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Does willingness to pay for green energy differ by source?

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Abstract

We present the findings of a choice experiment designed to estimate consumer preferences and willingness-to-pay (WTP) for voluntary participation in green energy electricity programs. Our model estimates WTP for a generic "green energy" source and compares it to WTP for green energy from specific sources, including wind, solar, farm methane, and biomass. Our results show that there exists a positive WTP for green energy electricity. Further, individuals have a preference for solar over a generic green and wind. Biomass and farm methane are found to be the least preferred sources.

Keywords: Solar; Wind; Choice experiment

1. Introduction

The United States generates its electricity using a wide variety of fuel sources, primarily oil, natural gas, nuclear, and coal. Of increasing concern are the adverse environmental impacts of these energy sources. Due to pollution externalities these traditional energy sources tend to have market prices below their true social cost. Green energy sources, in contrast, have higher market prices than traditional sources but, likely, lower social costs. In this study, green energy includes solar, wind turbines, biomass, and farm methane. There appears to be real and growing interest among many consumers for environmentally friendly energy production. These preferences may make it privately optimal for some consumers to pay a voluntary premium.

Existing research reports positive willingness to pay (WTP) for green energy electricity premia. These studies elicit WTP for various aspects of green energy, where "green energy" is a generic product (Byrnes et al., 1999; Ethier et al., 2000; Gossling et al., 2005; Zarnikau, 2003) or focus on the environmental attributes associated with green energy (Bergmann et al., 2006). For instance, Zarnikau (2003) found 50% of respondents in Texas were WTP at least one dollar per month to support renewable and energy efficiency investments. In contrast, Bergmann et al. (2006) used preferences for environmental attributes to infer preferences for green energy sources. Roe et al. (2001) estimated WTP for inputs and outputs associated with green energy in a multiattribute setting, including non-price attributes such as changes in air emissions, contract terms, and fuel mix (combination of traditional and green sources). Although fuel mix was part of the design in Roe et al. (2001), preferences and WTP for individual green sources were not estimated.

Despite the evidence of WTP for green energy, existing green power programs have shown a median participation rate of only 1.0% (Bird and Brown, 2005). Limited participation may arise from a failure in marketing research; previous studies may have suffered from a stated-preference bias or other error and overestimated WTP for these premia. Alternately, an education or communication failure—high information costs—may exist between producers and consumers so that true demand for green energy does not materialize. This paper is motivated by a third possibility. Consumers may have evaluated the products available, in terms of price and source, and decided not to purchase because the product offered is a generic green energy good or is perceived to be

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an inferior type of green energy when consumers want to reveal demand for specific or superior green energy source.

This paper builds upon Roe et al. (2001) and estimates preferences for specific green sources and offers an additional empirical test about whether preference varies between specific and generic green energy sources. A contingent choice experimental design is used to examine a specific set of green energy attributes to better estimate consumer WTP. Data are collected from a sample of New Castle County, Delaware, residents to test the hypothesis that consumers distinguish between a single, generic "green energy" source—as modeled in existing literature—and four specific green fuel sources. In addition, the results estimate the marginal WTP for four green energy sources. The results show that there exists a positive WTP for green energy electricity. Further, the specific green energy source affects WTP. In fact, individuals do exhibit preferences for solar versus a generic green or wind source. Biomass and farm methane are found to be the least preferred sources.

Changes in consumer welfare for the addition of green energy are estimated for two potential green energy program administration scenarios. First, changes in welfare are estimated for a voluntary program then a mandatory green energy program. The welfare estimation under these two scenarios results in different values. These results show the substantive significance of recognizing the variation in preferences for green energy sources.

The broader applicability of the results may be limited by several factors. Green energy preferences best reflect the geographical location where the data were collected. The sample was of small to moderate size. In addition, the choice was particularly salient at the time of enumeration given a recent large electric rate increase in the county. Nevertheless, the results are clear, and the findings may help to guide research and policy regarding green power programs in other regions.

The second section of this paper describes our model of consumer choice. The third section explains the experimental design, survey methods, sample, instrument, and descriptive statistics. The fourth section presents the econometric results and WTP estimations. A final section offers conclusions.

2. Conceptual model

This paper reports results from a contingent choice experiment administered through an intercept survey designed to examine preferences for green energy programs. These programs would deliver electricity to respondents via alternative green energy sources (wind, solar, biomass, farm methane) at some added cost to their monthly electricity bill. Respondents were asked to make choices between two green energy alternatives with varying attribute levels or to choose the status quo at no increase to their existing energy bill, following the approach of other papers in different settings. (see Bergmann et al., 2006; Johnston et al., 2002; McGonagle and Swallow, 2005). We analyzed the data from this experiment using random utility theory and discrete choice econometrics (Hensher et al., 2005; Louviere et al., 2000). We present the theory in the next section.

2.1. Random utility model

The utility of individual i for alternative j is assumed to take the form

$$U_{ij} = V(\mathbf{x}_j,\ Y - C, \mathbf{w}_i) + e_{ij},$$

where j is one of three choice alternatives—the two green energy options (A and B) or stay with the status quo (N); $\mathbf{x}_j$ is a vector of attributes describing choice alternative j; $\mathbf{w}_i$ is a vector of the individual attributes; Y is individual household income; and C is the additional cost of the green power program ($C_N = 0$). Utility has observable, $V(\cdot)$, and unobservable, e_{ij}, components.

Following random utility theory respondent i chooses alternative m if

$$U_{im} > U_{ij}, \quad \forall j,\ j \neq m. \tag{1}$$

The stochastic version of this model used in estimation is the probability of observing individual i choose alternative m

$$Pr_m = Pr(V_{im} + e_{im} > V_{ij} + e_{ij}), \quad j \neq m. \tag{2}$$

Although the multinomial logit (MNL) model is commonly used to estimate choice probabilities of this form, that model requires the restrictive assumption that choices are independent of irrelevant alternatives (IIA). Instead, we estimate a nested logit (NL) model, which generalizes the MNL and allows the IIA assumption to be relaxed (Louviere et al., 2000). The NL model partitions choice so that within each partition alternatives have similar unobserved effects. Fig. 1 reflects the nested green power choice problem. This structure accounts for the similarity of unobserved effects of the indirect utility from the two

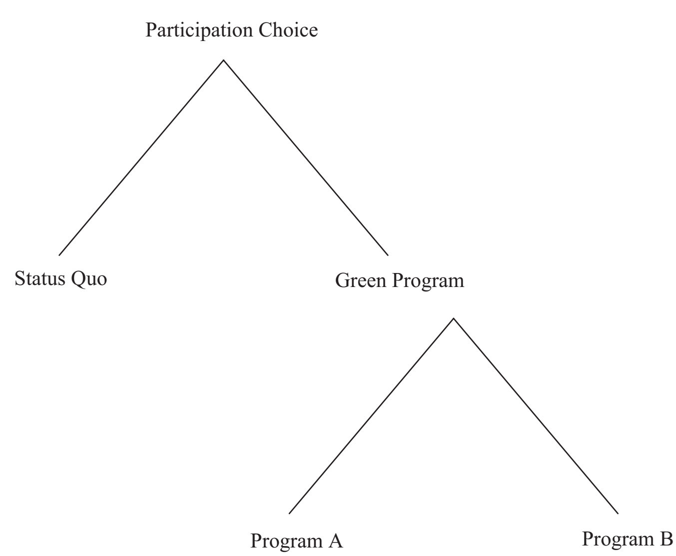

Fig. 1. Nested model of green power program choice experiment.

green power profiles by partitioning these alternatives into one nest. The random error terms are distributed extreme values and are correlated within nests, but not between. The probability of choosing green energy option A then is $P(A) = P(A|k)P(k)$ where $P(k)$ is the probability of choosing a green energy option and $P(A|k)$ is the probability of choosing option A given a green energy option is chosen. Following Greene (1997),

$$P(A|k) = \frac{e^{V_A/\lambda}}{e^{V_A/\lambda} + e^{V_B/\lambda}}, \tag{3}$$

$$P(k) = \frac{e^{\lambda I}}{e^{\lambda I} + e^{V_N}}, \tag{4}$$

where I is the inclusive value on the energy option nest,

$$I = \ln\{e^{V_A/\lambda} + e^{V_B/\lambda}\} \tag{5}$$

and λ is the inclusive value coefficient measuring the correlation of unobserved effects. The closer λ is to 0 the greater the correlation. To be consistent with utility maximization λ should lie on the unit interval. The probability of choosing option B takes the same form as the choice probability for A. An individual's probability of choosing the neither option is

$$1 - P(k) = \frac{e^{V_N}}{e^{\lambda I} + e^{V_N}}. \tag{6}$$

2.2. Willingness to pay and welfare measures

An individual's expected maximum utility of being offered a green energy option is

$$EU_G = \ln\{e^{\lambda I} + e^{V_N}\}. \tag{7}$$

This follows directly from the distributional assumptions of the error terms (see Hanemann, 1999 or Morey, 1999). Notice that this expected utility recognizes that an individual may choose to stay with the status quo even though a green energy option is offered—V_N is included as a term in the expected utility. At the same time an individual's expected maximum utility of not being offered a green energy option is

$$EU_N = \ln\{e^{V_N}\} = V_N. \tag{8}$$

The increase in expected maximum utility due to being offered a green energy alternative then is the well known log–sum difference:

$$\Delta w = EU_G - EU_N = \ln\{e^{\lambda I} + e^{V_N}\} - \ln\{e^{V_N}\}. \tag{9}$$

This is the difference in maximum expected utility with and without a green program offering. The compensating variation for this expected change in utility is Δw divided by the marginal utility of income. In our linear random utility model the marginal utility of income is the coefficient of the cost attribute—the additional cost charged for the green energy program.

2.3. Choice experiment and survey procedures

The contingent choice questions ask respondents to make one of four choices (see Fig. 2 for sample choice set). Respondents who are in the market for green energy make trade-offs between two programs with three varying attributes (source, quantity, and cost), while respondents who are not in the market choose neither program, i.e., the status quo. *Wind*, *solar*, *biomass*, *farm methane*, and a generic *green* energy source are the levels for the source attribute. The quantity attribute is a percentage of the respondent's monthly electrical usage, which would be generated from green energy. Levels of 10% and 25% of household monthly electric use were used, while selecting a status quo choice implies that 0% of the respondent's energy would come from a green source. Cost took one of five levels ($5, $10, $15, $20, and $30 per month), with $0 as the implied cost of the status quo. The payment vehicle was an additional cost on the household's monthly electric bill.

A main-effects, orthogonal design was developed for the three attributes and two choice options per profile. Because a full factorial design of $(5 \times 2 \times 5)^2$ choice sets was unwieldy, a fractional factorial design was used to limit the number of choices. Specifically, an orthogonal main effects initial set of profiles was created with 25 profiles; then, using the modular arithmetic procedure proposed by Bunch et al. (1996) these profiles were *shifted* to create a total of 50 choice sets (Louviere et al., 2000). To implement the experiment, each respondent was presented five randomly chosen choice sets, where the order of presentation (program A vs. program B) in each set was also randomized.

This study follows several other conjoint or contingent choice studies, which use an intercept method to implement a complex choice for a hypothetical good (e.g., Duke and Ilvento, 2004; Kline and Wichelns, 1998; McGonagle and Swallow, 2005). Interviews were conducted at the two New Castle County, Delaware, Department of Motor Vehicle (DMV) locations. Screening questions ensured that only individuals that were renewing drivers' licenses were included in the sample; this was important because it

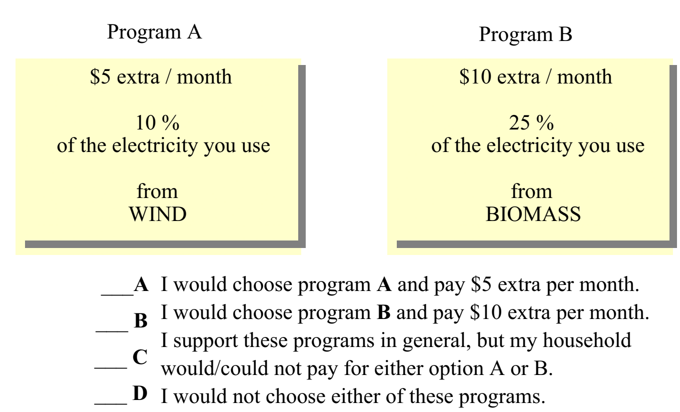

Fig. 2. Example of contingent choice set.

allowed the sample to be as near random as possible. All Delaware drivers are required to renew their licenses in person at regular intervals at DMV locations. In addition, screening questions isolated the respondents from the population of adults who receive and are responsible for paying an electric bill because this is the payment vehicle of this experiment. Individuals were randomly approached by enumerators. However, some respondents were attracted because signs were displayed with the University of Delaware logo and another with the title "Green Electric Power Survey." Also, some people passing by on DMV business were simply interested in talking with the enumerators. Potential bias due to these self-selections was estimated to be small. First, enumerators estimate that less than 5% of people approached were self-selecting in some way. Second, screening question eliminated many of these potential respondents. Finally, there was a benefit to the signage; the attention generated by the signs and the authenticity signaled by the logo likely helped attract respondents who would have otherwise declined to participate. On balance, it is not believed that this introduced substantive bias into the responses. In April and May 2006, 128 completed surveys were obtained through interviews.

We had a response rate of 34%, when non-response is defined as an individual who declined to participate after being approached. However, non-respondents were not asked screening question and so non-response among the target population is unknown. Available average demographic data suggest the sample represents the county population reasonably well (see Table 1 for a summary of socio-demographic statistics for the sample and for the County from the Census Bureau).

After screening, respondents were asked about their electric utility and the current cost of their monthly electric service. In addition, several six-point likert-scale questions were asked to get respondents thinking about various aspects of green energy and to measure concern about the cost of electric service, environmental externalities, and interest for paying for a reduction in externalities. The cost of electricity was particularly salient at the time because the local news media were covering the expiration of the rate freeze enacted during electricity restructuring, which was scheduled to raise some county resident's rates by 56% to 63% (Church, 2006).

The enumerator then introduced the green energy sources using a 8.5×11 in visual aid, showing a picture representation of the four potential sources along with verbal phrases of environmental benefits and costs associated with each source.[1] The visual aid was used as a teaching aid to introduce the green energy sources of interest in this study. As respondent familiarity with the sources and concepts may vary greatly, these were used to supplement the verbal descriptions. The four pictures of the sources were chosen and pretested to be as unbiased as possible. In addition, the visuals were not presented on the choice cards. It is believed that this approach allowed the enumerator to get the most out of the face to face survey approach by introducing the survey setting in a manner appropriate to most respondents, while minimizing the bias a visual might introduce with the choice questions.

Table 1
Summary statistics of sample respondents and county

	Sample	County[a]
Female	46%	51%
Age (mean)	43	47
Income (mean)	\$50,000—\$60,000	\$52,419
Persons in household (mean)	2.96	2.56
Monthly electric bill (mean)	\$122	\$95[b]

[a] US Department of Commerce, Bureau of the Census, 2006.
[b] Based on Delmarva Power "typical customer" usage of 1000 kWh/month.

Respondents were asked to use a six-point scale to rate their familiarity with the presented green energy sources.[2] Respondents were most familiar with solar (ave. = 5.2), wind (ave. = 4.9), and green energy in general (ave. = 4.4). Respondents were less familiar with biomass (ave. = 3.5) and farm methane (ave. = 3.5), yet still on average were familiar with the sources. An approximation of the current traditional fuel mix used to generate electricity in the county was displayed, and then the hypothetical programs were described.

The indirect utility for the status quo option is

$$\begin{aligned} V_{iN} = \alpha_N &+ \beta_1 Over50_i + \beta_2 Under30_i + \beta_3 Female_i \\ &+ \beta_4 Envt_i + \beta_5 LowInc_i + \beta_6 EBill_i \\ &+ \beta_7 EBill_i \cdot Inc_i + \varepsilon_{iN}. \end{aligned} \tag{10}$$

The variables used in the model are defined in Table 2. Several socio-demographic variables (*Over50*, *Under30*, *Female*, *LowInc*) are included in the status quo alternative to account for heterogeneity in program participation. *LowInc* indicates respondents checking income boxes below \$40,000. *Envt* is a dummy variable indicating a respondent answering with the likert rating "agree" or "strongly agree" to a statement regarding their concern about the environmental impacts of electricity generation. *EBill* is a self-estimate of the respondent's monthly electricity bill. *Inc* is a nine category variable of a household's annual income.

[1] For wind: no air emissions, no fuel inputs, highly visible, possible bird impacts, large land areas impacted; for solar: no air emissions, installed anywhere, electricity produced only during the day, uses large surface areas; for biomass: renewable fuel source, reliable technology, air emissions, may require fossil fuels to produce; for farm methane: naturally occurring gas, improves air quality, difficult to implement, limited opportunities in some areas.

[2] Respondents identified their level of familiarity in terms of the statement, "I am familiar with ___ energy:" 1 = "strongly disagree"; 2 = "disagree"; 3 = "somewhat disagree"; 4 = "somewhat agree"; 5 = "agree"; and 6 = "strongly agree".

Table 2
Model variables descriptions and summary statistics

Variable Name	Description	Values mean (min, max)
Cost	Monthly increase in electric bill	10.67 (0, 30)
Quant	Continuous variable in kWh of electricity supplied with alternative energy source	151.2 (0,1097)
Solar	Indicator for source	0.13
Wind	Indicator for source	0.13
Biomass	Indicator for source	0.13
FarmMethane	Indicator for source	0.12
Green	Indicator for source	0.14
Socio-demographic variables		
Over50	Indicator: respondent is over 50 years of age	0.26
Under30	Indicator: respondent is under 30 years of age	0.24
LowInc	Indicator: household income level below $40,000/year	0.29
Ebill	Continuous measure: self-reported monthly electric bill	$122 ($10, $400)
EBill × *Inc*	Interaction of electric bill and income level (where income is an ordinal representation of income categories)	542 (30, 2800)
Envt	Indicator: respondent agree or strongly agree with statement regarding their concern for electric generation's environmental impacts	0.72
Female	Indicator: respondent is female	0.47

The indirect utility for the green energy options is

$$V_{ij} = \beta_c Cost_j + \beta_q Quant_{ij} + \beta_w Wind_j + \beta_s Solar_j + \beta_b Biomass_j + \beta_f FarmMethane_j + \varepsilon_{ij}, \tag{11}$$

where $j = A$ or B. *Cost* is defined above and its coefficient serves as the marginal utility of income in our welfare calculation. The quantity variable used in the estimation, *Quant*, was derived from several questions on the survey. Respondents made program choice in response to a quantity attribute with levels representing the percentage of their monthly electric use, which would be generated from green energy: $GreenLevel \in \{0\%, 10\%, 25\%\}$. Respondents were also asked their electric supplier and provided an estimate of their monthly electric bill, *EBill*. Using published data on the cost, c_s, per kWh for each supplier, s, an estimate was calculated of a respondent's monthly electric usage: $HHkWh = EBill/c_s$.[3] The quantity variable in a given observation is calculated and treated as continuous: $Quant = GreenLevel \times HHkWh$.

Green energy sources are included as dummy variables, measuring relative changes from the reference level utility of generic *Green*. All else equal, one expects that each source of green power will provide more utility than the status quo. One also expects that some sources (*Wind* and *Solar*) should provide more utility than other sources (*Biomass* and *FarmMethane*) because they are probably perceived to be more commonly used, because respondents are more familiar with them, and because they may generate lower levels of negative externalities. In the empirical model, specific sources test the hypotheses that they offer different utility than a generic *Green* source.

[3]The cost is averaged over block pricing. *EBill* was modified by subtracting supplier fixed charges.

3. Results

LIMDEP software was used to estimate the NL model. Descriptive statistics are in Table 2 and NL results are shown in Table 3. Overall, the estimated NL model performs well, and the null is rejected using a chi-squared test ($p < 0.0001$) and the model has a pseudo $R^2 = 0.19$. The estimated inclusive value coefficient can be used to determine the appropriateness of the NL model. The test that the inclusive value is one can be rejected at the 1% level, which suggests that the single nest or MNL model specification is inappropriate. All key estimated coefficients match prior economic expectations and pass standard significance tests.

In the choice experiment, respondents choose alternative A in 32.5%, alternative B in 28.5%, and the status quo in 39.0% of the observations. Fig. 3 displays the percentage of respondents participating at or above a specified cost, out of the total profiles viewed at or above the specified cost. For example, of the observations including a cost option of $10 or more, 41% of the observations chose to participate (selected program A or B) at or above a cost of $10. However, at a cost of $20 or more, only 29% of respondent observations participated, and at the top level of $30, only 13% of the observations which viewed this option choose to participate at that price level.

The constant for the status quo is not statistically different from zero. The socio-demographic variables in the status quo utility are used to express heterogeneity in program preference. Positive coefficients suggest preference within the indicated group for the status quo, while negative coefficients suggest preference for a green power alternative. The likelihood of choosing neither program increased among lower income households. However, respondents over 50 and under 30 were more likely to

Table 3
Nested logit results

Variables	Parameter estimates	Std error
Status quo alternative:		
Constant	0.460*	0.274
Over50	−0.854***	0.220
Under30	−0.754***	0.233
Female	−0.270	0.194
Envt	−0.947***	0.206
LowInc	0.620**	0.239
Ebill	0.001	0.001
EBill × Inc	0.000	0.000
Green energy program:		
Cost	−0.075***	0.010
Wind	−0.171	0.231
Biomass	−0.794***	0.276
Solar	0.465*	0.263
FarmMethane	−0.549**	0.248
QuanKwh	0.001**	0.001
Inclusive Value	0.135	0.176

$N = 625$;*, **, *** indicate levels of significance of 0.1, 0.05 and 0.01, respectively.

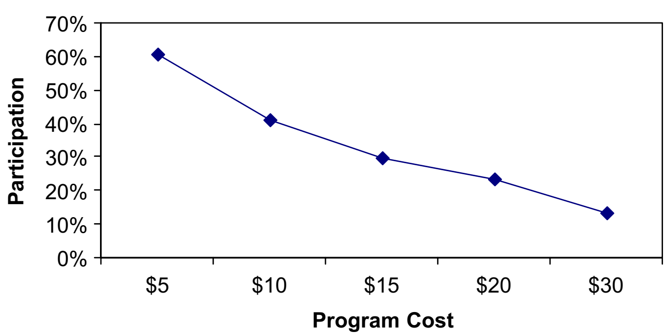

Fig. 3. Respondent participation at or above surveyed cost levels.

prefer a green alternative. As expected, a similar preference for the status quo was found among respondents who expressed concern for environmental impacts of electricity generation. There was no statistically significant impact of the current household electric bill on preference for the status quo, and this result was robust, i.e., when one controls for income.

As anticipated, the *Cost* coefficient is negative and statistically significant. In addition, the *Quant* coefficient is positive and statistically significant. These results demonstrate consistency with economic theory; ceteris paribus, higher costs decrease and higher green energy quantities increase the likelihood of choosing a green program. Further, the mean WTP, -β_q/β_c, for a marginal unit of generic green energy is 1.3 cents per kWh. This is a realistic price, as current green energy markets operate within this range (Bird and Swezey, 2005).

The null hypothesis that the generic *Green* source reference category provides the same utility as *Solar, Biomass,* and *FarmMethane* is rejected. This suggests that consumers do not perceive green energy sources as equivalent. The *Solar* coefficient is the only source coefficient that is positive. This means that, ceteris paribus, consumers seem to gain more utility from solar energy than any other green source, including a generic green source. Coefficients on *Biomass* and *FarmMethane* were estimated to be negative, indicating a decrease in utility, relative to *Green*. The *Biomass* and *FarmMethane* coefficients are not statistically different from each other.

The null hypothesis that *Wind* is different than the generic *Green* source cannot be rejected. Hence, wind and generic green power have undistinguishable impacts on utility. Overall, solar power is preferred to wind power, while biomass and farm methane tied for the third most preferred source. These results show that it is important to specify the source of green power when estimating preference and utility.

These results also can be used to estimate WTP for green energy by source. In agreement with previous papers (Ethier et al., 2000; Gossling et al., 2005; Roe et al., 2001; Zarnikau, 2003), the results will show a positive mean marginal WTP for change from the status quo to the provision of generic and all specific types of green power.

WTP is interpreted as the mean value to households for the option to purchase the specified amount and type of energy generation. Several program options are presented, reflecting the choice sets used in the experiment; Table 4 reports the minimum, mean and maximum WTP for each source in a 10% and 25% voluntary program. For example, the mean value to households for the option to participate in a program with a generic green source is \$14.77 per month. This exceeds the average WTP of \$8.92 per month for a program of 10% from a biomass source. A program of 10% solar generation generates mean WTP of \$19.03 per month. Given that \$122 per month was the average electric bill reported by the respondents, these values range from around 8% to 16% of the average monthly bill. In aggregate, New Castle County's households are WTP from \$1,685,300 for 10% biomass generation to \$3,595,433 for 10% solar generation.[4]

Second, it is possible to view green energy programs in terms of non-voluntary participation. This is the policy that reflects reality in some areas, where a utility unilaterally adopts a green program and then imposes a variable cost on consumers. A non-voluntary program still uses the WTP measure; however, EU_G does not include the status quo option. An individual's expected maximum utility from the green energy program in this case is

$$EU_G = \ln\{e^{\lambda I}\}. \tag{12}$$

EU_N remains unchanged. The change in expected maximum utility due to the mandatory green energy program,

[4]US Census reports 188,935 households in New Castle County, Delaware in 2000.

Table 4
Household willingness to pay per month for voluntary green energy programs

	10%			25%		
Source	Min ($)	Mean ($)	Max ($)	Min ($)	Mean ($)	Max ($)
Green	4.14	14.77	25.68	5.28	17.00	31.54
Solar	6.10	19.03	31.16	7.64	21.54	37.29
Wind	3.56	13.36	23.75	4.57	15.47	29.48
Farm methane	2.54	10.54	19.69	3.30	12.38	25.08
Biomass	2.03	8.92	17.23	2.64	10.59	22.35

Table 5
Household willingness to pay per month for mandatory green energy programs

	10%			25%		
Source	Min ($)	Mean ($)	Max ($)	Min ($)	Mean ($)	Max ($)
Green	−13.65	8.44	23.54	−9.99	11.58	30.19
Solar	−7.41	14.68	29.78	−3.75	17.82	36.43
Wind	−15.95	6.14	21.25	−12.28	9.28	27.90
Farm methane	−21.01	1.08	16.19	−17.34	4.22	22.84
Biomass	−24.31	−2.22	12.89	−20.64	0.92	19.54

using the log-sum difference is now just

$$\Delta w = EU_G - EU_N = \ln\{e^{\lambda I}\} - \ln\{e^{V_N}\}. \tag{13}$$

It is no longer a measure of expected maximum utility, but solely the difference between the status quo and the "forced" green power program, which is not necessarily utility maximizing for all respondents.

Table 5 provides the non-voluntary mirror to Table 4 voluntary program. Some consumers would be made worse off by being forced to participate because the status quo alternative is no longer available to those who do not prefer the specified green energy program.

4. Conclusions

This paper presents the results of a choice experiment designed to elicit WTP for green electricity and to determine respondents' relative preferences for specified green sources. The results suggest that respondents do exhibit positive WTP for green energy in general and for each of the specified green sources. However, some specific green sources are more preferred than others.

The results also show that there is a difference between voluntary or opt-in programs and non-voluntary programs. With a less preferred source, it seems likely that many consumers would have negative WTP for non-voluntary programs. This does not mean, however, that net social welfare is maximized with voluntary programs—only that each household's expected change in welfare when programs are voluntary is non-negative. Indeed, an inexpensive non-voluntary solar program may have higher social welfare than a voluntary biomass or methane program.

The results draw important implications for research, marketing, and policy decisions. These decisions could be improved by acknowledging to consumers and understanding that various sources of energy offer varying benefits to consumers. Green power is not generated generically, but often it is promoted generically. Specifying only a generic green energy, may in fact be over estimating benefits of some sources of energy while under estimating benefits of others. For example, *Biomass* and *FarmMethane* provide less utility than the other three green sources, so a program advertising green energy will overestimate the benefits of a biomass program. Policy makers will need to be careful in the design and implementation of socially beneficial green power programs. For honest accounting of consumer welfare there needs to be adequate information to consumers about what they are purchasing. Caution needs to be paid so as to not over estimate the benefits of program implementation.

Further understanding of consumers' preferences and WTP for green energy sources becomes more important as additional electricity markets open for competition and public policy continues to explore the further introduction of these sources into the electrical generation mix. Specifying energy source is important for all future research in this subject.

This work is limited by the geographical location in which it was completed. The results best fit the study area of New Castle County, Delaware. It is reasonable to assume that the welfare estimates of green power program options will vary by location given a region's unique population characteristics, geographical constraints, and ambient pollution levels. Nevertheless, one expects that the findings of this research will hold in other locations: the specific source of green energy does matter to consumers.

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