Discrete Choice Experiments

For valuing the benefits of improved NIE services

Technical report

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1. Introduction

Discrete Choice Experiments (DCE) is a survey-based technique used to investigate the trade-offs that people are prepared to make between different goods or policies. The technique can be used to find the monetary value that people place on goods and services or the value of a policy change. DCE is a stated-preference technique, in that it relies on individuals saying what they would do under hypothetical circumstances, rather than observing actual behaviours in marketplaces. Contingent valuation (CV), is a popular method for placing a value on a good, and is another example of a stated-preference technique, which can be interpreted as a special case of DCE.

In a typical DCE survey, respondent are shown alternative variants of a good described by a set of attributes, and are asked to choose the most preferred one. The alternatives differ from one another in the levels taken by two or more of the attributes. Statistical analyses of the responses can be used to obtain the marginal value of these attributes and the willingness to pay for any alternative of interest. In this project, the DCE process involves presenting customers with alternative bundles of characteristics of the service offered by NIE arranged according to the principles of experimental design, and asking them to choose their favourite bundle from the available set. In order to establish trade-offs between electricity service characteristics and money, one of these characteristics must be the cost of the bundle. When customers choose one bundle (package of electricity services) over others, they implicitly reveal their trade-off between money and the single services included in each bundle in their choice set. Such trade-off is the marginal value of that characteristic of the complex good.

2. Model and Econometric Analyses of the Responses

A. The Random Utility Model

In a DCE, respondents are shown a set of alternative representations of a good and are asked to pick their most preferred. The responses can be used to estimate the marginal rates of substitution between attributes. If one of the attributes is cost, it is possible to calculate the marginal price for an additional unit of each attribute. If the “do nothing” or status quo option is included in the choice set, the experiments can be used to compute the full value (willingness to pay or WTP) of each alternative. This approach has the advantage of simulating real market situations, where consumers face two or more goods characterized by similar attributes, but different levels of these attributes, and are asked to choose whether to buy one of the goods or none of them. Another advantage is that the choice tasks do not require as much effort by the respondent as in rating or ranking alternatives.

To motivate the statistical analysis of the responses to DCE questions, it is assumed that the choice between the alternatives is driven by the respondent’s underlying utility. The respondent’s indirect utility is broken down into two components. The first component is deterministic, and is a function of the attributes of alternatives, characteristics of the individuals, and a set of unknown parameters, while the second component is an error term. Formally,

(1) $$V_{ij} = \overline{V}(\mathbf{x}_{ij}, \boldsymbol{\beta}) + \varepsilon_{ij}$$

where the subscript i denotes the respondent, the subscript j denotes the alternative, x is the vector of attributes that vary across alternatives (or across alternatives and individuals), and is an error term that captures individual- and alternative-specific factors that influence utility, but are not observable to the researcher. Equation (1) describes the random utility model (RUM).

In many applications, it is further assumed that $\overline{V}$, the deterministic component of utility, is a linear function of the attributes of the alternatives and of the respondent’s residual income, (y - C):

(2) $$V_{ij} = \beta_0 + \mathbf{x}_{ij}\boldsymbol{\beta}_1 + (y_i - C_j)\beta_2 + \varepsilon_{ij} \ .$$

where *β_0* is the coefficient of the current situation, CS, y is income and C is the price of the commodity or the cost of the program to the respondent. Clearly, the coefficient β_2 is the marginal utility of income.

As mentioned, respondents are assumed to choose the alternative in the choice set that results in the highest utility. Because the observed outcome of each choice task is the selection of one out of K alternatives, the appropriate econometric model is a discrete choice model expressing the probability that alternative k is chosen. Formally,

(3) $$\pi_{ik} = \Pr(V_{ik} > V_{i1}, V_{ik} > V_{i2}, \ldots, V_{ik} > V_{iK}) = \Pr(V_{ik} > V_{ij}) \quad \forall j \neq k \ ,$$

where π_{ik} signifies the probability that option *k* is chosen by individual *i*. This means that

(4) $$\pi_{ik} = \Pr(\beta_0 CS + \mathbf{x}_{ik}\boldsymbol{\beta}_1 + (y_i - C_{ik})\beta_2 + \varepsilon_{ik} > \beta_0 CS + \mathbf{x}_{ij}\boldsymbol{\beta}_1 + (y_i - C_{ij})\beta_2 + \varepsilon_{ij}) \ \forall j \neq k \ ,$$

from which follows that

(5) $$\pi_{ik} = \Pr[(\varepsilon_{ij} - \varepsilon_{ik}) < (\mathbf{x}_{ik} - \mathbf{x}_{ij})\boldsymbol{\beta}_1 - (C_{ik} - C_{ij})\beta_2) \quad \forall j \neq k \ .$$

Equation (5) shows the probability of selecting an alternative no longer contains terms in (2) that are constant across alternatives, such as the intercept and income. It also shows that the probability of selecting k depends on the differences in the levels of the attributes across alternatives, and that the negative of the marginal utility of income is the coefficient on the difference in cost or price across alternatives.

B. Multinomial Logit Model

If the error terms are independent and identically distributed and follow a standard type I extreme value distribution, one can derive a closed-form expression for the probability that respondent i picks alternative k out of K alternatives.

Since the cdf of the standard type I extreme value distribution is $F(\varepsilon) = \exp(-e^{-\varepsilon})$, and its pdf is $f(\varepsilon_i) = \exp(-\varepsilon_i - e^{-\varepsilon_i})$, choosing alternative *k* means that $\varepsilon_k + V_k > \varepsilon_j + V_j$ for all j≠k, which can be written as $\varepsilon_j < \varepsilon_k + V_k - V_j$. The probability of choosing k is, therefore,

(6) $$\pi_{ik} = \Pr(\varepsilon_{ij} < \varepsilon_{ik} + V_{ik} - V_{ij}) \text{ for all } j \neq k$$
$$= \int_{-\infty}^{+\infty} \prod_{j \neq k} F(\varepsilon_{ik} + V_{ik} - V_{ij}) \cdot f(\varepsilon_{ik}) d\varepsilon_{ik} \ .$$

Expression (6) follows from the assumption of independence, and the fact that is an error term and not observed, so that it is must be integrated out of $F(\varepsilon_{ik} + V_{ik} - V_{ij})$. The product within expression (6) can be re-written as

(7) $$\prod_{j \neq k} F(\varepsilon_{ik} + V_{ik} - V_{ij}) \cdot f(\varepsilon_{ik}) = \prod_{j \neq k} \exp(-e^{-\varepsilon_{ik} - V_{ik} + V_{ij}}) \exp(-\varepsilon_{ik} - e^{-\varepsilon_{ik}})$$
$$= \exp\left[-\varepsilon_{ik} - e^{-\varepsilon_{ik}}\left(1 + \sum_{j \neq k} \frac{e^{V_{ij}}}{e^{V_{ik}}}\right)\right] \ .$$

Now write

(8) $$\lambda_{ik} = \log\left(1 + \sum_{j \neq k} \frac{e^{V_{ij}}}{e^{V_{ik}}}\right) = \log\left(\sum_{j=1}^{K} \frac{e^{V_{ij}}}{e^{V_{ik}}}\right) ,$$

which allows us to rewrite (6) as

(9) $$\int_{-\infty}^{+\infty} \exp(-\varepsilon_{ik} - e^{-(\varepsilon_{ik}-\lambda_{ik})}) d\varepsilon_{ik} = \exp(-\lambda_{ik}) \int_{-\infty}^{+\infty} \exp(-\varepsilon_{kk}^{*} - e^{-\varepsilon_{kk}^{*}}) d\varepsilon_{ik}^{*} ,$$

where $\varepsilon_{ik}^{*} = \varepsilon_{ik} - \lambda_{ik}$. The integrand in expression (9) is the pdf of the extreme value distribution and is, clearly, equal to 1. Equation (9) thus simplifies to $\exp(-\lambda_{ik})$, which by (8) is in turn equal to $\exp(V_{ik}) / \sum_{j=1}^{K} \exp(V_{ij})$.

Recalling (2), the probability that respondent i picks alternative k out of K alternatives is

(10) $$\pi_{ik} = \frac{\exp(\mathbf{w}_{ik}\boldsymbol{\beta})}{\sum_{j=1}^{K} \exp(\mathbf{w}_{ij}\boldsymbol{\beta})} .^{1}$$

where $\mathbf{w}_{ij} = \begin{bmatrix} \mathbf{x}_{ij} \\ C_{ij} \end{bmatrix}$ is the vector of all attributes of alternative j, including cost, and $\boldsymbol{\beta}$ is equal to $\begin{bmatrix} \boldsymbol{\beta}_1 \\ -\beta_2 \end{bmatrix}$.[1]

Equation (10) is the contribution to the likelihood in a multinomial logit model (MNL). The full log likelihood function of the MNL is[2]

(11) $$\log L = \sum_{i=1}^{n} \sum_{k=1}^{K} y_{ik} \cdot \log \pi_{ik} ,$$

where y_{ik} is a binary indicator that takes on a value of 1 if the respondent selects alternative k, and 0 otherwise. The coefficients are estimated using the method of Maximum Likelihood (MLE).

We can further examine the expression for π_{ik} in equation (10) to show that π_{ik} depends on the differences in the level of the attributes between alternatives. To see that this the case, we begin by re-writing (10) as

(12) $$\pi_{ik} = \frac{\exp(\mathbf{w}_{ik}\boldsymbol{\beta})}{\sum_{j=1}^{K} \exp(\mathbf{w}_{ij}\boldsymbol{\beta})} = \left[\frac{\exp(\mathbf{w}_{ik}\boldsymbol{\beta})}{\exp(\mathbf{w}_{i1}\boldsymbol{\beta}) + \ldots + \exp(\mathbf{w}_{ik}\boldsymbol{\beta}) + \ldots + \exp(\mathbf{w}_{iK}\boldsymbol{\beta})}\right] ,$$

which is equal to

[1] The intercept in equation (2) is not identified and is therefore normalized to zero.
[2] Note that "log" is the natural logarithm.

(13) $$= \left[\frac{\exp(\mathbf{w}_{i1}\boldsymbol{\beta}) + \ldots + \exp(\mathbf{w}_{ik}\boldsymbol{\beta}) + \ldots + \exp(\mathbf{w}_{iK}\boldsymbol{\beta})}{\exp(\mathbf{w}_{ik}\boldsymbol{\beta})} \right]^{-1},$$

and thus to

(14) $$= \{\exp[(\mathbf{w}_{i1} - \mathbf{w}_{ik})\boldsymbol{\beta}] + \ldots + 1 + \ldots + \exp[(\mathbf{w}_{ik} - \mathbf{w}_{iK})\boldsymbol{\beta}]\}^{-1}.$$

For large samples and assuming that the model is correctly specified, the maximum likelihood estimates $\hat{\beta}$ are normally distributed around the true vector of parameters β, and the asymptotic variance-covariance matrix, Ω, is the inverse of the Fisher information matrix. The information matrix is defined as

(15) $$I(\beta) = \sum_{i=1}^{n} \sum_{k=1}^{K} \pi_{ik} (\mathbf{w}_{ik} - \overline{\mathbf{w}}_i)(\mathbf{w}_{ik} - \overline{\mathbf{w}}_i)',$$

where $\overline{\mathbf{w}}_i = \sum_{k=1}^{K} \pi_{ik} \mathbf{w}_{ik}$.

C. Marginal Prices and WTP

Once model (11) is estimated, the rate of tradeoff between any two attributes is the ratio of their respective β coefficients. The marginal value of attribute *l* is computed as the negative of the coefficient on that attribute, divided by the coefficient on the price or cost variable:

(16) $$MP_l = -\frac{\hat{\beta}_l}{\hat{\beta}_2}.$$

The willingness to pay for a commodity is computed as:

(17) $$WTP_i = -\frac{\mathbf{x}_i \hat{\boldsymbol{\beta}}_1}{\hat{\beta}_2},$$

where **x** is the vector of attributes describing the commodity assigned to individual i. It should be kept in mind that a proper WTP can only be computed if the choice set for at least some of the choice sets faced by the individuals contains the "status quo" (in which no commodity is acquired, and the cost is zero). Expression (17) is obtained by equating the indirect utility associated with commodity $\mathbf{x}_i$ and residual income $(y - C)$ with the indirect utility associated to the status quo (no commodity) and the original level of income *y*, and solving for *C*.

When reporting the estimates of the marginal prices of the attributes and the WTP, it is important to report the standard errors around these estimates. As shown in (16) and (17), marginal prices and WTP are the ratios of variables that in large samples are jointly normally distributed. This means that standard errors around them must be computed using the delta method, or, alternatively, simulation-based procedures.

To apply the delta method to get the standard error around the estimate of the marginal price of attribute *l*, let $g = -\frac{\beta_l}{\beta_2}$. The variance around marginal price (16) is thus:

(18) $$Var\,(MP_l) = \frac{\partial g}{\partial \boldsymbol{\beta}'}\Omega\frac{\partial g}{\partial \boldsymbol{\beta}} \quad ,$$

where $\frac{\partial g}{\partial \boldsymbol{\beta}'}$ is a vector of zeros, except for the *l*-th element, which is $(-1/\beta_2)$, and the last element, which is β_l / β_2^2. In practice, all of the parameters in the expression for *g* and in (18) will be replaced with their estimates. The standard error is the square root of (18). When we use the delta method to produce the variance around (17), we still use expression (18), but $\frac{\partial g}{\partial \boldsymbol{\beta}'}$ is in this case equal to $[-\mathbf{x}_i / \beta_2 \quad \mathbf{x}_i / \beta_2^2]$.

D. Heterogeneity

The MNL described by equations (10)-(11) is easily amended to allow for heterogeneity among the respondents, as different respondents may have different tastes for an electricity service bundle. Specifically, one can form interaction terms between individual characteristics, such as age, gender, education, etc., and all or some of the attributes, and enter these interactions in the indirect utility function. For example, if it was believed that the marginal utility of the attributes of, say, a program that improves the provision of electricity services varies with the location where a customer lives, one might specify utility as:

(19) $$V_{ij} = \beta_0 + \mathbf{x}_{ij}\boldsymbol{\beta}_1 + (y_i - C_j)\beta_2 + (\mathbf{x}_{ij} \times R_i)\boldsymbol{\beta}_3 + \varepsilon_{ij} \quad ,$$

where R is a dummy denoting, for example, that the individual lives in a rural area. The interaction term $(\mathbf{x}_{ij} \times R_i)$ varies across the alternatives (*j*), and one retains the ability to estimate the coefficients $\boldsymbol{\beta}_3$. The marginal utilities of the attributes are thus $\boldsymbol{\beta}_1$ for customers living in urban areas, and $(\boldsymbol{\beta}_1 + \boldsymbol{\beta}_3)$ for customers living in rural areas.

However, it is possible that some of the heterogenieity in respondents' preferences may not be captured by respondents' characteristics, such as age, gender, income, location, electricity bill, etc., and be unobserved by the researcher.

The limitations of the MNL model in accommodating preference heterogeneity have given rise to a suite of models that fit under the mixed logit models umbrella. Such models have a number of attractions and can provide a flexible, theoretical and computationally practical econometric method for any discrete choice model derived from random utility maximisation. The central feature of mixed logit models is their ability to accommodate random taste variation which is generally shown to significantly improve model fit, as well as provide greater insights into choice behaviour and welfare estimation.

In mixed logit models the values of the coefficient estimates are allowed to vary across individual respondents. There is a variety of different behavioural specifications for the random variation. Choosing the appropriate specification depends on the empirical data and should be considered on a case-by-case basis. The behavioural specifications are typically based on either a continuous or discrete mixing distribution of the random taste variation (or some combination of the two).

Under continuous mixing distributions, such model specifications are commonly referred to as Random Parameters Logit (RPL) models. These models mainly provide the analyst with information on the mean, potentially the mode, and the spread, while more flexible distributions also give additional shape information. Retrieving such information provides a rich insight into the range of taste intensities held by the respondents. Not surprisingly, RPL models have become an established and frequently used specification. In the environmental economics literature it has become increasingly common and often expected practice to use RPL models to handle preference heterogeneity.

A key element with the specification of random taste variation in RPL models is the assumption regarding the distribution of each of the random parameters. The distribution of random parameters can take a number of predefined functional forms. While this gives the analyst some control and flexibility, the random parameters are not observed and there is typically little a priori information about the shape of its distribution except possibly a sign constraint. Consequently, the chosen distribution is essentially an arbitrary approximation requiring some possibly strong or unwarranted distributional assumptions about individual heterogeneity.

3. Blocking and complex good decomposition

When faced with a complex good whose utility can be attributed to many different aspects, analysts are faced with the challenge of making preference revelation tractable to respondents. Electricity services belong to this category as the number of characteristics that may vary is larger than what the average respondent can cognitively handle in standard comparisons. In order to simplify the task of preference revelation DCEs are arranged in blocks. Each block addresses trade-off across a subset of the larger set of attributes of interest along with a change in the cost of provision. In our case three sets (blocks) were employed, each dealing with a separate set of electricity service characteristics. The three blocks considered operational areas that NIE can invest more in (i) to deal with power cuts, (ii) to make the network stronger to cope with extreme weather, and (iii) to undertake special investments for the future. The blocks were assorted as follows (the names of the variables for level 1 and 2 used in the econometric models are reported in brackets and bold):

Table 1. (i) Investments to deal with power cuts

Attributes	Description	Current	Level 1	Level 2
Longest Duration	Number of customers per year who are experiencing power cuts over 10 hours in duration	About 5,000 customers per year.	About 3,750 customers per year (longdur1)	About 2,500 customers per year (longdur2)
Most at risk of power cuts	Customers experiencing 6 or more power cuts in the last 18 months	About 12,000 customers.	About 9,600 customers (mostriskcuts1)	About 7,200 customers (mostriskcuts2)
Communication during power cuts		Automated messages or telephone operators to respond to customer calls	Automated messages or telephone operators to respond to customer calls PLUS real-time information on NIE's website (communication1)	Automated messages or telephone operators to respond to customer calls PLUS real time information on NIE's website PLUS text messages to provide information updates (communication2)

Table 2. (ii) Reducing risk from extreme weather

Attributes Description	Current	Level 1	Level 2
Ice and snow has affected the network 3 times in the last 5 years and some customers were without power for a number of days. NIE know the areas which are most at risk to ice and snow and can strengthen the network in these areas	About 46,000 homes and businesses are deemed to be at higher risk	About 34,500 homes at higher risk. (Icesnow1)	About 30,820 homes at higher risk. (Icesnow2)
In an average year there are about 5 storms which cause power cuts to approximately 18,000 homes and businesses each time. Many of these power cuts are caused by trees falling on power lines. Some of these trees could be cut back over the next five years.	NIE will address 20% (one fifth) of the main network.	NIE will address 25% (one quarter) of the main network. (Storm1)	NIE will address 33% (one third) of the main network. (Storm2)
Over the next five years, NIE can protect substations from flooding to reduce the risk of power cuts. Since 2011, 2 major substations have flooded incurring costly repairs. In January 2014, 6 others came within inches of flooding due to tidal surges.	5 substations will be protected, leaving 38,500 homes and businesses at risk of power cuts due to flooding.	10 substations will be protected, leaving 27,000 homes and businesses at risk of power cuts due to flooding. (Flood1)	15 substations will be protected, leaving 15,500 homes and businesses at risk of power cuts due to flooding. (Flood2)

Table 3. (iii) Special investments for the future

Attributes	Description	Current	Level 1	Level 2
Overhead lines in urban areas	Over the next five years, NIE can put underground some of the 1,500km of overhead lines in urban areas	No overhead lines are put underground in urban areas	Underground 15km of overhead network in urban areas (UnderUrban1)	Underground 30km of overhead network in urban areas (UnderUrban2)
Overhead lines in tourist areas / areas of natural beauty	Over the next five years, NIE can put underground some of the 3,500km of overhead lines in tourist areas / areas of natural beauty	No overhead lines are put underground in tourist areas / areas of natural beauty	Underground 25km of overhead network in tourist areas / areas of natural beauty (UnderTour1)	Underground 50km of overhead network in tourist areas / areas of natural beauty (UnderTour2)
Smart network technology	Over the next five years, NIE can investigate new technology to support the rising levels of renewable energies which are now connecting to the electricity network (e.g. heat pumps, solar panels and electric vehicle charging points).	Background studies of what is done in other countries.	Background studies of what is done in other countries PLUS 3 small projects to improve the network for renewable technologies (Renew1)	Background studies of what is done in other countries PLUS 6 small projects to improve the network for renewable technologies (Renew2)

4. Partial versus total valuations

Our approach of partitioning the complex set of attributes of the electricity bundle service into three subsets of attributes – investments to deal with power cuts, reducing risk from extreme weather, and special investments for the future – poses the problem of value reconciliation. When aggregating the monetary value of the three subsets of improvements, the result typically overestimates the total willingness to pay (WTP) for the entire bundle of benefits. This is because respondents may fail to consider that the value they would commit to pay for one subset of attributes sums to the WTP for the other two subsets of attributes. Therefore, to estimate budget constraint consistent WTP estimates, it is common practice to scale the "partial" WTP estimates from each block to the total WTP estimates for the entire set of improvements proposed. To do so, we designed an incentive compatible contingent valuation (CV) exercise based on two "take it or leave it" questions followed by an open ended question to estimate the maximum WTP that respondents have for the complete bundle of optimal electricity services. In our study, therefore, after the DCE questions, we queried our respondents about their maximum WTP for a hypothetical scenario that offered the highest level of improvements to all the attributes. The aggregated values of the blocks are then scaled by this amount so as to obtain WTP estimates which are consistent with both the DCE models and the total WTP for the whole set of benefits. By scaling the marginal WTP estimates by the total WTP estimates a more realistic and conservative estimate of the value of unit change is obtained. To explain, the ‘scaling back’ requires constraining the sum of the marginal WTP from the selected DCE model to be equal to the maximum WTP from the CV questions.

5. Experimental design

Once the attributes and their levels of a DCE have been selected and have been grouped into subsets, researchers use the theory of experimental design to combine attribute levels into bundles of electricity services to produce the DCE choice cards to optimize the amount of information that can be collected from a sample of a given size. Researchers typically start with building a full factorial design, which comprises all the possible combination of attribute levels. However, as such a design tends to produce a very large number of possible combinations that cannot be evaluated with a limited sample of respondents, researchers use a fractional factorial design. Recent research in experimental design revolves around asymptotic measures of efficiency, such as the D-error. This is the determinant of the asymptotic estimator of the variance covariance matrix of a given model specification. This means that before deriving a design, first a specification must be assumed, and then some values for the unknown coefficients need also to be assumed. In this study a balanced D-error minimizing design was used in all cases. The model specification was the conventional MNL, which has been shown to produce well-performing designs with other specifications as well. The assumptions on the values of unknown coefficients were derived from the results of the pilot study. Using these assumptions, D-efficient designs were derived for all blocks. Attributes levels were as follows: cost had the status quo (no increase in the electricity bill under the current situation) and 5 levels (increase in the annual electricity bill of £0.5, £1, £3, £6, £10), and all the other attributes had the status quo (level 0) plus two improvements (level 1 and level 2). The design used included choice tasks of three alternatives each, one of which was the current situation and the other two involved improved NIE services. Each respondent was shown 6 choice cards per block, for a total of 18 choice cards per respondent. These designs were all blocked in orthogonal blocks of 6 runs each.

6. Estimation Strategy

The estimation of the DCE data started with basic MNL models that assume that all respondents have the same preferences. We then accommodate for heterogeneous preferences using first MNL models augmented with socio-economic characteristics, to explore how variables such as location where respondents live, respondents’ age, gender, employment status, household size, electricity bill, income, and experience with planned and unplanned power cuts affect WTP. Therefore, we built the following variables as shown in the table below and interact these variables with the Current Situation.

Table 4. Socio-economic variables and definitions

Variable	Definition
Male	Dummy variable equal to 1 if a respondent is male, 0 otherwise
Age	Age of respondents
Noage	Dummy variable equal to 1 if a respondent did not report his/her age, and 0 otherwise*
Fulltime	Dummy variable equal to 1 if a respondent works full time, 0 otherwise
Single	Dummy variable equal to 1 if the household is composed by only one member, 0 otherwise
Couple	Dummy variable equal to 1 if the household is composed by two members only, 0 otherwise
Urban	Dummy variable equal to 1 if the household lives in an urban area, 0 otherwise
Semi-rural	Dummy variable equal to 1 if the household lives in a semi-rural, 0 otherwise
LowInc	Dummy variable equal to 1 if the household is in income poverty, defined as below the 60% of the median Northern Ireland income, which was £21,100/year in 2014, 0 otherwise
MedInc	Dummy variable equal to 1 if the household's income is higher than the income poverty level, but lower than the median income, 0 otherwise
Lowbill	Dummy variable equal to 1 if the household's electricity bill is lower than the median household's electricity bill in Northern Ireland, 0 otherwise
Planned	Dummy variable equal to 1 if the household experienced at least one planned power cut in the last 12 months, 0 otherwise
Unplanned	Dummy variable equal to 1 if the household experienced at least one unplanned power cut in the last 12 months, 0 otherwise

* This variable captures any difference between respondents who reported and those who did not report their age; the inclusion of this variable allows us to run models with socio-economic variables without losing observations for people who did not report their age.

When estimating the models with socio-economic variables, we would expect that households with a higher income might be willing to pay more than households with lower income. For many other variables, we do not have clear a priori expectations. For example, on the one hand, it is possible that households with a low electricity bill might be willing to pay more because they might think that the price they are currently paying for electricity is low. On the other hand, it is also possible that households with a low electricity bill might be willing to pay less than customers with a high electricity bill because they might consider that, as they are consuming less electricity than other customers, it should be those consuming more electricity that should pay more for the service.

The coefficient estimate for the Current Situation (CS) will capture the effect of choosing the current situation, and all the other variation not captured by the attribute levels and the error term. A positive and statistically significant coefficient for CS, will indicate that respondents are, on average, more willing to pick the current situation than a hypothetical policy.

When estimating the models, to assess which models fit the data better, conventional information criteria, such as the Akaike Information Criterion (AIC), or the Bayes Information

Criterion can be used. These criteria measure the relative goodness of fit of statistical models for a given set of data. Therefore, AIC provides a means for model selection. The AIC is calculated from the Log likelihood function (LL) of the model and the number of estimated coefficients. With k estimated coefficients in the model, the AIC is given by the following:

(20) AIC=2*k-2*LL

Given a set of candidate models for the data, the preferred model is the one with the minimum AIC value. The AIC rewards goodness of fit (as assessed by the likelihood function), but it also includes a penalty that is an increasing function of the number of estimated parameters. The penalty discourages overfitting (increasing the number of parameters in the model almost always improves the goodness of the fit).

All these models had utility specified as changes from the current state of service provision, the Current Situation. This implies that only changes in utility are estimated from a common reference point and coefficients are easily interpretable as jumps from the baseline condition to the level of factor service improvement. For each attribute a coefficient for the two improvement levels were estimated. All models estimated by simulated maximum likelihood were estimated with at least 500 Halton draws. All the assumptions of random coefficients models were of normal distributions, while the cost coefficient was assumed to be constant.

It is typical in stated preferences studies to analyse the data after removing respondents who provide "protest" responses to the payment questions or who did not engage with the hypothetical scenarios. Protest respondents may decline to pay, or announce that their willingness to pay is zero, even if they hold positive values for the resource, because they disagree with certain aspects of the scenario or the provision mechanism. Depending on how numerous these responses are, they may lower the estimates of willingness to pay. In addition to protest respondents, it is also important to identify "yeah-sayers". These are respondents who did not pay attention to the cost of the hypothetical scenario, state a higher WTP than they actually have, and therefore did not engage with the hypothetical scenarios. These respondents may increase the WTP estimates. We identified as "protest" respondents and "yeah-sayers" those who motivated their DCE choices as follows: "I was just guessing mostly", "I didn't really understand the choice cards", "I always chose the current situation at no additional cost because I think that consumers should not pay for these improvements", "I was interested in improving the environment irrespective of the additional cost". When we analysed the data, we therefore reported the results for the full sample and for a 'clean sample', after deleting protesters and "yeah-sayers".

The full sample comprises 1,179 respondents, whilst the clean sample is composed of 929 respondents. This indicates that a total of 21.2% of respondents either protested the hypothetical scenarios or did not engage with the DCE questions, a percentage consistent with good quality DCE studies.

For policy recommendations, we suggest using the data from the 'clean sample' and to use the output from the models that fit the data best, that is models with the lowest values of the AIC. The output from models augmented with socio-economic variables are particularly useful if one wants to explore the expected effects on particular groups of society of a hypothetical change in the provision of the electricity service.

Next, as one may be particularly concerned with how a policy change might affect the welfare of the more vulnerable groups of society, we estimate the WTP from the CV data for households in income poverty, defined as households whose income is below 60% of the median household income. The median household income for Northern Ireland in 2014 was £21,100.[3] The total number of respondents in income poverty in our sample is 266. The clean sample from this subsample comprises 205 respondents.

7. Marginal WTP estimation results

It is useful to start with a brief reminder of what type of willingness to pay estimates one can obtain from the DCE approach. These are marginal WTPs, the correct interpretation of which is important to avoid unwarranted use of the estimates. A marginal WTP measure is the amount of money an economic agent is willing to pay to achieve a specific increase of an attribute keeping everything else equal. This does not mean that a change to the subsequent level (e.g. +2) will give rise to the same marginal WTP as the first level (+1), because of the decreasing marginal value over the range of change. The first unit is valued at least as much as the second one. Also, if another attribute is increased or decreased at the same time the "everything else equal" conditions fail to apply and the attribute's marginal WTP may change. Substitutions and income effect are responsible for these changes. In valuing a policy that changes multiple attributes, some of which are changed perhaps by a relatively large amount of units, marginal WTP estimates cannot be simply added across after multiplying each marginal value by the amount of unit changes of each attribute.

8. Results for the DCE of the investments to deal with power cuts block

Tables 5-10 report the estimation results from the 7,236 choices data collected from the DCE of the investments to deal with power cuts block, from the 1,179 respondents that completed the survey. A preliminary analysis of the data shows that the current situation was chosen 57.21% of the times for the full sample and 51.16% of the times for the clean sample.

For the goodness of fit of models using the full sample, the value for the AIC for the MNL model (Table 5) is 14,037.3[4], the AIC value for the MNL with socio-economic variables (Table 6) is 13,781.4, the AIC value for the RPL with error component (Table 7) is 9,088.1. We conclude that the RPL model captures the best fit for the full sample of respondents, and should be used for policy recommendations.

For the goodness of fit using the clean sample, the value for the AIC for the MNL model (Table 8) is 11,446.1, the AIC value for the MNL with socio-economic variables (Table 9) is 11,201.8, the AIC value for the RPL with error component (Table 10) is 7,553.5. We conclude that the RPL model captures the best fit for the clean sample of respondents also.

We therefore recommend using the results from the RPL models for estimating policy relevant marginal WTP values, and we encourage using the results from the 'clean sample', as they represent the views of respondents who fully engaged with the hypothetical scenarios presented in the survey.

[3] NISRA (2015) Households Below Average Income Northern Ireland 2013-14, available at https://www.dsdni.gov.uk/sites/default/files/publications/dsd/hbai-2013-14-full-report.pdf
[4] Using (20), for the MNL, full sample, with 8 coefficient estimates, the AIC is calculated as: 2*8-2*(-7010.67117) =14037.3.

Table 5 shows the result of the basic MNL model, with the attribute levels and the current situation as the only alternative specific constant. A positive and statistically significant coefficient estimate indicates that that, everything else being equal, respondents are more likely to choose an option which entails that particular level of the attribute. The larger the size of a particular coefficient the more likely are people to choose an option with that level of that attribute. The coefficient of the current situation captures the effect of the current situation on the probability of choosing either the hypothetical scenarios or the current situation. A positive coefficient estimate for the current situation indicates that people are more likely to choose the current situation than the other hypothetical options.

The second to last column of Table 5 reports the marginal WTP for each attribute level. These are computed, as indicated in equation (16), by dividing the coefficient estimate of the attribute level of interest by the negative of the coefficient estimate for the bill. For example, the marginal WTP for longdur1 is equal to -0.25729/-0.08076=£3.19.

When we include socio-economic variables in the MNL (Table 6 and 9), we find that marginal WTP values do not differ substantially from the MNL. The model with the socio-economic variables, despite being less effective in fitting the data than the RPL model, is particularly useful for investigating the preferences and WTP of different groups of respondents. We found that respondents who work full time, live in urban or semi-rural areas, have experienced at least one planned power cut in the last 12 months, live in a two-people household, have an electricity bill lower than the median household's electricity bill in Northern Ireland, have a household income that is higher than 60% of the median household income and lower than the median income in Northern Ireland are more likely to choose options that improve the current electricity service (option 1 or 2), and hence have a higher WTP compared to other respondents. Respondents coming from the lower income groups, i.e. respondents whose income is below the poverty line (60% of the median income in Northern Ireland) are, on average, against a change in the electricity bill and in the electricity service. The coefficient estimate of the current situation is positive and statistically significant, suggesting that, on average, respondents preferred the current situation to the alternative hypothetical scenarios.

The results from table 6 can be used to estimate the expected probability of choosing hypothetical changes to the electricity service and for estimating the compensating variation, defined as the amount of money that makes a respondent indifferent between the current situation and a hypothetical policy, given the characteristics of the respondent.

Table 6a presents the results for selected scenarios, and selected respondents' characteristics. The policies considered are Policy 2, which entails the high level of improvements (longdur2, mostriskcuts2, communication2) for all the attributes at an annual cost of £3, and Policy 1, which entails the low level of improvements (longdur1, mostriskcuts1, communication1) for all the attributes at an annual cost of £2. We provided two scenarios, one for the average characteristics of the population in Northern Ireland and one for a hypothetical Respondent A, who is male, 25 years old, works full time, lives in a two-persons household, lives in an urban area, has a household income above the income poverty level and below the median income level, has an electricity bill below the median electricity bill in Northern Ireland

(£55.10/month), has experienced at least one planned power outage in the last 12 months. [5] The results show that the average population in NI would prefer the current situation with about 49% of probability, followed by Policy 2 with 28% of probability and Policy 1 with 22% of probability. The table also shows that the average person in NI should be compensated with £10 per year for implementing Policy 1 (which costs £2), or £6.66 for implementing Policy 2 (which costs £3). The table also shows that a respondent with the characteristics of Respondent A would be willing to pay £3.14 for implementing Policy 2, in addition to the £3, the hypothetical cost of the policy to the respondent. This indicates that Respondent A would be indifferent between paying £6.14 for obtaining Policy 2 or not paying anything and staying with the current situation.

When we remove protest respondents and respondents who did not engage in the hypothetical scenarios, the results in Table 9 and 9a are similar to those in Table 6 and 6a. The current situation remains the most preferred option, even though there is an increase in the number of people preferring the alternative hypothetical options in the clean sample.

The RPL models (Table 7 and 10) show further evidence that preferences are heterogeneous among respondents. These models capture a better fit of the data, as shown by the AIC statistics, and should be used for policy recommendations. The results from the RPL model for the full sample shows that respondents, on average, have a positive and increasing WTP for reducing the number of customers per year who are experiencing power cuts over 10 hours in duration. They are not interested in paying more for improving the communication of power outages and for reducing the frequency of power outages for customers experiencing 6 or more power cuts in the last 18 months. The results from the clean sample still show that people have a positive and increasing WTP for reducing the number of customers per year who are experiencing power cuts over 10 hours in duration. In addition, they also show that people

[5] When estimating welfare effects, coefficient estimates not statistically significant were not considered in the analysis (see Haab and McConnell, 2003, "Valuing Environmental and Natural Resources: The Econometrics of Non-market Valuation").
For the average characteristics of the population of Northern Ireland, we used the following values: age 37.6, percentage of male is 49%, about 20% of people in Northern Ireland have a household income below the income poverty line, and 30% of people with an income between the median income and the income poverty line; full time workers are 26%; 50% of people have a bill below the average; 65% of people live in urban areas, 16% in semi-rural and the remaining in rural areas. Data for planned and unplanned outages were taken from our survey that finds that 22% of households had at least one unplanned outage in the last 12 months and 20% had at least one planned outage in the last 12 months.
We acknowledge that it is debatable whether it is correct to use average values for estimating expected probabilities, as the model should be used to estimate expected probabilities for specific characteristics of respondents, such as a female respondent, and it does not make to talk about a 51% female respondent. We do, however, believe that the model offers important insights for the average characteristics of the population in Northern Ireland.
References for the above data can be found at the following links:
http://www.ons.gov.uk/ons/rel/regional-trends/region-and-country-profiles/population-and-migration--december-2013/directory-of-tables.html#tab-Key-Statistics
http://www.nisra.gov.uk/archive/demography/population/midyear/MYE14_Infographic.pdf
https://www.gov.uk/government/statistics/households-below-average-income-in-northern-ireland-2013-to-2014
https://www.detini.gov.uk/publications/quarterly-employment-survey-statistical-bulletin
http://www.nisra.gov.uk/archive/census/2011/results/key-statistics/summary-report.pdf
(https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0CCEQFjAAahUKEwiF04_lx73IAhWHmBoKHd3WAlw&url=https%3A%2F%2Fwww.gov.uk%2Fgovernment%2Fuploads%2Fsystem%2Fuploads%2Fattachment_data%2Ffile%2F415792%2Fqep223.xls&usg=AFQjCNGssNNBWnvcqzDcx37EdFAnzwvtQw&sig2=HHA3xQ5DqGHjIfdn8NTBnA&cad=rja
http://www.nisra.gov.uk/archive/demography/publications/urban_rural/ks_info_paper.pdf

have a positive WTP for the high level of improvements for the communication of power outages and for reducing the frequency of power outages for customers experiencing 6 or more power cuts in the last 18 months, suggesting that whilst customers are indifferent between a small investment in these two attributes - Most at risk of power cuts and Communication during power cuts - they have a positive WTP for a large improvement in these two attributes. The result from tables 7 and 10 also show that the coefficient estimate associated with the current situation is positive and statistically significant, indicating that respondents on average, prefer the current situation, rather than the alternative hypothetical options.

The results from Table 10, which we would recommend using for policy recommendations, show a positive and increasing WTP for the “longest duration” attribute with a large spread of the preferences for these levels, captured by the coefficients S_longdur1 and S_longdur2. The coefficient estimates for the levels of the second attribute, “Most at risk of power cuts”, indicate that respondents cared for a large investment in this area, as mostriskcuts2 is positive and significant, but not for a low level of investments. In addition, we also found a large variation in preferences, with the coefficient estimates for the spread of these coefficients, S_mostriskcuts1 and S_mostriskcuts2, quite big and statistically significant. A similar result is found for the third attribute, “Communication during power cuts”, with communication1 not statistically significant, and communication2 statistically significant and the spread of these coefficients, S_communication1 and S_communication2, both statistically significant, indicating heterogeneous preferences for these attribute levels.

In sum, for this block of attributes, we conclude that, by using the data from the clean sample, we notice that about half of the sample, 51.16% of respondents preferred the current situation rather than other hypothetical options. The first attribute, “longest duration,” is the one that respondents consider most important and worth investing in.

Table 5. MNL results - investments to deal with power cuts, full sample

LL -7010.67117			AIC 14037.3			
Attribute	Coefficient estimate	t-stat	Marginal WTP			
Current situation (CS)	0.84799***	12.28	95% Confidence Interval WTP		Coefficient estimate	t-stat
longdur1	0.25729***	4.04	1.85955	4.51171	3.18563***	4.71
longdur2	0.4802***	8.69	4.46584	7.42558	5.94571***	7.87
mostriskcuts1	-0.04476	-0.78	-2.03368	0.92534	-0.55417	-0.73
mostriskcuts2	-0.07611	-1.05	-2.89401	1.00937	-0.94232	-0.95
communication1	-0.11612**	-2.26	-2.76192	-0.11373	-1.43782**	-2.13
communication2	0.04648	0.83				
Bill	-0.08076***	-6.97				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 6. MNL results - investments to deal with power cuts, inclusion of socio-economic variables, full sample

LL -6869.71571			AIC 13781.4			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	1.23934***	8.59	95% Confidence Interval WTP		Coefficient estimate	T-stat
longdur1	0.24682***	3.84	1.71804	4.37603	3.04703***	4.49
longdur2	0.48207***	8.67	4.4678	7.43467	5.95124***	7.86
mostriskcuts1	-0.05024	-0.87	-2.1153	0.87484	-0.62023	-0.81
mostriskcuts2	-0.07537	-1.03	-2.89319	1.03219	-0.9305	-0.93
communication1	-0.11263**	-2.18	-2.71281	-0.06819	-1.39050**	-2.06
communication2	0.0489	0.87	-0.69196	1.89938	0.60371	0.91
Bill	-0.08100***	-6.91				
CS*Age	0.00257	1.49				
CS*Noage	0.86847***	4.25				
CS*Male	0.16178***	3.21				
CS*Fulltime	-0.56159***	-9.47				
CS*Single	0.11706	1.57				
CS*Couple	-0.08428	-1.36				
CS*Urban	-0.32156***	-4.71				
CS*Semi-rural	-0.36578***	-4.32				
CS*LowInc	0.19554***	2.86				
CS*MedInc	-0.16217**	-2.40				
CS*Lowbill	-0.14206**	-2.50				
CS*Planned	-0.22889***	-3.45				
CS*Unplanned	-0.08011	-1.28				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 6a. Predicted probabilities and compensating variations from MNL model with socio-economic variables (Model Table 6), for selected characteristics of respondents, full sample

	Average characteristics of the population in Northern Ireland		Respondent A	
	Prob	Compensating variation (£)	Prob	Compensating variation (£)
Policy 1: low levels of improvements at a cost of £2	22.00%	-9.96	30.13%	-0.16
Policy 2: high levels of improvements at a cost of £3	28.73%	-6.66	39.35%	3.14
Current situation at no extra cost	49.28%	NA	30.52%	NA

Table 7. RPL results - investments to deal with power cuts, full sample

LL -4529.06840			AIC 9088.1			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	2.01653***	7.73	95% Confidence Interval WTP		Coefficient estimate	T-stat
longdur1	0.46033***	3.90	1.43105	3.35851	2.39478***	4.87
longdur2	0.78957***	8.42	3.27667	4.93854	4.10761***	9.69
mostriskcuts1	0.00168	0.02	-0.92444	0.94191	0.00873	0.02
mostriskcuts2	0.19582	1.53	-0.14055	2.17802	1.01873*	1.72
communication1	-0.00834	-0.10	-0.91366	0.82689	-0.04338	-0.1
communication2	0.15131	1.46	-0.18093	1.75522	0.78715	1.59
Bill	-0.19222***	-9.45				
S_longdur1	0.61570***	3.60				
S_longdur2	1.04340***	9.99				
S_mostriskcuts1	0.66728***	4.60				
S_mostriskcuts2	0.81736***	7.33				
S_communication1	0.00526	0.01				
S_communication2	0.80332***	7.03				
Sigma	7.10003***	18.17				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 8. MNL results - investments to deal with power cuts, clean sample

LL -5715.02832			AIC 11446.1			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	0.58861***	7.90	95% Confidence Interval WTP		Coefficient estimate	T-stat
longdur1	0.27974***	4.04	1.74596	4.21903	2.98249***	4.73
longdur2	0.50892***	8.55	4.12912	6.72264	5.42588***	8.2
mostriskcuts1	-0.02485	-0.40	-1.60541	1.07554	-0.26493	-0.39
mostriskcuts2	-0.06461	-0.81	-2.47886	1.10122	-0.68882	-0.75
communication1	-0.11749**	-2.12	-2.46821	-0.03714	-1.25267**	-2.02
communication2	0.06977	1.15	-0.44819	1.93581	0.74381	1.22
Bill	-0.09379***	-7.32				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 9. MNL results - investments to deal with power cuts, inclusion of socio-economic variables, clean sample

LL -5579.88246			AIC 11201.8			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	1.00259***	6.21	95% Confidence Interval WTP		Coefficient estimate	T-stat
longdur1	0.26273***	3.77	1.55535	4.04272	2.79904***	4.41
longdur2	0.51047***	8.51	4.13479	6.7421	5.43844***	8.18
mostriskcuts1	-0.03388	-0.54	-1.72359	1.00165	-0.36097	-0.52
mostriskcuts2	-0.06513	-0.81	-2.50462	1.11681	-0.69391	-0.75
communication1	-0.11268**	-2.03	-2.41747	0.0166	-1.20044*	-1.93
communication2	0.07312	1.20	-0.41455	1.97261	0.77903	1.28
Bill	-0.09386***	-7.22				
CS*Age	0.00186	0.94				
CS*Noage	1.33422***	5.30				
CS*Male	0.19630***	3.44				
CS*Fulltime	-0.57864***	-8.58				
CS*Single	0.1272	1.50				
CS*Couple	-0.06434	-0.92				
CS*Urban	-0.34095***	-4.45				
CS*Semi-rural	-0.37027***	-3.89				
CS*LowInc	0.24425***	3.13				
CS*MedInc	-0.1051	-1.38				
CS*Lowbill	-0.12933**	-2.00				
CS*Planned	-0.44559***	-5.84				
CS*Unplanned	0.02896	0.41				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 9a. Predicted probabilities and compensating variations from MNL model with socio-economic variables (Model Table 9), for selected characteristics of respondents, clean sample

	Average characteristics of the population in Northern Ireland		Respondent A	
	Prob	Compensating variation (£)	Prob	Compensating variation (£)
Policy 1: low levels of improvements at a cost of £2	31.62%	-3.55	30.38%	0.15
Policy 2: high levels of improvements at a cost of £3	24.23%	-6.39	39.66%	2.99
Current situation at no extra cost	44.15%	NA	29.96%	NA

Table 10. RPL results - investments to deal with power cuts, clean sample

LL -3761.74269			AIC 7553.5			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	0.93341***	3.13	95% Confidence Interval WTP		Coefficient estimate	T-stat
longdur1	0.51901***	4.10	1.49186	3.32394	2.40790***	5.15
longdur2	0.87909***	8.45	3.26131	4.89561	4.07846***	9.78
mostriskcuts1	0.04136	0.42	-0.68639	1.07017	0.19189	0.43
mostriskcuts2	0.26871*	1.89	0.13445	2.35882	1.24664**	2.2
communication1	0.03128	0.34	-0.6832	0.9734	0.1451	0.34
communication2	0.22634**	1.99	0.12749	1.97266	1.05008**	2.23
Bill	-0.21554***	-9.57				
S_longdur1	0.58942***	3.04				
S_longdur2	1.06592***	9.52				
S_mostriskcuts1	0.70581***	4.71				
S_mostriskcuts2	0.82169***	6.92				
S_communication1	0.01757	0.02				
S_communication2	0.83444***	7.02				
Sigma	7.18810***	15.93				
***, **, * ==> Significance at 1%, 5%, 10% level						

9. Results for the DCE of reducing risk from extreme weather block

Tables 11-16 report the estimation results from the 7,236 choices data collected from the DCE of the reducing risk from extreme weather block, from the 1,179 respondents that completed the survey. A preliminary analysis of the data shows that the current situation was chosen 51.45% of the times for the full sample and 44.71% of the times for the clean sample.

For the goodness of fit for models using the full sample, the value for the AIC for the MNL model (Table 11) is 14,789.5, the AIC value for the MNL with socio-economic variables (Table 12) is 14,540.7, the AIC value for the RPL with error component (Table 13) is 9,478.4. We conclude that the RPL model captures the best fit for the full sample of respondents.

For the goodness of fit for the clean sample, the value for the AIC for the MNL model (Table 14) is 11,922.1, the AIC value for the MNL with socio-economic variables (Table 15) is 11,712.4, the AIC value for the RPL with error component (Table 16) is 7,825.0. We conclude that the RPL model captures the best fit for the clean sample of respondents. Therefore, for policy analysis, the results from the RPL models should be used.

Table 11 reports the results from the basic MNL which shows that people, on average, prefer the current situation over the alternative hypothetical two options offered them, as indicated by the positive and statistically significant coefficient estimate for the current situation, have a positive and increasing WTP for reducing power outages from ice and snow, and from flooding, whilst they are indifferent between no new investments and investments in reducing power outages from storms causing trees to fall on the power connectors. Table 14 reports similar results when we use the clean sample.

Table 12 reports the results of the MNL with socio-economic variables. We found that respondents who work full time, live in urban or semi-rural areas, have experienced at least one planned power cut in the last 12 months, live in a two-people household, have an electricity bill lower than the median household's electricity bill in Northern Ireland, have a household income that his higher than the 60% of the median household income and lower than the median income in Northern Ireland are more likely to choose options that improve the current electricity service (option 1 or 2), and hence have a higher WTP compared to other respondents. Respondents coming from the lower income groups, i.e. respondents whose income is below the poverty line (below the 60% of the median income in Northern Ireland) are, on average, against a change in the electricity bill and in the electricity service. When we remove protest respondents and respondents who did not engage in the hypothetical scenarios, the results in Table 15 are similar to those in Table 12.

The results from table 12 can be used to estimate the expected probability of choosing hypothetical changes to the electricity service and for estimating the compensating variation, given the characteristics of the respondent, as we did for the investments to deal with power cuts block. Also for this analysis, we consider two policies, Policy 2, which entails the high level of improvements (icesnow2, storm2, flood2) for all the attributes at an annual cost of £3, and Policy 1, which entails the low level of improvements (icesnow1, storm1, flood1) for all the attributes at an annual cost of £2. Also for this case, we considered two hypothetical scenarios, one for the average characteristics of the population in Northern Ireland, and one for the hypothetical Respondent A, as described in section 8.

The results, reported in Table 12a for the full sample and 15a for the clean sample, show that, for the full sample, the most favourite option is the current situation with a probability of 45.04% of being chosen. For the clean sample, instead, the most likely option is Policy 2, with a probability of being chosen equal to 41.50%.[6]

Table 12a also shows that the average person in NI should be compensated with £3.84 per year for implementing Policy 2 (which costs £3). This means that, after a person paid £3 for the implementation of Policy 2, he/she should be paid back £3.84. The table also shows that a respondent with the characteristics of Respondent A would be willing to pay £10.98 for implementing Policy 2, in addition to the £3, the hypothetical cost of the policy to the respondent. This indicates that Respondent A would be indifferent between paying £13.98 for obtaining Policy 2 or not paying anything and staying with the current situation. The results, taken together with the results for the average respondent in NI show a large variation in preferences and WTP.

Table 15a further explores expected probabilities and compensating variations for the clean sample and clearly show that Policy 2 is the most preferred option, both the for the average respondent and for Respondent A. The average respondent is willing to pay £2.27 to implement Policy 2, in addition to the £3 that he/she was asked to pay when Policy 2 was offered in our simulation. For Respondent A, the WTP is even higher, equal to £16.97, in

[6] If Policy 2 and Policy 1 were offered at a cost of £1.50 and £1.00 respectively, the expected probabilities of selecting Policy 2, Policy 1 and the current situation would be 55.71%, 30.40%, and 13.89% respectively for the clean sample.

addition to the £3, the hypothetical cost of Policy 2. Policy 1, instead, is less favourite than the current situation for the average respondent, indicating that respondents, on average, prefer a large improvement to the services to reduce power outages from risks of ice and snow and from flooding, than no investments. However, they also prefer no investments to some limited investments.

The results from the RPL in Table 13 show that respondents, on average, have a positive and increasing WTP for reducing the risk of power outages from ice and snow. They also have a positive WTP for the highest level of improvements for reducing damages caused by storm and by flooding. When we remove protest respondents and “yeah-sayers” (Table 16), the results show that respondents have positive and increasing WTP for all the levels of the attributes, suggesting that investments in all of these areas should be carried out. The results from Table 16 also show a positive, but quite small coefficient estimate for the current situation, indicating that for this block of attributes the hypothetical options were chosen more often than the current situation. The results from the clean sample, Table 16, show evidence of heterogeneous preferences only for the high levels of investments. In fact, the coefficient estimates for S_Icesnow2, S_Storm2, S_Flood2 are statistically significant, indicating that there is quite a wide distribution of preferences among respondents.

In conclusion, we found that respondents considered quite important to invest in reducing extreme weather effects, as more than 55% of respondents in the clean sample preferred an alternative option ot the current situation. The output from Table 16, which should be used for policy recommendations, shows positive and increasing WTP for all the attributes. There is some variation in preferences, but only for the high levels of investments, whilst for the low levels of investments, respondents’ WTP does not show much variation.

Table 11. MNL results - Reducing risk from extreme weather, full sample

LL -7386.73868			AIC 14789.5			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	0.86829***	13.02	95% Confidence Interval WTP		Coefficient estimate	T-stat
Icesnow1	0.13490***	2.60	0.48847	3.66442	2.07645**	2.56
Icesnow2	0.39352***	7.24	4.11308	8.00133	6.05721***	6.11
Storm1	-0.06669	-1.25	-2.78267	0.72978	-1.02645	-1.15
Storm2	-0.04358	-0.71	-2.66215	1.32041	-0.67087	-0.66
Flood1	0.10803*	1.95	-0.06482	3.39038	1.66278*	1.89
Flood2	0.43774***	7.58	4.48439	8.99132	6.73785***	5.86
Bill	-0.06497***	-5.78	0.48847	3.66442	2.07645**	2.56
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 12. MNL results - Reducing risk from extreme weather, inclusion of socio-economic variables, full sample

LL -7249.37253			AIC 14540.7			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	1.37344***	9.66	95% Confidence Interval WTP		Coefficient estimate	T-stat
Icesnow1	0.13772***	2.64	0.50245	3.53539	2.01892***	2.61
Icesnow2	0.40286***	7.36	4.07348	7.73788	5.90568***	6.32
Storm1	-0.05697	-1.06	-2.49167	0.82139	-0.83514	-0.99
Storm2	-0.02909	-0.47	-2.28912	1.43626	-0.42643	-0.45
Flood1	0.10754*	1.93	-0.07132	3.22416	1.57642*	1.88
Flood2	0.44536***	7.68	4.4102	8.64722	6.52871***	6.04
Bill	-0.06822***	-5.98				
CS*Age	0.00017	0.10				
CS*Noage	0.84722***	4.22				
CS*Male	0.16306***	3.27				
CS*Fulltime	-0.56213***	-9.51				
CS*Single	0.18086**	2.46				
CS*Couple	-0.14075**	-2.28				
CS*Urban	-0.26529***	-3.98				
CS*Semi-rural	-0.20958**	-2.51				
CS*LowInc	0.09563	1.43				
CS*MedInc	-0.30892***	-4.56				
CS*Lowbill	-0.16200***	-2.89				
CS*Planned	-0.20301***	-3.08				
CS*Unplanned	-0.04591	-0.74				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 12a. Predicted probabilities and compensating variations from MNL model with socio-economic variables (Model Table 12), for selected characteristics of respondents, full sample

	Average characteristics of the population in Northern Ireland		Respondent A	
	Prob	Compensating variation (£)	Prob	Compensating variation (£)
Policy 1: low levels of improvements at a cost of £2	20.30%	-11.68	28.46%	3.14
Policy 2: high levels of improvements at a cost of £3	34.65%	-3.84	48.58%	10.98
Current situation at no extra cost	45.04%	NA	22.97%	NA

Table 13. RPL results - Reducing risk from extreme weather, full sample

LL -4724.22350			AIC 9478.4			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	1.16950***	4.21	95% Confidence Interval WTP		Coefficient estimate	T-stat
Icesnow1	0.28528***	4.47	0.89461	2.38649	1.64055***	4.31
Icesnow2	0.69475***	7.93	3.09426	4.89629	3.99528***	8.69
Storm1	0.11512	1.31	-0.23976	1.56378	0.66201	1.44
Storm2	0.18800*	1.82	0.09678	2.06546	1.08112**	2.15
Flood1	0.12452	1.56	-0.1743	1.6064	0.71605	1.58
Flood2	0.68319***	7.52	2.96023	4.89739	3.92881***	7.95
Bill	-0.17389***	-8.42				
S_Icesnow1	0.03031	0.04				
S_Icesnow2	1.09719***	12.85				
S_Storm1	0.02109	0.03				
S_Storm2	0.37623**	2.55				
S_Flood1	0.36388*	1.68				
S_Flood2	0.85368***	8.82				
Sigma	7.61032***	17.26				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 14. MNL results - Reducing risk from extreme weather, clean sample

LL -5953.03622			AIC 11922.1			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	0.62667***	8.65	95% Confidence Interval WTP		Coefficient estimate	T-stat
Icesnow1	0.15133***	2.70	0.54888	3.63507	2.09197***	2.66
Icesnow2	0.42107***	7.13	3.97026	7.67158	5.82092***	6.16
Storm1	-0.03231	-0.55	-2.08759	1.1944	-0.4466	-0.53
Storm2	-0.0279	-0.41	-2.29257	1.52117	-0.3857	-0.4
Flood1	0.12389**	2.07	0.03395	3.39131	1.71263**	2.00
Flood2	0.48309***	7.76	4.46565	8.8909	6.67827***	5.92
Bill	-0.07234***	-5.77	0.54888	3.63507	2.09197***	2.66
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 15. MNL results - Reducing risk from extreme weather, inclusion of socio-economic variables, clean sample

LL -5835.20396			AIC 11712.4			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	1.01746***	6.35	95% Confidence Interval WTP		Coefficient estimate	T-stat
Icesnow1	0.15675***	2.78	0.59169	3.57527	2.08348***	2.74
Icesnow2	0.43291***	7.28	3.9761	7.53222	5.75416***	6.34
Storm1	-0.02763	-0.47	-1.94718	1.21277	-0.36721	-0.46
Storm2	-0.01878	-0.28	-2.07319	1.57402	-0.24959	-0.27
Flood1	0.12369**	2.06	0.02862	3.25942	1.64402**	1.99
Flood2	0.49089***	7.85	4.41134	8.63834	6.52484***	6.05
Bill	-0.07523***	-5.91				
CS*Age	0.00256	1.30				
CS*Noage	1.45391***	5.94				
CS*Male	0.11474**	2.01				
CS*Fulltime	-0.47980***	-7.07				
CS*Single	0.19427**	2.29				
CS*Couple	-0.12873*	-1.83				
CS*Urban	-0.34740***	-4.58				
CS*Semi-rural	-0.19206**	-2.03				
CS*LowInc	0.12971*	1.68				
CS*MedInc	-0.25533***	-3.28				
CS*Lowbill	-0.13713**	-2.12				
CS*Planned	-0.36223***	-4.72				
CS*Unplanned	0.04023	0.56				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 15a. Predicted probabilities and compensating variations from MNL model with socio-economic variables (model Table 15), for selected characteristics of respondents, clean sample

	Average characteristics of the population in Northern Ireland		Respondent A	
	Prob	Compensating variation (£)	Prob	Compensating variation (£)
Policy 1: low levels of improvements at a cost of £2	23.51%	-5.28	30.70%	9.42
Policy 2: high levels of improvements at a cost of £3	41.50%	2.27	54.18%	16.97
Current situation at no extra cost	34.99%	NA	15.12%	NA

Table 16. RPL results - Reducing risk from extreme weather, clean sample

LL -3897.48027			AIC 7825.0			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	0.07531	0.23	95% Confidence Interval WTP		Coefficient estimate	T-stat
Icesnow1	0.28882***	4.09	0.78669	2.3431	1.56489***	3.94
Icesnow2	0.73236***	7.51	3.01948	4.91664	3.96806***	8.2
Storm1	0.19654*	1.95	0.12543	2.00437	1.06490**	2.22
Storm2	0.22028*	1.95	0.19637	2.19072	1.19354**	2.35
Flood1	0.16682*	1.88	-0.03632	1.84401	0.90385*	1.88
Flood2	0.76088***	7.50	3.09263	5.15261	4.12262***	7.84
Bill	-0.18456***	-8.14				
S_Icesnow1	0.15619	0.36				
S_Icesnow2	1.20063***	12.54				
S_Storm1	0.01396	0.02				
S_Storm2	0.42609***	2.85				
S_Flood1	0.37011	1.54				
S_Flood2	0.92109***	8.82				
Sigma	7.61356***	15.28				
***, **, * ==> Significance at 1%, 5%, 10% level						

10. Results for the DCE for the block on special investments for the future

Tables 17-22 report the estimation results from the 7,236 choices data collected from the DCE of the special investments for the future block, from the 1,179 respondents that completed the survey. A preliminary analysis of the data shows that the current situation was chosen 56.43% of the times for the full sample and 50.48% of the times for the clean sample.

For the goodness of fit of models using the full sample, the value for the AIC for the MNL model (Table 17) is 14,254.3, the AIC value for the MNL with socio-economic variables (Table 18) is 14,007.0, the AIC value for the RPL with error component (Table 19) is 8,954.5. We conclude that the RPL model captures the best fit for the full sample of respondents.

For the goodness of fit for the clean sample, the value for the AIC for the MNL model (Table 20) is 11,607.1, the AIC value for the MNL with socio-economic variables (Table 21) is 11,367.0, the AIC value for the RPL with error component (Table 22) is 7,374.1. We conclude that the RPL model captures the best fit for the clean sample of respondents. For both the full and the clean sample, the RPL results should be used for policy recommendations.

Table 17 reports the results from the basic MNL model. The positive and significant coefficient estimate for the current situation indicates a general preference for the current situation, confirming that most respondents chose the current situation most often than the alternative hypothetical options. The results from this model show that respondents preferred large investments in undergrounding power lines in urban areas (UnderUrban2), rather than the current situation or some investments to underground power lines in urban areas (UnderUrban1 is not statistically significant). However, we also found that respondents preferred some investments to underground power lines in tourist areas and areas of natural beauty (UnderTour1), rather than a lot of investments in this attribute, as indicated by the sign of UnderTour2 which is not statistically significant. This may sound counterintuitive. A similar counterintuitive results appear for the last attribute, Smart Network Technology, which shows that respondents are willing to pay a positive WTP for some investments (Renew1), but not for a lot of investments (Renew2). We will explore possible explanations for these results in the following models that relax the assumption of homogeneity of preferences among respondents.

Table 18 reports the results of the MNL with socio-economic variables. This model is useful to examine heterogeneous preferences of respondents. We found that younger respondents, respondents who work full time, live in urban or semi-rural areas, have experienced at least one planned power cut in the last 12 months, larger size households, households that have a household income above the poverty line are more likely to choose options that improve the current electricity service (option 1 or 2), and hence have a higher WTP compared to other respondents. When we remove protest respondents and respondents who did not engage in the hypothetical scenarios, reported in Table 21, we found similar results as for the full sample. A notable difference is for respondents who have experienced unplanned power cuts. These are more likely to choose the current situation in this block of DCE questions and shy away from paying for improvements to the electricity service.

The results from table 18 and 21 can be used to estimate the expected probability of choosing hypothetical changes to the electricity service and for estimating the compensating variation, given the characteristics of the respondent. Also for this analysis, we consider two policies, Policy 2, which entails the high level of improvements (UnderUrban2, UnderTour2, Renew2) for all the attributes at an annual cost of £3, and Policy 1, which entails the low level of improvements (UnderUrban1, UnderTour1, Renew1) for all the attributes at an annual cost of £2. Also for this case, we considered two hypothetical scenarios, one for the average characteristics of the population in Northern Ireland, and one for the hypothetical Respondent A, as described in section 8.

The results, reported in Table 18a for the full sample and 21a for the clean sample, show that, for the full sample, considering the characteristics of the population of NI, the most favourite option is the current situation with an expected probability of 54.14% of being chosen. For the clean sample, the most likely option is still the current situation, with an expected probability of being chosen equal to 47.49%.

Table 18a also shows that the average person in NI should be compensated with £30.21 per year for implementing Policy 2 (which costs £3). The table also shows that a respondent with the characteristics of Respondent A would be willing to accept £11.62 for implementing Policy 2, minus the £3 he was asked to pay for implementing that policy.

Table 21a further explores the expected probabilities and compensating variations for the clean sample. The current situation is the most preferred option for the average characteristics of NI, whilst for Respondent A the most preferred option would be Policy 1. The average respondent should be compensated for implementing either Policy 1 (£16.59 minus £2, the hypothetical cost of the policy) or Policy 2 (£23.82 minus £3, the hypothetical cost of the policy). Focussing on Respondent A, we found that he is more likely to choose Policy 1, and that he is willing to pay £10.74, in addition to the cost of £2, for implementing Policy 1. Policy

2 is less valuable to this customer, as it is valued at £3.51, plus the hypothetical cost of £3 of the policy.

The results from the RPL in Table 19 show that respondents, on average, have a positive and increasing WTP for undergrounding overhead network in urban areas. Respondents have also a positive WTP for undergrounding overhead network in tourist areas and areas of natural beauty, even though it would appear that respondents prefer a small amount of investment in this area rather than a large investment. Respondents also have a positive WTP for some limited investment in renewable technologies (Renew1). Similar results are confirmed in Table 22 when we analyse the clean sample. A notable difference is that with the clean sample it appears that respondents are indifferent between no investments and a lot of investments to underground overhead network in tourist areas.

As we discussed in the MNL model with socio-economic variables, the RPL model shows evidence of heterogeneous preferences among respondents. This is shown by the spread of the coefficient estimates in Table 19 and Table 22. For example, focusing on the output of Table 22, whilst the coefficient estimates for UnderTour2 and Renew2 are not statistically significant, the coefficient estimates for the spread of these two coefficients, S_UnderTour2 and S_Renew,2 are positive significant, indicating that, there is a large spread in the distribution of WTP for supporting these two levels of investments. There are some respondents with a large and positive WTP for implementing a lot of investments in these areas, and other respondents against such investments. Preferences are very heterogeneous, and therefore it is difficult to identify a point WTP for these attributes, and for attributes of this block in general.

In conclusion, focusing on the clean sample, for this block of attributes, we noticed a preference towards the current situation, with 50.48% of respondents preferring no special investments for the future. We also find strong preferences heterogeneity for these attribute levels. The only attribute where respondents appeared to have clear preferences is for undergrounding network connectors in urban areas.

Table 17. MNL results - special investments for the future, full sample

<table>
<tr><td colspan="3">LL -7119.13529</td><td colspan="4">AIC 14254.3</td></tr>
<tr><td>Attribute</td><td>Coefficient estimate</td><td>T-stat</td><td colspan="4">Marginal WTP</td></tr>
<tr><td>Current situation (CS)</td><td>1.10467***</td><td>14.84</td><td colspan="2">95% Confidence Interval WTP</td><td>Coefficient estimate</td><td>T-stat</td></tr>
<tr><td>UnderUrban1</td><td>0.02824</td><td>0.47</td><td>-2.81346</td><td>4.70161</td><td>0.94408</td><td>0.49</td></tr>
<tr><td>UnderUrban2</td><td>0.16967***</td><td>2.95</td><td>1.1834</td><td>10.16099</td><td>5.67219**</td><td>2.48</td></tr>
<tr><td>UnderTour1</td><td>0.23649***</td><td>4.01</td><td>2.5197</td><td>13.29285</td><td>7.90628***</td><td>2.88</td></tr>
<tr><td>UnderTour2</td><td>0.08636</td><td>1.14</td><td>-1.04906</td><td>6.82349</td><td>2.88721</td><td>1.44</td></tr>
<tr><td>Renew1</td><td>0.16788***</td><td>3.27</td><td>1.05929</td><td>10.16536</td><td>5.61232**</td><td>2.42</td></tr>
<tr><td>Renew2</td><td>0.07223</td><td>1.02</td><td>-1.60578</td><td>6.4355</td><td>2.41486</td><td>1.18</td></tr>
<tr><td>Bill</td><td>-0.02991***</td><td>-2.59</td><td>-2.81346</td><td>4.70161</td><td>0.94408</td><td>0.49</td></tr>
<tr><td colspan="7">***, **, * ==> Significance at 1%, 5%, 10% level</td></tr>
</table>

Table 18. MNL results - special investments for the future, inclusion of socio-economic variables, full sample

LL -6982.49931			AIC 14007.0			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	1.11125***	7.59	95% Confidence Interval WTP		Coefficient estimate	T-stat
UnderUrban1	0.02546	0.42	-2.80569	4.42247	0.80839	0.44
UnderUrban2	0.16905***	2.91	1.2095	9.5242	5.36685**	2.53
UnderTour1	0.23528***	3.96	2.54163	12.39704	7.46934***	2.97
UnderTour2	0.08852	1.15	-0.96982	6.59022	2.8102	1.46
Renew1	0.16813***	3.24	1.11771	9.55756	5.33763**	2.48
Renew2	0.07608	1.07	-1.41996	6.25054	2.41529	1.23
Bill	-0.03150***	-2.69				
CS*Age	0.00373**	2.16				
CS*Noage	0.74743***	3.83				
CS*Male	0.08399*	1.67				
CS*Fulltime	-0.39766***	-6.77				
CS*Single	0.17390**	2.35				
CS*Couple	-0.05512	-0.90				
CS*Urban	-0.23242***	-3.45				
CS*Semi-rural	-0.31674***	-3.78				
CS*LowInc	0.47880***	6.93				
CS*MedInc	-0.05028	-0.75				
CS*Lowbill	-0.01336	-0.24				
CS*Planned	-0.12942*	-1.96				
CS*Unplanned	-0.00774	-0.12				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 18a. Predicted probabilities and compensating variations from MNL model with socio-economic variables (model Table 18), for selected characteristics of respondents, full sample

	Average characteristics of the population in Northern Ireland		Respondent A	
	Prob	Compensating variation (£)	Prob	Compensating variation (£)
Policy 1: low levels of improvements at a cost of £2	24.96%	-24.58	32.84%	-5.99
Policy 2: high levels of improvements at a cost of £3	20.90%	-30.21	27.50%	-11.69
Current situation at no extra cost	54.14%	NA	39.66%	NA

Table 19. RPL results - special investments for the future, full sample

LL -4462.23865			AIC 8954.5			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	2.42877***	8.18	95% Confidence Interval WTP		Coefficient estimate	T-stat
UnderUrban1	0.20178**	2.13	0.35223	4.98864	2.67044**	2.26
UnderUrban2	0.30200***	3.52	2.02278	5.97091	3.99684***	3.97
UnderTour1	0.38898***	4.11	3.052	7.2439	5.14795***	4.81
UnderTour2	0.24941*	1.87	0.67816	5.92354	3.30085**	2.47
Renew1	0.22882***	2.82	1.24983	4.80671	3.02827***	3.34
Renew2	0.08438	0.73	-1.63745	3.87088	1.11671	0.79
Bill	-0.07556***	-4.36				
S_UnderUrban1	0.02115	0.03				
S_UnderUrban2	0.82379***	7.63				
S_UnderTour1	0.01293	0.01				
S_UnderTour2	0.56877***	4.35				
S_Renew1	0.07612	0.13				
S_Renew2	0.98670***	8.04				
Sigma	7.87765***	16.83				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 20. MNL results - special investments for the future, clean sample

LL -5795.54869			AIC 11607.1			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	0.90550***	11.06	95% Confidence Interval WTP		Coefficient estimate	T-stat
UnderUrban1	0.05931	0.90	-2.29979	6.62439	2.1623	0.95
UnderUrban2	0.23438***	3.72	1.27463	15.81565	8.54514**	2.3
UnderTour1	0.25578***	3.98	1.81989	16.8313	9.32560**	2.44
UnderTour2	0.04641	0.56	-3.37835	6.76266	1.69216	0.65
Renew1	0.16915***	3.02	0.36313	11.97085	6.16699**	2.08
Renew2	0.07725	1.00	-1.90802	7.54119	2.81659	1.17
Bill	-0.02743**	-2.14	-2.29979	6.62439	2.1623	0.95
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 21. MNL results - special investments for the future, inclusion of socio-economic variables, clean sample

LL -5662.51167			AIC 11367.0			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	0.79676***	4.85	95% Confidence Interval WTP		Coefficient estimate	T-stat
UnderUrban1	0.05505	0.83	-2.29826	6.01526	1.8585	0.88
UnderUrban2	0.22997***	3.61	1.49388	14.03485	7.76436**	2.43
UnderTour1	0.25041***	3.86	2.03027	14.8791	8.45469***	2.58
UnderTour2	0.0472	0.56	-3.19064	6.37768	1.59352	0.65
Renew1	0.16421***	2.89	0.50921	10.5793	5.54426**	2.16
Renew2	0.0813	1.04	-1.6574	7.14722	2.74491	1.22
Bill	-0.02962**	-2.28				
CS*Age	0.00427**	2.17				
CS*Noage	1.34960***	5.63				
CS*Male	0.04404	0.78				
CS*Fulltime	-0.26825***	-4.02				
CS*Single	0.25915***	3.07				
CS*Couple	0.03182	0.46				
CS*Urban	-0.25719***	-3.38				
CS*Semi-rural	-0.29343***	-3.10				
CS*LowInc	0.61673***	7.86				
CS*MedInc	0.03203	0.42				
CS*Lowbill	-0.05784	-0.90				
CS*Planned	-0.34081***	-4.49				
CS*Unplanned	0.14772**	2.08				
***, **, * ==> Significance at 1%, 5%, 10% level						

Table 21a. Predicted probabilities and compensating variations from MNL model with socio-economic variables (model Table 21), for selected characteristics of respondents, clean sample

	Average characteristics of the population in Northern Ireland		Respondent A	
	Prob	Compensating variation (£)	Prob	Compensating variation (£)
Policy 1: low levels of improvements at a cost of £2	29.06%	-16.59	39.45%	10.74
Policy 2: high levels of improvements at a cost of £3	23.45%	-23.82	31.84%	3.51
Current situation at no extra cost	47.49%	NA	28.70%	NA

Table 22. RPL results - special investments for the future, clean sample

LL -3672.03828			AIC 7374.1			
Attribute	Coefficient estimate	T-stat	Marginal WTP			
Current situation (CS)	1.31753***	3.90	95% Confidence Interval WTP		Coefficient estimate	T-stat
UnderUrban1	0.27147***	2.61	0.96977	7.29295	4.13136**	2.56
UnderUrban2	0.39761***	4.24	2.98053	9.12145	6.05099***	3.86
UnderTour1	0.41276***	3.99	3.33669	9.22632	6.28150***	4.18
UnderTour2	0.19527	1.37	-0.33631	6.27962	2.97166*	1.76
Renew1	0.20206**	2.29	0.84683	5.30334	3.07508***	2.7
Renew2	0.05784	0.44	-2.79808	4.55849	0.8802	0.47
Bill	-0.06571***	-3.50				
S_UnderUrban1	0.22635	0.69				
S_UnderUrban2	0.90003***	7.74				
S_UnderTour1	0.01595	0.02				
S_UnderTour2	0.50479***	3.07				
S_Renew1	0.07193	0.11				
S_Renew2	1.09997***	8.20				
Sigma	8.14433***	14.99				
***, **, * ==> Significance at 1%, 5%, 10% level						

11. Results for the WTP estimates for the highest improvement

We used the answers to a double-bounded CV question exercise followed by an open ended question to estimate the WTP for the highest improvements in all attributes. For the full sample of respondents, we found a mean and a median WTP of £8.65 and £5 respectively. For the clean sample, we found a mean and median WTP of £9.94 and £7 respectively.

As policy makers may be concerned with the welfare of the most vulnerable groups in society, it is worth exploring the distribution of WTP of respondents in income poverty, defined as those households whose income is below the 60% of the median household income. In our sample, there are 266 respondents in income poverty. This group of respondents has a mean and median WTP equal to £6.53 and £2 respectively. When we remove protesters and “yeah-sayers” we are left with a sample of 206 respondents, whose mean and median WTP are £7.61 and £5 respectively.

Table 23 summarizes the distribution of WTP for our respondents, both for the full sample and the clean sample, and also only for respondents in income poverty. Figures 1-4 depicts the distribution of WTP for the four groups: all respondents (Figure 1), clean sample (Figure 2), respondents in income poverty (Figure 3) and respondents in income poverty after removing protesters and “yeah-sayers” (Figure 4).

For policy decisions, we recommend using the values from the clean sample, as they report more robust and credible WTP figures. It is standard practice in environmental economics to use the median WTP value for policy recommendations, as it is a more conservative value and because it represents the value at which the policy change would be implemented at a referendum vote.[7]

If one is therefore concerned with the welfare of the most vulnerable groups in society, then it is advisable to use the median WTP from the clean sample of the income poverty group and use the value of £5 per household as the maximum annual increase in the electricity bill to implement the highest levels of improvements to the electricity service.

To reconcile the WTP from the CV with the WTP estimates from the DCE, we need to "scale back" the marginal WTP estimated from the DCE models. For example for the WTP that uses the median WTP from the clean sample of the income poverty group as maximum WTP, the values are calculated as follows. We summed the marginal WTP of the high levels of attributes from the RPL models of the clean sample from Tables 10, 16, and 22. We only used the values that were statistically significant. Therefore, we summed the marginal WTP of the following levels: longdur2, mostriskcuts2, communication2, IceSnow2, Storm2, Flood2, UnderUrban2, and UnderTour2. We then constrained this sum to be equal to £5. The WTP for UnderUrban2 is calculated as: 6.05099*5/24.68205=1.23, where 6.05099 is marginal WTP estimated from Table 22 for UnderUrban2, 5 is the median WTP from the clean sample of the income poverty group, and 24.68205 is the sum of the marginal WTP from the high levels of the attributes (using only statistically significant values). The WTP for UnderUrban1 was calculated using the value estimate for the marginal WTP for UnderUrban1, UnderUrban2 from Table 24 and the scaled value of UnderUrban2, as follows: 4.13136*1.23/6.05099=0.84.

Table 24 reports the WTP for each attribute level, using the data from the clean sample and the results from the RPL models, after the "scaling back" exercise using the median WTP from the open ended CV question. The last column uses the median WTP from the clean sample of respondents in income poverty. The RPL models are those estimated from the sample that includes all respondents after deleting protesters and "yeah sayers", as it is important to use the preferences, as expressed by the DCE data, from the whole set of respondents, as they are representative of the NI population, rather than focusing on the preferences for the attributes expressed by the income poverty group, representing a subset of customers.

When using the data from Table 24 one should remember not to sum the WTP for two levels of the same attribute. For example, using the data from the last column of Table 24, this means that households' WTP is either £0.49 per year for reducing to 3,750 the number of customers per year who are experiencing power cuts over 10 hours in duration, or £0.83 for reducing to 2,500 the number of customers per year who are experiencing power cuts over 10 hours in duration.

We also recommend some caution when using the WTP values for Renew1 and UnderTour1, as they show WTP values higher than Renew2 and UnderTour2 respectively. These results are due to the very heterogeneous preferences we found for these attribute levels. A

[7] Carson points out that "for most environmental goods, WTP distributions will be quite asymmetric with mean WTP larger than median WTP, in part because the income distribution is asymmetric and in part because there is often a sizable part of the population that is fairly indifferent to the environmental good and a smaller group that care a great deal about its provision. Mean WTP is the traditional measure used in benefit - cost analysis, while median WTP, which corresponds to the flat amount that would receive majority approval, is a standard public choice criterion." P.1416 (Richard Carson, (2000) "Contingent Valuation: A User's Guide" Environmental Science and Technology, 34, 1413-1418).

conservative approach would be to constrain the WTP for Renew1 and UnderTour1 to the WTP of Renew2 and UnderTour2 respectively.

Table 25 reports a ranking of importance of each attribute level arising from the results of Table 24, using the data related to the WTP from the income poverty group, clean sample. We recommend some care when using this table, especially when using the WTP values from the special investments for the future block, as we found a large degree of heterogeneity in customers' preferences for this block of attributes. The preferences for the first and second blocks of attributes are less heterogeneous among respondents. Therefore, investments in the attributes described by the first and second blocks, highlighted in green in Table 25, would be better supported by the population in NI.

In conclusion, we recommend using the value of £5 as the maximum value to increase the household electricity bill in NI per year for the delivery of the highest levels of improvements to the electricity service. This is the value that most people among the most vulnerable groups of households in our survey are willing to pay.

Areas where households have shown stronger preferences for new investments are: reducing power outages from the risk of flooding, reducing the number of customers affected by power outages lasting longer than 10 hours, reducing the number of customers at high risk of power outages from ice and snow, reducing power outages to customers experiencing 6 or more power cuts in the last 18 months, reducing power cuts from storms causing trees to fall on power lines, and improving the communication with customers in the event of a power outage.

Using the clean sample, we also found that the majority of respondents prefers the current situation when presented with hypothetical changes to the attribute levels offered in blocks 1 (investments to deal with power cuts) and 3 (special investments for the future), whilst for block 2 (reducing the risk from extreme weather) we found that the majority of respondents would prefer to see an improvement to the service.

If a policy maker wanted to invest only to improve the levels of the attributes related to reducing the risk from extreme weather, using the results from Table 25, we would recommend using a WTP equal to £(0.84+0.80+0.24)=£1.88 to improve the electricity service in the next five years by reducing to about 30,820 the number of homes at higher risk of power outages from ice and snow, by protecting 15 substations, leaving 15,500 homes and businesses at risk of power cuts due to flooding, and by addressing 33% (one third) of the main network from risks of trees falling on power lines. If the policy maker further wanted to invest to reduce to about 2,500 the number of customers per year who are experiencing power cuts over 10 hours in duration, we would recommend adding £0.83 to the annual household's WTP, for a total of £2.71.

Table 23. WTP from the open ended CV question by percentile and selected measures, all respondents and only for respondents in income poverty.

	All respondents		Only respondents in income poverty	
	Full sample (n=1,179)	Clean sample (n=929)	Full sample (n=266)	Clean sample (n=205)
mean	8.65	9.94	6.53	7.61

median	5	7	2	5
min	0	0	0	0
25th	0	0	0	0
50th	5	7	2	5
75th	10	12	10	10
max	100	100	60	60

Figure 1. Distribution of WTP, CV open ended questions, full sample, n=1,179

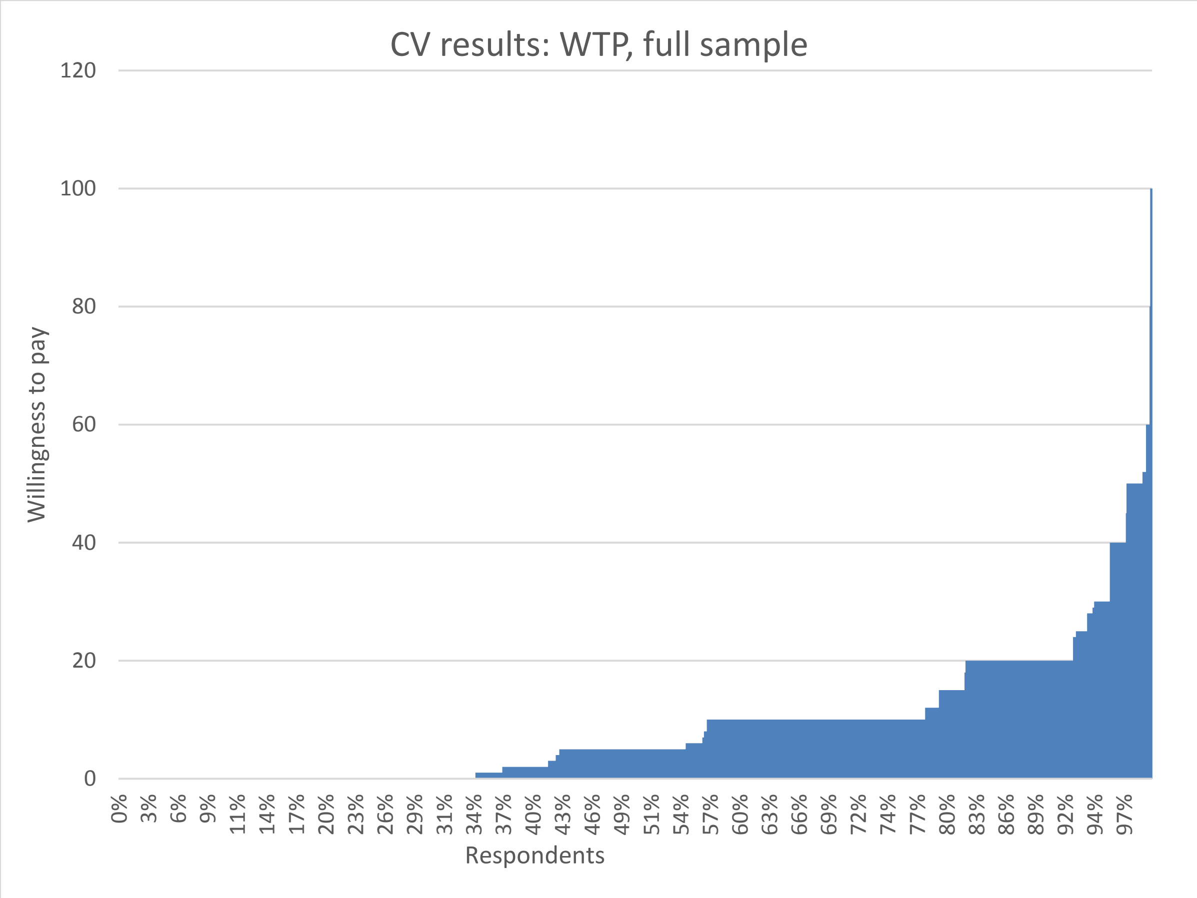

Figure 2. Distribution of WTP, CV open ended questions, clean sample, n=929

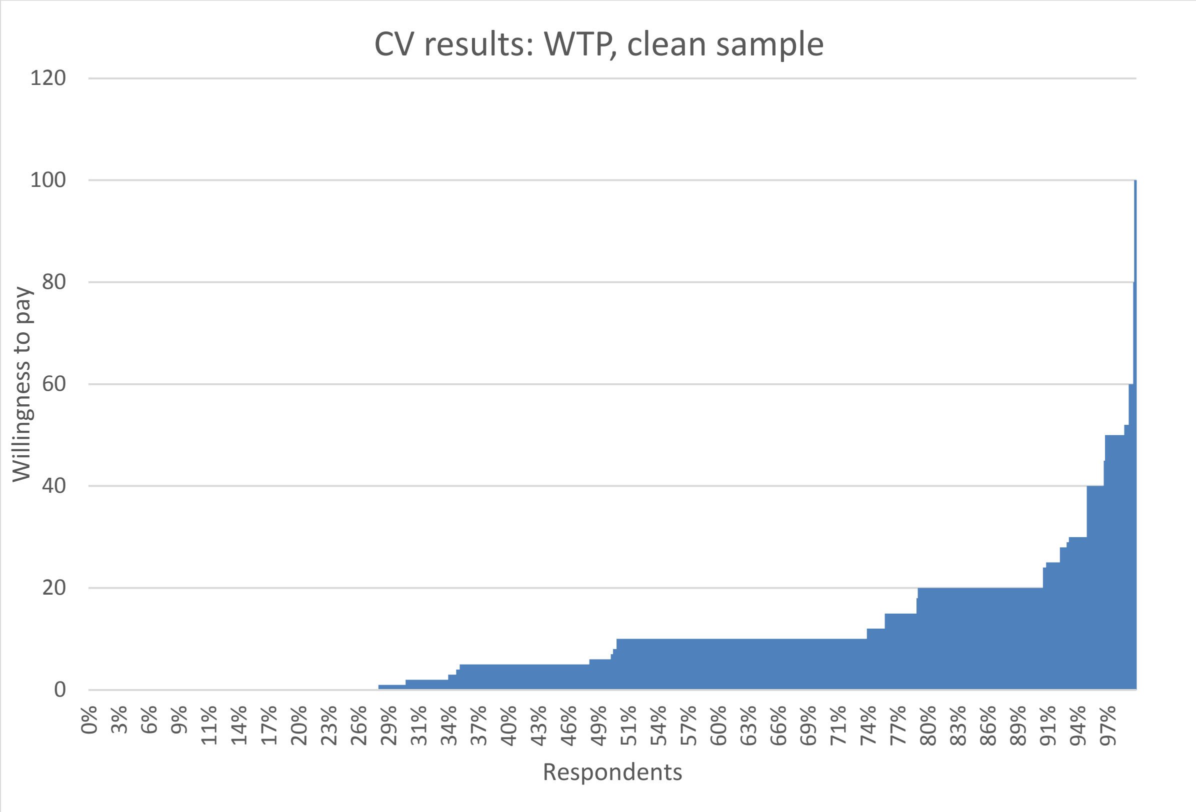

Figure 3. Distribution of WTP, CV open ended questions, full sample, only respondents in income poverty (income < 60% of median household income in NI), n=259

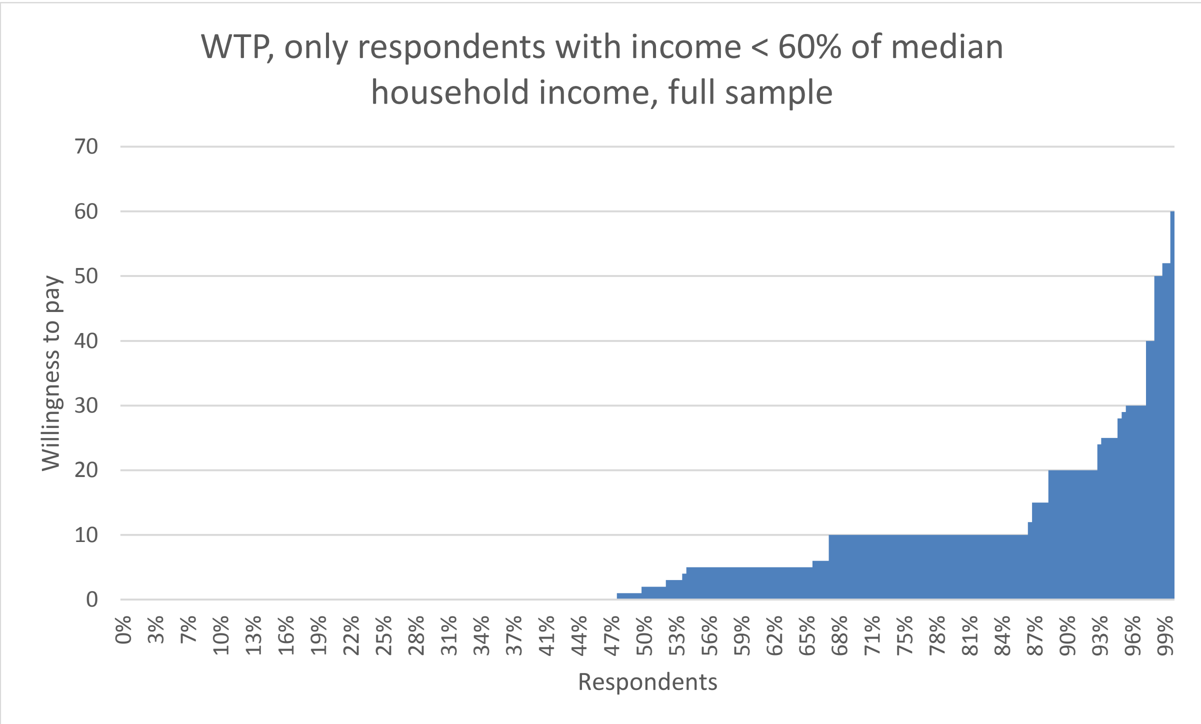

Figure 4. Distribution of WTP, CV open ended questions, clean sample, only respondents in income poverty (income < 60% of median household income in NI), n=204

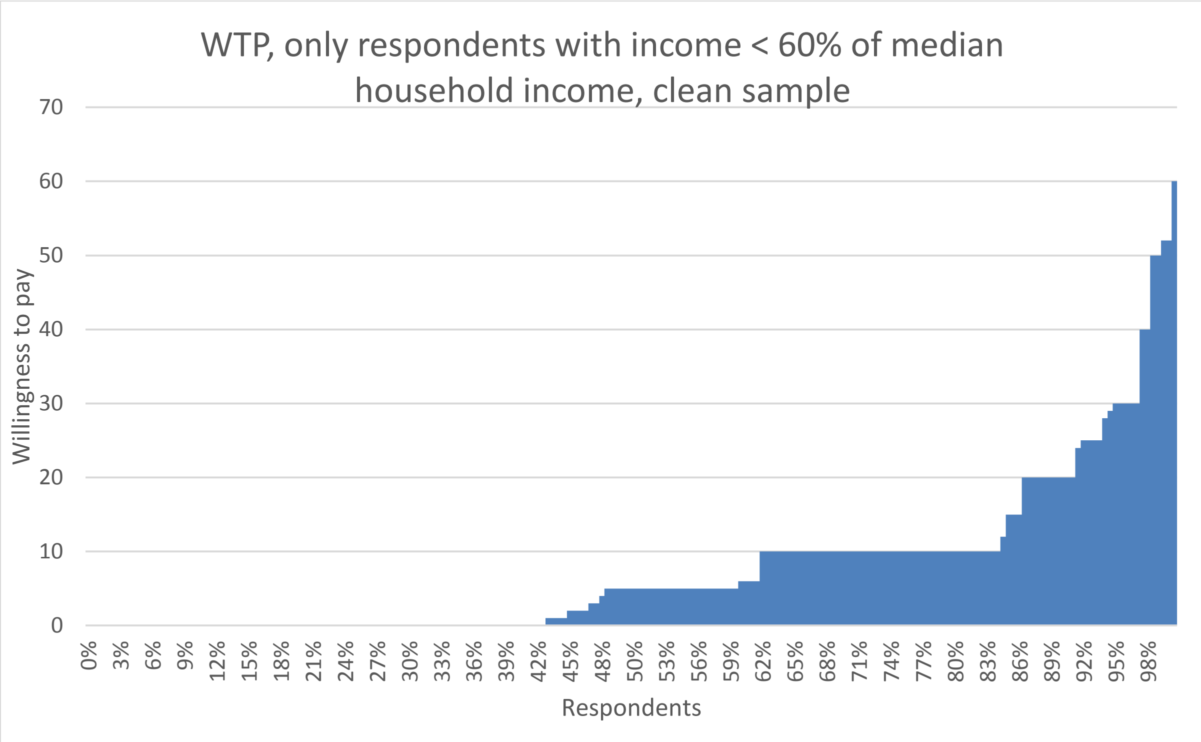

Table 24. WTP (£) for each attribute after scaling back from CV analysis, clean sample

	WTP, all respondents (n=929; median WTP = 7)	WTP, only respondents in income poverty (n=204; median WTP = 5)
longdur1	0.68	0.49
longdur2	1.16	0.83
mostriskcuts1	0.00	0.00
mostriskcuts2	0.35	0.25
communication1	0.00	0.00
communication2	0.30	0.21
Icesnow1	0.44	0.32
Icesnow2	1.13	0.80
Storm1	0.30	0.22
Storm2	0.34	0.24
Flood1	0.26	0.18
Flood2	1.17	0.84
UnderUrban1	1.17	0.84
UnderUrban2	1.72	1.23
UnderTour1	1.78*	1.27*
UnderTour2	0.84	0.60
Renew1	0.84*	0.60*
Renew2	0.00	0.00
*Caution should be used with these WTP values.		

Table 25. Ranking in terms of WTP values using WTP from the clean sample, using WTP values from the income poverty group, after scaling back.

Attribute level	WTP	Ranking	Attribute level	WTP	Ranking
UnderTour1	1.27*	1	Icesnow1	0.32	10
UnderUrban2	1.23	2	mostriskcuts2	0.25	11
Flood2	0.84	3	Storm2	0.24	12
UnderUrban1	0.84	4	Storm1	0.22	13
longdur2	0.83	5	communication2	0.21	14
Icesnow2	0.80	6	Flood1	0.18	15
UnderTour2	0.60	7	mostriskcuts1	0	16
Renew1	0.60*	8	communication1	0	17
longdur1	0.49	9	Renew2	0	18
*Caution should be used with these WTP values.					