Journal of Environmental and Resource Economics at Colby

Volume 01
Issue 01 *Spring 2014*

Article 6

2014

Willingness-to-Pay for Renewable Wind Energy: Differences in Preferences Between Demographic Groups

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1. *Introduction:*

Wind power development has grown rapidly in recent years and that growth will continue in the coming years (GWEC, 2008). Driven by further improvements in the cost-competitiveness of wind technology relative to fossil fuel alternatives, experts predict that wind power will account for the largest share, roughly 30%, of new power capacity added in terms of gigawatts by 2030 (Bloomberg, 2013). While increased reliance on wind energy will decrease the need for fossil fuels and increase renewable energy production, generally regarded as a positive, there is considerable resistance throughout the United States within local communities for the implementation of wind power developments. Our research focuses on capturing variations in public preferences for wind power.

Concerns over environmental damage, relative community benefits, aesthetics, and impact on home values all characterize public aversion to wind energy projects in general. We reached out to an executive at First Wind in Portland, Maine to discuss what wind companies can do to appease wind implementation in new communities. We went over the company's successes and failures to try to understand what characteristics were important in new wind developments. The main concerns for local communities in Maine ranged from concerns over environmental damage and community benefits to aversion to changing the natural landscape and home values. In addition, local residents were concerned with the idea that their local communities would not be directly using the wind power generated in their town, but instead used by residents in other parts of New England. In some cases, when wind power companies surveyed residents, the respondents showed that they were not interested in any time of renewable energy production taking place in their community, regardless of perceived benefits to society and their community. Given that the attitudes in Maine may not be representative of the overall population of the United States, the choice experiment surveys individuals throughout the country. By utilizing a choice experiment that collects information from respondents from across the United States, our results are more generalized.

For this paper, we aim to answer three questions: Why do people oppose wind facilities in their local communities? What incentives can best be used to motivate local communities and residents to adopt wind energy? Which demographic groups are more or less likely to oppose wind energy? This paper uses choice experiments to gather data from respondents throughout the United States in regard to implementation of wind power in their local communities.

Using the data that we collect, we run multiple regression analyses using conditional and mixed multinomial logit models to calculate consumer preferences and their willingness to pay for different attributes in relation to wind power implementation.

2. Literature Review:

Although there has been previous literature done that discusses either hedonic analysis of the effects of wind energy facilities for local communities and the willingness to pay for renewable energy, we aim to be the first to combine these two areas of research into one paper. Our paper attempts to answer different questions using choice experiments, using previous literature on each subject as a springboard for further discussion.

For the first part of our research questions, as discussed above, we hope to better understand the reasons for wind energy facility opposition, which are complex and differentiated between different locations and subgroups. One consistent theme between various groups throughout the country is the perception that the proximity of wind facilities to individual homes has a negative impact on value and sale price. Ben Hoen and his research partners have written several papers, namely "A Spatial Hedonic Analysis of the Effects of Wind Energy Facilities on Surrounding Property Values in the United States" (R4 8) and "Wind Energy Facilities and Residential Properties: The Effect of Proximity and View on Sales Prices" (R4 6), that aim to uncover the truth about this perception. Interestingly, through hedonic analyses, he and his research partners are able to determine that the proximity to wind facilities has no statistically significant effect on housing value or sales prices. The data used spans the period before announcement, during construction, and after construction. In addition, the dataset included homes throughout the country, with wind farms of varying distances to individual homes, eliminating potential bias. These finding are significant in relation to the first research question we posed. Given that the proximity of wind farms does not have a significant effect on sales prices, we can assume that there are other factors that individuals and communities care about when discussing the potential implementation of wind power in their local communities. However, even though there is no statistical evidence that proximity to a wind energy facility impacts housing prices, being in close proximity is still a perceived disamenity that should be considered in evaluating public acceptance of renewable energy projects.

In the second part of our research question, we aim to better understand individual consumer's willingness to pay for certain attributes in regards wind energy implementation. To understand these preferences on an individual level, Riccardo Scarpa and Ken Willis' previous research, a choice experiment on a household basis in the United Kingdom, was particularly useful. While their research focused on a variety of renewable energy solutions, their findings are relevant to renewable energy implementation on a local level. They found that while households significantly value renewable energy adoption, this value is not sufficiently large. In addition, the results have showed that consumers attached a greater relative importance to capital in relation to ongoing energy savings. Consumers' time horizon for cost is between 3 to 5 years, much less than the technology lifetime of 10 to 25 years. These findings, while based on choice experiments from the United Kingdom, have significant implications for our experiment. The relative importance consumers attached to capital in relation to energy savings shows that on a household basis, consumers are less likely to value renewable energy on a long-term basis.

3. Methods:

The foundation of this study is a choice experiment that aims to uncover willingness to pay for renewable wind energy. Choice experiments are based upon consumer demand theory, which assumes that utility to customers derives from the characteristics of these goods. This idea is based on the notion that individuals are not only interested in different attributes, but the different levels of said attributes. The choice experiment used in our surveys presented customers with sets of alternative combinations of attributes with regard to wind energy facility implementation, asking individuals to choose their most preferred alternative. The choices by individuals from sets of alternatives reveal the trade-offs they are willing to make between attributes. Each individual was asked to choose one alternative from each choice set. This choice is modeled as a function of the attributes of that implementation design.

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 no typically valid and recent literature has started using the mixed multinomial logit model (MMNL)[1] as one of the

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

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

$$U_{qit} = \alpha_{qi} + \beta_q X_{qit} + \varepsilon_{qit} \qquad (1)$$

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. 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

$$L_q(\beta_q) = \prod_t \frac{\exp(\alpha_{qi} + \beta_q X_{qitq})}{\sum_{j \in J} \exp(\alpha_{qj} + \beta_q X_{qjt})} . \qquad (2)$$

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

$$P_q(\Omega) = \int L_q(\beta) f(\beta \mid \Omega) d\beta . \qquad (3)$$

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

$$\tilde{P}_q(\Omega) = \frac{1}{R} \sum_{r \in R} L_q(\beta_r) . \qquad (4)$$

random coefficient logit model.

[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 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 in (9) (Dissanayake, 2014).

$$MWTA_i = \frac{\beta_i}{\beta_{cost}} \tag{9}$$

4. *Questionnaire and Data:*

In this choice experiment, respondents traded-off between six attributes. Below in Figure 1, are the different attributes levels and descriptions. Image 2 depicts a sample choice experiment question.

The sample comprised of 199 individual respondents to our survey posted on Amazon Turk, a website that allows researchers to pay respondents for survey responses. The study was conducted in April 2014. In the survey, we asked respondents to identify themselves within demographic questions such as age, number of children, annual household income, and educational background. The sample was spread across different regions within the United States, allowing us to generalize the results for not just New England, but the entire country.

Each respondent completed one survey, which contained a total of seven choice questions. In order to increase variation between responses to allow for statistically significant responses, three different surveys were used. In each survey, there were six unique choice questions, with the seventh question a repeat of the first question. This was done because some respondents do not fully grasp the concept through reading the instruction and thus use the first question as a practice. Out of 199 respondents, only 102 of said respondents were well informed, having correctly answered a question hidden in the description of the survey.

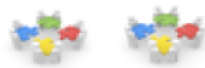
Figure 1: Attribute Levels

Community Engagement Levels Some Engagement — No Engagement Full Engagement	• **Full:** Multiple meetings between the financing company and the town where any questions or concerns can be asked and voiced. Company will reimburse town for any town contracted wind or environmental specialists hired as a third party consultant • **Some:** Some meetings between the financing company and the town where any questions or concerns can be asked and voiced. There is no reimbursement to the town if the town contracts and any wind or environmental specialists as a third party consultant • **None:** No meetings between the financing company and the town, however, towns can still hold meetings amongst themselves
Benefit Distribution Levels 50% Community, 50% Tax benefit 75% Community, 25% Tax benefit 25% Community, 75% Tax benefit	• **50% Community 50% Tax benefit:** $300,000 a year to the community for the duration of the windfarms contracted life and $1,000 reduction in property taxes for the duration of the windfarms contracted life. • **75% Community 25% Tax benefit:** $500,000 a year to the community for the duration of the windfarms contracted life and $500 reduction in property taxes for the duration of the windfarms contracted life. • **25% Community 75% Tax benefit:** $100,000 a year to the community for the duration of the windfarms contracted life and $2,000 reduction in property taxes for the duration of the windfarms contracted life.
Project Size Small — Large	• Large: Includes 10 or more wind turbines • Small: Includes fewer than 10 wind turbines
Distance from Site Within 5 miles Farther than 5 miles	• Within 5 miles: Distance from site to home is less than 5 miles • Farther than 5 miles: Distance from site to home is more than 5 miles
Environmental Damage No Precautions Taken — Precautions Taken	• Precautions taken: Precautionary measures include technology to reduce noise and bird deaths • No Precautions taken: No precautionary measures taken
Increase in Monthly Bill Costs:	• These are measure and specified in dollar amounts

While these results are undesirable, we determined that the attribute levels we included in our survey were relatively simple; therefore the un-informed respondents were still able to successfully understand and complete the survey.

Of the 199 respondents, 105 were male and the other 94 were female. Nearly a quarter of the respondents were between the ages of 18-25 and 55% of the respondents were under the age of 35. Thirty percent of the respondents only had a high school degree (or equivalent), while another thirty percent had higher than a bachelor's degree. Forty two percent of the respondents had an average annual income of $50,000 or more, with the remaining 58% earning less than $50,000 a year.

Image 2: Sample Choice Question

Attributes	Alternative 1	Alternative 2	Status Quo
Community Engagement Level	 Full Engagement	 Some Engagement	N/A
Benefit Distribution Levels	25% Community 75% Tax benefit	50% Community 50% Tax benefit	N/A
Project Size	Large	Small	N/A
Distance from Site	Within 5 miles	Within 5 miles	N/A
Environmental Damage	 No Precautions Taken	 Precautions Taken	N/A
Increase in monthly bill costs	10	50	N/A
Option:	❒ A	❒ B	❒ C

5. Results and Discussion:

As mentioned in the methods section of this paper, our results were determined from the choice experiment data by using both mixed and conditional logit regression models. The WTA calculations were used as a tool to compare an attributes effect and significance between different demographic groups. The magnitude and sign of each attribute's WTA coefficient helps explain how the average person feels about said attribute. A negative coefficient means that people associate the attribute with having a negative effect, and must be compensated before they will accept the project in question. If the coefficient is positive, then people would be willing to pay for the attribute to be included in the project in question. All "Willingness-To-Pay" coefficients can be found in tables 1 and 2.

In the conditional logit and mixed logit models, we found three common attributes to be statistically significant: engagement level, project size, and environmental precautions. In the conditional logit model, distance was also statistically significant. As expected, both engagement level and environmental precaution attributes had positive coefficients, while project size and distance had negative coefficients.

Table 1: depicts the WTP for all attributes of the mixed logit, conditional logit and male and female conditional logit models

	[1] mlogi	[2] clogit	[3] Male	[4] Female
Engagement Level	0.8854***	0.8268***	1.093***	0.5204
Benefit Distribution	0.0776	-0.0909	0.1794	-0.3996
Project Size	-1.207***	-1.251***	-1.283***	-1.292**
Distance	-0.4685	-0.7878**	-0.9818*	-0.54
Environmental Precautions	5.1754***	5.0779***	4.444***	5.788***
Observations	4179	4179	2205	1974

*ρ<0.05, **ρ<0.01, ***ρ<0.001

Distance is negative, however, it is only negative because of the way the variable was coded in our model. The first level of distance was farther than five miles, while the second level was within five miles. Thus people would be willing to less for a wind facility in the second tier of the distance attribute; installed within five miles. The largest coefficient in both models was environmental precautions. The trends in the basic conditional logit models, when dissected to compare differences in WTP between different demographic groups, present interesting results.

Table 2: depicts the WTP for all attributes of the conditional logit age and income models

	[1] Under 45	[2] Over 45	[3] <$50,000	[4] >$50,000
Engagement Level	0.8181***	0.8331*	0.7736**	0.6063
Benefit Distribution	0.0015	-0.3832	-0.0759	-0.3503
Project Size	-1.345***	-0.9972	-1.294**	-3.349***
Distance	-0.6555	-1.107*	-1.028**	0.2589
Environmental Precautions	5.0827***	5.049***	4.957***	8.342***
Observations	3066	1113	1616	884

*ρ<0.05, **ρ<0.01, ***ρ<0.001

The demographic groups that were analyzed were gender, age, and yearly income levels. Due to the small nature of our survey, we did not have the ability to measure and compare each specific level of a demographic group in this study. However, by dividing demographic groups into two, we were able to produce significant results that can be used to make generalized assumptions. The divided groups are as follows: males to females; people 45 years of age and older to people who were under 45 years of age; people who had a yearly income of $50,00 or more to those who made under $50,000 a year.

The first demographic comparison made was between genders. We found that four attributes held significance to males (engagement level, project size, distance and environmental precautions), while only two attributes held significance to females (project size and environmental precautions). Interestingly, our research shows that men care for, and are willing to pay more than females for better community involvement with wind companies. Community engagement for females is not statistically significant, meaning no generalizations can be made. The adverse effects of project size are similar between men and women, however women are willing to pay more for environmental precautions.

When separated by age (over and under 45), respondents have unique differences within each group. Both age groups are willing to pay high amounts for environmental precautions and better community engagement, yet project size was only an influential(statistically significant) factor for those under 45. Distance only had a significant effect on those over 45. Both WTA coefficients for project size and distance are negative. For some reason, people under the age of 45 seem to be much more worried about the projects size, and not so much the projects distance from their home. A potential explanation for the younger people being more concerned about project size rather than distance could be that they feel that larger projects invasive to nature as well as more likely to lower property values.

The most telling demographic comparison group was yearly income. Not only were there the most statistically significant results from all of the demographic comparison groups, but the results also tell the best story. All attributes except for benefit distribution are statistically significant for those who make less than $50,000 a year. The only two statistically significant attributes for those who make more than $50,000 a year are project size and environmental precautions.

The level of community engagement plays very different roles for each of our two income groups. Those who make under $50,000 a year are willing to pay a statistically significant amount of money for higher levels of community engagement, while those who make over $50,000 are not. Probable reasons for this discrepancy was that those who make over $50,000 value their time more than they value community meetings to go over the fine print of installment plans. On top of opportunity cost reasons, many people who make higher wages also have the ability and know-how to access information on their own without going to a community meeting.

Project size plays an important role for both income groups. Both coefficients are negative and statistically significant at a 5% level of confidence. The higher income group needs to be reimbursed three times more than the lower income group in order to accept a bigger project. Though the richer demographic requires a higher reimbursement for bigger projects, they were also willing to pay nearly double what the poorer demographic was for environmental precautions to be taken. These drastic differences in willingness to pay for a small, less invasive and environmentally friendly wind-farm can be explained by the two groups drastic differences in disposable income.

6. *Conclusion:*

The results of this research showed that different people have different preferences about wind energy. The results supplement previous theories that people are, in general, less willing to accept big, intrusive and disruptive wind installments, however the extent of such objections differ between certain demographic groups. The major differences in WTP for wind installations were found to be between the different income levels, although observable differences also appeared between the different age and gender demographics as well. The only attribute that was statistically significant across all of the tested models was environmental precautions.

The continuous high coefficients of environmental precautions, along with their significance throughout all models, suggests that people care most about being safe to the environment. People are willing to use what money they can to try to fund smaller, less invasive wind projects. The only attribute that failed to be significant in every logit model was the benefit distribution attribute. The lack of significance of the benefit distribution attribute can be attributed to the confounding nature of the attribute itself. Looking back, the two levels (community and personal) of benefit payments should have been separated into two different attributes: community payments and property tax reimbursements. The separation of benefit levels can explore who puts more of a priority on self benefit (property tax reimbursement) vs. community benefit (community payments).

Though many of our results are statistically significant, our sample size is relatively small and generalizations of the U.S. population cannot be made based off of this study. Stronger and more influential results could be found by re-administering the survey to tens of thousands of people. By drastically increasing the sample size, the specific levels of each attribute could be compared in greater detail, and better conclusions could be made. Should this test be administered to a much larger sample and have similar results, multiple recommendations could be made. Wind companies should focus their efforts on smaller, less invasive projects that are outside of wealthy communities but in wealthy counties. When contracting large wind farms, wind companies should look towards uninhabited land where there is minimal exposure to residents. With all wind projects, it would be wise to make sure that environmental precautions are taken and advertised, as to limit the amount of resistance from activist groups and local residents.

7. References

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