CaPPRe

Pilot Survey Report

Synergies
ECONOMIC CONSULTING

VALUE OF CUSTOMER RELIABILITY: WILLINGNESS TO PAY STUDY

Prepared for the **AER**
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OVERVIEW

BACKGROUND

The Australian Energy Regulator (the AER) is required to review its Values of Customer Reliability (VCR) methodology, then use this methodology to update VCR to determine the economic value that electricity customers place on reliable supply and publish the updated values. The next VCR update needs to be completed by 18 December 2024.

Synergies Economic Consulting ('Synergies'), together with Community and Patient Preference Research (CaPPRe), have been commissioned to perform econometric analysis using customer survey data collected by Lonergan Research.

The method of data collection, cleansing and econometric analysis remains substantially consistent with the methodology established for the previous VCR study conducted in 2019. AER signalled its intention to keep any changes to a minimum (as much as is practicable) to enable greater comparability between the 2019 VCR and the 2024 VCR and to allow an assessment of how customer values for reliability have changed over time, absent any confounding factors created through changes in questionnaire design.

The approach adopted for 2019 and to be repeated for 2024 includes two surveys: one for residential and another for business cohorts. The analysis uses contingent valuation and discrete choice experiments (DCEs). These valuation techniques are used to understand preferences and willingness to pay to avoid electricity outages for a representative sample of customers in the National Electricity Market (NEM) as well as specific customer sub-segments. At this stage the AER has made only minor changes to the questions that make up each survey.

The analysis conducted by CaPPRe and Synergies in this report confirms that the 2024 pilot study uncovered no critical flaws in the survey instruments or data collected. Our assessment, along with discussions with AER, confirms that the DCE model results align with prior expectations. The pilot study findings, therefore, provide sufficient confidence to proceed with the full launch of the survey to the larger customer sample.

DATA AND METHODOLOGY

METHODOLOGY

The contingent valuation and DCE techniques used in this study are summarised below.

Contingent Valuation

The contingent valuation survey asked participants (both in the business and residential surveys) for their willingness to pay to avoid experiencing baseline outages. To determine average willingness to pay across the sample, the survey includes three questions, with the second question contingent on the response provided to the first.

*Would you be willing to pay an increase of $**<$BILL>** in your **<frequency>** electricity bills (over six months this is a total of $**<$6M>**) to avoid both the power outages described in the above scenario?*

If the answer is ‘yes’,

*Would you be willing to pay an increase of $**(<$BILL>*2)** in your **<frequency>** electricity bills (over six months this is a total of $**(<$6M>*2)**) to avoid both the power outages described in the above scenario?*

If the answer is ‘no’,

*Would you be willing to pay an increase of $**(<$BILL>*0.5)** in your <<insert billing period>> electricity bills (over six months this is a total of $**(<$6M>*0.5)**) to avoid both the power outages described in the above scenario?*

The third question is;

*What is the maximum increase in $ you would be willing to pay in your **<frequency>** electricity bill to avoid both the power outages described in the above scenario?*

Residential survey

The first question in the residential survey proposed a specific willingness to pay amount ('bid'), asking if participants are willing to pay the stated bid to avoid an outage (indicated as “$BILL” above). The bid is a randomised number from 2 to 11 (inclusive). Only whole numbers were possible including 2,3,4,5,6,7,8,9,10,11.

A second question was used to introduce a different bid based on the individual’s response to the first question. Respondents were asked once again if they are willing to pay this bid. Depending on their initial response, subsequent bids were adjusted accordingly: a 'yes' response resulted in a higher bid (initial bid x 2), while a 'no' response led to a lower bid (initial bid x 0.5). The answer to the third of these three contingent valuation questions was used to determine willingness to pay.

In the residential survey, the answer to the third question was used as a measure of respondents’ maximum willingness to pay, except for respondents that entered a value greater than $32 for the third question above. These respondents were shown an additional question that appeared later in the survey (see below).

Imagine a company could install a backup power system at your premises. The system will readily provide electricity at your premises for one hour if an outage occurs. The total cost of the system, including installation, would be $32 per month.

Would you get the company to install the backup system at your premises at a cost of $32 per month?

The benchmark value of $32 represents the estimated average cost to Australian households of acquiring a backup system that would provide electricity to their premises for one hour (duration of baseline outage)[1]. If respondents indicated that they would have a backup system installed at their premises for $32 per month, their maximum willingness to pay value was assumed to be $32 per month.

For those respondents that indicated they are not willing to pay $32 per month, a follow-up question was asked, as given below:

What is the maximum $ you would be willing to pay per month for this system?

The response to this question was then used as a measure of maximum willingness to pay. Responses were capped at $32.

Business survey

The business survey used a similar sequence of contingent valuation questions to that developed for the residential survey, with some minor differences, which are discussed below.

The bid amounts presented for the first two contingent valuation questions were based on a randomised percentage point increases in bills (ranging from 1 through to 10 percentage point increases[2]). This percentage of bill was applied to a bill estimate to give the dollar value presented for the first two contingent valuation questions.

The third question was phrased as follows:

What is the maximum increase in $ you would be willing to pay in addition to your <HV2> electricity bill to avoid both the power outages described in the above scenario?

Respondents were asked to indicate the maximum additional amount they would be willing to pay, beyond their current electricity bill, to avoid the described power outages. The response was presented as a percentage increase relative to their last bill on the screen. A respondent's willingness to pay was then calculated using this percentage increase, capped at 100%.

[1] This value was $22 in the 2019 study (KPMG & Insync, 2019).

[2] Only whole numbers were used, for example 1%, 2% through to 10%.

Discrete Choice Experiments

An overview of the DCE approach is presented in Figure 1.

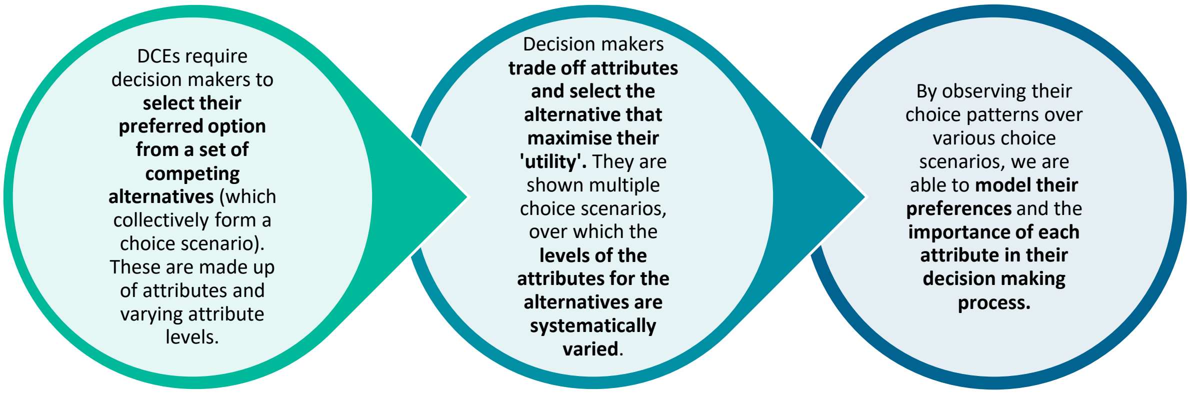

Figure 1: DCE approach

The attributes and levels used in the DCE are provided in Table 1.

Table 1: Attributes and levels used in the DCE

Attribute	Level	
	Residential	Business
Discount	No change	No change
	$4/month[3]	1% of bill
	$8/month[3]	2% of bill
	$18/month[3]	3% of bill
Localised/widespread	Localised	
	Widespread	
Duration	1 hour	
	3 hours	
	6 hours	
	12 hours	
Frequency (fixed)	Twice a year	
Summer/winter	Summer	

[3] Levels were scaled based on billing frequency.

	Winter
Weekdays/weekends	Weekdays
	Weekends
Time of day	Peak
	Off-peak

The DCE design or experimental design refers to the process of generating specific combinations of attributes and levels that participants evaluate in choice scenarios. This was generated by AER.

An example DCE scenario from the 2024 pilot survey is given in Figure 2.

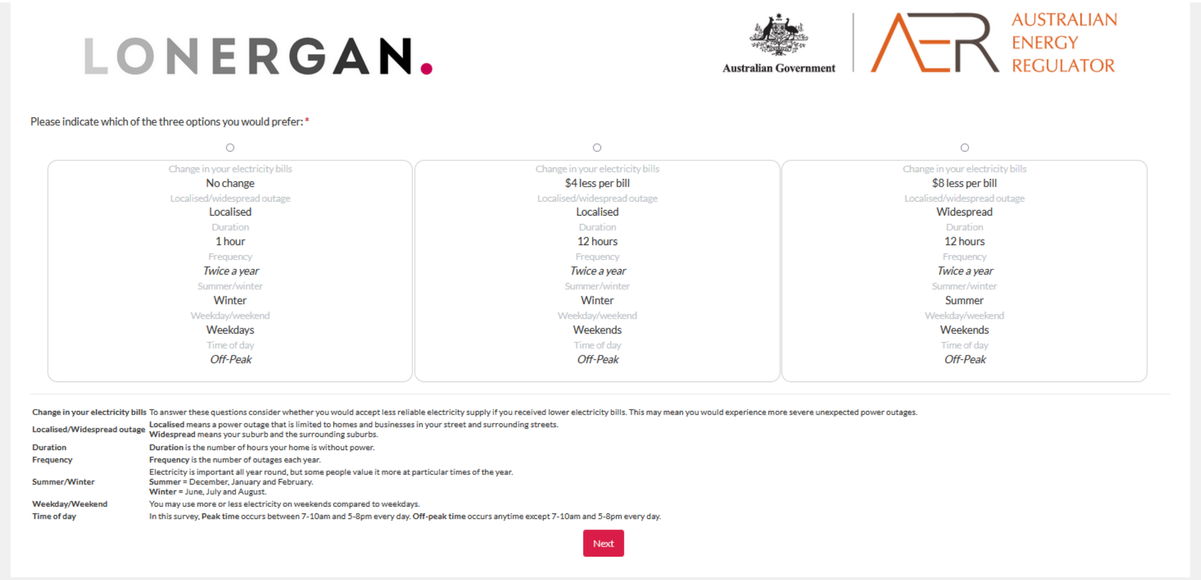

Figure 2. An example scenario from the 2024 pilot survey

SURVEY STRUCTURE

Two surveys were conducted: one for residential respondents and another for business cohorts. Each survey included an online questionnaire consisting of contextual and demographics questions, contingent valuation questions and a DCE. The survey content closely resembled the VCR 2019 study developed by AER (KPMG & Insync, 2019). The 2024 fieldwork is conducted by Lonergan Research.

DCE ANALYSIS

For the DCE analysis, a Multinomial Logit (MNL) model was used to estimate the parameters of the choice model, consistent with the approach used in 2019. Further information on DCE analysis is contained in Appendix 1.

RESULTS

RESIDENTIAL

The pilot testing for the residential sample was only conducted with respondents from the Climate Zone 5 – CBD and suburban postal areas within NSW supplied by the AER, and therefore the results are specific to this geographical region.

Contingent valuation baseline values: residential

The baseline willingness to pay is given in Table 2 and is expressed as a $ value per month.

Table 2: Baseline outage

Item	Baseline outage $
$/month per two 1-hour outages	3.97
$/month per single 1-hour outage	1.98

The majority of residential baseline willingness to pay values are clustered between $0 and $5, with a decline in response numbers beyond this range.

DEC model coefficients for scenario attributes: residential

MNL model results

The structure of the utility functions specified within the MNL are given in Appendix 2. The model parameter estimates, and their associated standard errors (SE), Z value and P value are displayed in Table 3.

Table 3: MNL model results: residential

Parameters	Symbol	Coefficient	SE	z-value	P value
Constant					
Status Quo	constant	-0.071	0.128	-0.55	0.582
Severity					
Widespread	wide	-0.218	0.079	-2.75	0.006
RC: Localised					
Duration					
3 hours	3h	-0.826	0.100	-8.25	0.000
6 hours	6h	-1.415	0.110	-12.91	0.000
12 hours	12h	-1.869	0.127	-14.69	0.000
RC: 1 hour					
Season					
Summer	summer	-0.160	0.080	-2.01	0.045
RC: Winter					
Time of day					
Peak	peak	-0.321	0.082	-3.93	0.000
RC: Off-peak					
Weekend/weekdays					
Weekend	weekend	0.144	0.080	1.81	0.070

Parameters	Symbol	Coefficient	SE	z-value	P value
RC: weekdays					
Discount					
Discount (continuous)	*discount*	0.071	0.007	10.51	0.000
Number of respondents: 218; Number of choice observations: 1744; RC: Reference category; SE: Standard error					

When considering the severity of the outage, residential respondents showed a preference for localised outages over widespread ones. They favoured shorter durations, with a preference for a 1-hour outage over 3 hour, 6 hour or 12 hour outages. Winter outages were preferred over summer ones, and off-peak times were preferred over peak times. Additionally, higher discount amounts corresponded with a higher preference among respondents.

Subgroup analysis: residential

A subgroup 'face validity' analysis was conducted similarly to the 2019 study. As requested by AER, willingness to pay to avoid baseline outages was calculated for a number of selected subgroups given in Table 4. It should be noted that some of these subgroups have low sample sizes in this pilot study, and therefore, definitive conclusions should not be drawn from the results.

Table 4: Subgroup analysis: residential

Subgroup	Label	Baseline willingness to pay $/month per two 1-hour outages	Number of respondents (n)
Current financial situation	Live comfortably	$5.28	40
	Meet basic expenses with a little left over for extras	$3.66	98
	Just meet/don't have enough to meet basic expenses & prefer not to say	$3.70	80
Rooftop solar	No rooftop solar	$3.84	168
	Rooftop solar owners	$4.40	50
Working from home	Never work from home	$3.90	173
	Work from home at least one day per week	$4.23	45

The above results show that:

- those with higher incomes and less financially constrained had a higher baseline willingness to pay
- respondents who work from home at least one day per week had a higher baseline willingness to pay

- respondents with rooftop solar had a higher baseline willingness to pay compared to those without[4].

These results do not contradict what one would expect based on economic theory and provide us with a degree of confidence that the survey instruments are performing as intended and generating valid measures of willingness to pay.

BUSINESS

Contingent valuation baseline values: Business

In the business sample, the baseline willingness to pay was expressed as a percentage increase in the total bill and is presented in Table 5, for the total sample, as well as for the industrial and commercial subgroups. The agriculture subgroup was not separately reported due to a low sample size.

Table 5: Business willingness to pay as a percentage increase in total bill

Cohort	Sample size	Percentage increase in total bill
Total sample	**218**	**12.06%**
Industrial subgroup	36	8.73%
Commercial subgroup	180	12.26%

The distribution of willingness to pay as a percentage increase in the total bill for business respondents is highly left-skewed, with the majority of respondents indicating a low percentage.

DCE model coefficients for scenario attributes: Business

MNL Model results

The structure of the utility functions specified within the MNL are given in Appendix 2. The model parameter estimates, and their associated SE, Z value and P value are displayed in Table 6.

[4] There could be several explanations for why solar photovoltaic (PV) owners might exhibit higher willingness to pay. For instance, PV owners may forego export income, potentially increasing their willingness to pay. Additionally, PV owners might be accustomed to lower electricity costs and consequently consume more electricity, which could also elevate their willingness to pay. On the contrary, some PV owners may possess islandable batteries (or believe they do), which could decrease their willingness to pay.

Table 6: MNL model results: business

Parameters	Symbol	Coefficient	SE	z-value	P value
Constant					
Status Quo	constant	0.494	0.145	3.40	0.001
Severity					
Widespread *RC: Localised*	wide	-0.178	0.082	-2.18	0.030
Duration					
3 hours	3h	-0.501	0.106	-4.74	0.000
6 hours	6h	-0.566	0.105	-5.39	0.000
12 hours *RC: 1 hour*	12h	-0.761	0.103	-7.38	0.000
Season					
Summer *RC: Winter*	summer	-0.042	0.076	-0.55	0.579
Time of day					
Peak *RC: Off-peak*	peak	-0.119	0.076	-1.57	0.117
Weekend/weekdays					
Weekend *RC: weekdays*	weekend	0.334	0.079	4.25	0.000
Discount					
Discount (continuous)	*discount*	0.224	0.046	4.86	0.000
Number of respondents: 218; Number of choice observations: 1744; RC: Reference category; SE: Standard error					

When considering the severity of the outage, business respondents preferred smaller outages that affected only a local area (localised) instead of larger ones that affected many places (widespread). They favoured shorter durations, with a preference for a 1 hour outage compared to 3 hour, 6 hour or 12 hour outages. Business respondents also preferred outages that occurred on weekends compared to weekday ones. Additionally, higher discount amounts corresponded with a higher preference among respondents.

Subgroup analysis: business

A subgroup analysis for the business cohort was not included in the report as suggested by AER, due to small subgroup sample sizes.

CONCLUSION

The 2024 pilot study uncovered no critical flaws in the survey instruments or data collected. Our assessment, along with discussions with AER, confirms that the DCE model results align with economic theory about expected relationships between variables in the survey response data.

The pilot study findings therefore provide sufficient confidence for moving to the full launch of the survey to the larger customer sample.

REFERENCES

AER (2024). Values of Customer Reliability Methodology: Revised draft determination. Australian Evergy Regularor. June 2024. Canberra ACT.

KPMG & INSYNC (2019). Value of customer reliability. Main survey report.

APPENDIX 1: DCE ANALYSIS

Econometric software, Nlogit version 6, was used to model the DCE data. The model structure was consistent with Random Utility Theory (RUT), which states that decision makers compare alternative goods and services within a market and select the bundle of attributes or goods that yield the maximum utility (i.e., the respondent is a utility maximiser) (Hensher et al., 2005). In the following, U_{nsj} denotes the utility of alternative j by respondent n in choice situation s. RUT proposes that overall utility U_{nsj} can be written as the sum of the observable component[5], V_{nsj}, expressed as a function of the attributes presented and a random or unexplained component, ε_{nsj} as shown in equation (1).

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

where:

U_{nsj} is the overall utility of alternative *j* by respondent *n* in choice situation *s*

V_{nsj} is the observed or explained component of utility (for alternative *j* by respondent *n* in choice situation *s*)

ε_{nsj} is the random or unexplained error component.

The multinomial logit model (MNL)

Consistent with the 2019 study, the selected functional form to be 'fitted' to the DCE data was the multinomial logit model (MNL). For this model the parameter weights (β) are assumed to be invariant across the sample. This assumption can be represented by the observed utility component in equation (2) below. V_{nsj} is referred to as the observable or explained component because this is where the set of attributes that are observed are stored. The betas in equation (2) represent the relative weights attached to each attribute. These weights define the importance of each attribute in its contribution to relative utility. Sigma (σ_n) represents the scale and is typically normalised to one to allow for identification of parameters. V_{nsj}, in its simplest form, is typically assumed to be a linear relationship of observed attribute levels and the corresponding parameter weights.

MNL is often used to estimate the V_{nsj} component of the utility equation as a function of the alternative's defining attributes. It takes the following form, where β_{jk} is the parameter coefficient for attribute k of alternative j, and x_{nsjk} is the data variable indicating the level shown for attribute k of alternative j in choice scenario s for participant n.

$$V_{nsj} = \sigma_n \sum_{k=1}^{K} \beta_{jk}\, x_{nsjk} \tag{2}$$

The MNL model structure relies on certain assumptions that impose restrictive conditions on its behaviour. Firstly, it assumes that the error terms (ϵ_{nsj}) are independent and identically distributed (IID) of extreme value type 1 (EV1). This leads to further restrictions around the independence of observed choices and independence of irrelevant alternatives (IIA), where the relative probabilities of

[5] Otherwise referred to as the systematic or observed component.

two alternatives being chosen are not affected by the inclusion or exclusion of other alternatives. Furthermore, the parameter coefficients (β_{jk}) are assumed to be invariant across the sample. This means that it limits itself to only one set of parameter coefficients (or parameter weights) to describe the trade-off behaviour of all survey participants combined (i.e., homogeneity of preferences).

APPENDIX 2: UTILITY EQUATIONS

The structure of the utility functions that were specified within the MNL model are shown below. There are utility functions for the Option 1, Option 2 unlabelled alternatives and Option 3 which is defined as the status quo/current below. The parameter coefficients were generic/consistent across alternatives.

$$U_{Option1} = \beta_{wide}x_{wide} + \beta_{3h}x_{3h} + \beta_{6h}x_{6h} + \beta_{12h}x_{12h} + \beta_{summer}x_{summer} + \beta_{weekend}x_{weekend} + \beta_{peak}x_{peak} + \beta_{discount}x_{discount} + \epsilon_A$$

$$U_{Option2} = \beta_{wide}x_{wide} + \beta_{3h}x_{3h} + \beta_{6h}x_{6h} + \beta_{12h}x_{12h} + \beta_{summer}x_{summer} + \beta_{weekend}x_{weekend} + \beta_{peak}x_{peak} + \beta_{discount}x_{discount} + \epsilon_B$$

$$U_{Option3} = \beta_{SQconstant} + \beta_{wide}x_{wide} + \beta_{3h}x_{3h} + \beta_{6h}x_{6h} + \beta_{12h}x_{12h} + \beta_{summer}x_{summer} + \beta_{weekend}x_{weekend} + \beta_{peak}x_{peak} + \beta_{discount}x_{discount} + \epsilon_{SQ}$$

The position of the "status quo" option was varied in the experiment; In other words, it was not always presented as Option 3 in all scenarios, despite being represented that way in the utility equations above.