.252
	(2.492)	(2.015)	(3.373)	(3.142)
Wind	12.89***	14.78***	-4.714	-1.032
	(3.651)	(3.031)	(4.683)	(5.344)
Tidal	7.533***	4.186*	0.810	-0.517
	(2.212)	(1.718)	(2.825)	(2.809)
Solar	12.02***	12.47***	2.323	3.437
	(2.068)	(2.184)	(2.943)	(3.248)
distance	3.201	1.678	5.684*	4.978*
	(1.790)	(1.502)	(2.332)	(2.533)
visible	2.467	1.469	6.391**	4.540
	(1.496)	(1.230)	(2.030)	(3.314)
Environment	14.50***	13.56***	10.63***	10.20***
	(1.451)	(1.536)	(1.927)	(2.080)
Econ	0.911	0.302	2.182**	1.619*
	(0.613)	(0.550)	(0.810)	(0.799)
Job	0.857***	0.891***	0.637***	0.709***
	(0.0714)	(0.0800)	(0.0904)	(0.111)
N	3738	3738	1674	1674

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6. Conclusion

Increasing our renewable energy capacity in the U.S. is a promising solution to addressing the problem of climate change and lowering the carbon footprint of our energy economy. The inherent sustainability of renewable energy projects should provide significant motivation for our transition away from fossil fuel derived energy sources. At the same time, policy makers must consider the potential external socio-economic and environmental costs associated with new renewable energy investments.

Overall, the results of this study show that increases in electricity prices significantly reduce consumer utility. Another major finding is that people care significantly about the environmental impacts of renewable energy projects and are, on average, willing to pay more for a project where actions are taken to reduce the environmental costs. These findings are consistent with the Bergmann et al. (2006) study, which found that all of the environmental attributes significantly impacted public acceptability for renewable energy projects in the Scotland. In addition, the type of energy source is significant in determining the likelihood that a person will choose one project over another, however these results differ when you divide the sample based on having experienced an extreme weather event. For the sample as a whole, the results showed that individuals were willing to pay more for solar and wind energy. This could be representative of the fact that people know relatively more about these technologies because they are more visible in comparison to others. Finally, local job creation appears to significantly affect public preferences for renewable energy projects, with higher levels of permanent job creation increasing a respondent's individual utility for a particular project.

In considering the heterogeneity in preferences between urban and rural subgroups, it appears that their preferences do slightly differ. It was interesting to find that rural groups place higher value on wind energy projects and that they care less about the distance of the project from where they live. However, the results did not show that rural residents value local job creation any more significantly than urban residents. Given that rural areas tend to have more land available to develop renewable energy projects, it may be more beneficial for policymakers to site bigger wind energy and solar energy projects in these locations where the relative impact on proximity is minimized.

Above all, these results highlight the public's heightened concern for the environmental impacts of renewable energy projects, suggesting that these effects should be prioritized as our nation seeks to further expand its renewable energy investments. In balancing some of the economic trade-offs between different development options, policymakers can utilize the information derived from this choice experiment study to develop a set of sustainability criteria that can be applied to reduce the economic welfare and environmental costs associated with new energy investments.

7. Works Cited

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