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Willingness To Pay for Renewable Energy
A Case in Ho Chi Minh City, Vietnam

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List of Acronyms

ASC	Alternative specific constant
CLM	Conditional Logit Model
CEM	Choice Experiment Method
CVM	Contingent Valuation Method
DCE	Discrete Choice Experiment
EEPSEA	Economy and Environment Partnership for Southeast Asia
EVN	Vietnam Energy Corporation
HCMC	Ho Chi Minh City
IEA	International Energy Agency
iid	Independent and identical
kWh	Kilo-Watt Hours
LCM	Latent Class Model
MXL	Mixed Logit Model
MW	Mega-Watts
RE	Renewable Energy
RUT	Random Utility Theory
USD	United States Dollar
WTA	Willingness To Accept
WTP	Willingness To Pay

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Abstract

This research estimates willingness to pay (WTP) for renewable energy and examines its determinants using the Discrete Choice Experiment. The data was collected in 2020 from 286 households with electricity connections in Ho Chi Minh City, Vietnam. In addition to Conditional Logit as the standard model, Mixed Logit and Latent Class are applied in this study to fix its limitations. Several outstanding findings are presented as follows. Firstly, an explicit linear relationship is found between the value of WTP and the increase in renewable energy (RE) share. Secondly, similar to previous literature, solar energy is the most valued RE source; however, the WTP for RE generated from biomass exceeds that from wind, although knowledge of wind energy is more popular than biomass through statistics, implying a huge potential for the development of biomass energy projects. Furthermore, two different latent classes are identified, including awareness of wind and biomass energy, home ownership, the number of people at home during the day and the total number of outages. Noticeably, there is no relationship between the WTP for clean energy and income found in this study, while almost all research found a positive correlation. The estimated results show comparative similarities in all three models, indicating the high reliability of research results.

Relevance to Development Studies

Increased access to RE in underdeveloped nations is hindered due to high service costs and low electricity consumption. However, so far there has been no referendum to elicit the opinion of households about this issue. Hence, it is understandable that household willingness to pay (WTP) plays an important role in the feasibility of the proposed strategy. This research was conducted based on information from the Vietnam Power Development Plan (2019). An investigation based on this information may provide policymakers and investors with important insights and contribute to making these goals more feasible as they develop the directions for further plans regarding RE use and generation. Moreover, there appears to be a clear consensus on WTP for RE sources, which supports the wide range of WTP estimates in the RE literature.

Keywords

Renewable energy resources, willingness to pay, choice experiment method, conditional logit model, mixed logit model, latent class analysis

Chapter 1
Introduction

1.1 Research background

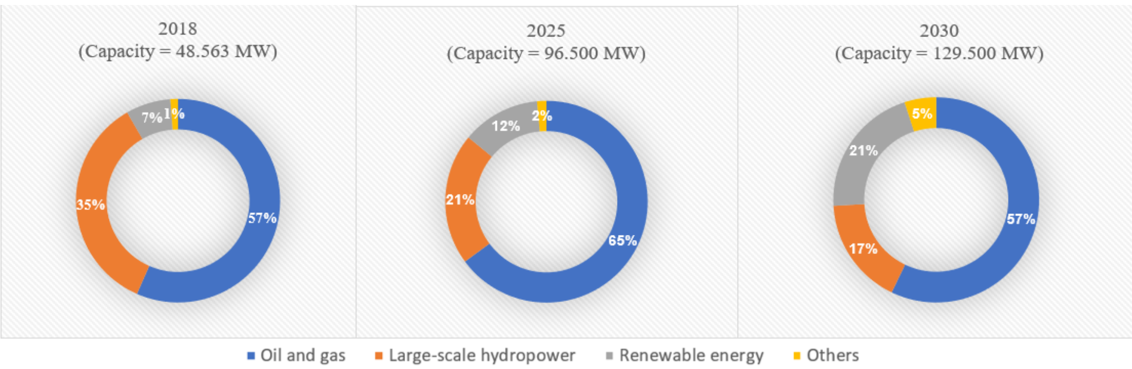
Renewable energy (RE) resources offer many potential benefits for both users and the environment. In particular, in addition to meeting energy needs, switching fossil fuels to RE sources is not only considered to be an important measure to solve the problem of limits on existing fossil-fuel reserves, but also minimizes negative impacts on the environment from the viewpoint of dangerous emissions, diversifying the portfolio of energy sources (Menegaki, 2008). Because of the primary advantages, a social push to accrete the proportion of RE in overall energy consumption is gaining traction. Following the first dissemination of the solar panel system, wind farms have been pushing the stage of commercial operation among various energy sources in Vietnam, closing the gap in comparison with solar popularity. Furthermore, biomass energy is considered a viable energy source, and research on the use of various RE sources has been conducted.

The available advantages of Vietnam bring potential to the development of renewable electricity industries from the sun, wind and biomass. A result of modern technology, however, is that the retail price of electricity may have to increase, leading to the price of green electricity being relatively more expensive than that of the market, which is 10% - 15% higher than electricity from coal- and gas-fired thermal power plants. Therefore, RE usage has not yet developed because the high cost of exploiting and using clean energy is considered a primary barrier for consumers (Eshchanov *et al.*, 2013; Kardooni *et al.*, 2018 and Yaqoot *et al.*, 2016).

Policy makers and legislators have been exploring a variety of methods to increase the proportion of RE. According to the report on the implementation of power projects in the National Power Development Plan VII (Vietnam Energy, 2019), the proportion of electricity sources in 2018 was 57% for oil and gas, 35% for large-scale hydropower, and 7% for RE. In the last ten years, the demand for energy in Vietnam has increased significantly. The overall capacity of all power plants in 2018 was 48,500 MW, which is projected to double by 2025 and triple by 2030. As a result, the proportion of RE will rise in the future. In 2025, the total capacity will be 96,500 MW, with coal-thermal and gas accounting for 65%, large-scale hydro accounting for 21%, and RE accounting for 12% of production. The total capacity is expected to reach 129,500 MW by 2030, with coal-gas accounting for 57%, large-scale hydro accounting for 16.9%, and RE increasing to 21%.

Figure 1.1

Vietnam power development plan from 2018 - 2030



Source: Vietnam Energy (2019)

So, as the share of RE increases, the electricity bill must increase as well. Increased access to RE in underdeveloped nations is hindered due to high service costs and low electricity consumption. However, so far there has been no referendum to elicit the opinion of households about this issue. Hence, it is understandable that household willingness to pay (WTP) plays an important role in the feasibility of the proposed strategy. The Discrete Choice Experiment (DCE) is compatible with consumer theory, allowing the computation of WTP values for each characteristic (Alpizar *et al.*, 2001). It is, therefore, particularly helpful for evaluating non-market commodities and developing supply plans. The DCE should be estimated by a standard logit model as Conditional Logit model (CLM), which helps to estimate the utility function. However, it also encounters scale heterogeneity and preference heterogeneity, which can be fixed by the Mixed Logit model (MXL) and the Latent Class model (LCM). To our best knowledge, this study would be the first study concentrating on clarifying the advantages and disadvantages of three logit models, then doing a result comparison amongst them to conclude the best one. The results of estimation models reveal the utility of consumers affected by attributes and socio-economic variables. Therefore, the preferences in this research interpret that increases in the share of RE enhance consumer utility under the impact of the above elements. Meanwhile, the estimation of WTP is based on the outcome of utility function to determine how much electricity consumers are willing to pay for increases in the share of RE.

This research aims to find out firstly if households in Vietnam would be willing to pay higher monthly electricity bills for an increase in the share of each RE source, namely, solar, wind and biomass energy, and secondly, the determinants motivating household preferences. The current stated preference study is available for a specific country, Vietnam, and specifies the types of RE, the increase in proportion of RE, and how an increased share of RE impacts total household electricity bills. An investigation based on this information may provide policymakers and investors with important insights, and contribute to making these goals more feasible. Moreover, there appears to be a clear consensus on WTP for RE sources, which supports the wide range of WTP estimates in the RE literature.

1.2 Research objectives and questions

This study is conducted to estimate the WTP for RE sources and specify determinants on RE preferences. The study poses two questions:

- *How much are consumers willing to pay for increases in the share of RE?*

The Choice Experiment Method (CEM) is applied to measure WTP for RE types as a percentage of monthly electricity bills; in particular, how much of an increase in the current monthly electricity bill is acceptable for respondents if the share of RE increases to 21% as planned in 2030 (Vietnam Energy, 2019). Hence, we can compare and evaluate respondents' WTP according to different increases in share levels and types of RE.

- *Which determinants motivate household preferences among groups of households?*

The attributes are determined by the percentage of RE share, types of RE and cost increase that are selected from previous literature, while the levels of these characteristics are set according to the RE target of the Vietnam Power Development Plan (2019) and Contingent Valuation Method (CVM) pre-test. Finally, they are confirmed by the Discrete Choice Experiment (DCE) pre-test outcomes. In addition to the attributes of RE, the impacts of socio-economic, demographic and awareness factors on preference for RE are also detected. This analysis contributes to a better comprehension of which segments of society are and are not willing to pay for RE. It is interesting to see which elements have a greater impact on the preferences of consumers. Besides the application of the Conditional/Mixed Logit to analyze the impact of attributes and socio-economic elements on the preferences of consumers in the current research, Latent Class models allow respondents to be classified into different groups based on their characteristics.

In short, the answers to these questions will be useful to policymakers as they develop the directions for further plans regarding RE use and generation.

1.3 Scope of the study

To answer the research questions, the research narrows to estimate WTP for increases in the share of solar, wind and biomass energy, which is based on the Vietnam Power Development Plan (2019) (RE target is 21% by the year 2030 from only 7% in 2018) and respondents are asked to make 7 - 8 hypothetical choices. This study will concentrate on electricity household consumers, randomly selected from the list of Vietnam Electricity Corporation (EVN) customers in Ho Chi Minh City, the most developed and populated city in Vietnam, where there is the highest standard of living, to see how citizens react to increases in RE share and their WTP. The survey was conducted over two months, from May to July 2020, immediately following the withdrawal of the COVID-19 social distancing order.

1.4 Structure of the research

This research will be structured as follows. Chapter 2 summarizes previous papers and the application used in the current research, including (i) public perceptions of RE in developing countries; (ii) other relevant WTP studies; (iii) application of CVM/CEM in WTP for RE sources; and (iv) estimation models and the impact of factors on preference. Next, Chapter 3 details the analytical framework, econometric models and data. Chapter 4 presents descriptive statistics and the results of econometric models covering some key socio-demographic and energy-related variables. The WTP analysis for RE sources is described in this chapter. Chapter 5 concludes with a discussion and the limitations of the research.

Chapter 2
Literature Review

To frame the present work, this chapter explores previous WTP research on RE. Numerous meta-analyses on this trend have revealed a focus on high-income nations (Alló and Loureiro, 2014; Bigerna and Polinori, 2014; Fizaine *et al.*, 2017; Ma *et al.*, 2015; Oerlemans *et al.*, 2016; Streimikiene *et al.*, 2019; Sundt and Rehdanz, 2015; Taylor *et al.*, 2014). However, it is logical to suppose that poorer nations have distinct conditions that necessitate different techniques and may result in unique conclusions. For example, differences in consumption and disposable income may result in differing WTP levels. Furthermore, socioeconomic and demographic variables will change between situations. As a result, the purpose of this chapter is to establish methodological implications for WTP research development for RE sources, which will be applied to a specific instance among developing nations. Previous research on the public perception of RE is presented first. From empirical evidence, the WTP for cleaner energy is summarized in the next section. Previous studies primarily focus on the impact of socio-economic elements on household preferences to green power (Goett *et al.*, 2000), and hence, the literature will be classified according to demographic factors. The following subsection exhibits studies that adopted the CEM and CVM, which are primarily utilized to evaluate WTP for RE use as well as standard estimate models.

2.1 Perceptions on RE: the context of developing countries

RE sources are not only regarded as alternative energy in a time of rising oil prices and limiting the impact of climate change but also contribute to energy source variety, sustainability, and security. Although the market prices of green energy are greater than traditional fuels, the social costs of using the former can be considerably reduced. To expand the use of RE, assessing community preference for the energy transition is critical. Thus, governments should learn about citizens' opinions regarding measures that promote greener energy mixes. Through a comparative WTP study in different locations, this review attempts to give a complete evaluation of public attitudes.

According to some literature related to perceptions of RE and environmental issues in emerging economies, overall, most studies found a positive attitude toward RE development in various research subjects (Alsabbagh, 2019; Hanger *et al.*, 2016; Jamaludin *et al.*, 2020; Kardooni *et al.*, 2018; Zyadin *et al.*, 2014). However, these studies, as well as another by Assali *et al.* (2019), highlighted a lack of understanding of RE sources across diverse populations, which were favorably related to the high degree of acceptance (Hanger *et al.*, 2016). Chen *et al.* (2016) discovered that consumers had a high level of preference for RE sources in China, the biggest producer of greenhouse emissions in the world. A positive and statistically significant reaction was produced by the energy security frame; however, neither air pollution nor the framework of climate change had a statistically significant impact on the general consensus.

Yaqoot *et al.* (2016) reviewed obstacles to the progress of decentralized RE systems as part of a larger investigation into consumer perceptions. The widespread adoption of decentralized RE systems may be hampered by a variety of obstacles. In particular, technology (a lack of technology, spare parts shortages), economic concerns (high costs, credit constraints, limited purchasing power, competing priorities, unfair energy pricing), institutional aspects (skilled labor shortages, inadequate training on decentralized RE systems' operation and maintenance), social and environmental perspectives (lack of information or awareness) are highlighted as major issues. Alsabbagh (2019) performed research on the public acceptance of domestic solar panels and the main impediment to widespread adoption of RE in Bahrain's residential sector by distributing a virtual survey. The findings, which were consistent with those of Abdullah *et al.* (2017) and Jamaludin *et al.* (2020), indicated that while a sizable proportion of respondents expressed an interest in solar panel installation, they identified capital expenditures, lack of knowledge, and maintenance needs as obstacles to buying and installing solar panel systems.

Additionally, Eshchanov *et al.* (2013) reported that residents of urban-style multi-story homes in Uzbekistan have somewhat limited opportunities for RE installation owing to the smaller surface area of rooftops and a lack of suitable surface area in the neighborhood. Economic considerations, according to respondents, were one of many roadblocks to the broad adoption of RE sources. Eshchanov *et al.* (2013) and Kardooni *et al.* (2018) highlighted that one of the principal impediments to the progress of RE systems in developing settings was the higher cost of energy generated by RE sources, which had a direct effect on people's desire to use RE. In a developing environment, the majority of respondents saw RE as costly.

In summary, according to the assessment of the past studies on RE sources stated above, the genuine interest of consumers in environmentally friendly energy generation has been growing. When questioned about the acceptability of RE sources, the majority of respondents provided a positive response. Nonetheless, despite the importance of social cost reduction, public knowledge of RE sources initiatives remains mostly unknown. Furthermore, the findings revealed that the greater cost of green power is a key deterrent in underdeveloped nations.

2.2 WTP for green energy

This section draws more attention to studies on the WTP for RE. In general, the findings of surveys indicating respondents' WTP for quantities or surcharges for green power differ. It is due to the fact that the research covers a wide range of nations, locations, and time periods. Furthermore, they use a variety of techniques and questionnaire designs.

In a study conducted by Vecchiato and Tempesta (2015) in Italy, interviewees were willing to pay more for RE, while a marginal unit of cleaner energy, according to Borchers *et al.* (2007), had a mean WTP of 1.3 USD/kWh, the WTP for increased RE sources penetration in the power mix in Nikaia, a Greek urban municipality, was projected to be 31.2 USD per electricity bill for each three-month period (Ntanos *et al.*, 2018). Murakami *et al.* (2015) examined consumers' WTP for nuclear and green energy as a strategy to reduce carbon emissions. They conducted an investigation related to the WTP of American and Japanese consumers in the aftermath of the Fukushima nuclear plant catastrophe. Consumers in the United States and Japan favored RE sources, with a WTP of USD 0.71 and USD 0.31 per month, respectively, to boost RE source use by 1%. Meanwhile, consumers in Korea were willing to pay an extra USD 3.21 per month for RE (Lee and Heo, 2016). Noticeably, Borchers *et al.* (2007) and Vecchiato and Tempesta (2015) claimed that individuals made distinctions in WTP between various types of RE.

Exploring the relevant contexts, on the other hand, might be helpful to the current research. There is an obvious increase in research interest in WTP for RE sources to drive climate change policy in poor nations. For example, the claimed average monthly WTP was almost 1.5 times higher than the actual payment in Ghana (Twerefou, 2014). In northern

Ethiopia, the amount was 0.66 USD per month per family for five years (Arega and Tadesse, 2017), whereas Malaysian consumers agreed to pay more than 0.82 USD per month for RE usage (Azlina *et al.*, 2018). In China, the average WTP of Beijing inhabitants was estimated to be 2.7–3.3 USD per month (Guo *et al.*, 2014), while Zhang and Wu (2012) found that the monthly average WTP varied from around USD 1.15–1.51 for citizens in Jiangsu Province. According to Ayodele *et al.* (2021), Nigerian respondents were ready to spend 5–10% more on energy, indicating that the cost of WTP for renewable electricity was around 0.065 USD per kWh.

The WTP of respondents among nations varies greatly. Noticeably, the WTP of developed countries is seemingly greater than that of emerging economies. In general, prior research has shown a positive WTP for RE. The claimed WTP disclosed in these researches, on the other hand, does not correspond to actual involvement in green energy initiatives (Byrnes *et al.*, 1995; Holt, 1997; Wiser, 2007). After comparing WTP surveys with market simulations and actual tariff schemes, Byrnes *et al.* (1995) found that less than 15% of respondents expressed a positive WTP premium when given a choice. A wide range of factors, including socioeconomic and demographic traits, may be used to explain both problems.

2.3 Application of CVM/CEM in WTP for RE sources and estimation models

Stated preference studies estimate WTP by accounting for differences in survey design and elicitation format (choice experiment or contingent valuation). Some research assessed consumers' WTP for RE using the CVM, which is at the top of the list of well-known methodologies for valuing environmental commodities. The following are some of the CVMs used in estimating WTP for RE sources: Arega and Tadesse (2017), Ayodele *et al.* (2021), Dagher and Harajli (2015), Guo *et al.* (2014), Twerefou (2014), and Zhang and Wu (2012). Meanwhile, Abdullah and Mariel's (2010) study addressed WTP to minimize power interruptions or blackouts among rural families in Kisumu, Kenya. Similarly, Suanmali *et al.* (2018) discovered Thai citizens' WTP for solar home systems by applying the CVM in their research.

Aside from CVM, which is used to analyze environmental concerns, the CEM is a top choice for estimating customers' WTP for a market commodity. CEM has been used to compute WTP in a number of different sectors, comprising the environment, health, and tourism (Garcia *et al.*, 2020; Huang *et al.*, 2018; Hole and Kolstad, 2012; Nguyen *et al.*, 2015; Vecchiato and Tempesta, 2015; Woretaw *et al.*, 2017). Borchers *et al.* (2007) assessed respondents' WTP for green power sources in the RE industry. According to the findings, individuals consented to pay an additional cost for utilizing green energy. The study also delved deeper into their WTP using various renewable sources, such as solar, wind, farm methane, and biomass. The study also proved that the highest WTP was expressed for solar energy, compared to wind energy in general, while electricity generated from biomass and agricultural methane sources received the least support from consumers in the United States.

Similarly, Cicia *et al.* (2012) completed a comparison between various kinds of RE sources. As a result, Italian homes might be divided into three groups, each having similar tastes. Energy produced by wind and solar was preferred to biomass and nuclear power by the first group (35%). The next group (33%) revealed a slight interest in solar and wind energy but rejected nuclear and biomass energy, much as the previous group does. The last group (32%) was vehemently opposed to nuclear power and supported green energy from solar, wind, and biomass sources.

DCE, like other economic valuation methods, has drawbacks. DCE is based on hypothetical situations rather than actual behavior (Carson and Groves, 2007). Second, it is more difficult for respondents to understand than CVM; this complexity raises the risk that respondents would reply using basic rules of thumb (Hensher and Collins, 2011; Hanley and Roberts, 2002). Additionally, Perman (2003) shows a drawback of strategic behavior, which may lead to either an overestimation or underestimation of welfare estimates. Furthermore, according to Hensher *et al.* (2005), the trend of the preference curves will differ from person to person, alternative to alternative, and even at different points in time. Hence, the challenge for the researchers is to identify, capture, and use as much of the information that an individual takes in when processing a situation that leads to a choice.

Comparison of CEM and CVM:

- CEM is highly appreciated and widely applied in many fields because it follows the assumptions of choice theory, which is easy to implement and the collected data can be used to estimate many types of functions.
- The main advantage of CEM over CVM lies in its ability to measure attribute values. The attributes of the CEM approach can be qualitative or quantitative, and the method allows for combinations of different attributes as we build a scenario. In contrast, the CVM produces a single value for the overall change in quality. CEM also avoids some of the errors due to the hypothetical scenarios in CVM.
- The CEM clearly shows the attributes and levels in each set of choices to help respondents choose easily and accurately. The attributes are identified in the choice set, and respondents receive repeated sets of choices to reveal their preferences.
- The monetary attribute is redefined and included in the selection experiments, which can avoid the large difference between willingness to accept (WTA) and WTP in CVM.
- The CE method does not require such a large sample size as CVM, so the application of CEM is an advantage that saves time and costs.

The primary advantage of DCE is its compatibility with consumer theory, which allows for calculating WTP values for each attribute (Alpizar *et al.*, 2001). DCE is thus especially useful for valuing complicated non-market commodities and designing strategies to supply such goods. In short, by practical application and comparison of these methods, the CEM will be applied in estimating the WTP for RE of electricity consumers in HCMC as the most rational approach.

2.4 Estimation model and impact of factors on consumer preferences

2.4.1 Estimation models

To simulate the WTP via the DCE method, most studies use a variety of estimation models, such as the Random Parameter Logit model (Nienhueser and Qiu, 2016), Multinomial Probit model (Ku and Yoo 2010, Navrud and Bråten, 2007; Zhang and Wu, 2012), Tobit model (Dagher and Harajli, 2015), Binary Logit model (Guo *et al.*, 2014; Ntanos *et al.*, 2018; Suanmali *et al.*, 2018), Mixed Logit model (Amador *et al.*, 2013; Hole and Kolstad, 2012; Longo *et al.*, 2008; Zemo *et al.*, 2019), Latent Class model (Cicia *et al.*, 2012; Garcia *et al.*, 2020; Nguyen *et al.*, 2015; Sagebiel *et al.*, 2014). Scarpa and Willis (2010) compared the results of the Conditional Logit model and Mixed Logit models, which estimate the distribution of utility coefficients, and then derived the WTP value as the relationship between attribute coefficients and price coefficients, where the WTP distribution was directly estimated from the space of utility in monetary space. In addition to the standard model (CLM), Woretaw *et al.* (2017) utilized a combination of the Random Parameter logit model (known as MXL) and the LCM to estimate WTP for improvements in solid waste management using the CEM. Similarly, Siyaranamual *et al.* (2020) utilized these two models to get a deeper understanding of electricity consumers' preferences.

The DCE should be estimated by a standard logit model as CLM, which helps to estimate the utility function. This model implies that all people have the same marginal utility. This may be untrue because each respondent may have a different marginal utility for each attribute. As a result, the MXL model allows for the possibility of each coefficient being a random number rather than a set value. Meanwhile, the LCM has the benefit of being straightforward, reasonable, and tested statistically. It is, however, less flexible than the MXL model due to the set parameters that are connected with each variable in each segment (Shen, 2009). By contrast, the primary drawback of the MXL model is that the analyst must specify any assumptions about parameter distributions.

2.4.2 Determinants affecting preferences to RE

In terms of the socioeconomic and demographic determinants' impact, there are numerous hypotheses on the variables that explain differences in the research of utility for RE sources. Gender, household size, job position, income, age, education, ownership, and awareness of RE are all exploratory factors in most energy research. According to the most popular results, the utility is favorably linked to income (Abdullah and Jeanty, 2011; Akcura, 2015; Arega and Tadesse, 2017; Bollino, 2009; Guo *et al.*, 2014; Islam and Meade, 2013; Lee and Heo, 2016; Mozumder *et al.*, 2011; Oliver *et al.*, 2011; Suanmali *et al.*, 2018; Urpelainen and Yoon, 2015; Zhang and Wu, 2012), business (Abdullah and Jeanty, 2011), ownership (Abdullah and Jeanty, 2011; Bollino, 2009; Dagher and Harajli, 2015). Awareness of RE sources or attitudes to the environment (Dagher and Harajli, 2015 and Lee and Heo, 2016), with the exception of Bollino's (2009) result, highlights a negative and statistically significant value between general RE sources knowledge and utility.

However, it is important to note that countless papers show a positive relationship between income and utility; there still exists research against the majority by Ek (2005). Although the coefficient for income was extremely tiny, the negative sign indicated that respondents with a greater income were less likely than the typical respondent to feel favorable about wind energy. In other words, the fact that those who have lower income expected a greater value on the favorable benefits of wind energy projects might be one potential explanation for this uncommon assessment of the industry.

In research on WTP, one of the most common variables examined is the participant's age. The findings of research (Abdullah and Jeanty, 2011; Akcura, 2015; Borchers *et al.*, 2002; Islam and Meade, 2013) agreed that utility seems to be lower in elderly individuals, but Arega and Tadesse (2017) concluded the contrary, while Guo *et al.* (2014) and Urpelainen and Yoon (2015) revealed no impact. The preference to RE of males was greater than that of females in the vast majority of research that takes gender into account (Arega and Tadesse, 2017; Bollino, 2009; Borchers *et al.*, 2002); this is not consistent with the findings of Guo *et al.* (2014), Lee and Heo (2016), and Mozumder *et al.* (2011) which showed that the coefficient of gender was not statistically significant. Similarly, the number of schooling years is also a vital factor in determining utility, which illustrates two main aspects that a positive relationship with the utility of consumers (Abdullah and Jeanty, 2011;

Bollino, 2009; Dagher and Harajli, 2015; Islam and Meade, 2013; Urpelainen and Yoon, 2015). In contrast, Guo *et al.* (2014) and Lee and Heo (2016) showed inconclusive data about the impact of schooling years. The result by Mozumder *et al.* (2011) exhibited a non-significant coefficient of household size while a positive correlation was identified in studies by Abdullah and Jeanty (2011) and Urpelainen and Yoon (2015).

In particular, in terms of the new parameters investigated and their impact on the utility for service characteristics, Amador *et al.* (2013) exhibited coefficients of outage length with high statistical significance in their research, suggesting that respondents revealed a strong interest and substantial impact on the preference for electricity outage cutback. Noticeably, a double willingness to pay for continuity of supply was indicated by those who have prior experience with the frequency of power outages.

In conclusion, numerous studies have been conducted to estimate WTP for RE and assess consumer attitudes and perceptions using the CVM or the CEM. This study will address mainly CEM to investigate the example of Vietnam using plentiful sources of solar, wind, and biomass energy. The former technique is used to determine methodological factors, while the latter is used to estimate WTP for RE sources and evaluate variables influencing respondents' decisions. Conditional logit probability will be used as the conventional estimation model in DCE (McFadden, 1974); however, this model has several limitations that can be addressed by the MXL model and the LCM. Since each model has its own set of advantages and disadvantages; therefore, it is important to compare the analysis of these two models in the study.

Chapter 3
Methodology and Data[1]

The purpose of this study is to apply DCE to estimate the WTP for increases in the share of RE sources. The first part discusses the theoretical foundations of these techniques, attribute determination, and experimental design. The next section discusses the data collection procedure, including how the sample size was determined and how the survey was conducted. According to McFadden (1974), the estimation model is based on the Random Utility theory (RUT), which allows for the study of stated preferences under the assumption of utility maximization. This is followed by applying MXL and LCM to specify the effect of share, types of RE, and a cost increase on their WTP decision.

3.1 Discrete Choice Experiment

3.1.1 Theoretical background

This study expands on the DCE method, an approach that has received growing attention, particularly in the context of environmental assessments, but not exclusively (Hoyos, 2010). Discrete choice models depict the alternatives available to decision-makers, including individuals, households, or businesses, among others. Three features, according to Train (2015), are required for effective choice sets:

> First, the alternatives must be mutually exclusive from the decision maker's perspective. Choosing one alternative necessarily implies not choosing any of the other alternatives. The decision-maker chooses only one alternative from the choice set. Second, the choice set must be exhaustive, in that all possible alternatives are included. The decision-maker necessarily chooses one of the alternatives. Third, the number of alternatives must be finite. The researcher can count the alternatives and eventually be finished counting. (p.11)

In the discrete choice model, decision-makers are expected to weigh attributes and choose the option with the greatest utility (Hensher *et al.*, 2005). The choice scenarios are specified using a number of different attributes that vary according to preset levels. In this research, the DCE collects preferences by requiring interviewees to state their choice from a range of options. Each option set includes three alternatives, and each alternative contains a collection of attributes with defined levels as shown in Figure 3.1, the example of a choice set. Respondents must reveal their most preferred option from each choice set.

[1] The survey is part of the research project of the Institute for Future Initiatives, The University of Tokyo. The survey in HCMC was conducted by EEPSEA (eepsea.org).

Figure 3.1

A sample choice set from DCE survey

Block: 1 **Sequence: 8** **CSID: 8**

	Option A	Option B	Option C (Currently)
Share of RE	 10%	 10%	 7%
Type of RE	 Solar energy	 Biomass energy	 Solar energy
Increase in monthly electricity bill	**Increase of 10%**	**Increase of 5%**	**unchanged**
Your choice is	☐	☐	☐

3.1.2 Information for RE sources

The generation of coal- and gas-fired thermal energy produces a large quantity of greenhouse gases, which contribute significantly to global warming. Greenhouse gas emissions from RE generation are considerably lower, making it an essential metric for global warming prevention. The increase in RE from 7% of production in 2018 to 21% by 2030 is consistent with Vietnam's international commitments (Vietnam Energy, 2019), such as the Nationally Determined Contribution in The Paris Agreement (2016). This commitment is stated in the Vietnam Strategy of Renewable Energy Development to 2030 (IEA, 2016), which establishes the objectives of developing RE to decrease CO_2 emissions by 5% in 2020 and 25% in 2030. This will contribute to the mitigation of global warming and sea-level rise.

Vietnam holds remarkable potential for RE development. In particular, Vietnam is located in a tropical monsoon area, where there is a lot of solar radiation. The Central and Southern regions have total sunny hours in a year ranging from 1,400-3,000 hours. Moreover, with the advantage of a coastline longer than 3,200km and the average annual wind speed in the East Vietnam Sea greater than 6m/s at an altitude of 65m, the development of wind energy in Vietnam has great potential, especially in coastal areas, the Central Coast, the Central Highlands and off-shore islands. However, wind power development is progressing slowly, due to many barriers — legal, technical, financial and human difficulties. The main reason why few businesses invest in alternative energy is that the electricity purchase price is too low while the cost of connecting to the electrical network is relatively high (Tạp chí *Năng* lượng Việt *Nam,* 2019). As a predominately agricultural country, there is a huge amount of wood waste, other agricultural by-products, municipal waste and other organic waste after production. In Vietnam, the potential to utilize biomass resources for energy generation in a sustainable manner is estimated to be about 150 million tons per year. Taking advantage of these leftover products to develop the renewable electricity industry brings several benefits. In addition to fulfilling energy requirements, the proper use of biomass aids in reducing greenhouse gas emissions (PetroTimes, 2014).

Due to the availability of accessible resources in Vietnam, this research will focus on RE produced from the sun, wind, and biomass, which are characterized as follows: Solar energy is defined as electricity generated by photovoltaic cells from sunlight. Solar energy may be generated in large-scale facilities (solar farms), but it can also be generated by small-scale rooftop solar systems. Wind, on the other hand, may be used to generate energy. Wind turbine blades spin and produce energy as the wind blows. Last but not least, biomass energy is generated by the combustion of organic wastes, which produces less greenhouse emissions than fossil fuels.

3.1.3 Attributes and levels

The design of experiments is a critical stage in the choice set process. First, a table with the attributes and levels of each characteristic must be created. The characteristics included in the test should be carefully chosen to address research objectives, be practical and comprehensible.

The experiment included three characteristics as shown in Figure 3.1, an example of a choice set, namely, the future proportion of RE, types of RE, and the increase in monthly energy bill. Table 3.1 describes the definitions of various characteristics, as well as their levels.

It is worth noting that the attributes chosen for the current study are not solely based on prior research, for example, types of RE (Borchers *et al.*, 2007; Cicia *et al.*, 2012; Scarpa and Willis, 2010; Vecchiato and Tempesta, 2015), how increases in share of RE would impact on WTP for RE (Gracia *et al.*, 2012; Komarek *et al.*, 2011; Murakami *et al.*, 2015), and cost increase (Botelho *et al.*, 2018; Kosenius and Ollikainen, 2013; Susaeta *et al.*, 2011; Yoo and Ready, 2014), but also mainly on the particular circumstance of the study area. RE share levels were set according to the RE target of each government, as confirmed by the March 2020 DCE pre-test. The DCE pre-test was performed in Ho Chi Minh City (HCMC), and 33 responses were received. The cost attribute was defined as the percentage increase in residents' monthly electricity bills. The levels of increase in the monthly electricity bill were determined based on the CVM pre-test results in January 2020 and confirmed by the DCE pre-test results.

Table 3.1

Attributes and their levels

Attributes	Definition	Current value	Levels
Future share of RE	The percentage of RE share increase in total capacity	7%	10%/15%/25%/35%
Type of RE	RE generated from different sources	Solar	Solar/ Wind/ Biomass
Increase in monthly electricity bill	The percentage of monthly cost increase	0%	2%/5%/10%/15%/25%

Each alternative is distinguished by three characteristics:

Future share of RE: The current share of RE in Vietnam is 7%, based on the Power Development Plan of Vietnam (Ministry of Industry and Trade, 2019). The government aims to increase the share of RE to 21% by 2030 (Ministry of Industry and Trade, 2019), which is in the middle-level of the share of RE in this survey, in particular rising to 10%/15%/25%/35% in 2030 in order to better understand respondents' preferences for RE.

Type of RE: Renewable energy includes many types. Popular types of renewable energy are wind power, solar energy, biomass energy, and small-scale hydropower. In addition to the most popularity and feasibility of solar power as status quo, wind energy and biomass energy are also important in Vietnam. Therefore, the choice set of this research concentrates on three potential sources above. The growth in RE will be fuelled by just one of these sources, despite the fact that the present share of 7% is a combination of those renewable power sources.

Increase in monthly energy bill: as producing renewable energy is likely more costly at this moment, the monthly electricity bill of households in Viet Nam may also increase when the share of renewable energy increases. The increase in monthly bills is expressed as a percentage, so households with higher monthly electricity bills would have to pay larger additional amounts.

Noticeably, it is assumed that the monthly bill will not increase until the share of renewable energy indicated in each choice question is achieved and any attributes other than the three attributes presented in the alternatives remain identical, since the researcher would like to know which alternative respondents most prefer.

3.1.4 Blocks and choice sets

The attributes and their levels yielded numerous choice sets. The orthogonal array method (Kuriyama *et al.*, 2013) allows a reduction of the necessary number of choice sets for calculating WTP. Three attributes were set with four, three, and five levels. Combining these (4x3x5) created 60 distinct alternatives. The R program developed by Aizaki (2012) is applied to lessen the number of alternatives.

Next, the choice sets are developed by randomly combining alternatives. When two scenarios occur in the same choice set, they should seldom have the same attribute levels, to minimize overlap (Ryan *et al.*, 2012). Moreover, the inclusion of the option "status quo" is in keeping with reality since consumers have the right not to change their preferences. The status quo alternative is often included in a choice set as an assessment criterion (Kuriyama *et al.*, 2013). In this research, a choice set consists of 2 alternatives and one "status quo" alternative, similar to previous research by Yoo and Ready (2014).

Finally, a total of 86 choice sets divided into 11 blocks were set as it was observed that the response quality degraded when 8–16 comparisons were made (Pearmain and Kroes, 1990). The blocks assigned to respondents consisted of 7-8 choice sets. Each block was configured such that the number of occurrences of alternatives was equal.

3.2 Data

3.2.1 Sample size

A certain number of sample sizes are needed to evaluate WTP in DCEs. Kuriyama *et al.* (2013) reported that 200 samples are sufficient for statistical analysis in DCEs. The formula below provided by De Bekker-Grob *et al.* (2015) was followed in this research.

$$\frac{nta}{c} > 500$$

where n is the required number of interviewees, t denotes the minimum number of tasks in a block, a denotes the number of options in a task, and c denotes the number of attribute levels with the greatest number. In this design, c = 5, t = 7, and a=2 since the status quo alternative should not be counted. As a result, n > 178.6 respondents are required, and 286 samples are obtained.

3.2.2 Questionnaire and sampling procedure

The questionnaire included seven sections:

- Part 1: Electricity consumption
- Part 2: Electric appliance use
- Part 3: WTP and follow-up questions
- Part 4: Attitudes toward environmental issues
- Part 5: Household businesses
- Part 6: Household information
- Part 7: Quality management

Information sheets were provided to all respondents, and informed consent was obtained from all respondents. In the full-scale survey, 300 households in Ho Chi Minh City were interviewed. Households were randomly selected from the customer records of the Electricity Corporation of Ho Chi Minh City. The survey was conducted over two months, from May to July 2020, immediately following the withdrawal of the COVID-19 social distancing order. The survey teams included four groups, each with seven researchers and one supervisor. Enumerators were provided with participant addresses. They visited the households to ask for permission to interview them. Researchers introduced themselves as students participating in a research project at the university rather than working for EVN or the government.

The following protocol was implemented:

- If an address cannot be found, a replacement is provided.
- If nobody was home at the chosen address, the enumerator paid a second visit at the end of the day or the next day. If nobody is home the second time, a replacement address is provided.
- If the chosen household refuses, the enumerator goes to the closest neighbour to interview and reports to the supervisor.

3.2.3 Implementation process

The household survey in HCMC was conducted with 300 households randomly selected from the list of EVN HCMC customers. Each interview took approximately 60 minutes. The questionnaire was an electronic tablet-based questionnaire presented to respondents using the Survey Solutions Program established by the World Bank (2018). The use of an electronic questionnaire allowed for the following features:

- Close monitoring of survey completion (for instance, the data specialist can closely record the pace at which each question was administered),
- Interview recording,
- Live-checks and warnings,
- Interactive features such as time and location recording, picture capturing, interactive map navigation, etc., and
- Tools that allow the enumerator to undertake quick calculations to ensure reliability. The enumerators followed a stepwise protocol when approaching the respondents as follows:

Step 1: Go to the provided address. If it is impossible to find the address, another alternative will be replaced.

Step 2: Check whether the targeted respondent who often pays the electricity bill or uses electricity the most frequently is home. If nobody is home, return at the end of the day or make an appointment. If it is impossible to find a respondent, investigators will go to the house to the right of that house and return to this step. If Step 3 cannot be performed after many tries, report it to the supervisor.

Step 3: Ask for permission to interview. If the respondent agrees, begin the procedure presented in "During the interview." Otherwise, if the respondent refuses, go to the house to the right of that house and restart Step 2.

3.3 Estimation models

The DCEs are based on RUT in economics. The DCE technique was used in conjunction with McFadden's RUT (McFadden, 1974). This implies that the alternative selected must provide the person with more value than other alternatives. If a person i's utility in selecting a state j is denoted by U_{ij}, then the alternative j is selected if and only if U_{ij}, >U_{il}, for $j \neq 1$.

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

U_{ij} is composed of an observable anticipated utility, V_{ij}, based on the choice's characteristics and an unobservable random component, ε_{ij}. If ε_{ij} were known, researchers would be able to determine U_{ij} and therefore predict which option would be selected. Since researchers do not know ε_{ij}, the most they can do is provide a probabilistic prediction of the ultimate result.

The likelihood of respondent i selecting alternative j can be expressed as follows:

$$\begin{aligned} P_{ij} &= \mathrm{P}(U_{ij} > U_{il}) \\ &= \mathrm{P}((V_{ij} + \varepsilon_{ij}) > (V_{ij} + \varepsilon_{il}) \\ &= \mathrm{P}((\varepsilon_{il} - \varepsilon_{ij}) < (V_{ij} - V_{il})) \text{ for all } j \neq 1. \end{aligned} \tag{2}$$

The next step is to assume:

$$V_{ij} = \alpha' Z_{ij} \tag{3}$$

where Z_{ij} is a vector of observable attributes or explanatory variables, while the parameter *a* indicates how Z_{ij} affects the choice, which is estimated by Conditional logit, Mixed logit and many other models. We, then, impose a probability density function on ε_{ij} in order to resolve Equation (2). Each probability distribution applied to ε_{ij} generates a unique discrete choice model.

3.3.1 Conditional Logit model (CLM)

Assumptions regarding the distribution of the random error term result in a variety of different kinds of models. The most straightforward model is CLM, which is based on the assumption that *ij* has an extreme value distribution. More significantly, this approach requires all ε_{ij} to be dispersed independently and identically (iid). Individual i's likelihood of selecting option j may be represented as the following expression:

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}} = \frac{e^{\alpha' Z_{ij}}}{\sum_j e^{\alpha' Z_{ij}}} \tag{4}$$

Equation (4) enforces the IIA assumption if ε_{ij} is iid. Consider the following likelihood that person i prefers option j to option l:

$$P_{ij} = \frac{e^{\alpha' Z_{ij}}}{\sum_j e^{\alpha' Z_{ij}}} \text{ ; and } P_{il} = \frac{e^{\alpha' Z_{ij}}}{\sum_j e^{\alpha' Z_{il}}}$$

The likelihood of selecting j over l is as follows:

$$\frac{P_{ij}}{P_{il}} = \frac{\sum_j e^{\alpha' Z_{ij}}}{\sum_j e^{\alpha' Z_{ij}}} \; x \; \frac{e^{\alpha' Z_{ij}}}{e^{\alpha' Z_{il}}} = \frac{e^{\alpha' Z_{ij}}}{e^{\alpha' Z_{il}}} \qquad (5)$$

The probability ratio solely relies on j and l characteristics and does not rely on other options' attributes.

Noticeably, there are two significant faults in the CLM that should be considered: scale heterogeneity and preference heterogeneity. First, the model assumes that all respondents and choice tasks assess utility equally well (or equally badly) in response to choice questions. This is called scale heterogeneity. Second, preference heterogeneity means it is interpreted that CLM does not account for unobserved systematic variations in respondents' preferences (Hess and Rose, 2012). Alternative approaches are still being developed; however, this study concentrates on two statistical methods that are widely utilized in DCE environment applications. Mixed Logit (also known as Random-Parameters Logit) and Latent Class analysis are two of these statistical methods. As with random utility theory, these techniques use restricted dependent variable models that guarantee the projected chance of selecting any option is between 0% and 100%. These methods are more complicated statistically than CLM, but each offers potential benefits. These two methods are described below.

3.3.2 Mixed logit model (MXL)

The MXL model is identical to the CLM, except that parameter estimations may differ across individuals. Take into account the utility function in the equation (1) and (3):

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$
$$= \alpha' Z_{ij} + \varepsilon_{ij}$$

The MXL model makes the same assumption as the conditional logit model that the error terms, *εij*, are iid with an extreme value distribution. In comparison, an MXL model dispenses with the need that α be constant among individuals, allowing it to be stochastic. An individual's utility is expressed in the following way when utilizing an MXL model:

$$U_{ij} = \alpha_i' Z_{ij} + \varepsilon_{ij} \qquad (6)$$

where α varies from one person to the next. If the probability density function (pdf) for α is known, it is possible to estimate U_{ij}, resulting in the imposition of a certain kind of distribution for α. (e.g., normal, lognormal, uniform). Assuming α is constant across all people, the probability of person i selecting state j (P_{ij}) can be represented precisely by Equation (4), which was previously used to explain the CLM. The likelihood of a person i selecting option j (denoted M_{ij} in this instance) can be calculated when α is changed by calculating P_{ij} across all of the potential values of α.

$$M_{ij} = \int P_{ij}(\alpha) f(\alpha). d\alpha$$
$$= \int \left(\frac{e^{\alpha' Z_{ij}}}{\sum_j e^{\alpha' Z_{ij}}}\right) f(\alpha). d\alpha \qquad (7)$$

As a result, the average weighted probability of mixed logits is that of the logit formula assessed for various values of α with density weight $f(\alpha)$. The equation is a multi-dimensional integral such that the solution is not closed. As a result, simulation must be solved. Another approach to see an MXL model is by showing the utility as a particular feature component. α may be considered as its mean, *a*, and a deviation around mean, ξ, that varies across people. This is the following:

$$\begin{aligned} U_{ij} &= \alpha_i' Z_{ij} + \varepsilon_{ij} \\ &= (a + \xi_i)\, Z_{ij} + \varepsilon_{ij} \\ &= a' Z_{ij} + \xi_i' Z_{ij} + \varepsilon_{ij} \end{aligned} \qquad (8)$$

The ε_{ij} are still considered to be iid in this instance. $\eta_{ij} = \xi_i' Z_{ij} + \varepsilon_{ij}$ is the value of utility's unobserved components. $\xi_i' Z_{ij}$ is identically zero in the conditional logit model, indicating no connection between alternative utility values. With non-zero error components, $\xi_i' Z_{ij}$, utility becomes linked across options, allowing the IIA condition to be relaxed. An MXL model may reflect differences in individuals' utility functions by allowing *a* to vary. Each individual has a unique value for α, which implies that each individual may have a distinct weighting for each characteristic. An MXL model takes into account the individual differences in taste.

3.3.3 Latent Class model (LCM)

As for other models for the study of choice behavior, the LCM is also based on McFadden's (1974) RUT. The LCM is developed from the Multinomial Logit model that incorporates latent classes, often known as latent segments or groups. Greene and Hensher (2003), for example, provide detailed explanations of the concept, as does Train (2009). A limited and defined number of segments is used to calibrate segment-specific sets of parameters using the LCM, and the likelihood of respondents allocated to a class is a probabilistic function based on individual characteristics. If individual i belongs to segment s and performs a utility function for attribute j, the following is the expression for the utility function:

$$\mathrm{U}_{\mathrm{ij|s}} = \alpha_{\mathrm{s}} + \beta_s' Z_{ij} + \varepsilon_{ij|s} \qquad (9)$$

where α_s denotes an unknown parameter vector for segment s; Z_{ij} is a vector of alternative-dependent characteristics; β_s is a vector of segment-specific parameters to be estimated; and $\varepsilon_{ij|s}$ represents the utility function's random error. The likelihood of person i selecting attribute j is calculated using the LCM as follows:

$$P_i(j) = \sum_{s=1}^{s} P_i(j|s).\, M_i(s) \qquad (10)$$

Where

$$P_i(j|S) = \frac{e^{\alpha_s + \beta_s' Z_{ij}}}{\sum_{j' \in C_i} e^{\alpha_s + \beta_s' Z_{ij'}}} \qquad (11)$$

$$M_i(S) = \frac{e^{(\gamma_s' Z_i)}}{\sum_{s=1}^{s} e^{(\gamma_s' Z_i)}} \qquad (12)$$

Where the segmentation vector Z_i represents individual socioeconomic characteristics; and γ_s is a vector of segment-specific parameters ($\mathrm{s} = 1,2. \ldots, \mathrm{S}$). The likelihood of selecting attribute j is composed of two components. The multinomial logit model is used to calculate the choice probability inside the segment $P_i(j|S)$, and the choice set C_i comprises a set of alternatives that includes attribute j. $M_i(S)$ is the likelihood of respondent i belonging to segment s (i.e., the segment membership function), which utilizes a standard logit formulation based on respondent demographics. To facilitate identification, one of the segments' coefficients of segment membership is normalized to 0.

To estimate segment membership functions, socioeconomic and demographic factors must be specified. Following that, each responder is allocated to one of the segments based on their highest percentage. Finally, the size of each section may be determined, as well as the characteristics of the respondents inside each sector. The models may aid in comprehending each class's perspectives, preferences, attitudes, and knowledge. Additionally, the Latent Class modelling findings are readily understandable by the general public and policymakers.

3.3.4 Expected WTP estimation

Estimates of WTP for different levels of RE shares and different types of RE were calculated using the results of the conditional logit. The utility function of households can be expressed as follows:

$$V_j = ASC_J + \beta_1 REshare_j + \beta_2 Wind_j + \beta_4 Biomass_j + \beta_5 Price_j \quad (13)$$

Where V_j is the utility of choice set *j*. *ASC* is a variable to capture consumers' preferences towards proposed conditions; *cost* is the increase of monthly electricity price which should be negative, suggesting a utility decrease. $REshare_j$ is the share of RE among total electricity production of choice set j , which is expected to positively correlate with consumers' utility.; $Wind_j$ and $Biomass_j$ are dummy variables that represent RE types of choice set j; and WTP_j represents the percentage of increasing monthly electricity bills. Solar is considered the status quo in the model.

$$WTP_j = -\frac{\beta_1(REshare_j - REshare_{sq}) + \beta_2 Wind_j + \beta_3 Biomass_j}{\beta_5} \quad (14)$$

To examine WTP for a change in RE from sq to j at different $REshare$ levels, $REshare_j$ = 10%, 15%, 25% and 35% are determined by using the above function (14). It is noticeable that in order to construct a valid WTP metric, both characteristics must be statistically significant.

Chapter 4
Results

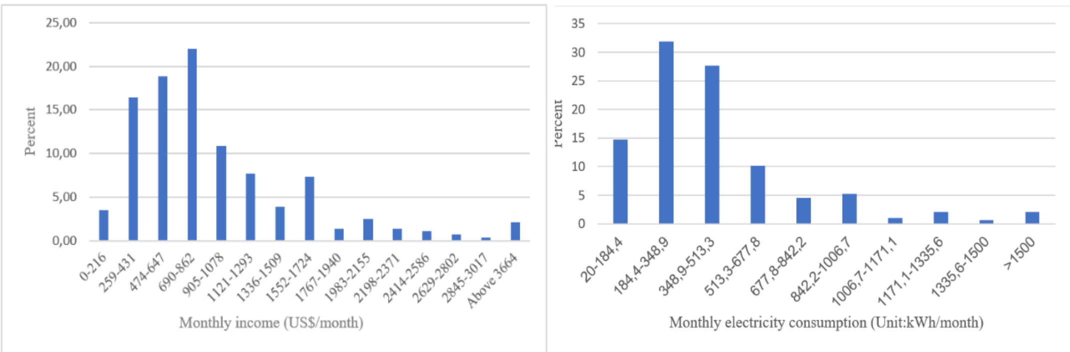
The survey was conducted over two months, from May to July 2020. The final sample utilized in the study included 286 respondents, each of whom provided answers to 7-8 completed choices, resulting in 6,708 observations (286 respondents × 7/8 choices x 3 alternatives for each choice). Stata software was used to analyze descriptive statistics and estimate econometric models.

4.1 Descriptive results

Figure 4.1 illustrates the allocation of monthly electricity consumption and income achieved by 286 Vietnamese households. Overall, the distribution of monthly electricity consumption follows a similar pattern to the distribution of monthly income in the examined geographical region. According to descriptive statistics from Table 4.1, the average income is more than 935 USD/month. In particular, the highest allocation of income (approximately 22% of the whole figure) ranks from 690-862USD. Whereas the percentage of households exceeding 1,760 USD/month is finite, accounting for under 2%; meanwhile, the other concentrations of income range from 4% to 18%.

Figure 4.1

Distribution of monthly income and electricity consumption



Source: Survey results (2020)

In terms of monthly electricity consumption, the highest range of electricity usage is from 184 to 350 kWh/month, which makes up a third of the population. This is followed by groups of 350-510 and 20-185, reporting about 27% and almost 15%, respectively, and 10% of electricity users consuming 515 to 680 kWh/month. The percentage of consumers using more than 680 kWh/month is less than 5%. Moreover, if the average monthly electricity consumption is about 485 kWh/month, the mean value of the bill that households need to pay is 52 USD/month.

Table 4.1

Descriptive statistics results of demographic and socio-economic variables.

Variable	Description	Obs	Mean	Std. Dev	Min	Max
Income	*The total monthly income of household (USD/month)*	286	935.16	683.03	107.76	3771.55
Gender	*1 = male, 2 = female*	286	1.71	0.45	1	2
Edu	*1=Under primary school,* *2=Primary school,* *3=Secondary school,* *4=Highschool,* *5=College,* *6=University,* *7= Master degree or higher*	286	3.85	1.41	1	7
Age	*Age of respondent*	286	44.10	1.37	20	86
HH members	*Number of family members*	286	4.71	2.16	1	15
Home_people	*Number of members regularly staying home during daytime*	286	2.22	1.61	0	15
Ownership	*1=Owned house,* *2= Rented house,* *3= Relatives' house without rent*	285	1.21	0.52	1	3
Business	*Run a business. 1=Yes, 0=No*	286	1.58	0.49	0	1
Outage	*Times of power outage per year*	286	1.70	4.97	0	60
Appliances	*Number of appliances*	285	32.48	2.38	8	312

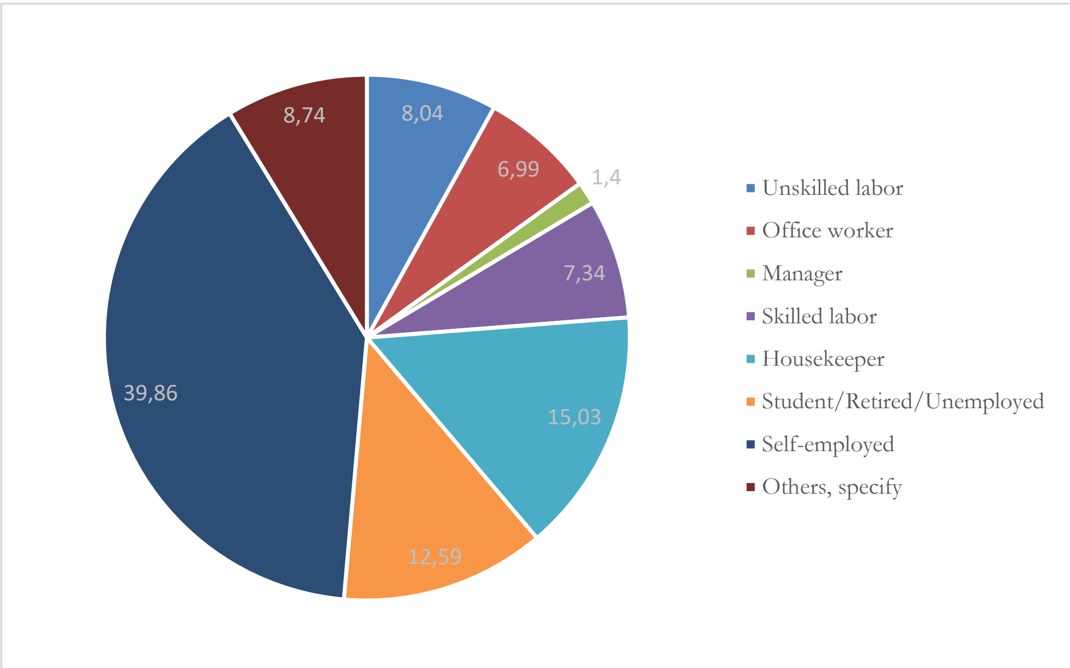
Source: Survey results (2020)

Table 4.1 depicts the demographic and socio-economic characteristics of respondents and households. The age of respondents is between 20 and 86. Of the 286 respondents, 82 are male, accounting for 29%. In terms of education, about 10% have primary schooling; the number of consumers enrolling in secondary school and high school is equal, making up 28% each; around 19% are bachelor's degree holders, approximately double the number of people who have college; under 4% each have a master's degree or higher and under primary school. About 85% of the 286 respondents live in their own homes, while the proportion of households residing in rented houses is 15%, and 5% for those staying rent-free in relatives' homes. Each household usually has 4-5 members, close to the average number of families in HCMC. Based on data statistics from Table 4.1, there will be two people, on average, often at home during the daytime. Furthermore, about 42% of the total surveyed households are running a business. In particular, being the owner of a grocery, restaurant, coffee shop, or household manufacturing plant is the most popular business. The number of electronic appliances in households ranges from 8 to 312, with an average of 32 items/household including, but not limited to, LED light bulbs, fans, air conditioners, electric cookers, TVs, computers, refrigerators, microwaves, dishwashers and clothes dryers. Depending on interviewing areas, households experience different frequencies of power outages per year, ranging from 0-60 times per year. However, most households will encounter power outages on average twice a year.

Figure 4.2 shows the share of typical occupations of respondents in the survey on electricity consumption. The majority of interviewees are self-employed (almost 40%). The housekeeper role takes second place, making up 15%, followed by students/retired/unemployed, at about 13%. The allocations of office workers, unskilled labor, skilled labor, and other occupations (e.g., freelancers, drivers, baby sisters, translators) are relatively similar, ranging from 7 - 9%. Meanwhile, only 1.4% of respondents hold management positions.

Figure 4.2

Respondents' occupation percentages



Source: Survey results (2020)

4.2 Attitudes toward environmental issues

HCMC citizens have encountered various environmental problems, as detailed in Table 4.2. The top three issues are considered as the most urgent and important, including air pollution (36.01%), flooding (17.83%), and solid waste management (17.83%). In addition, some people are concerned about contamination of groundwater and surface water, global warming, and climate change, ranging from 5-7%. Meanwhile, the percentage of respondents preoccupied with water shortages, hazardous waste from industries, noise, and electricity shortages are reported at less than 4%. In addition, interviewees mentioned other environmental matters such as traffic congestion in rush hours or narrow alleys causing bottlenecks.

Table 4.2

Environmental issues considered as issues of importance

	Environmental issues	Most important		Second important	
1.	Air pollution	103	(36.01%)	44	(15.38%)
2.	Groundwater contamination	18	(6.29%)	41	(14.34%)
3.	Solid waste management	43	(15.03%)	50	(17.48%)
4.	Flooding	51	(17.83%)	33	(11.54%)
5.	Surface water contamination	19	(7%)	18	(6%)
6.	Noise	2	(1%)	4	(1%)
7.	Hazardous waste from industries	12	(4%)	33	(11.54%)
8.	Water shortage	11	(4%)	9	(3.15%)
9.	Electricity shortage	8	(2.8%)	12	(4.2%)
10.	Global warming and climate change	16	(5.59%)	37	(12.94%)
11.	Others	3	(1.05%)	4	(1.4%)

Source: Survey results (2020)

Table 4.3 presents respondents' perspective statements on environmental issues and electricity. Statistical results of survey data through the application of a 6-level scale to assess the perception of electricity users on environmental issues and electricity consumption according to suggested levels.

In general, the majority of respondents strongly agree with almost all statements asked during the interview. The specific statistics for each statement are as follows: *"Installing a solar panel system helps reduce the heat of the house"* (40.21%), *"the government should provide electricity below cost to all households"* (67.83%), *"households installing a solar panel system help reduce the dependence on electricity produced by coal and hydropower*" (56.29%), *"I don't care whether it is an electricity grid or a solar panel system, I would use the one that is less costly"* (46.5%), *"I'm very concerned about global warming and climate change"* (77.27%) and *"the government should purchase solar power at a higher price"* (25.87%), which has a similarity to the perspective *"neither agree nor disagree in the same statement."* Besides, the percentage of respondents in somewhat disagreement and strong disagreement with those statements mentioned above is not significant.

However, roughly 38% and 66% are significantly less willing to pay more for electricity if there are fewer blackouts and that the government should provide electricity at a higher price to encourage electricity saving practices, respectively. Meanwhile, the remaining shares, including "*Agree somewhat," "Neither agree nor disagree" and "Don't know"* fluctuate under 25%.

Table 4.3

Respondent's perspective about statements regarding to environmental issues and electricity

	Very Environmen-tally Friendly	Environmentally Friendly	Not sure	Environmentally Unfriendly	Very Environmentally Unfriendly
Solar power	**145** (50.70%)	**119** (41.61%)	**18** (6.29%)	**4** (1.40%)	**0** (0%)
Wind power	127 (44.41%)	119 (41.61%)	34 (11.89%)	6 (2.10%)	0 (0%)
Biomass power	43 (15.03%)	86 (30.07%)	108 (37.76%)	45 (15.73%)	4 (1.40%)

Source: Survey results (2020)

Table 4.3

Respondent's statement about RE sources

Statement	Don't know	Strongly agree	Agree somewhat	Neither agree nor disagree	Disagree somewhat	Strongly disagree
. Installing SPS helps reduce heat of the house	42 (14.69%)	115 (40.21%)	69 (24.13%)	40 (13.99%)	13 (4.55%)	7 (2.45%)
. Government should purchase solar power at a higher price.	51 (17.83%)	74 (25.87%)	31 (10.84%)	75 (26.22%)	27 (9.44%)	28 (9.79%)
. Government should provide electricity below costs to all HHs	9 (3.15%)	194 (67.83%)	31 (10.84%)	23 (8.04%)	17 (5.94%)	12 (4.2%)
. Households installing SPS helps reduce the dependence on the electricity produced from coal and hydropower	18 (6.29%)	161 (56.29%)	73 (25.52%)	24 (8.39%)	6 (2.1%)	4 (1.4%)
. I don't care whether it is an electricity grid or solar panel system, I would use the one that is less costly	12 (4.2%)	133 (46.5%)	58 (20.28%)	36 (12.59%)	34 (11.89%)	13 (4.55%)
. I am willing to pay more for electricity if there are fewer blackouts	9 (3.15%)	42 (14.69%)	29 (10.14%)	25 (8.74%)	72 (25.17%)	109 (38.11%)
. The government should provide electricity at a higher price to encourage electricity saving practices	13 (4.55%)	16 (5.59%)	14 (4.9%)	17 (5.94%)	37 (12.94%)	189 (66.08%)
. I'm very concerned about global warming and climate change	8 (2.8%)	221 (77.27%)	39 (13.64%)	11 (3.85%)	3 (1.05%)	4 (1.4%)

Source: Survey results (2020)

It is assumed that statements about RE sources might influence their WTP decision. The respondent's statement about RE sources is shown in Table 4.4. Solar power is the most well-known RE source in Vietnam (Table 4.5). More than half of the responses state that solar energy is very environmentally friendly. A significant percentage of interviewees agree that renewable electricity generated from solar is an environmentally friendly product (41.61%). Around 6% of the population is not sure about the contribution of solar power to the environment. Few respondents suppose that solar energy has a negative effect on the environment, accounting for only 1%.

Similarly, in the distribution of statements between solar energy and the environment, the statement that wind power is very environmentally friendly dominates at 44.41%, followed by the statements *"environmentally friendly"* (41.61%) and *"not sure"* (11.89%). It is reported that under 2% of consumers think that wind energy is environmentally unfriendly.

The final type of energy in this study is biomass energy. This type of energy makes a significant contribution to the reduction of environmental pollution because it is generated by using the waste of agroforestry products such as straw, bagasse, bark, corn fiber, dried leaves, wood chips, shredded paper, or methane from landfills, wastewater treatment stations, and manure from cattle and poultry farms. However, biomass energy is still very unfamiliar to HCMC citizens. Therefore, electricity consumers predominantly state that they are not sure about the influence of this energy source on the environment, accounting for 37.76%. Meanwhile, a surprising number of respondents answer that biomass is environmentally unfriendly (15.73%). Besides, few individuals reveal a stronger response to this negative impact. Only 15% of the population is aware that biomass power is a very environmentally friendly product, which is half that of the environmentally friendly statement.

4.3 Knowledge of electricity consumers about RE resources

Table 4.4

Comprehension of respondents about RE sources

Knowledge of energy	**Yes**	**No**
Solar	91.96%	8.04%
Wind	69.93%	30.07%
Biomass	18.18%	81.82%

Source: Survey results (2020)

Regarding knowledge of RE, the descriptive statistics report that some electricity consumers seem to be more familiar with solar energy than others. It accounts for 92% of the whole population, while the popularity of wind power takes second place, at almost 70%. However, people's knowledge of biomass energy is quite limited. Only 18% out of 286 have heard of this energy source.

4.4 Estimation results

4.4.1 Estimation results of Conditional Logit model

The attributes of RE influencing consumers' utility are analyzed by the RUM model and estimated by the CLM. This research estimates two variants of this model. In particular, the standard CLM model includes only RE characteristics, while the CLM with interaction integrates socio-economic variables into the estimation model. Noticeably, these variables cannot be included directly in the CLM because they do not change between the alternatives. The only way to introduce socio-economic characteristics into the model is to interact with attributes or ASC.

Individuals with higher incomes or monthly electricity bills may react differently to cost levels. Hence, income and bills are interacted with the attribute cost and are added to the model. By contrast, with the popularity of solar energy in Vietnam, the information and understanding about wind energy and biomass is still very limited. Therefore, knowledge about wind and biomass energy is interacted with attributes types of energy sources expected a positive interaction. As the results from previous studies, variables incomes, running a business or having more rooms affect consumers' preferences for RE. Thus, the interaction between these variables and the attribute share will be included in the model. In addition, to further analyze the impact of socio-economic attributes on the utility of electricity consumers, the RUM model, analyzing the impact of RE attributes, will add interaction variables between ASC and educational level, experience of electricity outages, total number of electronic appliances in the household, number of family members regularly staying home during the daytime, as well as gender and age of respondents.

Table 4.6 presents the estimated results of the CLMs. In general, the estimated coefficients are mostly significant and relatively identical in the two models, showing the stability of the results. Moreover, the signs of the cost and share coefficients give relatively similar results to previous studies (Gracia *et al.*, 2012; Komarek *et al.*, 2011; Yoo and Ready, 2014).

In the basic model, four of five attributes are highly and statistically significant. Particularly, the sign of cost and the kinds of RE are negative parameters, revealing that the utility of electricity consumers is inversely proportional to expenses and that consumers prefer solar energy to other ones. The coefficient of ASC is also negative in this model, implying that respondents prefer RE. However, this variable is not statistically significant. Meanwhile, only the increase in RE share yields positive utility to consumers.

In terms of the interaction model, all the attributes show significant parameters (1% significant level). The negative and significant parameter of attribute cost indicates that utility decreases as monthly electricity cost increases, which means that consumers wish to pay lower electricity costs. Furthermore, the coefficient of the interaction variable between cost and bill is negative and significant, which means that marginal disutility is higher (more negative marginal utility) for those with higher electricity bills. In other words, people who pay lower monthly electricity bills will be more concerned with cost. However, the interaction between cost and income is not statistically significant in the interaction model, showing no difference in the reaction to costs from individuals with various income levels. As expected, the positive and significant parameter of variable share exhibits that a rise in the percentage of shares per month will increase utility. In the model that includes socio-economic variables, the marginal utility of share is greater for those with higher incomes and families running a business. Attributes regarding diverse types of RE also affect respondents' utility. The negative and statistically significant coefficients of variable wind and biomass from Table 4.6 indicate that consumers prefer solar energy to wind and biomass energy. However, consumers tend to choose energy produced by wind if they have information about this energy, whereas this is not true in the case of biomass energy, which does not impact consumers' preferences for RE.

Similarly, ASC term is interacts with various socio-economic characteristics. The results are as follows: older people prefer to maintain the status quo, indicating that older people will not favor RE as much as younger people. It appears that RE usage might help to maintain the stability of the electricity used. However, the estimated results of this research indicate that individuals living in their own homes, which are located in areas with frequent power outages or with many people at home during the day are not likely to favor the increase in RE share. On the other hand, the influence of gender and the more electronic appliances in households are somewhat limited. These factors do not change consumers' preferences for RE. The presented result from Table 4.6 includes separate levels of education coded as dummy variables. In this analysis, under primary school level as a base category, those who attended primary school, secondary school, college and university prefer RE. Otherwise, holding a high school degree and a master's or higher degree does not impact respondents' increasing RE share.

Table 4.5

Regression results of CLM

Variables	Standard CLM	CLM with interaction
Cost (%monthly bill)	-0.138***	-0.135***
RE share (%)	0.047***	0.031***
Renewable energy types (Base category = Solar)		
wind	-0.252***	-0.921***
biomass	-0.357***	-0.381***
ASCSQ	-0.005	-0.888**
Interaction variables		
ASC*[Primary school=1]		-0.358**
ASC*[Secondary school=1]		-0.183**
ASC*[Highschool=1]		0.040
ASC*[College=1]		-0.181***
ASC*[University=1]		-0.134***
ASC*[Master degree or higher=1]		-0.088
ASC*[Outage=times]		0.098***
ASC*[Appliances=units]		-0.003
ASC*[people at home = persons]		0.190***
ASC*[male=1]		-0.103
ASC*[Age=years]		0.012***
ASC*[Owned house=1]		0.305**
Share*[income=USD/month]		0.000***
Share*[business=1]		0.014***
Cost*[income= USD/month]		0.000
Cost*[bill=USD/month]		-0.0002**
WIND*[Knowledge=1]		0.991***
BIOMASS*[Knowledge=1]		0.277
Obs	6,708	6,663
No. of households	286	286
Log-likelihood	-1926.241	-1790.773

Notes: * p<0.1, **p<0.05, ***p<0.01

4.4.2 Estimation results of Mixed Logit model

By estimating the extent to which electricity users varying preferences for RE resources, the MXL provides more information than the traditional logit. The parameter standard deviations are highly significant, suggesting that an MXL represents the choice scenario better than a conventional logit, which assumes that all respondents' coefficients are the same. The MXL models use simulation-based estimate methods, and the number of Halton draws reflects the number of distinct MXL simulation runs. For minimizing simulation-induced variation, it is critical to perform simulations large enough. The simulation was performed using 500 random draws to ensure a robust output (Ryan *et al.*, 2012).

Table 4.7 presents the estimated results of the MXL model regarding the utility of electricity consumers for RE. The coefficients reflect the utility for each level of characteristics in the choice experiment. The standard deviations represent heterogeneity of preferences. It is assumed that different respondents have different marginal utility for money, share, and the types of RE. Ultimately, the estimated coefficients of the cost, share, and ASC attributes are assumed to be random variables in this model, which means that the standard deviations of these coefficients are estimated simultaneously with their means. The estimated coefficients of the other attributes (wind and biomass) after the regression test found that their standard deviations are less than zero, so they should be better at a fixed parameter rather than assumed to be random ones.

Overall, the estimated standard deviations of coefficients are highly significant, suggesting that parameters vary throughout the population. Furthermore, the probability that the ratio index increases significantly when the parameters are varied shows that the MXL has much higher explanatory power than the conventional logit model. The estimated results of MXL are similar to that of CLM. Most respondents prefer RE originating from the sun to wind and biomass.

The signs of coefficient disclosure that the utility of electricity users correlates positively with the expansion of the RE share and negatively with the additional payment on the monthly electricity bill. However, it should be noted that if the ASC term does not witness statistical significance in the standard model, its coefficient shows a negative and statistically significant value in the MXL model. The distribution of the coefficient of ASC obtains an estimated mean of -1.098 and an estimated standard deviation of 4.428, such that RE resources are preferred by 60% of consumers. In comparison, around 40% of consumers prefer the status quo, indicating that they reject increasing the share of RE to more than 7% as well as the rise in monthly bills. Meanwhile, the cost coefficient yields an estimated mean of -1.092 and an estimated standard deviation of 0.853, meaning that 90% of the population has a utility that declines when costs increase, implying that the majority of respondents' utilities are influenced by cost fluctuations. Only under 10% of the population is not affected by the increase in electricity costs. In terms of the share attribute, which has an estimated mean of 0.095 and a standard deviation of 0.071, which suggests that a rise in the percentage of shares per month will increase the utility of 91% of the population, whereas only 9% of the distribution is below zero, showing a negative interaction.

Table 4.6

Regression results of MXL and LCM with 2 classes

Variables	MXL model		LCM2		LCM2-SE	
	Mean	*SD*	*Class1*	*Class2*	*Class1*	*Class2*
Utility function						
Cost (%monthly bill)	-1.092***	0.853***	-0.275***	-0.171***	-0.279***	-0.172***
RE share (%)	0.095***	0.071***	0.076***	0.070***	0.078***	0.070***
Renewable energy types (Base category = Solar)						
wind	-0.323**		-0.813***	0.008	-0.829***	0.024
biomass	-0.487***		-0.993***	-0.156	-1.009***	-0.149
ASC	-1.098***	4.428***	1.136***	-2.023***	1.181***	-1.973***
Membership functions						
[Primary school=1]					-0.345	-
[Secondary school=1]					-0.200	-
[High school=1]					0.150	-
[College=1]					-0.123	-
[University=1]					-0.063	-
[Master degree or higher=1]					-6.718	-
[Male=1]					-0.051	-
[Age=years]					0.015	-
[Income=USD/month]					-0.000	-
[Business=1]					-0.337	-
[Solar knowledge=1]					0.020	-
[Wind knowledge=1]					-0.833**	-
[Biomass knowledge=1]					-1.063**	-
[Outage=times]					0.130**	-
[Appliances=units]					-0.003	-
[People at home=1]					0.197*	-
[Owned house = 1]					0.753*	-
Constants			0.158		-0.511	
Class Share			0.539	0.461	0.531	0.469
Log-likelihood	-1299.0425		-1416.453		-1376.430	

Notes: * p<0.1, **p<0.05, ***p<0.01

4.4.3 Estimation results of Latent Class model

Table 4.7 displays the results of the two-segment LCM. The initial LCM panel, known as LC2, does not contain variables, while the second panel, LC2-SE, adds socioeconomic variables in the membership function. The latter model in the LC with sociodemographic variables is normalized to zero, allowing identification of the model's residual coefficients (Boxall and Adamowicz, 2002). As expected, the estimated utility functions of both models are relatively similar, except for the parameter of the ASC term, the effect on utility varies between the two segments, both in size and sign. Since both models yielded almost identical interpretations, only the model with sociodemographic variables is presented in the following. Table 4.7, LCM2-SE results, shows that all tested attributes are significant determinants in both classes, except wind and biomass in segment 2.

cost: In line with economic theory, in all cases, *cost* has a statistically significant coefficient, indicating that members of both segments prefer RE with lower costs, but Class 1 has the strongest sensitivity to cost.

ASC: The ASC term is the most significant variable in both segments, with the greatest absolute magnitude. Segment one has a positive ASC sign, suggesting that customers like the status quo. Whereas that of segment 2 is negative, suggesting that members favor RE profiles above current consumption.

wind and biomass: Two types of RE, namely wind and biomass, are not as important as solar energy for class 1 since all coefficients are negative and statistically significant. For class 2, these kinds of energy are not as statistically significant as for class 1 members, suggesting that consumers value solar energy less than class 1 and put no utility on wind and biomass energy.

RE share: In general, for all classes, the coefficients of share are positive and statistically significant, although this impact is pretty small, especially for class 1 of consumers, whose members are minimally more concerned about the percentage of share than class 2.

Using this procedure, consumers are allocated to a segment based on the greater of the two likelihood ratings. Model LCM2-SE categorizes electricity consumers into two segments (1 and 2) with the proportions of 53.7 and 46.3 respectively. For segment 1, the utility coefficients reveal that the percentage of share has a positive connection with the customer's utility, the most preference for solar energy, followed by wind and biomass, and members of this class have less sensitivity to cost. The membership coefficients for segment one indicate that these consumers are living in their own homes, are not likely to get information about wind and biomass energy, encounter increasing times of experience in electricity outages, and there are more people regularly staying at home during the daytime. In the second segment, by comparing the signs of the statistically significant parameters calculated for the other segment, the membership coefficients for segment two may be understood implicitly. Consumers are less sensitive to the cost, have a lower share of the impact of utilities, value solar energy less than segment 1, and put no utility on wind and biomass energy. They are more likely to belong to this segment, as are customers staying in rented houses or relatives' houses without rent, those who have heard of wind and biomass energy, and those who live in an area with a stable electricity network and few people at home during the daytime. Meanwhile, there is no influence from income, gender, age, running a business, the total number of electronic appliances, and education on classification, implying that these variables do not change the preference of consumers for RE.

4.4.4 Estimation results of WTP for RE

The mean value of the bill that households need to pay is 52 USD/month. Table 4.7 shows the estimation of marginal WTP in the percentage of monthly electricity bills when the share of RE increases by 3%, 8%, 18%, and 28% from the initial percentage at 7%. This result is calculated from the CLM. The estimated results in Table 4.5 of the standard CLM and CLM with interaction are relatively similar. However, the ASC variable has no significance in the former model while showing a negative and significant coefficient in the latter one. Noticeably, computation of WTP requires statistical significance of included parameters. Therefore, the CLM with interaction model seems to be better for WTP calculation.

It appears that RE share is an influential attribute when households evaluate RE types. Overall, households prefer a higher renewable proportion in the electricity mix, and moreover, electricity consumers reveal the highest WTP for solar energy.

Table 4.7

WTP estimates for RE types in % of monthly electricity bill

RE share increases[2]	Solar % monthly electricity bill *(USD)*	Wind % monthly electricity bill *(USD)*	Biomass % monthly electricity bill *(USD)*
By 3%	14% (7.28)***	0.85% (0.44)	8.56% (4.45)*
By 8%	16.19% (8.42)***	3.06% (1.59)	10.75% (5.59)**
By 18%	20.60% (10.71)***	7.44% (3.87)	15.15% (7.88)***
By 28%	25% (13.00)***	11.85% (6.16)**	19.56% (10.17)***

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

The value of WTP for solar energy is highly and statistically significant in all levels of share increase (at the 1% significance level). In particular, respondents are willing to pay an extra 7.28 USD, which accounts for 14% of the monthly electricity bill, for an increase of 3% in solar energy share, compared to 16.19% (8.42 USD/month) for a RE share rise of 8% and 20.6% (10.71 USD/month) for a solar share increase of 18%. Meanwhile, the WTP for an increase of 28% in solar power share is 13 USD/month, lifting the monthly bill to 25%.

As can be seen from the results, wind energy seems to be the least preferred of the three types of RE. The WTPs for rises of 3%, 8% and 18% in wind electricity share are 0.44 USD/month, 1.59 USD/month and 3.87 USD/month respectively. However, these values are not statistically significant. By contrast, the remaining RE share generated from wind, which is statistically significant, including increases of 28%, is expected to pay 6.16 USD/month, respectively.

The WTP for Biomass energy takes second place because its WTP exceeds that of wind energy but is less than that of solar power. Consumers are willing to pay an extra 5.59 USD/month, equivalent to 10.75% of the monthly electricity bill, for a biomass energy share increase of 8%, which is approximately half of the highest growth. Meanwhile, the figures for share increases of only 3% and 18% are accounted for at 4.45 USD/month (8.56% of the monthly bill) and 7.88 USD/month (15.15% of the monthly bill), respectively.

[2] As the level of attribute share in the choice set, the current share of RE is 7%, which is expected to rise by 3%, 8%, 18% and 28%, corresponding to an increase from 7% to 10%, 15%, 25% and 35%, respectively.

Chapter 5
Conclusion and Limitations

5.1 Discussion and Conclusion

Measures to tackle climate change are an important and urgent issue today. Increased usage of RE is one method for nations to fulfill their reduction goals. The Vietnam Strategy of Renewable Energy Development to 2030 (IEA, 2016) commits to establishing the objectives of developing RE to lessen CO_2 emissions by 5% in 2020 and 25% in 2030. This will contribute to the mitigation of global warming and sea-level rise. Consequently, policymakers' interest in household adoption of RE has risen, resulting in an increase in the number of scientific papers that assess public willingness to pay for RE.

The objective of this research is to adopt DCE to estimate the WTP of citizens for RE increase in HCMC and factors motivating preferences for RE. By using an electronic questionnaire survey, the data used for the independent variable only includes 286 electricity users living in HCMC, Vietnam in the customer list from EVN, collected by a simple sampling method. The present study distinguishes itself from previous ones by comparing WTP for share increases in a variety of RE sources (including solar, wind and biomass). Furthermore, socio-economic, demographic and awareness elements are included to evaluate their impact on electricity consumers' utility. This research attempted to quantitatively determine the factors that affect the utility of electricity consumers because improved user satisfaction could contribute to an expansion of the use of clean electricity in the long run. If the CLM assumes that choice questions measure utility equally well (or equally poorly) across all responses and choice tasks, the MXL model can overcome this limitation. On the other hand, if CLM does not account for unobserved systematic differences in preferences across responses, a limited and defined number of segments is used to calibrate segment-specific sets of parameters using the LCM, and the likelihood of allocated responses to a class is a probabilistic function based on individual characteristics. The statistical and regression examination of the data reveals several summaries:

As its advantages, LCM can estimate different utility functions for separate groups and classify individuals into specific groups based on socioeconomic variables. MXL cannot explain which determinants motivate the difference in preferences but measures the utility function for each individual instead of a group. Therefore, MXL explains better than LCM in comparison. It is straightforward from the values of log-likelihood amongst models given in results that MXL should be the best model amongst others. Relative similarities in all three models are shown through the estimated results, indicating that the research results are relatively reliable. The econometric analysis reveals that the types of RE, RE share in the electricity mix, and the increasing percentage of monthly electricity bills as three key characteristics are highly and statistically significant in the CLMs, MXL model and the first segment of LCM. In contrast, the types of RE are not statistically significant in segment 2 of this model. These factors help explain the actual variations in WTP across the population since WTP estimates cannot be directly compared without such information (Ma *et al.*, 2015).

In particular, the utility of electricity users correlates positively with the expansion of the RE share and negatively with the additional payment on the monthly electricity bill. Furthermore, individuals place a far greater value of WTP on solar energy than they do on wind and biomass energy. In addition, an explicit linear relationship is found between electricity consumers' WTP and the increase in RE share, which is identical to the findings of Murakami *et al.* (2015), Gracia *et al.* (2012) and Komarek *et al.* (2011). Moreover, the results of WTP estimation reveal that respondents are willing to pay more for solar energy than they are for wind and biomass energy, similar to the finding of Gracia *et al.* (2012). In that view, the WTP for solar energy over other RE sources may be anticipated since solar panel systems are widely utilized at the home level. Hence, families are likely to be better acquainted with solar energy and the viability of its adoption. More studies are needed, however, to verify this assumption and evaluate the motivating reasons behind support for solar energy. On the other hand, although Komarek *et al.* (2011) showed that respondents are willing to pay a fee for an additional percentage increase in RE, not solar energy as in the current research and some previous literature, wind energy appears to be slightly more preferable than solar for interviewees. Noticeably, the finding of the current research also indicates that the WTP for RE generated from biomass exceeds that from wind. However, knowledge of wind energy is more widespread than biomass through statistics, implying a huge potential for the development of biomass energy projects.

As a result of the XML model, RE resources are preferred by 60% of consumers. In comparison, around 40% of consumers prefer the status quo, indicating that they reject increasing the share of RE by more than 5%. The majority of respondents' utilities are generated by electricity price fluctuations. Less than 10% of the population is not affected by the increase in electricity prices. In terms of the share attribute, this suggests that a rise in the percentage of shares per month will increase the utility of 91% of the population, whereas only 9% of the distribution is below zero, showing a negative interaction.

On the other hand, there are only two types of respondents classified in LCM: The first segment consists of those who have a positive connection between an increase in RE share and customer's utility, while the greatest preference is for solar energy, followed by wind and biomass, and members of this class have less sensitivity to cost. The membership coefficients for segment 1 indicate that these consumers are living in their own homes, are not likely to get information about wind and biomass energy, encounter increasing times of experience in electricity outages, and there are more people regularly staying at home during the daytime. In the second segment, consumers are less sensitive to the cost, have a lower share of the impact of utilities, value solar energy less than segment 1, and put no utility on wind and biomass energy. They are more likely to belong to this segment, as are consumers staying in rented houses or relatives' houses without rent, those who have heard of wind and biomass energy, and those who live in an area with a stable electricity network and few people at home during the daytime.

Several socio-demographic factors are found to influence respondents' preferences. The total number of power outages, the total number of people who are often at home during the day, and ownership and awareness of RE are statistically significant. Although the variables education, gender, age and business variables were statistically significant in previous studies, these variables had no impact on consumer preferences for RE in the present study. Noticeably, as mentioned in the literature review, almost all research shows that people with higher incomes will be willing to pay more for RE, but the parameter of this variable from LCM and from the CLM, interacted with the price variable with the expectation that people with lower incomes would be more sensitive to price increases, in this study shows no relationship between preference for clean energy and income. Based on the results of the LCM model to explain this, electricity consumers are divided into two main groups, comprising those who prefer all types of RE (group 1) and those who only reveal a preference for solar energy (group 2). Therefore, it is concluded that respondent preference for RE in the current study depends on the type of RE rather than their income. Another interpretation is that the cost attribute is the percentage increase in monthly electricity bills, not a specific value. Therefore, the different income levels of respondents cannot be shown through proportion.

5.2 Limits of the study

Finally, as with any other type of research, this one has some limitations. First, although the research findings may apply to other emerging areas with comparable demographics, locations with distinct economic and housing factors may consider modifying the survey design. Second, since this study represents a snapshot of environmental and energy views, the results are temporary benchmarks that must be updated periodically. WTP for RE questions may be processed without long survey narratives as householders get familiar with the distribution of RE sources. A final caution is that the object of this study is the household, while households account for a very small share of the nation's electricity consumption. In contrast, the problem of environmental pollution is caused by industrial zones, which consume most of the country's electricity. Besides the consumption of electricity and the need for sustainable stability of the power source from residential areas, these necessities are also required for companies, schools and hospitals, and so on. Therefore, future studies should focus on these subjects and on rectifying these inherent limitations.

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Appendices

Appendix 1 Stata analysis

1.1 Demographic variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Income	286	935.164	683.0304	107.7586	3771.552
male	286	.2867133	.4530192	0	1
Edu	286	3.853147	1.409034	1	7
Age	286	44.1014	13.67647	20	86
HHnumbers	286	4.706294	2.159702	1	15
Home_people	286	2.216783	1.607613	0	15
ownership	286	1.545455	.5458266	1	3
Business	286	.4160839	.4937718	0	1
Outage	285	2.733333	2.547944	0	20

1.2 Household average income

What is the total monthly income of household members?	Freq.	Percent	Cum.
0-5 million VND	10	3.50	3.50
6-10 million VND	47	16.43	19.93
11-15 million VND	54	18.88	38.81
16-20 million VND	63	22.03	60.84
21-25 million VND	31	10.84	71.68
26-30 million VND	22	7.69	79.37
31-35 million VND	11	3.85	83.22
36-40 million VND	21	7.34	90.56
41-45 million VND	4	1.40	91.96
46-50 million VND	7	2.45	94.41
51-55 million VND	4	1.40	95.80
56-60 million VND	3	1.05	96.85
61-65 million VND	2	0.70	97.55
66-70 million VND	1	0.35	97.90
Above 85 mil. VND	6	2.10	100.00
Total	286	100.00	

1.3 Electricity consumption

Consumption	Freq.	Percent	Cum.
1	42	14.69	14.69
2	91	31.82	46.50
3	79	27.62	74.13
4	29	10.14	84.27
5	13	4.55	88.81
6	15	5.24	94.06
7	3	1.05	95.10
8	6	2.10	97.20
9	2	0.70	97.90
10	6	2.10	100.00
Total	286	100.00	

1.4 Knowledge of RE sources

Knowledge_SOLAR	Freq.	Percent	Cum.
0	23	8.04	8.04
1	263	91.96	100.00
Total	286	100.00	

Knowledge_WIND	Freq.	Percent	Cum.
0	86	30.07	30.07
1	200	69.93	100.00
Total	286	100.00	

Knowledge_BIOMASS	Freq.	Percent	Cum.
0	234	81.82	81.82
1	52	18.18	100.00
Total	286	100.00	

1.5 Occupation

What is your occupation?	Freq.	Percent	Cum.
Unskilled labor	23	8.04	8.04
Office worker	20	6.99	15.03
Manager	4	1.40	16.43
Skilled labor	21	7.34	23.78
Housekeeper	43	15.03	38.81
Student/Retired/Unemployed	36	12.59	51.40
Self-employed	114	39.86	91.26
Others, specify	25	8.74	100.00
Total	286	100.00	

1.6 The basis Conditional Logit model

```
Conditional (fixed-effects) logistic regression

                                                Number of obs     =      6,708
                                                Wald chi2(5)      =     560.84
                                                Prob > chi2       =     0.0000
Log pseudolikelihood =  -1926.241               Pseudo R2         =     0.2159

                                    (Std. Err. adjusted for clustering on task)
```

choice	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
price	-.1382868	.0071607	-19.31	0.000	-.1523215	-.1242521
share	.0474054	.0039185	12.10	0.000	.0397253	.0550855
wind	-.2523495	.0861277	-2.93	0.003	-.4211567	-.0835423
biomass	-.357429	.0894296	-4.00	0.000	-.5327078	-.1821503
ASCSQ	-.0051743	.096504	-0.05	0.957	-.1943186	.18397

1.7 The Conditional Logit model with interaction

```
Conditional (fixed-effects) logistic regression

                                                Number of obs     =      6,663
                                                Wald chi2(23)     =     669.24
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -1790.7725               Pseudo R2         =     0.2661

                                    (Std. Err. adjusted for clustering on task)
```

choice	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ASCSQ_Outage	.0979286	.0217614	4.50	0.000	.055277	.1405801
ASCSQ_Appliances	-.0032881	.0026604	-1.24	0.216	-.0085024	.0019262
ASCSQ_Home_people	.190034	.0374911	5.07	0.000	.1165529	.2635151
ASCSQ_male	-.1027518	.114273	-0.90	0.369	-.3267228	.1212191
ASCSQ_Age	.011644	.0041589	2.80	0.005	.0034928	.0197952
ASCSQ_Ownedhouse	.3054984	.1492343	2.05	0.041	.0130046	.5979921
share_income	.0000154	5.11e-06	3.00	0.003	5.33e-06	.0000254
share_business	.0144117	.0052185	2.76	0.006	.0041837	.0246397
price_income	-7.49e-08	.0000104	-0.01	0.994	-.0000205	.0000204
price_bill	-.0002108	.0000971	-2.17	0.030	-.0004011	-.0000204
W_Knowledge_WIND	.9906028	.1662222	5.96	0.000	.6648132	1.316392
B_Knowledge_BIOMASS	.2766937	.2093163	1.32	0.186	-.1335587	.6869462
ASCSQ_Edu2	-.3579589	.1424361	-2.51	0.012	-.6371285	-.0787892
ASCSQ_Edu3	-.182809	.0866976	-2.11	0.035	-.3527332	-.0128848
ASCSQ_Edu4	.0402996	.0661757	0.61	0.543	-.0894025	.1700016
ASCSQ_Edu5	-.180553	.0602841	-3.00	0.003	-.2987077	-.0623982
ASCSQ_Edu6	-.1342923	.047883	-2.80	0.005	-.2281412	-.0404433
ASCSQ_Edu7	-.0877373	.1079785	-0.81	0.416	-.2993713	.1238968
price	-.1347702	.0120157	-11.22	0.000	-.1583206	-.1112198
share	.0308267	.0067471	4.57	0.000	.0176026	.0440507
wind	-.9214182	.1522884	-6.05	0.000	-1.219898	-.6229385
biomass	-.3811011	.0984237	-3.87	0.000	-.574008	-.1881941
ASCSQ	-.888489	.3500601	-2.54	0.011	-1.574594	-.2023837

1.8 Mixed Logit model

```
Mixed logit model                                  Number of obs     =      6,708
                                                   LR chi2(3)        =    1254.40
Log likelihood = -1299.0425                        Prob > chi2       =     0.0000
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Mean						
wind	-.3231537	.1336328	-2.42	0.016	-.5850691	-.0612382
biomass	-.4869314	.1291122	-3.77	0.000	-.7399867	-.2338761
share	.0948485	.0088255	10.75	0.000	.0775508	.1121462
ASCSQ	-1.097999	.3399833	-3.23	0.001	-1.764354	-.4316442
mprice	-1.091756	.0979318	-11.15	0.000	-1.283699	-.8998131
SD						
share	.0710358	.0109637	6.48	0.000	.0495473	.0925243
ASCSQ	4.427818	.4125474	10.73	0.000	3.61924	5.236396
mprice	.8526068	.0957956	8.90	0.000	.6648509	1.040363

1.9 Latent Class model

Latent class model with 2 latent classes

Variable	Class1	Class2
price	-0.275	-0.171
share	0.076	0.070
wind	-0.814	0.008
biomass	-0.993	-0.156
ASCSQ	1.137	-2.023
Class Share	0.539	0.461

Latent class model with 2 latent classes

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Class1						
price	-.2749748	.0257922	-10.66	0.000	-.3255265	-.2244231
share	.0761588	.0091245	8.35	0.000	.0582751	.0940425
wind	-.8134849	.2042929	-3.98	0.000	-1.213892	-.4130781
biomass	-.9930437	.2140622	-4.64	0.000	-1.412598	-.5734896
ASCSQ	1.136388	.2199547	5.17	0.000	.7052847	1.567491
Class2						
price	-.1714481	.0098252	-17.45	0.000	-.1907052	-.1521911
share	.0698195	.0065902	10.59	0.000	.056903	.082736
wind	.0076086	.1319798	0.06	0.954	-.2510669	.2662842
biomass	-.1557212	.1231669	-1.26	0.206	-.3971238	.0856814
ASCSQ	-2.023101	.1770563	-11.43	0.000	-2.370125	-1.676077
Share1						
_cons	.1584309	.1262038	1.26	0.209	-.0889241	.4057858

1.10 Latent Class model with membership function

Choice model parameters and average classs shares

Variable	Class1	Class2
price	-0.279	-0.172
share	0.078	0.070
wind	-0.829	0.024
biomass	-1.009	-0.149
ASCSQ	1.180	-1.973
Class Share	0.531	0.469

Class membership model parameters : Class2 = Reference class

Variable	Class1	Class2
Coef of		
male	-0.051	0.000
Age	0.015	0.000
Income	-0.000	0.000
Business	-0.337	0.000
Knowledge_~R	0.020	0.000
Knowledge_~D	-0.834	0.000
Knowledge_~S	-1.064	0.000
Outage	0.130	0.000
Appliances	-0.003	0.000
Home_people	0.197	0.000
Owned_house	0.753	0.000
Edu2	-0.345	0.000
Edu3	-0.200	0.000
Edu4	0.150	0.000
Edu5	-0.123	0.000
Edu6	-0.063	0.000
Edu7	-1.846	0.000
_cons	-0.511	0.000

Latent class model with 2 latent classes

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Class1						
price	-.2788251	.0261752	-10.65	0.000	-.3301276	-.2275227
share	.0779363	.0093469	8.34	0.000	.0596166	.0962559
wind	-.8291969	.2117146	-3.92	0.000	-1.24415	-.4142439
biomass	-1.008916	.2196574	-4.59	0.000	-1.439437	-.5783953
ASCSQ	1.180694	.2231783	5.29	0.000	.7432723	1.618115
Class2						
price	-.1715703	.0097388	-17.62	0.000	-.1906579	-.1524826
share	.070168	.0065252	10.75	0.000	.0573788	.0829572
wind	.0241992	.1303201	0.19	0.853	-.2312236	.279622
biomass	-.1487944	.1217163	-1.22	0.222	-.387354	.0897652
ASCSQ	-1.97299	.1768036	-11.16	0.000	-2.319518	-1.626461
Share1						
male	-.0505616	.3251726	-0.16	0.876	-.6878883	.586765
Age	.0151094	.0115472	1.31	0.191	-.0075228	.0377415
Income	-.0002309	.0002574	-0.90	0.370	-.0007355	.0002737
Business	-.3371269	.3045105	-1.11	0.268	-.9339565	.2597027
Knowledge_SOLAR	.0198282	.5580872	0.04	0.972	-1.074003	1.113659
Knowledge_WIND	-.833451	.3625193	-2.30	0.022	-1.543976	-.1229262
Knowledge_BIOMASS	-1.063342	.4201809	-2.53	0.011	-1.886881	-.2398025
Outage	.1299445	.062064	2.09	0.036	.0083014	.2515877
Appliances	-.0030068	.0085656	-0.35	0.726	-.019795	.0137814
Home_people	.1969708	.1066988	1.85	0.065	-.012155	.4060966
Owned_house	.7533603	.4023325	1.87	0.061	-.0351969	1.541918
Edu2	-.344743	.3926104	-0.88	0.380	-1.114245	.4247592
Edu3	-.1997579	.2389679	-0.84	0.403	-.6681263	.2686106
Edu4	.1496965	.1870323	0.80	0.423	-.2168802	.5162731
Edu5	-.123404	.1679796	-0.73	0.463	-.4526381	.20583
Edu6	-.0628071	.1349402	-0.47	0.642	-.3272849	.2016708
Edu7	-6.718232	23869.77	-0.00	1.000	-46790.6	46777.17
_cons	-.5107297	1.000076	-0.51	0.610	-2.470843	1.449384

1.11 WTP estimation

Solar WTP

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
WTP10	7.278826	2.593989	2.81	0.005	2.194701	12.36295
WTP15	8.422501	2.558224	3.29	0.001	3.408473	13.43653
WTP25	10.70985	2.546131	4.21	0.000	5.719525	15.70018
WTP35	12.9972	2.613453	4.97	0.000	7.874925	18.11947

Wind WTP

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
WTP10	.4418688	2.769849	0.16	0.873	-4.986935	5.870672
WTP15	1.585543	2.73479	0.58	0.562	-3.774547	6.945634
WTP25	3.872893	2.72028	1.42	0.155	-1.458758	9.204544
WTP35	6.160242	2.780261	2.22	0.027	.7110311	11.60945

Biomass WTP

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
WTP10	4.451042	2.58291	1.72	0.085	-.6113696	9.513453
WTP15	5.594716	2.547857	2.20	0.028	.6010086	10.58842
WTP25	7.882066	2.537456	3.11	0.002	2.908743	12.85539
WTP35	10.16942	2.606698	3.90	0.000	5.060381	15.27845