INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH
Galina Ivanova, Vol.2, No.4, 2012

Are Consumers' Willing to Pay Extra for the Electricity from Renewable Energy Sources? An example of Queensland, Australia

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Received: 19.09.2012 Accepted: 23.10.2012

Abstract- The results of a survey of Queensland households regarding their willingness to pay (WTP) for renewable energy suggest that while on average the respondents were willing to pay about $28/quarter on the top of their quarterly electricity bill to support the increase in electricity generation from renewable energy sources, there is significant heterogeneity in WTP. The heterogeneity in WTP is accounted for by estimating a latent class model. Three classes of respondents are identified using attitudinal and knowledge questions. Results indicated that there are significant differences in WTP among classes. The mean WTP in class 1 was $29 (or 12.7% of their average electricity bill), in class 2 was $13 (or 4.5% of their average electricity bill), and in class 3 was $36 (or 14.4% of their average electricity bill). Tobit analysis for each latent class indicated the importance of socio-demographic variables in respondents stated WTP for electricity generated from renewable energy.

Keywords- Renewable energy, willingness to pay, voluntary, Queensland.

1. Introduction

The possible threat of global warming has led to policy reforms focusing on emission reductions to be proposed and implemented in some countries. The electricity sector contributes a significant proportion (35%) of Australia's total greenhouse gas (GHG) emission due to Australia's reliance on generating electricity mainly from coal [1]. In Australia the share of electricity generated from renewable energy technologies totals to about 7% and is mainly from large hydro [2].

The cost of electricity production from the renewable energy technologies is usually much higher than the cost of electricity production from fossil fuels. The average cost of production of electricity from coal fired electricity generation technology (A$50/MWh) is much cheaper than the cost of production of electricity from renewable energy, for example from the wind farm (A$110/MWh) [3]. In 2011-12, in Queensland an average price of the electricity on the electricity market was $29/MWh [4] that is much lower than the cost of electricity production from most renewable energy technologies. Therefore producers of electricity from most renewable energy sources need to receive a premium for their electricity in order to cover their costs of production.

A range of policy measures have been implemented in Australia to account for a negative environmental impact from electricity generation. The Mandatory Renewable Energy Target (MRET) policy is designed to increase the competitiveness of renewable energy technologies and increase its adoption and thus diversify the electricity technologies mix and reduce GHG emissions from electricity generation. The mandatory target was for a 2% increase in renewable electricity market share by 2010, growing from 10.5% to 12.5% of the total electricity production [5]. The expanded MRET started from 2010 and reflects the Australian Government commitment to increase the Australian Electricity supply from renewable energy sources to 20 percent by 2020. That requires an additional 45,000 GWh a year of renewable energy to be produced by 2020. This target was separated in to two parts the Small-scale

Renewable Energy Scheme (SRES) and the Large-scale Renewable Energy Target (LRET) [6]. This policy is an extension of the initial MRET policy that was only a supply side measure. However, consumers of electricity might be willing to support such a policy, or if they are given a choice, to voluntarily buy green energy for their households and thus support electricity production from renewable energy sources. The extended policy has recognised that not only supply of electricity need to be targeted but also the demand from households, small business and community classes.

In Australia, there has been an increase in the awareness of Green Power options. In 2008, more than half of all households reported that they are aware of Green Power options and about 10% of households buy Green Power [7]. In 2008, Queenslanders were buying more electricity generated from renewable sources than people in other states. The quarterly report of the National Green Power Accreditation Program showed 37% of the 221GWh of "green power" sold to residential customers during the period between 1 January and 31 March 2011 were in Queensland [8].

Previous surveys (e.g. 9, 10, 11, 12 and 13) have indicated that consumers are willing to pay for more for electricity generated from renewable energy. Batley et al. [9] analysed WTP for the electricity generated from renewable energy in the UK. Their results suggested that about 34% of respondents were willing to pay 16.6% extra for electricity generation from renewable energy sources. The respondents with higher income were more likely to state that they were willing to pay more for electricity generated from renewable sources.

Kim et al [10] using contingent valuation method analyzed the willingness of Korean households to pay more for electricity generated by wind, photovoltaic and hydropower. They estimated that the average WTP for renewable energy was approximately 3.7% of the average monthly electricity bill in 2010. The results for different renewable energy sources such as wind, solar and hydropower were mixed. Age, awareness of renewable energy, attitudes towards environmental problems, expectations concerning dominancy of renewable sources in future and income were among the significant predictors of WTP for hydropower [10].

The public acceptance and WTP for renewable energy sources in Crete using contingent valuation survey was evaluated by [11]. They found that on average, the respondents are willing to pay around 10% on the top of their quarterly electricity bill for renewable energy. Respondents with higher income, larger residence size, those having a higher level of knowledge regarding climate change and those who have invested in energy saving measures and who have more electricity shortages are willing to pay more for electricity generated from renewable energy.

Roe et al [12] found that many population segments are willing to pay particularly for the emission reduction due to the increased reliance upon renewable energy source not just for the emission reduction due to change in fossil-fuel mix.

Wiser [13] stated that younger respondents, those with higher income, women, with high education and without children are willing to pay more for renewable energy. The attitudinal questions revealed that those who expected that others such as their family and friends would also pay for renewable energy are more willing to pay for renewable energy than those respondents who did not believe that others will pay for renewable energy [13].

While above mentioned studies indicated that there is a demand for the green energy, there is potentially a significant heterogeneity in preferences for emission reduction using renewable energy. For example, some respondents might prefer to pay more for electricity generated from renewable energy and their WTP is positive and high. Others prefer to reduce emissions by other means but still prefer to pay for electricity produced from green energy due to other benefits [14] and therefore have a different WTP. Some respondents might not believe that by paying more for electricity from renewable energy they will reduce the emissions and therefore their WTP is zero. This heterogeneity can be accounted for using latent class modeling. This paper used latent class modeling to identify classes of respondents from Queensland whose WTP defer among classes but homogeneous within the class. The classes of respondents were identified using respondents' attitudes and perceptions regarding renewable energy and climate change. Then WTP for each class was estimated using the data from the contingent valuation part of the survey.

The analysis of latent class was performed using R software, poLCA package [15]. The poLCA estimates the latent class models for categorical variables using expectation-maximization and Newton-Raphson algorithms to estimate the parameters of the model. The rest of the paper is structured as follows. Section 2 briefly explains the latent class approach and contingent valuation. Section 3 describes the application. Section 4 presents the results. Section 5 concludes.

2. The Latent Class Approach and Contingent Valuation

The attitudinal, perception and knowledge questions are usually asked during the contingent valuation survey but seldom used in econometric models due to possible correlation among those questions. In studies when these questions are used in valuation, they mainly used in three ways: as covariates in the model, form a latent variable or they can be used to identify classes of respondents. A conceptual framework on how to incorporate attitudes in economic valuation was provided by [16]. He suggested that "the critical constructs in modeling the cognitive decision process are perceptions or beliefs regarding the products, generalized attitudes or values, preferences among products, decision protocols that map preferences into choices, and behavioral intentions for choice".

The latent class analysis (latent structure analysis) introduced by [17] uses the cross-sectional data to measure the latent class variable. It identifies the classes, their probabilities, relates probabilities to covariates and classifies individuals into classes. It was suggested by [17] to consider a latent membership likelihood function that classifies individuals into one of the S classes. The classification is influenced by latent general attitudes and perception, and socioeconomic characteristics of individuals.

The latent class model assumes that there are a finite number of preference classes with homogenous preferences within each class. These preferences are assumed to vary significantly across classes. Answers to attitudinal questions are used to estimate the unconditional probability that a respondent belongs to class s. Then the conditional probability that an individual belongs to a certain class can be estimated.

While the latent class models have been widely used in social sciences (20, 21, 22), there are only several similar applications in environmental economics. For example, [23], [24], and [25] applied the latent class models to environmental economics issues. There is some disagreement in the environmental economics literature on how to use the attitudinal questions in latent class modeling. Boxall and Adamowicz [23] assumed that the probability that an individual belongs to a particular preference class is a function to their answers to the attitudinal questions. Provencher et al [26] and Morey et al [19] on the other hand, assumed that the probability of a certain response to an attitudinal question is a function of one's class. However, Provencher and Moore [27] came to the conclusion that these two approaches are structurally similar and that the choice depends on the analyst's judgement.

While there are several methods to account for heterogeneity of preferences, the advantages of using the latent class models are numerous. For example, the latent class models do not rely on traditional modeling assumptions of linear relationship, normal distribution and homogeneity that are often violated in practice [28].

The latent class models can be used to identify the classes of respondents that are not willing to pay for environmental improvement or electricity from renewable energy. It can estimate the size of the class and its' socio-economic characteristics. Furthermore, the models might assist in understanding perceptions, preferences, attitudes and knowledge of each class. The results of the latent class modeling can be easily understood by the general public and by policy makers.

This paper follows [29] approach to the latent class model. The contribution of this paper is to provide a more sophisticated analysis of willingness to pay for electricity generated from renewable energy by first identifying latent classes and then use these classes to estimate WTP by class.

3. Application: Willingness to Pay for Renewable Energy, Queensland, Australia

3.1. Willingness to Pay Survey

In 2001, according to Australian Bureau of Statistics, the number of households in Queensland totalled 1,287,135. The conservative approach to estimate sample size was taken. Mail survey was chosen given the budgetary restrictions. While mail survey impose some problems and limitations, such as the respondents may not follow the order in which the material is presented or complex aspects cannot be clarified as it is possible with in person or telephone survey, the careful questionnaire design can minimise these problems. The lower response rate of mail survey was taken into account when estimating the sample size. The characteristics of the sample were close to the Queensland population: there are 54% of males in sample compared with 49% of males over 18 years old in Queensland, median age of sample was 51years old, while in Queensland the median age over 18years old is 46, 28% of sample were with higher degree of education compared with 26% in Queensland, the median income of the sample was $39k compared with $46.8k in Queensland.

A simple random sample of 820 households from the entire Queensland population using Telstra's White Pages phonebook was drawn in August 2004 by the University of Queensland Social Research Centre (UQSRC). The first mail out was done in August with reminders send in September. The total response rate was 26%.

The attitudinal data and the contingent valuation data were collected in the same survey following [29].

3.2. Latent Class Variables

The latent class model assumes that there are several unobserved (latent) preference classes in the population. The attitudinal, knowledge and perception questions (ie, the manifest variables) in Table 1 were used to identify classes. The manifest variables were in the Likert scale format. The respondents were asked to choose the appropriate answer. For example, for the statement "*I am willing to pay more for electricity generated from renewable energy sources*" respondents could choose one of the following answers: Strongly Agree, Agree, Unsure, Disagree and Strongly Disagree.

It is assumed that there is heterogeneity in WTP for renewable energy that can be accounted for by identifying a number of classes based on attitudinal data and knowledge. For example, the class that shows the highest amount of agree and strongly agree responses to question v9 is expected to have the lowest probability to state high WTP.

Since attitudinal questions are common in WTP surveys, this paper demonstrates one of the possible approaches on how to incorporate this data in valuation analysis. Once the classes were identified and respondents probabilistically assigned to the relevant class, the analysis was extended to estimate WTP for electricity generated from renewable energy sources for each identified latent class.

Table 1. Variables used in latent class modelling

Variable	Description
v3	I am willing to pay more for electricity generated from renewable energy sources
v9	Somebody else can pay for renewable not me
v32	How willing would you be to pay much higher prices for goods in order to protect the quality of your local environment
v41	A rise in the world's temperature caused by the 'greenhouse effect' is dangerous to the environment
v43	I am not concerned about climate change because it won't have an effect for at least 50 years
v46	Climate change is a serious environmental problem
v55	Burning coal, oil, or gas does not cause global climate change

3.3. Contingent Valuation Question

This research employed the contingent valuation (CV) method to elicit monetary willingness to pay for renewable energy. CV methods usually employ either dichotomous choice or open ended approaches. The dichotomous choice approach has many advantages over the open ended approach, e.g. it is simple for respondents, it reduces the incentive for respondents to provide strategic responses [30] and the method of employing "close-ended" formats rather than "open-ended" was recommended by the NOAA panel [31]. However, the dichotomous valuation question was not suitable for this study because the range of possible bids are very large to be used in dichotomous type of valuation question, dichotomous choice models can result in a biased price estimate due to the anchoring effects (32, 33). Therefore the decision was made in favor of using open-ended question.

One of the contingent valuation questions that was offered to respondents in the survey was asking about voluntary contribution to increase the generation of the electricity from renewable energy sources (i.e. representing voluntary support for the renewable energy). The analysis of the responses to the valuation question that was asking respondents about voluntary contribution to increase the generation of the electricity from renewable energy sources (i.e. representing voluntary support for the renewable energy) is discussed in this paper.

4. Survey Results

4.1. Choosing the Number of Classes

The R statistical computing environment was used to define the number of latent classes. The poLCA software package was used to estimate latent class models for polytomous outcome variables. The respondents were asked to provide answers (on the Likert scale) to several attitudinal and knowledge questions (Table 1). The response variables were the manifest variables of a latent class model. The basic model with no covariates was estimated first.

In estimating the latent models, 1, 2, 3, 4 and 5 classes' solutions were attempted. Table 2 summarizes the statistics for these models. The best fitting model minimizes the information criteria. Information criteria compare the improvement in the degree of fit with the number of extra parameters. The commonly used tests are Akaike information criteria (AIC) and Bayesian information criteria (BIC) (34, 35). The AIC and BIC are calculated as follows [15]:

$AIC=-2LL+2*p$, and

$BIC==-2LL+ p*\ln(N)$,

where LL is log likelihood at convergence,

p - number of parameters,

N - sample size.

The BIC is considered to be more conservative due to its more stringent penalty for the number of additional parameters [35].

The statistics in Table 2 supports the existence of heterogeneity in the data. It suggests the existence of a number of latent classes. The log likelihood values at convergence reveal improvement in the model fit as the classes are added to the estimation, particularly with 2 and 3 classes models. The reduction in log likelihood is diminishing dramatically after adding the fourth and fifth classes. The minimum BIC and AIC statistics associated with 3 latent classes suggesting that model with 3 classes is optimal.

Table 2. Parameters on converged latent class models without covariates

N of classes	p	LL	LL-LL1	BIC	AIC
1	28	-1,904.6		3,951.7	3,865.1
2	57	-1,731.1	**173.5**	3,752.6	3,576.2
3	86	-1,630.8	100.3	**3,699.6**	**3,433.6**
4	115	-1,601.9	28.8	3,789.7	3,433.9
5	144	-1,578.2	23.8	3,889.9	3,444.4

The predicted response probabilities (Figure 1) indicate the differences in responses among classes.

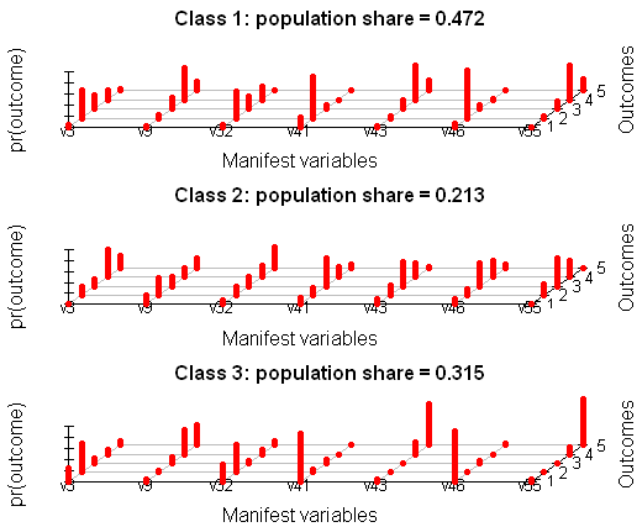

Fig 1. Probability of outcome by classes

4.2. Characterizing Classes and Compare the Models

The estimated class-conditional outcome probabilities were used to characterize the classes. The probability higher than 0.75 (shown in bold in Table 3) was used to describe each of the three identified classes.

Class 1: "*Concerned*" class. About 47% of respondents were probabilistically assigned to this class. Around 94% of this class respondents stated that they agree or strongly agree with the statement "*A rise in the world's temperature caused by the 'greenhouse effect' is dangerous to the environment*". About 81% of respondents from "*Concerned*" class disagreed and strongly disagreed with the statement that "*I am not concerned about climate change because it won't have an effect for at least 50 years*" implying that they are concerned about climate change. About 93% of this class respondents agreed or strongly agreed with the statement "*Climate change is a serious environmental problem*". Finally, 82% of respondents from class 1 disagreed and strongly disagreed that "*Burning coal, oil, or gas does not cause global climate change*" indicating their knowledge about causes of climate change.

Table 3. Class conditional outcome probabilities

Question	Response	Class 1	Class 2	Class 3
I am willing to pay more for electricity generated from renewable energy sources	Strongly agree & agree	0.56	0.15	**0.77**
	Unsure	0.25	0.12	0.09
	Disagree & strongly disagree	0.19	0.73	0.14
Somebody else can pay for renewable not me	Strongly agree & agree	0.06	0.49	0.07
	Unsure	0.21	0.16	0.11
	Disagree & strongly disagree	0.73	0.35	**0.81**
How willing would you be to pay much higher prices for goods in order to protect the quality of your local environment	Fairly willing & willing	0.53	0.24	**0.82**
	Unsure	0.22	0.16	0.04
	Unwilling & fairly unwilling	0.24	0.59	0.14
A rise in the world's temperature caused by the 'greenhouse effect' is dangerous to the environment	Strongly agree & agree	**0.94**	0.25	**0.93**
	Unsure	0.06	0.50	0.07
	Disagree & strongly disagree	0.00	0.25	0.00
I am not concerned about climate change because it won't have an effect for at least 50 years	Strongly agree & agree	0.04	0.28	0.05
	Unsure	0.15	0.44	0.00
	Disagree & strongly disagree	**0.81**	0.28	**0.95**
Climate change is a serious environmental problem	Strongly agree & agree	**0.93**	0.21	**0.93**
	Unsure	0.06	0.42	0.04
	Disagree & strongly disagree	0.01	0.37	0.03
Burning coal, oil, or gas does not cause global climate change	Strongly agree & agree	0.04	0.20	0.04
	Unsure	0.14	0.51	0.00
	Disagree & strongly disagree	**0.82**	0.29	**0.96**

It is interesting that while only about a half of respondents from this class (56%) were willing to pay for renewable energy, about 73% of them disagreed and strongly disagreed with the statement that somebody else can pay for renewable energy. More than a half of respondents from class 1 are willing to pay much higher prices to protect the environment.

Class 2: "*Protest*" class. Less than 22% of respondents were probabilistically assigned to this class. About 73% of them disagreed and strongly disagreed with the statement "*I am willing to pay more for electricity generated from renewable energy sources*". The responses to other statements were mixed. There is a high probability (59%) that those respondents are not willing to protect local environment by paying much higher prices. About 50% of respondents from this class indicated that somebody else can pay for renewable energy. About half of respondents from class 2 are unsure whether "*Burning coal, oil, or gas does not cause global climate change*".

Class 3: "*Willing to pay*" class. About 31.5% of respondents were probabilistically assigned to this class. About 77% of them disagreed and strongly disagreed with the statement "*I am willing to pay more for electricity generated from renewable energy sources*". About 81% of them disagreed and strongly disagreed with the statement "*Somebody else can pay for renewable not me*". About 82% of them stated that they are willing and very willing to pay to protect the environment (statement: "*How willing would you be to pay much higher prices for goods in order to protect the quality of your local environment*"). Almost 93% of this class respondents stated that they agree or strongly agree with the statement "*A rise in the world's temperature caused by the 'greenhouse effect' is dangerous to the environment*". About 95% of respondents from "*Willing to pay*" class disagreed and strongly disagreed with the statement that "*I am not concerned about climate change because it won't have an effect for at least 50 years*" implying that they are concerned about climate change. About 93% of this class respondents agreed or strongly agreed with the statement "*Climate change is a serious environmental problem*". Finally, 96% of respondents from class 3 disagreed and strongly disagreed that "*Burning coal, oil, or gas does not cause global climate change*" indicating their knowledge about causes of climate change.

Second, the model with covariates was estimated. When the socio-economic variables such as age, gender, income and education were added, the results indicated that statistically significant predictor of membership in class 3 with respect to class 1 was age. The younger respondents were more likely to be probabilistically assigned to class 3 than to class 1 (Figure 2). The statistically significant predictor of membership in class 2 with respect to class 1 was gender. Men were more likely than women to be assigned to class 2 compared with class 1 and 3.

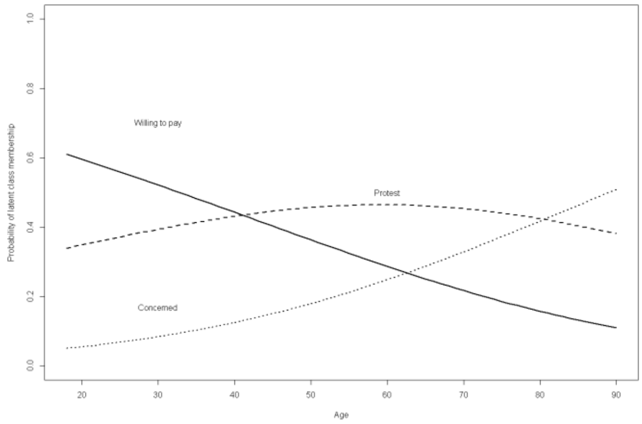

Fig 2. Age as a predictor of respondent's WTP class

4.3. How does WTP for renewable energy vary by class?

The results from the whole sample showed that about 30% of respondents are prepared to pay $45/quarter extra on their electricity bills for renewable energy (the voluntary option) [14]. According to [14] the average bid for the voluntary option in the whole sample is $27.99, with a standard deviation of $25.86. The median bid is $20.

The analysis of WTP for renewable energy by latent class shows a different response. The ANOVA test of the responses to valuation question for WTP for electricity generated from renewable energy indicated that there are significant differences between classes. Therefore the t-test was performed for three latent classes determined in section 4.1.

The t-test for three classes showed that there are significant differences in WTP between classes 1 and 2, 1 and 3 and 2 and 3. It is interesting to note that the percentage of zero bids is very high in the Protest class, while those who are in "*Willing to pay*" class reported the lowest percentage of zero bids (Table 4). It is a common phenomenon in contingent valuation analysis to have a large number of zero bids. The zero bids can be classified either as protest bids or true zero values of the good [36]. There are different ways to account for this issue. For example, zero observations can be treated by using only positive observations, adding a small number to zeros or assume that the distribution of WTP is censored at zero and use Tobit regression or other models such as the Spike Model (37, 38, and 39). The results of this analysis showed that possibly there is a latent class of respondents who are stating a zero willingness to pay based their perceptions and knowledge of the causes of climate change. Therefore, each class responses need to be analyzed separately using the above mentioned methods.

Table 4. Descriptive statistics for three classes

	N	Mean	Std. Dev	% of zeros
class 1 "*Concerned*"	94	29.05	24.15	7.4
class 2 "*Protest*"	41	12.88	22.49	56.1
class 3 "*Willing to pay*"	62	36.37	26.47	4.8

Regression analysis was used to estimate several different bid functions of different functional form. The Tobit regression with lower limit of $0 was estimated for three latent classes. The models are reported in Table 5. Three classes have different willingness to pay for renewable energy shown by the coefficients and the 95% confidence interval. In class 1 the socio-demographic variables such as age and education are significant predictors of respondents' willingness to pay for renewable energy. In class 2 the "*Protest*" class none of the socio-economic variables are significant. That result highlights the importance of identifying the classes with different WTP. In class 3, women and younger respondents are more willing to pay for renewable energy. Age is an important predictor in two classes (1 and 3).

The results of the models show that there is heterogeneity among respondents regarding their willingness to pay for electricity generated from renewable energy. Using respondents' attitudes towards climate change issues, environmental protection and knowledge of climate change drivers to identify classes of respondents that vary in their WTP can be a useful tool to account for heterogeneity preferences among respondents.

Table 5. Models for willingness to pay for the renewable energy (voluntary) by class

	Class 1 "*Concerned*"			Class 2 "*Protest*"			Class 3 "*Willing to pay*"		
	Estimate	LL	UL	Estimate	LL	UL	Estimate	LL	UL
Intercept	47.07***	26.19	67.95	4.49	-58.61	67.60	55.16***	23.95	86.36
men	0.45	-10.02	10.92	15.93	-20.36	52.21	14.38**	-1.09	29.85
age	-0.45***	-0.82	-0.09	-0.29	-1.36	0.78	-0.62**	-1.28	0.04
educ	14.62***	2.76	26.47	-28.18	-66.89	10.54	5.09	-12.02	22.20
hiincome	2.60	-10.33	15.52	28.69	-8.40	65.78	3.88	-13.72	21.48
df	168.00			60.00			104		
LL	-377.75			-91.30			-247.792		
n	94			41			62		

* < .1 **< .05 *** < .01 Source: Queensland Survey on Renewable Energy (2004).

5. Conclusion

This article presents the extended analyses of Queensland consumers' willingness to pay for electricity generated from renewable energy sources. Many stated preferences surveys contain attitudinal questions. In this paper, the heterogeneity of preferences is explained using the latent class modeling. It was assumed that there is a finite number of preference classes.

Statistically, three classes were identified: class 1 "*Concerned*" class, class 2 "*Protest*" class and class 3 "*Willing to pay*" class. The answers o questions revealing attitudes, perceptions and knowledge of climate change helped to explain preference heterogeneity using the latent class model.

Once the classes were identified, the respondents were probabilistically assigned to each class and the WTP in each class was estimated.

About 83% of the respondents in the whole sample indicated that they were willing to pay for electricity generation from renewable energy sources by voluntary payment. The mean WTP of $28/quarter has been estimated for the whole sample if a voluntary payment could be made for the renewable energy [14]. The t- test indicated that there are significant differences in WTP between three classes. The "*Concerned*" class was estimated to be willing to pay $29/quarter on the top of their electricity bill. The "*Protest*" class respondents were only willing to pay $13/per quarter, while the "*Willing to pay*" class respondents showed the highest willingness to pay among classes: $36/quarter. Age and gender were significant predictors of respondents' class. It is an imporatant result, as socio-economic variables are commonly used in valuation studies with various degrees of success. Perhaps the latent class models will help to identify classes where these variables behave consistently as significant predictors.

The Tobit regression further identified the differences among the classes. In class 1 the socio-demographic variables such as age and education are significant predictors of respondents' willingness to pay for renewable energy. In class 2 the "*Protest*" class none of the socio-economic variables are significant. In class 3, women and younger respondents are more willing to pay for renewable energy. Therefore the results indicated that there is a significant heterogeneity among respondents regarding their willingness to pay for electricity generated from renewable energy.

Future research will benefit from carefully designed questionnaire that includes attitudinal, knowledge and perception questions that allow for latent class modeling. This approach allows identifying the protest group/class and/or class with certain characteristics who has zero willingness to pay for environmental improvement. This will help to estimate better models of willingness to pay.

While the data gathered from the survey was drawn in 2004, it provides a valuable insight into respondents preferences towards electricity generated from renewable energy that is relevant in the current socio-economic situation. Further research in different regions of the world, Queensland inclusive is warranted.

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