**The cost of electric power outages in the residential sector: A Willingness to Pay Approach**

1. **Introduction**

Customer interruption costs, the costs arising due to interruptions in customer electricity supply, are seen as a major component in providing the justification for infrastructure and energy system investment (Kariuki and Allan, 1996; Praktiknjo et al., 2011; [Küfeoğlu](http://www.sciencedirect.com/science/article/pii/S0142061514004815#!) & [Lehtonen](http://www.sciencedirect.com/science/article/pii/S0142061514004815#!), 2015a). The estimation of customer interruption costs provides important information for current and future energy investment and policy. In Europe, the need to replace aging infrastructure, meet the demands of an increasing global population, and to connect an increasing share of energy from renewable sources to the grid requires major investments in electricity transmission and distribution networks in the coming decades (Küfeoğlu & Lehtonen, 2015b; Richter & Weeks, 2016). At the same time, it is increasingly acknowledged that climate change may constrain future electricity generation capacity by (a) increasing the incidence of extreme heat and drought events (Bartos and Chester, 2015; Van Vliet et al., 2012) and (b) changing the temporal, spatial and operational patterns of energy supply and demand (Riechl et al., 2013). Together these factors mean that the high reliability of electricity supply currently enjoyed in Europe may be compromised in the future. As such new and adaptive energy policies are required that account for both the value of constant electricity supply across different sectors, such as residential versus industrial sectors, but also differing preferences within sectors.

A widespread approach to estimating the value of constant electricity supply has been to estimate ‘production functions’ for households and firms on the basis of aggregate electricity consumption and value added data by economic sector. In this way one can assess the value of lost load, i.e. the economic damage caused to that sector for each kilowatt-hour (kWh) not supplied to end users. Recent examples using a production function approach include [de Nooij et al. (2007, 2009)](http://www.sciencedirect.com/science/article/pii/S0301421512007732%22%20%5Cl%20%22bib5) study in the Netherlands and [Leahy and Tol (2011)](http://www.sciencedirect.com/science/article/pii/S0301421512007732%22%20%5Cl%20%22bib12) study for Ireland. These methods can provide reasonable approximations of electricity interruption costs, particularly when coupled with sensitivity analyses to account for the uncertainty associated with them (Zachariadis & Poullikkas, 2012). However, while a production function approach may be an appropriate approach to estimating the value of lost load for the industrial sector, in reality the costs arising from interruptions in the residential electricity supply market are a blackbox (Böske et al., 2007; de Nooij et al., 2007; Reichl et al., 2008). In contrast to businesses where lost turnover can be used as a proxy for the value of constant electricity supply (de Nooij et al., 2007), the costs accrued to households during a power outage are more complex. Non-material losses such as inconvenience or fear, as well as material losses such as spoiled food, occur side-by-side in the case of power outages. Both non-material and material losses are relevant for the analysis of households' perception of access to constant electricity (Baarsma and Hop, 2009). Representing 27% of overall electricity consumption in the UK (DECC, 2015), the cost to the residential market for these losses, particularly non-material costs, are not represented in the market place (de Nooij et al., 2007; Schmidthaler and Reichl, 2016).

Within a policy context, this lack of information may lead to misinterpretation of the benefits of reliability improvements to domestic consumers and result in the postponement of infrastructure investments (Böske et al., 2007; Reichl et al., 2008) or delay policy changes. It should also be recognized that the optimal reliability of electricity supply could be customer specific (Pepermans, 2011). The burden or ‘cost’ of an electricity outage may be assumed to vary based on the demographic and socio-economic characteristics of a household. For example, larger households with may experience higher objective and subjective costs as more people experience the power outage. A lack of information on how different households value electricity may lead to further sub-optimal investment decisions that impact disproportionally on certain sub groups of the population (i.e. larger households, older households). In the face of changing demand and supply of electricity, the efficiency of the electricity system for the residential sector could be maximised by understanding differing patterns of electricity demand across different household groups. Understanding electricity demand across different household groups would mean that potentially limited generation, transportation and distribution capacities could be allocated to their most valuable use (Pepermans, 2011). With the recent development of smart grids, and commercial growth of smart homes and smart metering this also becomes technically feasible. For the purpose of investment decisions, a method that accounts for different electricity needs or ‘preferences’ across different households is required to obtain the value of constant electricity supply to residential consumers.

In the face of changing demand and supply of electricity, this paper outlines a choice experiments (CE) and mixed logit framework to understand the value of continuous electricity supply in northwest England. The willingness to pay (WTP) estimates obtained from the CE and mixed logit framework may be used as the value of continuous electricity supply in northwest England within future decision-making on investment in the electricity system. Given recent developments in smart technology and the capacity to deliver bespoke electricity options depending on household preferences, one of the main aims of this paper is to capture and begin to understand if different electricity needs or ‘preferences’ for constant electricity exists across the residential sector. Previous research by Abdullah & Mariel (2010) and Pepermans (2011) demonstrate the usefulness of choice experiments, when incorporated within a mixed logit model as a method to account for the heterogeneity of preferences for constant electricity across different household types. Finally, whilst most energy policy originates at the national level, another key aim of this paper is to demonstrate that households even within relatively small regions such as the northwest of England have heterogeneous preferences for constant electricity supply, and that future energy policy should consider sub-regional circumstances.

The paper is structured as follows. Section 2 provides an overview of previous research that has using Choice Experiments to elicit the value of constant electricity supply in the residential sector. Section 3 continues by describing the data and the data collection process. Section 4 presents the choice experiment methodology and the development of the choice sets. Section 5 provides the theoretical framework. Section 6 provides the model results and continues by presenting WTP estimates for changes in power outage attribute levels and their distribution sample. Finally, Section 7 concludes and emphasizes the significance of the findings.

1. **Review of the Literature of Willingness to Pay for Constant Electricity using Choice Experiments**

A small but growing number of studies have used Choice Experiments to understanding the value of constant electricity supply to the residential sector. Table 1 provides an overview of this research by econometrical model used, the payment vehicle and the estimates to avoid a 1 hour power outage for both Developed and Developing Countries. Focusing on research from Developed countries first, research in the UK using a conditional logit to produce WTP estimates by London Economics (2013) for the whole of Great Britain found respondents were WTP between £0.03 and £0.97 to avoid a one hour power outage depending on the on the season, time of day and time of week. Further research in Great Britain using a nested logit modelling approach by the consultancy company Accent (2008) on behalf of Ofgem (the office of the electricity regulator in Great Britain) found that depending on the their electricity Distribution Network Operator households were WTP between £2.40 and £9.60 and on average £4.20 to avoid a one-hour power outage. Using a mixed logit model, Carlsson & Martinsson (2008) found that Swedish households were WTP between 8.50SEK (£0.77) and 28.40SEK (£2.59) to avoid a 4-hour power outage. Also using a mixed logit model approach, Pepermans (2011) found that household residents in Belgium were WTP between €39.00 (£33.76), €31.20 (£27.00), €26.40 (£22.85) depending on their income categorisation (high, middle, low) to avoid a one hour power outage. Using a random effects binary probit model, Bliem (2009) found that households in Austria required a 16.07% reduction in their current bill (average bill €72.00) to accept a four-hour power interruption.

One of the few cross country studies to examine WTP to avoid power outages, Cohen et al., (2016) used a recursive binary choice model and found that households were WTP between €1.035 (£0.89) and €3.994 (£3.45) (except for low outlier France €0.364 (£0.31)) to avoid a one hour outage during wintertime. They further reported that WTP was generally highest for countries classified in the lowest electricity reliability tier (Romania, Bulgaria, Greece, Hungary, Poland), and for some of the wealthiest nations in sample (Finland, Denmark, Germany). Ozbafli & Jenkins (2016) found that household residents in North Cyprus were WTP between 0.28YTL (£0.06) to avoid a one-hour power outage in summer and 1.08YTL (£0.23) in winter. Research in the Canary Islands (Amador et al., 2013) found that an individual with an average household income, is willing to pay €1.99 more per month (approximately 4.2% of the monthly bill) to reduce the number of unscheduled outages by one unit. In the same income stratum, respondents are willing to pay almost €1 per month to reduce the outage duration by five minutes (33% of the average outage duration). Whilst categorised as Developed nations, residents of both the Canary Islands and North Cyprus have much lower household incomes and this is reflected in the much lower WTP estimates associated with these two countries. Finally, only one study was identified from outside of Europe. Using a mixed logit modelling approach, Hensher et al., (2014) found that average WTP to avoid a common set of events such as outages, power surges and flickers in electric current varied from AU$60 (£37.00) per customer per event for an 8-h electricity outage when it occurs once a year through to AU$9 (£5.56) per event for a flicker in electric current.

With regard to the studies from Developing countries, Abdullah & Mariel (2010) estimated that household residents in rural Kenya are WTP 61.87Ksh (£0.48) to avoid a 3-hour power outage. In Israel, Blass et al., (2010) found that respondents were WTP US$0.42 (£0.33) for a one-minute reduction when outages have a duration of 60 minutes. Using a latent class approach research by Sagebiel & Rommel (2014) in Hyderabad, India, found that a 20% increase in monthly bill costs would have to be compensated with 97 minutes of reduced scheduled power cuts. Focusing on WTP studies that used choice experiments to estimate the value of constant electricity supply, this Section demonstrates that there is large variation in reported WTP to avoid a one-hour power cut (or similar) both within (for example Great Britain) and across countries.

1. **Data Sample**

The analysis in this paper focuses on the residential sector in NW England and is based on data collected via an online survey platform hosted by PureProfile (https://www.pureprofile.com/int/) during October 2015. The fast pace of changes in technology and the increasing ease of developing online surveys via companies such as SurveyMonkey® (https://www.surveymonkey.co.uk/) has resulted in web-based surveys attracting considerable interest from academic researchers (Fleming and Bowden, 2009; Strabac & Aalberg, 2011). Internet surveys are cost efficient and provide a wide range of new possibilities for data collection and, importantly for surveys with choice experiments, allow for the incorporation of complex visual information into a questionnaire (Fleming and Bowden, 2009; Strabac & Aalberg, 2011). Given the convenience and added flexibility that online surveys offer, web-based surveys have become increasingly common in the CE literature (Bliem, 2009; Olsen, 2009; Reichl et al., 2013). With regard to the robustness of WTP estimates obtained via web-based surveys, examining preferences for protecting different types of landscape from road encroachment in Denmark, Olsen (2009) found no significant differences in the unconditional WTP estimates between web- and mail-based respondents. Examining biodiversity protection plans, Lindhjem and Navrud (2011) found that the share of “don't knows”, zeros and protest responses to the WTP question with a payment card is very similar between web- and postal-based surveys and the equality of the mean estimated WTP cannot be rejected.

The sample in this study consisted of a random sample of clients of Pureprofile, living in the NW region of England and paying electricity bills. NW England is of interest as although 75% of its electricity cables are underground, the NW region had the 3rd highest number of power outages in 2015 (75 power outages) across the UK regions, with a total of 233,000 customers affected throughout the year and the average power outage lasting 27 minutes.

*A note on the calculation of Sample Size*

Stated choice experiments (SCE) represent the dominant data paradigm in the study of behavioral responses of individuals, households as well as other organizations. However, to date little emphasis has been placed on estimating the optimal sample size requirements for models estimated from such data (Rose and Bliemer, 2013). As a result, researchers using a SCE framework have had to resort to simple rules of thumb or ignore the issue and collect samples of arbitrary size. However, using the expected asymptotic variance covariance (AVC) matrix generated for a SCE, Bliemer and Rose (2005) showed that a relationship exists between the expected standard errors of a design and the sample size requirements for that design. They further demonstrated that this relationship can be manipulated to provide an indication as to what sample size will be required for each parameter estimate to be statistically significant. In doing so, Bliemer and Rose (2013) derived a statistical measure, the S-error, which they defined as the overall sample size that minimizes the required sample size for all parameters specified by focusing on the most difficult to estimate parameter (i.e., the parameter with the maximum required sample size). As with the *D*-*error*, the objective is to find a design that minimises the *S*-*error* value.

NGENE is an off-the shelf software programme that allows users to generate designs for a wide variety of discrete choice model specifications, including Bayesian priors, D-efficient, S-efficient and other optimality criteria. Specifying the design criteria, NGENE will display the overall efficiency measures (i.e. D-efficiency) of the design followed by S-error measures for each of the parameter estimates (including any standard deviation or spread parameters). Using NGENE to calculate an efficient Bayesian design in order to generate the choice situations, this paper found that a sample size of 200 people would be the theoretical minimum sample size required for this SCE. Rose and Bliemer (2013) note however that the specified sample size as calculated by the S-error should be taken as the minimum sample requirement, particularly if other covariates such as age and gender will be included in further analysis. Taking into account Rose and Bliemer’s (2013) suggestion to use the S-error as a minimum sample size indictor, this paper sampled 283 households across the NW region of England. With regard to sample representativeness, 54% of the respondents were female, 26% were aged 65 plus and 4.2% were unemployed. This is closely comparable with data on gender (female, 51%), age structure (aged 65 plus, 21%) and unemployment (5%) for the NW region according to the Census of Population 2011 for England and Wales.

A pilot study with 30 respondents was run in August 2015. To validate the results of the first survey a second pilot study was run in early September. The questions included in both pilot studies were based on previous research on the value of constant electricity supply (Abdullah and Mariel, 2010; Carlsson and Martinsson, 2008; Pepermans, 2011) and two focus groups conducted with residential customers in May and June 2015. The first part of the survey collected information about the respondent’s experience with power outages. These questions also prepare the respondent for the choice experiment questions by forcing them to think about the issue of continuous power supply, about past experiences and the possible consequences of power outages. For example, what would be the impacts on household activities of the loss of electricity-powered amenities in their home should a power outage occur. The second part the survey collected information on the respondent’s attitude towards power outages and their self-reported ability to cope during power outages of different durations and during winter and summer. The third part consisted of the choice sets (see Section 3) and the fourth part of the survey collected information on relevant socio-demographic, spatial and household characteristics. On average, it took about 18 minutes to complete the questionnaire.

Table 2 reports on survey respondents’ experience and attitude to power outages. For the purpose of the WTP survey, power outages were defined within the survey as ‘a temporary interruption to the electricity supply’. As presented in Table 2, 7% of respondents generated their own electricity and on average these respondents generated 34% of their own electricity. A relatively high number of respondents, 60% relied on electricity as their only source of heating. The survey found that 31% of respondents had not experienced a power outage in the previous 10 years. Allowing the respondents to define frequency of outages, a further 56% of survey respondents reported that they experienced power outages very infrequently. Only 0.7% of survey respondents reported that they had experienced power outages ‘very frequently’ over the last 10 years. Examining power outages in the preceding 12 months to being surveyed, 21% of respondents reported that they had experienced a power outage, with the average power outage last 1.75 hours. As a means to encourage respondents to begin thinking about their reliance on electricity, a question was posed on how respondents felt they would be able to cope with a 24-hour power outage in (a) winter months and (b) summer months.

Examining respondents self-reported ability to cope with a 24-hour power outage in the summer, 38% of respondents stated that they would cope ‘fairly well’, 28% recorded that they would cope ‘fairly poorly’, and 12% said that they would cope ‘extremely poorly’. Examining the responses to a 24-hour power outage in winter, the percentage of individuals that stated that they would cope ‘fairly well’ dropped to 12%. The percentage of respondents who would cope ‘fairly poorly’ during a winter power outage increased from 28% to 35%, while the percentage of people that would cope extremely poorly increased from 12% to 33%. Indeed, the percentage of respondents reporting that they would cope either ‘fairly poorly’ or extremely poorly during a 24-hour power outage during the winter comprised 68% of the sample. The substantial increase in the number of people responding that they would cope ‘extremely poorly’ between summer and winter months indicates the importance of electricity supply to residents of NW England during the winter.

**Table 2 Survey respondents experience and attitude to power outages**

**Table 3 Demographic and Socio-economic Characteristics of Respondents**

Examining the demographic and socio-economic characteristics of the sample, Table 3 indicates that 46% of the respondents were male, average age was between 30 and 64 years old, 37% of the sample were in full-time employment, while 4% of respondents were unemployed. Although 12% of respondents chose not to reveal their income, the largest proportion of respondents (34%) earned between £20,000 and £39,999. Table 3 also indicates that the largest proportion of respondents live in 2 person households (49%). The largest percentage of respondents lived in small towns (30%) or suburban areas (28%).

1. **The Choice Experiment**

The WTP estimates produced as part of this survey feed into a larger ESPRC-funded ARCC project “Adaptation and Resilience of Coastal Energy Supply” (ARCoES) on energy resilience. At the start of the survey, respondents were provided with the following information:

*‘The electricity supply in the United Kingdom is generally very reliable and available continuously. However, the power stations that generate electricity, and towers and pylons that deliver electricity to our homes are often close to the coast or to rivers that may be affected by future sea-level rise and subsequent flooding. This survey will ask about the use of electricity in your daily routine and the value that your household places on the availability of 24-hour electricity supply. The purpose of this survey is to help inform policymakers when to invest in anti-flooding measures for the electricity network’.*

It is also stated that the information obtained from the surveys would be used to inform policy at the present day, rather than the asking respondents about future payments, which would be a more cognitively burdensome request.

Based on previous research (Abdullah and Mariel, 2010; Carlsson and Martinsson, 2008; Pepermans, 2011) and the focus groups conducted with residential customers, five groups of attributes were introduced for the choice experiment used in this study. These five attributes are: duration of the power outage (20 minutes, 1 hour, 8 hours and 24 hours), the day of the week that the outage occurs (working days and weekends/public holidays), season (winter, summer), timing of the outage (peak and off-peak) and a payment attribute (£1, £5, £10, and £25). Figure 1 provides an overview of the attributes used in this survey.

**Figure 1. Attributes and levels used in the Choice Experiment**

Given that power supply is so reliable in the UK, the manner in which the choice experiment was presented to the respondents was crucial. Respondents were asked to imagine that there would be a power cut affecting their whole neighbourhood and that they could pay a one off price to avoid this power cut and in this instance have an uninterrupted supply. Respondents were further instructed when making their choices to take into account each member of their household's electricity needs. Respondents where then told that they would be faced with eight questions that presented a choice between two alternative power cut situations. An introduction to the attributes and each of their levels (Figure 1) was made and respondents were asked to imagine that by paying the one-off price shown, they could avoid the power cut.

**Figure 1 Example of a choice set**

Two important points should be noted about the design of this choice experiment. First, to avoid information overload frequency of outage was not included as an attribute in the choice card (Abdullah and Mariel, 2010; Carlsson and Martinsson, 2008; Pepermans, 2011). However, given the importance of frequency of outage found in previous studies (Abdullah and Mariel, 2010; Carlsson and Martinsson, 2008; Pepermans, 2011) respondents were asked about their experience of power outages over the last 10 years, 12 months, and the number of outages experienced over the last few months. Thus, the impact of frequency of outages can therefore still be included in the final model as a case specific variable.

Second, the choice experiments were designed as forced choice exercises. In a forced choice exercise, an opt-out option (usually a status quo option) is not available and respondents must choose one out of the available alternatives. Hensher et al., (2005) and Hensher et al., (2014) respectively previously argued that the use of forced choice in CE is consistent with the nature of utility services, in that customers cannot do without the service, and the only question is what are the attributes of the service that all customers prioritise. Within the context of NW England, this sentiment was validated with focus group participants reporting that they believed that they have the right to constant electricity supply and, particularly among the older participants (Focus group 2), that lengthy power outages were a ‘thing of the past’.

*Design of the Choice Experiments*

As is best practice in designing choice experiments (Hoyos, 2010), an efficient Bayesian design was used in order to generate the choice situations. An initial pilot survey was developed in NGENE (ChoiceMetrics, 2010) with all the coefficients set equal to zero to construct the hypothetical choice situations. Efficiency is a measure of the level of precision in which effects are estimated. Various efficiency criteria have been proposed, such as A-error or D-error. The D-error has become the most widely used measure of efficiency because of its insensitivity to the magnitude of the scale of the parameters (Hoyos, 2010; Scarpa and Rose, 2008). Using the estimated *a priori* values obtained from the pilot survey, the final built design minimized the D-error. Due to the difficulty of knowing in advance the final model specification, this paper opted to generate an efficient design for a logit multinomial model with a linear-in-parameters specification of the utility function. The design was coded to produce a set of 16 choice situations that were divided into two blocks. This was to prevent respondents facing 16 choice situations with 4 - 6 choice sets considered the optimum (Bateman et al., 2002). Therefore each respondent was presented with 8 choice situations where each of these represented the choice between two electricity outages. The final D-efficiency error was 0.0037.

1. **Theoretical Framework**

According to Lancaster (1966), to understand consumer preferences one must analyze the individual’s choice in relation to the characteristics (attributes) of the product. Consumer preferences for a good (or service) are defined over the bundles of characteristics of any one good and its demand is therefore a derived demand. Based on Lancaster’s theory of consumer demand, choice experiments comprise a number of choice sets that vary according to the levels of attributes or characteristics of the good or service under consideration. Individuals are then asked to make repeated selections of their preferred alternative in the choice sets presented to them. Random Utility Models (RUM) (McFadden, 1974) provide a statistical framework for modelling the choices individuals make in a choice experiment setting. In a choice experiment, we do not directly observe the marginal WTP but only the respondents' choices in certain situations. However, as a price attribute is always included in choice experiments it becomes possible to convert the marginal utilities of the attributes into WTP estimates via the parameters of the estimated models (Hoyos, 2010; Mørkbak et al., 2010).

*Modelling WTP*

Of the nine regions of the England, the NW has the [fourth highest Gross Value Added per capita](https://en.wikipedia.org/wiki/Countries_of_the_United_Kingdom_by_GVA_per_capita)—the highest outside southern England. However, despite this and the heavily concentrated wealth in areas like rural Cheshire, rural Lancashire and south Cumbria, in terms of socio-economic status, the population is very heterogeneous. For example, as measured by the Indices of multiple deprivation 2010, the region has many more [Lower Layer Super Output Areas](https://en.wikipedia.org/wiki/Super_Output_Areas) in the 20% most deprived districts than the 20% least deprived council districts (Department of Communities and Local Government, 2010). This heterogeneity also extends to the electricity infrastructure in the NW region. Although 75% of the power lines in the region underground, this still leaves 25% of the power lines above ground and susceptible to storms and big weather events and a higher likelihood of power outages due to weather-related events. Thus, this paper assumes that the customer base in NW England will have heterogeneous preferences for constant electricity supply and therefore will differ in their WTP for constant supply.

Considered the ‘state of the art’ in choice experiment-based modelling, Mixed Logit (ML) models makes it possible to account for heterogeneity in preferences across the sample. Preference heterogeneity in a ML model is introduced through analyst-specified parametric distributions for the random parameters. The parameters of this distribution, such as the mean and the standard deviation in the case of a normal distribution, are then estimated using either classical or Bayesian estimation techniques (Hole and Kolstad, 2012). A major issue in estimating a choice experiment via ML is therefore the choice of an appropriate mixing distribution (Giergiczny et al., 2012; Hess, 2010; Hole, 2007).

For modeling convenience (please see Hole, 2007) the distribution of the cost variable is often assumed to be fixed, however given the large variation in income levels in the NW region it may be unreasonable to assume that all individuals have the same preferences for price. Further there is no theoretical argument why the cost parameter should be non random (Sagebiel, 2017). Meijer and Rouwendal (2006) (p. 242) argue that “Treating the coefficient of the monetary variable as a fixed constant […] gives markedly different distributions of the [willingness to pay] and cannot be recommended.” To test for potential heterogeneity in prices, WTP was calculated using cost as both a random and fixed parameter. Model sensitivity found that the model fit was maximized allowing for price heterogeneity (likelihood ratio test). Following, Sagebiel (2017), the cost was included in the model as a random, normally distributed variable.

Using the Lagrange Multiplier test of McFadden and Train (2000) the remaining four parameters - Duration of Outage, Season (Winter or Summer), Time of Outage (peak or off-peak) and Day (Weekday versus weekend/public holiday), emerged as being random in the applied model. Regarding the specification of the non-cost random parameters, two distributions, the normal and log-normal distribution were tested. Specifying a parameter in log form constrains the coefficient to be positive (Hole, 2007). It was hypothesised that for the attribute ‘duration’, a log-normal distribution might be more appropriate, while a normal distribution would be appropriate for ‘season’, ‘day of the week’ and ‘time of day’.

However, similar to research reported by Hensher and Greene (2003), the estimation of the duration variable using a lognormal distribution resulted in unreasonable/unrealistic values due to the very long right-hand tail. A normal distribution was thus specified for each of the random parameters. The duration variable was converted to its natural log. The model was estimated with simulated maximum likelihood using Halton draws with 1000 replications (see Train, 2003), and the econometric software Stata was used. Confidence intervals for the WTP values (taking into account their distribution) are produced using the Krinsky-Robb method with 1000 random draws (Hole, 2007). It is important to note that the WTP values are for respondents with preferences equal to the sample mean, and that this is not the same as the confidence intervals for a respondent with preferences randomly drawn from the preference distributions. Three models were estimated, a conditional logit (CL), a main effects mixed logit model with correlated preferences (MXL) (Eq. 1) and a mixed logit model with interaction effects and correlated preferences (MXL+IA) (Eq. 3).

*Model Specification*

Observed utility is specified as a linear function of the selected power outage attributes (duration of the power outage, the day of the week that the outage occurs, season, timing of the outage and price level). In its most general form, the utility for individual n of alternative *i* in choice set *t*, is written as:

$U\_{it}= β\_{i}ASC\_{i}+β\_{2}Price\_{it}++β\_{3}Season\_{it}+β\_{4}Time of Day\_{it}+β\_{5}Time of Week\_{it}+β\_{6}Duration\_{it}$ Eq (1)

where the ASCi is an alternative specific constant which represents the intrinsic preference for alternative *i*. Duration is measured as minutes per outage and price is presented to survey respondents as a once off payment. It is important to note that in specifying the final model outlined in Eq. (1), duration of outage was tested as both a continuous and a non-linear variable. Testing the duration of outage as a non-linear variable did not reveal non-linearities in its effect, thus duration was included as a continuous variable.

Although the choice experiment and mixed logit models do not provide direct estimates of the WTP, owing to the linearity of income in the utility function, the marginal WTP for an attribute is the ratio between the attribute’s coefficient and the cost or payment coefficient and is formulated as (Hensher et al., 2005; Hensher et al., 2014):

$WTP\_{attribute}= - \frac{\hat{β}\_{attribute}}{\hat{β}\_{cost}}$ Eq. (2)

Accounting for preference heterogeneity across respondents, Equation 3 includes the attributes specified in Equation 1 and a number of demographic, socio-economic and household variables interacted with the duration variable. The first variable included is a dummy variable for respondents aged 65 years and over. This captures the possible effect that older generations may be less fussy about constant electricity supply because they have known times when reliable electricity could not be guaranteed, or because they have no or only older children living at home. The second variable is male gender.

$U\_{it}= β\_{i}ASC\_{i}+β\_{2}Price\_{it}+β\_{3}Season\_{it}+β\_{4}Time of Day\_{it}+β\_{5}Weekday\_{it}+β\_{6}Duration\_{it} +β\_{8}Duration\_{it}Age65plus+β\_{9}Duration\_{it}Male+β\_{10}Duration\_{it}FTEmploy+β\_{11}Duration\_{it}ElectricHeatOnly$ Eq. (3)

The third variable included is full time employment. The relationship between WTP and full-time employed may be nuanced. On one hand, it is expected that respondents in full-time employment will have higher incomes and thus higher disposable income and therefore the impact of a once off payment to avoid a power outage would be less burdensome. Conversely, if respondents are working full-time, they will spend less time at home and power outages may not be seen as an inconvenience. The inclusion of full-time employment is an interesting variable to explore as it represents a tension between household income and the respondents employment status.

For the final variable, electrical heating as the household’s only source of heating, it is expected that households using electrical heating will be more sensitive for changes in power supply reliability levels. This analysis may have further benefitted from the inclusion of income variable. However, as noted above, 12% of respondents selected ‘prefer not to state’ for their income thus making the income variable unusable. It is important to further note that the frequency of outages experienced in the last 10 years or 12 months, and residential location were initially included in the model 2. However, none of these covariates were found to be significant and their inclusion did not improve the reported log likelihood as measured by changes observed in the log likelihood.

1. **Results**

In total, 300 respondents completed the survey on behalf of their household; however due to incomplete responses only 283 questionnaires were used. Each respondent were asked to pay a one off fee to avoid a power outage. As each respondent had to make eight choices, this yielded 4528 observations. Although the following choice experiments was (a) unlabelled and (b) did not include a status quo option, an ASC was included to estimate whether respondents systematically opted for either the first (labelled as choice 1) the second alternative (choice 2). The non-zero constant observed indicates that the respondents had some inherent propensity to choose Option 2 over Option 1 for reasons that are not captured in the model.

For each of the three models (CL, MXL and MXL + IA) presented in Table 4 the means of the coefficients have the expected signs and are consistent with previous research on power outages in Europe (Carlsson and Martinsson, 2008; Pepermans, 2011). Allowing the parameters to vary within a mixed logit framework sees the estimated coefficients increase in magnitude. *Ceteris paribus*, these estimates suggest that longer power outages, power outages at peak periods, and paying to avoid an outage will reduce household utility. Power outages in summer are preferred above outages in winter. A log-likelihood ratio test rejected the hypothesis that the correlated mixed logit model has no additional explanatory power compared to the CL model.

**Table 4 Estimation results of the Conditional Logit (CL, Model 1), Mixed Logit Main Effects Model (MXL, Model 2) and the Mixed Logit Main Effects + Interaction Affects Model (MXL + IA, Model 3).**

**Table 5 Cholesky matrix for the Mixed Logit Main Effects + Interaction Affects Model**.

The inclusion of interaction terms in Model 3 makes the main effects more difficult to interpret (Pepermans, 2011). However, what is important is the significance of the estimates of the standard deviations or the elements of the Cholesky matrix (Table 5), which suggests that preferences for a number of the attributes are indeed heterogeneous. The inclusion of the covariates in Model 3 slightly improved the model fit as measured by the log likelihood ratio, which decreased from 1142 in Model 1 to 1133 in Model 3. All interactions were significant. The negative coefficient of the interaction term obtained for duration by age 65+ variable (-0.0034) and duration by full-time employment (-0.0026) indicates that the over 65’s and those in full-time employment were less likely to pay for constant electricity supply. In contrast, respondents with electric heating only are significantly more likely to pay for constant electricity supply (0.0029). The positive gender interaction term (.0034) indicated that women respondents were significantly more likely to pay for constant electricity supply than men.

*Willingness to pay a once off payment to avoid uninterrupted power supply in the NW of England*

The results provided in Table 6 can be used to estimate household specific mean WTP values. As the MXL models out performed the CL model, only the mean WTP estimates from the correlated MXL will be presented. WTP based on MXL models are calculated as unconditional mean parameter estimates. Examining the WTP obtained from the MXL model suggests that a household in NW England is willing to pay £5.29 to avoid having power outages in peak periods, £7.37 to have outages during the week rather than the weekend/public holiday, £31.37 to avoid power outages in winter. Sensitivity analysis found that the willingness to pay to pay to avoid an outage decreases as the duration of the outage increase. Respondents are WTP £1.17 to avoid a 20 minute outage, however this decreases to £0.05 for an 8 hour power outage. Since this is a marginal WTP, it means that reducing the interruption length from 20 minutes to 19 minutes is worth more to customers than reducing the length from 480 minutes to 479 minutes.

Increasing the complexity of the model by allowing for interactions and random preferences reveals the distribution of the WTP values for households in the Northwest of England. As this paper assumed that the random parameters followed a normal distribution, this means that individual specific preferences can take positive or negative values. This means that a percentage of households may have ‘perverse’ WTP values, i.e. they value longer rather than shorter power outages or prefer outages in winter rather than summer. Table 6 presents the number of households with positive WTP for each of the 4 non-cost parameters. 23% of households were WTP for longer power outages, 86% of the population preferred summer outages meaning that 14% of households preferred outages in winter. With regard to peak versus off peak hours, 19% of respondents would prefer to have outages during peak time and 48% of respondents would prefer to have power outages at the weekend rather than during the week. Given differentiated work patterns such preferences are unsurprising and may be exhibited by individuals who predominately work at the weekend or at night.

To account for preference heterogeneity across households, Table 7 summarizes estimates of WTP when socio-demographic and household covariates are accounted for within the mixed logit. To account for preference heterogeneity the WTP formula presented in Eq. 2 is extended to take into account the interactions with the socio-demographic and household covariates. The WTP of a 65 plus year old (a binary variable) for the normally distributed attribute Season (Summer) becomes:

$ WTP\_{Season}= - \frac{\hat{β}\_{Season}}{\hat{β}\_{cost}+\hat{β}\_{age65\*Duration}\*1+\hat{ β}\_{FT\*Duration}\*0+\hat{β}\_{ElectricOnly\*Duration}\*1+\hat{β}\_{Male\*Duration}\*0}$ Eq. 4

The same process is repeated for the Day and Time of Day attribute and each of the socio-demographic and household covariates. For the duration variable (entering the MXL+IA as a natural log), sensitivity analysis across the 4 attribute levels for the duration of the power outage (20, 60, 240 and 480 minutes) are calculated for each of the socio-demographic and household covariates in turn. Calculating the WTP of a 65 plus year old to avoid a 20-minute electricity outage becomes:

$ WTP\_{Duration20minutes}= - \frac{\frac{\hat{β}\_{Duration}}{20+1}}{\hat{β}\_{cost}+\hat{β}\_{age65\*Duration}\*1+\hat{ β}\_{FT\*Duration}\*0+\hat{β}\_{ElectricOnly\*Duration}\*1+\hat{β}\_{Male\*Duration}\*0}$ Eq. 5

Focusing on the duration attribute first, respondents aged 65 plus have the lowest WTP across each of the outage durations and respondents with electricity only to heat their homes have the highest. However, as duration of the power outage increases (240 minutes, 480 minutes) the difference in WTP decreases until each of the 4 groups are only WTP £0.06 to avoid an hour power outage of 480 minutes. This is an important finding and indicates that, WTP to avoid a power outage decreases as the duration of the outage increases and preference heterogeneity decreases across households as the duration of a power outage increases.

Examining heterogeneity in preferences across the remaining three random parameters, the Season, Day and Time of Day of the outage, respondents that are dependent on electricity as their only source of heating have the highest WTP (Table 7). Respondents with only electric heating are WTP £30.85 to avoid a power outage in Winter, £5.70 to avoid a power outage during peak periods and £13.70 to avoid a power outage at the weekend or on a bank holiday. Male respondents have the second highest WTP across all random parameters. Similar to research reported elsewhere (Abdullah and Mariel, 2010; Pepermans, 2011) respondents aged 65+ have lower WTP then respondents aged less than 65 years old. Two hypotheses may be offered here. One is that respondents that are older have tighter budget constraints and therefore have lower WTP for even a hypothetical annual payment to prevent electricity outages. This may be particularly true as the scenario modelled is for an individual aged 65+, not in full-time employment. The second hypothesis is that older individuals are very likely to have experienced power outages in their youth (a trend observed in the focus groups) and see them as a lesser inconvenience than respondents aged 16-64 years of age.

With regard to hypothesis one (tighter budget constraints), annual income was interacted with age to determine if there was a significant association between age, income and WTP by each parameter, however a significant relationship was not found. With regard to hypothesis two (perceived level of inconvenience), an analysis of respondents’ replies to ability to cope by age and ability to cope with a 24-hour power outage in winter found that respondents aged 65+ reported a slightly higher ‘extremely poorly’ ability to cope (35%) compared to respondents age 16-64 years old (32%). Respondents in fulltime employment had the second lowest WTP after those aged 65 plus. This may be because they spend more time out of the house. These results indicate that as Pepermans (2011) for the Flemish population, optimal reliability level is customer/household specific in the northwest of England. Operationalizing new energy technology such as smart metering and remote mobile applications, policy has the potential to efficiently allocate limited capacity based on each customer’s willingness to pay rather than current one policy, one price fits all approaches to electricity supply.

**Table 6 Willingness to pay a once of payment to avoid an unintended power outage Main Effects Model (Confident Intervals: Krinsky-Robb method)**

**Table 7 Willingness to pay a once of payment to avoid an unintended power outage accounting for preference heterogeneity**

**7. Conclusions and Policy Implications**

Constant electricity supply is a fundamental requirement for well-functioning modern societies; however the various supply and demand factors outlined in the Introduction means that the current high levels of reliability in the European electricity system may not be sustainable (nor desirable) in the future. From a social point of view, efficiency of the electricity system would be further increased if power quality could be targeted to customers based on their household characteristics and willingness to pay. Residential customers represent 30% of global electricity consumption, however, as the losses associated with power outages in this sector do not have a ready market value, the full welfare cost of power outages for households remain relatively unknown to the energy sector.

Power outages can be expected to cause varying levels of disutility depending on the characteristics of the individual and the household that they live in. Some households may prefer power outages at the weekend if they work weekend shifts compared to households that work Monday to Friday. Information on household’s preferences on power outages can serve many purposes (Pepermans, 2011). At an aggregate level, household level information can be used by regulators, utilities, policymakers and other stakeholders in the industry to evaluate the appropriateness of reliability investments, or to decide on which sectors or customer groups to ration when power shortages occur (Pepermans, 2011). Capturing heterogeneity at the household level is also important as it makes it possible to offer a menu of tariff structures, such as time-of-use pricing or critical-peak pricing, based on customers willingness to pay (see Wolak, 2007; Woo et al., 2008), potentially inducing more demand response into the energy market (Pepermans, 2011). Within a policy context, the possibilities of offering such tariff structures are increasingly realistic with the widespread commercialisation of smart metering and various mobile applications now on offered. Within this context, an important component of this analysis was the use of a mixed logit and socio-demographic and household variables to understand preference heterogeneity for constant electricity supply across households. Innovatively, preference heterogeneity across the 4 power outage duration levels was also examined.

Characterizing power outages by 5 attributes - duration, peak or off-peak, day of the week (weekday versus weekend), winter or summer and, as is typical in a choice experiment, price the results presented in Section 6 suggest that a household in northwest England is willing to pay £5.29 to avoid having power outages in peak periods. Households are willing to pay £7.37 to have outages during the week rather than the weekend or bank holiday, and are willing to pay £31.37 to avoid power outages in winter. Importantly for a policy perspective, greater heterogeneity is observed for shorter power outages and differences in WTP decrease across different groups as the length of power outages increase, with households willing to pay between £1.17 (20 minutes) and £0.05 (480 minutes) to avoid a power outage depending on the length of the power outage.

Including individual and household level information in the analysis this study observed heterogeneity in preferences for constant electricity supply across households depending on the gender, age, employment and heating system of respondents. Older respondents, individuals working fulltime, and men have lower willingness to pay to avoid power outages than households with only electric heating. Within a policy context, the higher willingness to pay across the four random variables for respondents with only electric heating indicates that areas without natural gas connections may be disproportionally impacted by power outages.

To conclude, whilst eliciting the value of constant electricity supply to households in the northwest of England, this paper also provided an empirical demonstration of the heterogeneity of preferences for constant electricity supply at a regional level. Whilst most energy policy is made at the national level, this study indicates that even within a small region, households will have differentiated preferences for electricity supply. From a policy perspective, the heterogeneity of preferences captured in this paper demonstrates that energy decisions must incorporate sub national analysis.

**8. Acknowledgements**

We would like to acknowledge the ESPRC-funded ARCC “Adaptation and Resilience of Coastal Energy Supply” (ARCoES) project (EPSRC EP/I035390/1)

**References**

Abdullah, S., Mariel, P., 2010. Choice experiment study on the willingness to pay to improve electricity services. Energy Pol. 38, 4570–4581.

Amador, F.J., González, R.M. and Ramos-Real, F.J., 2013. Supplier choice and WTP for electricity attributes in an emerging market: The role of perceived past experience, environmental concern and energy saving behavior. Energy Econ. 40, 953-966.

Baarsma, B.E., Hop J.P., 2009. Pricing power outages in the Netherlands. Energy 34, 1378–1386.

Bartos, M., Chester, M.V., 2015. Impacts of climate change on electric power supply in the Western United States. Nat. Clim. Chang. 5, 748–752.

Bateman, I.J., Carson, R.T., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., Loomes, G., Mourato, S., Ozdemiroglu, E., Pearce, D.W., Sugden, R., & Swanson, J., 2002.Economic valuation with stated preference techniques: a manual. Edward Elgar,

Cheltenham.

Bliem, M., 2009. Economic Valuation of Electrical Service Reliability in Austria – A Choice Experiment Approach. IHSK Working Paper 01/2009, Institute for Advanced Studies Carinthia, Austria.

Bliemer, M.C.J., Rose J.M. 2005. Efficiency and Sample Size Requirements for Stated Choice Studies. Working paper ITLS-WP-05-08, Institute of Transport and Logistics Studies, The University of Sydney.

Bliemer, M., Rose, J.M., 2013. Confidence intervals of willingness-to-pay for random coefficient logit models. Transp. Res. Part B 58, 199-214.

Böske, J., Pfaffenberbger, W., Ströbele, W. (Eds.), 2007. Zur Ökonomie der Versorgungssicherheit in der Energiewirtschaft. Lit Verlag, Münster.

Carlsson, F., Martinsson, P., 2008. Does it matter when a power outage occurs? A choice experiment study on willingness to pay to avoid power outages. Energy Econ. 30, 1232–1245.

ChoiceMetrics, 2010. Ngene 1.0.2 User Manual and Reference Guide: The Cutting Edge in Experimental Design. ChoiceMetrics. Sydney.

Cohen JJ, Moeltner K, Reichl J, Schmidthaler M. Linking the value of energy reliability to the acceptance of energy infrastructure: Evidence from the EU. Resour Energy Econ 2016;45:124-43.

De Nooij, M., Koopmans, C., Bijvoet, C., 2007. The value of supply security: The costs of power interruptions: Economic input for damage reduction and investment in networks. Energy Econ. 29,277-295.

de Nooij, M., Lieshout, R., Koopmans, C., 2009. Optimal blackouts: empirical results on reducing the social cost of electricity outages through efficient regional rationing. Energy Economics 31, 342–347.

DECC, 2015. Energy Consumption in the UK (2015). Department of Energy and Climate change, London.

Department of Communities and Local Government, 2010. English indices of deprivation 2010. [https://www.gov.uk/government/uploads/system/uploads/attachmentdata/file/6871/1871208.pdf](https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/6871/1871208.pdf)

Fleming, C., Bowden, M., 2009. Web-based surveys as an alternative to traditional mail methods. J. Environ. Manag. 90, 284-292.

Giergiczny, M., Valasiuk, S., Czajkowski, M., De Salvo, M., Signorello, G., 2012. Including cost income ratio into utility function as a way of dealing with ‘exploding’ implicit prices in mixed logit models. J. For. Econ. 18(4), 370-380.

Hensher, D.A., Greene, W.H., 2003. The mixed logit: the state of practice. Transportation 30, 133–176.

Hensher, D.A., Shore, N., Train, K., 2005. Households’ willingness to pay for water service attributes. Environ. Resour. Econ. 32, 509–531.

Hensher, D.A., Shore, N., Train, K., 2014. Willingness to pay for residential electricity supply quality and reliability. Appl. Energy 115, 280–292.

Hess, S., 2010. Conditional parameter estimates from Mixed Logit models: distributional assumptions and a free software tool. J. Choice Model. 3(2), 134-152.

Hole, A.R., 2007. A comparison of approaches to estimating confidence intervals for willingness to pay measures. Health Econ. 16, 827–840.

Hole, A.R. and Kolstad, J.R., 2012. Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and WTP space using data from a health-related choice experiment. Empir. Econ. 42(2), 445-469.

Hoyos, D., 2010. The state of the art of environmental valuation with discrete choice experiments. Ecol. Econ. 69, 1595–1603.

Kariuki, K.K., Allan, R.N., 1996. Evaluation of reliability worth and value of lost load. IEE Proc.-Gener. Transm. Distrib. 143 (2) 171-180.

Küfeoğlu, S. and Lehtonen, M., 2015a. Interruption costs of service sector electricity customers, a hybrid approach. *International J. Electr Power & Energy Syst*, *64*, 588-595.

Küfeoğlu, S., Lehtonen, M., 2015b. Comparison of different models for estimating the residential sector customer interruption costs. Electr. Power Syst. Res. 122, 50-55.

Lancaster, K., 1966. A new approach to consumer theory. J. Political Econ. 74, 132–157.

Leahy, E. and Tol, R.S., 2011. An estimate of the value of lost load for Ireland. *Energy Policy*, *39*(3), pp.1514-1520.

Lindhjem, H., Navrud, S., 2011. Are Internet surveys an alternative to face-to-face interviews in contingent valuation? Ecol. Econ.70, 1628–1637.

London Economics. The Value of Lost Load (VoLL) for Electricity in Great Britain: Final report for Ofgem and DECC. London Economics; 2013 Jul. Sponsored by Ofgem & DECC, UK. [https://www.gov.uk/government/uploads/system/uploads/attachmentdata/file/224028/valuelostloadelectrictygb.pdf](https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/224028/value_lost_load_electricty_gb.pdf)

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior, in: Zarembka, P. (Ed.) Frontiers in econometrics. Academic, New York.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Econom. 15, 447–470.

Meijer E, Rouwendal J. 2006. Measuring welfare effects in models with random coefficients. *Journal of Applied Economics*, 21:227–44.

Mørkbak, M.R., Christensen, T., Gyrd-Hansen, D., 2010. Choke price bias in choice experiments. Env. Resour. Econ. 45(4), 537-551.

Ozbafli A, Jenkins GP. Estimating the willingness to pay for reliable electricity supply: A choice experiment study. Energy Econ 2016;56:443-52.

Olsen, S.B., 2009. Choosing between internet and mail survey modes for choice experiment surveys considering non-market goods. Env. Resour. Econ. 44(4), 591–610.

Pepermans, G., 2011. The value of continuous power supply for Flemish households. *Energy Pol*. 39(12), 7853-7864.

Praktiknjo, A.J., Hähnel, A. and Erdmann, G., 2011. Assessing energy supply security: Outage costs in private households. *Energy Pol*, *39*(12), 7825-7833.

Reichl, J., Kollmann, A., Tichler, R., Schneider, F., 2008. The importance of incorporating reliability of supply criteria in a regulatory system of electricity distribution: an empirical analysis for Austria. Energy Pol. 36, 3862–3871.

Reichl, J., Schmidthaler, M. and Schneider, F., 2013. The value of supply security: The costs of power outages to Austrian households, firms and the public sector. Energy Econ. 36, 256-261.

Richter, L. and Weeks, M., 2016. *Flexible Mixed Logit with Posterior Analysis: Exploring Willingness-to-Pay for Grid Resilience* (No. 1631). Faculty of Economics, University of Cambridge.

Rose, J.M., Bliemer, M.C.J., 2013. Sample size requirements for stated choice experiments. Transp. 40, 1021-1041.

Sagebiel, J., 2017. Preference heterogeneity in energy discrete choice experiments: A review on methods for model selection. *Renewable and Sustainable Energy Reviews*, *69*, pp.804-811.

Sagebiel J, Rommel K. Preferences for electricity supply attributes in emerging megacities - Policy implications from a discrete choice experiment of private households in Hyderabad, India. Energy for Sustain Dev 2014;21:89-99.

Scarpa, R., Rose, J., 2008. Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why’. Australian J. Agric. Econ. 52, 253–282.

Schmidthaler M.,  Reichl J., 2016. Assessing the socio-economic effects of power outages ad hoc: An application of BLACKOUT-SIMULATOR.com covering 266 European regions, 9 economic sectors and households separately. Comput. Sci. Res. Dev. 31, 157-161.

Strabac, Z., Aalberg, T., 2011. Measuring political knowledge in telephone and web surveys: A cross-national comparison. *Soc. Sci. Comput.* Rev. 29(2), 175-192.

Train, K., 2003. Discrete Choice Methods with Simulation. Cambridge University Press, New York.

Van Vliet, M.T.H., Yearsley, J.R., Ludwig, F., Kabat, P., 2012. Vulnerability of US and European electricity supply to climate change. *Nature Clim. Chang*. 2, 676-681.

Zachariadis, T, Poullikkas, A., 2012. The costs of power outages: A case study from Cyprus. *Energy Pol*, *51*, 630-641.