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ERSA working paper 727

January 2018

Economic Research Southern Africa (ERSA) is a research programme funded by the National Treasury of South Africa.

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January 9, 2018

Abstract

South African households, like households in many other developing countries, are faced with regular power outages. This is a big problem, since the outages that the households experience are both frequent and long in duration. Efficient electricity infrastructure investment decisions are possible only if the welfare loss of electricity blackouts is determined. We estimate a measure for welfare analysis. The surveys were conducted using electronic equipment (gadgets/tablets) instead of the orthodox paper method. We subject respondents to eight power outage scenarios. We use a random parameter panel Tobit model to account for both zero willingness to pay (WTP) and cross-sectional heterogeneity. In addition to exploring more scenarios, this study contributes as it extends basic analysis found in the literature by allowing for a proportion of the sample to have a zero WTP. A zero WTP is in many cases not unrealistic. The picture that emerges is that WTP increases with duration, which was expected. Overall, South African households place a significant value towards avoiding the interruption. The WTP values presented in this paper are as an approximation of the value of supply security. Improving reliability of supply to households requires significant and continuous investment in electricity infrastructure.

* **Acknowledgements.** The paper has benefitted from input from Fredrik Carlsson, University of Gothenburg, Sweden. The Funding from the National Research Fund and the University of Johannesburg Research Committee (URC) internal research grant is gratefully acknowledged.

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1 Introduction

At the end of 2007, South Africa began experiencing widespread blackouts, as electricity demand surpassed supply. This problem came about due to the government's failure to invest in new power plants, in the face of significant growth in the heavily energy reliant economy, and the electrification programme that was embarked on in 1994. In 2008, there were extensive blackouts, which had a negative effect on the economy and on households. Given the threat they posed to the national grid, 'load shedding'[1] commenced. This proved insufficient; hence, power-supply restrictions on mines and large industries were introduced.

Households are end-users of electricity, and their welfare is negatively affected by power cuts, due to increased electricity dependence over the years. Although the welfare 'lost' by households cannot easily be quantified, the fact that households are heavily reliant on power suggests this impact should be analysed. South African households, like households in many other developing countries, are faced with regular power outages. This is a big problem, since the outages that the households experience are both frequent and long in duration. Despite every effort, South African households will continue to face electricity-supply challenges in the foreseeable future.

Load-shedding is not a choice; it is not a strategy; it is an emergency that the policy makers want to avoid at all. Therefore, all that decision-makers can do is to minimize the costs of the implementation. The paper's purpose is to examine the different dynamics and linkages of households to their perceived loss due to power cuts.

The costs associated with power outages may be direct, indirect or ongoing (Schmidthaler, 2012). Costs may be monetary and/or non-monetary. Ketelhodt and Wocke (2008) point out that financial costs from outages may also result from defects caused in electrical appliances, which may need to be repaired or replaced. As stated by Lawton *et al.* (2003), Praktiknjo *et a*l. (2011) and Jha *et al.* (2012), welfare losses because of power outages are inconvenience and loss of leisure. Schmidthaler (2012) also point outs that a welfare loss, especially in a case where the outage is not communicated beforehand, can also lead to emotional stress - households do not know when the power will be back on again, which causes panic and anxiety.

According to Pasha and Saleem (2012), the cost of an outage differs along with income level. Higher-income earners may lose more during an outage because of a higher dependence on electricity. For example, a low-income

[1] Load shedding is an emergency whereby one area is supplied with power and the other cut off to save the national power grid from total collapse.

household will typically use a paraffin stove during an outage. By contrast, a high-income earner is more likely to use a gas stove or a generator, which is more expensive. In most instances, high-income households have expensive appliances that can be costly to fix or replace if they are damaged.

Since households are also highly affected by power outages, it is probable that households will be willingness to pay (WTP) to avoid or reduce outages. Some of the outage elements households regard as important are the timing and frequency, and whether there is a warning beforehand (Hensher *et al.,* 2013). The consequences of an outage may be larger or smaller depending on the timing. Weather conditions also affect WTP. Households may be WTP more to avoid outages in winter than in summer. This analysis will determine the extent to which households are dependent on electricity service in different situations.

The primary objective of this study is to quantify household's WTP to avoid power cuts. In this study, the contingent valuation method (CVM) is used to elicit outage costs. Reliable power supply is increasingly important, especially as households have become more dependent on electricity. Our study contributes to the scant literature on WTP to avoid power outages in developing countries, particularly in Africa. In particular, it provides more information about households' WTP to avoid power outages in South Africa. Most importantly, this study extends work done in studies such as by Moeltner and Layton (2004); Carlsson and Martinson (2007) by subjecting respondents to many more outage scenarios. We subject respondents to eight outage scenarios compared to two in the latter study. Furthermore, we contribute by extending basic analysis found in the literature by allowing for a proportion of the sample to have a zero WTP. A zero WTP is in many cases not unrealistic.

2 Background

Thanks to overinvestment, South Africa had a healthy electricity supply in the 1980s - the result of optimistic electricity-demand forecasts by Eskom engineers. The result of this excess supply was lower electricity tariffs; Eskom entered long-term deals in which electricity was sold to power-intensive industries at below cost-reflective tariffs, to utilise excessive power reserves. They also mothballed some power stations, and cancelled or delayed upcoming construction plans.

Eskom was instructed to stop building more power stations, with the eventual aim of privatising the entity. In fact, more investment was needed, given the government's electrification programme to substantially increase the number of electrified households. The fact that Eskom funded the electrification programme with no private capital put severe pressure on the power utility's resources. Eskom raised capital by selling bonds, and secretly hiking electricity tariffs. These measures did not raise sufficient revenue, forcing the power utility to seek outside investment (Eberhard 2004). They failed to attract investors, and the government came to Eskom's rescue; however, it was too late to avert the inevitable power cuts.

Furthermore, there were significant reductions in coal stockpiles across all power stations. This was due to higher global coal prices, which led to local suppliers preferring to export their coal instead. The quality of coal sold to Eskom was also questionable (Public Protector South Africa, 2009). Wet coal, due to the heavy rainfall experienced between October 2007 and February 2008, also contributed to production problems - wet coal can cause blockage to conveyer belts, making smooth running difficult and resulting in below-average output.

The period from 2000 on was characterised by decreasing reserves, as power demand continued to grow faster than supply. By end of 2007, South Africa had begun to experience regular power outages. There are many reasons for the electricity supply shortage that resulted in blackouts from 2008. The main reason was inadequate generating capacity, because of poor planning.

Around 2007, the reserve margin dropped to around eight per cent. At this level, it is difficult to meet demand during maintenance; the international reserve margin is about 15 percent. South Africa's economic growth was faster than expected, and the low stockpiles could not meet demand; hence, load shedding was adopted (Calldo, 2008).

3 Literature Review

Power outages result in economic losses for both the power utility and the users. Many empirical studies have attempted to measure the cost of power outages to households, mainly using the CVM and choice experiments (CE). Generally, household losses due to power blackouts are moderate. However, longer, more sustained and disruptive power blackouts due to the complete collapse of the national power grid are likely to result in more significant losses for households; hence the need to ascertain WTP to avoid such prolonged power interruptions.

Despite a growing number of studies in this area, studies focusing on household welfare losses due to power interactions remain limited, especially in developing countries. Kufeoglu and Lehtonen (2014) classify outages into three categories, namely 'brief', 'sporadic' and 'chronic' outages. The first type lasts for a very short period - often a few seconds. The second type often stems from bad weather, and is longer in duration. The third type is mostly caused by inadequate power generation, or under-performance of old power plants. It is usually of a longer duration, relative to the others. Chronic outages are the most common type of outages in developing countries, because of insufficient resources.

Carlsson and Martinsson (2007) study in Sweden about households' WTP to reduce power outages found that people are likely to be WTP for longer outages. Moreover, there is a low WTP among respondents who do not live in big cities, because in most cases those areas are not prioritised and tend to experience more outages; hence, they are usually prepared for them. WTP also has a positive relationship to income. Those with high income often have more electrical appliances, and are WTP more for a reduction in outages.

Lim *et al.* (2013) estimated the value of electricity in the Republic of Korea. The country experienced an electricity crisis in 2011, due to increased demand. To remedy the situation, policymakers had to know how much households were WTP, so they could increase investment in electricity. On average, households value a reliable and consistent electricity supply, and were WTP for that. However, WTP went down as the bid went up; meaning the respondents were only prepared to pay a base price, which was 10 Korean Won (KRW) per kWh; but not the highest bid, of 60 KRW per kWh.

Another CVM study done in South Korea estimated inconvenience costs from outages. There has been a major increase in electricity consumption in South Korea - in fact, in 2012 the country was rated the 11^{th} -highest electricity consumer in the world. Their reserve margin has been dropping since 2003, thanks to growing electricity demand coupled with electricity prices that were lower than their generation cost. On the other hand, supply was growing at a slower pace; hence the pressure on the national grid. It was found that WTP was high for those households that consume more electricity, as well as in the high-income brackets. Respondents were WTP, but were more sensitive to bid increases. It was concluded that WTP is higher for unannounced outages than it is for announced outages (Kim *et al.*, 2015).

Woo *et al.* (2014) conducted a study in Hong Kong, estimating outage costs. Although the electricity supply in Hong Kong is very reliable, outages would occur, mostly during summer afternoons. These outages would last for between five and 30 minutes. More than half of the respondents in the study sample would have traded some reliability for a lower electricity bill. On the other hand, about 23 percent of the respondents were WTP five percent more on their electricity bill in order to eliminate five minutes of outages; 13 percent were WTP 10 percent more for a 30-minute outage reduction; while the rest did not want to pay more at all.

Households in the Flemish region of Belgium were not WTP for extra reliability of electricity supply. A CE analysis showed how unimportant reliability of supply was for the respondents. Only nine percent of the sample was WTP for increased reliability. Moreover, households preferred outages in summer and during off-peak periods. It is argued that the reason for Flemish households is so tolerant of power outages may be because outages in the area are rare. Around 75 percent of households experienced no more than two outages in two years (Pepermans, 2011). This in in contrast with Townsend (2000)'s analysis, which found that when people are not accustomed to power outages, they tend to be WTP more for reliability.

A WTP study using a CE was done in Kenya, to determine how much people were WTP to reduce unannounced electricity outages. A warning before a power outage was found to be a significant factor, as it allowed users to make the necessary arrangements, especially for households with home businesses. Furthermore, it was found that older people, and people who had stayed in the area for a longer period, had lost confidence in government policies, and were not WTP more for power reliability. However, those with bigger families and with businesses were WTP more for increased reliability (Abdullah and Mariel, 2011).

Results from previous studies highlight several demographic and behavioural factors that influence WTP valuations. Households are generally WTP higher tariffs to reduce power outages, especially those that use electricity more and those that are self-employed. By contrast, when outages are frequent, some households may get used to outages, and end up not being WTP to avoid them. In addition, households from remote areas that are not usually given the same attention as big cities are not WTP to avoid power outages. This study will reveal the impact power outages have on households and their WTP for different outage scenarios. The study also sheds light on the significant determinants of WTP, which has generated vital information for policymakers.

4 Empirical approach

The aim of our study is two-fold. Firstly, we want to estimate a measure for welfare analysis. Secondly, we would like to find the relevant determinants of WTP. The type of information we gather depends solely on the elicitation format. An open-ended format is used for power-outage analyses. Tisdell *et al.* (2008) state that an advantage of open-ended questions is that it is the respondents' privilege to formulate their own answers. The interviewer does not influence the response, and therefore the answer is based on what is most relevant to the respondent at that moment. It is free from starting-point bias which could otherwise influence the respondent's answer, especially when they are not familiar with or do not have enough information about the good in question.

In addition, open-ended questions do not restrict respondents to only a few options to choose from, and cater for possibilities that the interviewer did not anticipate, and which might be beneficial (Boyle, 2003; Kong *et al.,* 2014). The respondents may even elaborate on their answers (Ertor-Akyazi *et al.*, 2012). Disadvantages include respondents not being able to give relevant answers immediately; they may have to think about them for some time. Some people may even misunderstand the question(s) and disclose other information that is not relevant. In such cases, the interviewer can help the respondent by simplifying the question, or by asking follow-up questions that can direct the respondent to think of relevant answers (Champ, 2007).

In addition, open-ended questions are notorious for extreme responses, which may have a large impact on the mean WTP. This problem can be addressed by reporting both the mean and the median, since the median is not sensitive to outliers. As respondents are free to answer whatever they want, the second major problem with the open-ended format is the prevalence of 'zero' answers to the question of WTP. It is reported that between 10 and 50 percent of all respondents' state zero WTP (Carlsson, 2008). Valid zero WTP account for 41 percent of all respondents in our study, which is within the range in the literature.

Due to a large proportion of 'zero WTP' responses generated by the open-ended method, it is vital that a distinction between conditional and unconditional WTP is made, to illustrate the impact of the zero. Two types of responses exist, namely, zero WTP responses and positive WTP responses. It should be noted that the mean WTP could be for the whole population, and for the population with positive WTP. Let P (Zero) be the probability that a respondent has a zero WTP, and let P (Positive) = 1-P (Zero) be the probability that a respondent has a positive WTP. In the case where the mean WTP for the conditional sample (positive WTP) is: E [WTP|WTP>0], the mean WTP for the unconditional sample is: E [WTP] = Pr (Zero) * 0 + E (WTP|WTP>0) * Pr (Positive) = E (WTP|WTP>0) * Pr (Positive). To estimate the WTP function, the WTP function for an individual k is:

$$WTP_K = f(Z_K, a, \varepsilon_K) \tag{1}$$

where Z is a vector of socio-economic characteristics, a is a vector of experiment-specific characteristics, and ? is an error term. As discussed earlier, WTP is expected to be zero for a portion of the observations. Different types of models are used for censored variables. The ordinary least squares (OLS) method is not suitable for this analysis, because it may underestimate or overestimate the results (Wooldridge, 2013). Standard OLS gives biased coefficient estimates. But by using a Tobit model, this can be done twofold: by Tobit type I model or by a Two-equation independent model. In the Tobit model, the 'true' latent WTP function is:

$$WTP_K^* = (\beta_K + \varepsilon_K) \tag{2}$$

What we observe is the following:

$$WTP_K = max(0, WTP_K^*)_{\varepsilon_{K \sim N(O,\sigma_K^2}} \tag{3}$$

So, in this case, the dependent variable is a censored variable (i.e. we do not observe the value of WTP when it is below a certain threshold); Tobit type 1 model. Formally, it is equivalent to a corner solution model (i.e. WTP is positive, continuous and observable, but = 0 for a non-trivial fraction of the population). However, the Tobit model assumes that the same data-generating process (DGP) that explains the zeros also explains the positive values. Not distinguishing between the zero responses and the positive responses in a clear way could lead to mis-specification problems. An alternative that addresses this challenge is the two-equation model. The easiest possible model involves firstly deciding whether to state a positive WTP or not (Carlsson, 2008).

$$d^* = (\gamma Z_K + \mu_K) \tag{4}$$

Then we have the latent WTP:

$$WTP_K^* = (\beta Z_K + \varepsilon_K) \tag{5}$$

However, we make the following observation:

$$\begin{gathered} WTP = 0 \ if \ d^* = 0 \ WTP = WTP^* if \ d^* = 1 \\ E[WTP|WTP > 0] = \beta Z_K \end{gathered} \tag{6}$$

Our survey results in several observations from each respondent, which generates a cross-sectional heterogeneity (which is even more reason for an OLS to give biased coefficient estimates). Because respondents are free to state zero WTP in the survey, the censoring aspect is considered when modelling. As Carlsson and Martinsson (2007) did, we use a random parameter panel Tobit model to account for both zero WTP and cross-sectional heterogeneity. According to Anastasopoulos *et al.* (2012), a random parameter Tobit model can be estimated as follows:

$$Y_i{}^* = \beta X_i + \varepsilon_i, i = 1, 2, \ldots, N \tag{7}$$

where N is the number of observations, $Y_i{}^*$ is the WTP dependent variable, X_i represents independent variables, β is a vector of estimable coefficients (duration and other socio-economic characteristics), and $?_i$ is the error term. The likelihood function is as follows:

$$L = \Pi[1 - \Phi(\beta X/\sigma]\Pi[\sigma - 1\Phi[(Yi - \beta X)/\sigma \tag{8}$$

where Φ is the standard normal distribution function, and $\sigma$is the standard normal density function. We compare the random parameter Tobit model results with the standard Tobit model. As stated by Carlsson (2008), different models imply different WTP distribution. For instance, an exponential WTP model restricts WTP to being non-negative, while a linear WTP model allows for a negative WTP. However, these models do not make provision for a proportion of the sample stating zero WTP. Modelling of zero WTP can be done in two main ways: by modelling it in a separate analysis, or as a two-stage analysis.

The former analyses the probability of zero WTP (for example, with a Probit model). Then it analyses the probability of a 'yes' response on the restricted sample WTP>0. It is a simple approach; however, it does not handle sample selection. A two-stage approach analyses the probability of zero WTP and the probability of a 'yes' response as a sample selection problem - for example, running a Tobit model for open-ended data, or alternatively a bivariate Probit in the case of a closed-ended format. In our analysis, the random parameter Tobit model is chosen as the main model of interest, as it can address the zero responses while analysing the positive responses and addressing sample selection.

5 The survey

5.1 *Survey instrument*

The study was undertaken in and around Johannesburg, Gauteng province and Thyspunt, Eastern Cape province. Johannesburg is the economic hub of not only South Africa, but Africa. According to Stats SA (2013), about 84 percent of households have access to electricity. The province boosts the highest number of households of any province, and is most likely the worst affected by power cuts; hence, it was deemed most appropriate for our study.

The Eastern Cape is one of the poorest provinces in South Africa. For this reason, our sample is representative as it includes the wealthiest and poorest province. The sample included households across all income levels. The face-to-face surveys that were undertaken targeted household heads; however, in cases where surveys were done during the week while household heads were at work, another individual involved in household decision-making was interviewed. The fieldwork was performed between May and June 2015, and yielded a total sample of 695 respondents (i.e. the initial sample consisted of 768 responses, but 73 'protest' responses were excluded). Protest zero bids were identified by follow-up questions that examine the respondents' motivation for providing zero bids. In the case of this study, reasons cited for zero bids was the belief that the good should be provided by means other than personal payments.

The surveys were conducted using electronic equipment (gadgets/tablets) instead of the orthodox paper method. This new method has gained momentum lately because of its efficiency. It minimises human error, because the coding of the survey into the gadget occurs in advance, to make it easier and less time-consuming for the enumerator when collecting data. This systematic method reduces mistakenly skipped questions that might otherwise occur when rushing to complete the survey, or entering incorrect information when capturing data, since data capturing occurs automatically when the survey is completed.

The survey instrument comprised three parts. The first part consisted of warm-up questions; general information regarding outages. Since Eskom[2] has load-shedding schedules for different areas, households were asked to reveal outage frequency and duration, to determine the reliability of Eskom's load-shedding schedule. The respondents also had to list financial losses they incurred because of outages, if any. Over 50 percent of the respondents had experienced financial losses due to power-outage-related damages. In addition, there was a question asking how well Eskom was dealing with the power crisis. Most respondents were of the view that the power utility was doing its best to resolve it. According to Akcura (2015), when households trust the supplier, they are likely to be WTP.

Furthermore, with the outages having become more prevalent, households were asked what back-up[3] options they had, or if they were planning to invest

[2]Eskom is the state-owned utility responsible for generating and distribution electricty in South Africa

[3]We refer to backup electricity devices which were acquired for backup purposes during power outages that can give the household the needed power for some essential electronic

in such options. We also asked respondents about their current monthly electricity bill, which is used as a reference in the WTP scenarios. This is in line with the view of Munro and Sugden (2003) that reference-based scenarios provide estimations that are more reliable. However, it would have been ideal to use the price of electricity per kilowatt-hour (kWh) as a reference, since the outage scenarios are measured in hours.

This was not possible, as according to Eskom (2015), not only different classes of consumers pay different amounts for the same quantity of electricity, depending on area of residence but also consumers in different geographical regions because the households do not pay Eskom directly but the municipalities. By contrast, in a study by Ma *et al.*, (2015), the WTP's measure is kWh; however, some respondents found their monthly bill more meaningful than what they paid per hour. This is true for household electricity users in general, since most of users do not know the hourly rate they are charged for electricity.

The second part of the questionnaire covered the WTP scenarios. Households were asked to respond to the following statement: " *Imagine if the National Energy Regulator (NERSA) supplies back-up electricity when there is an outage. Your electricity needs will be taken care of when there is an outage. Payment to the regulator will only be required when there is an outage. If you do not have a willingness to pay, you will not be covered, and the outage will occur as usual. In some cases, there will be a notification before the outage, and in other cases there will be no notification. We would like to know: how much is your willingness to pay to avoid outages of different durations and at different times of the day, week or seasons.*"

In other words, we asked responds how much they would be prepared to pay to another supplier, in this case the energy regulator for provision of electricity during emergencies. WTP during power cuts to another supplier as a means of avoiding power outages approximates the value of supply security. From this information, the costs due to power cuts are computed for households. The third part of the questionnaire asked for demographic information, including gender, age, marital status, household size and income, which is standard in this kind of study.

5.2 *Descriptive Statistics*

Table 1 below presents the descriptive statistics from our sample. Ages ranged from 21 to 78 years old, with the youth accounting for a large proportion. Those between 21 and 35 years old made up about 57 percent of

devices, cooking and/or lighting when utility power is cut.

the sample, followed by 36- to 55-year-olds who accounted for 36 percent, with the remainder being those over 56 years old. Our sample is in line with South African demographics, with the youth making-up for the majority of the country.

On average, household size was roughly four people, while the largest household in the sample had 15 people. More than half (56.8 percent) of the respondents were employed full-time, followed by 15.3 percent self-employed and 11.4 percent employed part-time. A significant proportion of our sample (44.6 percent) earned less than R50 000 ($4 167) per annum. Most respondents had gone as far as high school (45.6 percent). This is consistent with Stats SA (2013) statistics showing that for most South Africans (about 64 percent of the population), highest education achieved is completion of high school.

The average electricity tariff paid was R928.89 ($77.42). About 15 percent of the respondents had back-up options, generators and batteries being among the most common. Generators themselves carry certain risk factors for health, such as fumes and noise pollution. In addition, 14 percent of the sample depended on electricity for their health, needing to refrigerate their medicines or use electrically-powered medical equipment.

Approximately 63 percent indicated the period from 18:00 to 22:00 as the most disruptive time for an outage to occur. The most important activity to be disrupted at that time was preparing for dinner (60.9 percent), followed by general household disruption, such as electrical appliances that could not be used (34.5 percent), and preparing kids for school and preparing for work for the next day (30.8 percent). In another study, Baarsma and Hop (2009) discovered that similarly, households in the Netherlands did not want outages in the evenings. Over 40 percent of the respondents felt that the electricity supply was reasonable, and that all households experience load-shedding fairly.

According to 'A survey of energy-related behaviour and perceptions in South Africa', 14 percent of household expenditure in South Africa goes to electricity. This is higher than the international average of 10 percent (Department of Energy, 2012). According to Dikgang and Muchapondwa (2016), having access to electricity enables households to benefit from the 'free 50kW' that the government gives every month to poor South Africans. Therefore, respondents in our sample reporting electricity bills of only R10 most probably receive this basic 50kW per month free electricity. It is likely that the free basic electricity allocation is just shy of being adequate for the whole month.

A year was chosen as a reasonable period for the respondents to recall the number of outages they had experienced in the past, to get an indication of how often power outages occurs. Households that experienced outages the most indicated an occurrence rate averaging seven times in the past year, while those affected the least indicated one occurrence in the past year.

The shortest duration reported for an outage was two hours, and the longest was eight hours. This raises questions for Eskom, since according to their load-shedding schedule, no outage should last more than four and a half hours. According to Eskom (2015), the average load-shedding period lasts between two and four hours. However, a 'two-hour' outage may end up lasting two and half hours because of the block connecting time, which is usually 30 minutes. The same applies to the 'four-hour' outage, which may end up being four and half hours.

Respondents also added their concerns about the load-shedding schedule, saying that in most cases Eskom did not stick to the schedule. Beside the unreliable predicted durations, sometimes an expected scheduled outage would not occur, or an outage would occur when none was expected. Households also suffered costs including damaged electrical appliances and food spoilage, because of power disruptions.

6 Empirical results for determinants of power outages

The following section discusses the results of an analysis of power outages obtained from three models, using the same dependent and independent variables. This analysis caters for different outage situations, including planned and unplanned outages, summer and winter outages, peak and off-peak outages, and weekday and weekend outages. WTP differences are expected, because electricity usage differs across the above situations, hence we estimate a WTP function that allows for differences in valuation between these eight cases of outages. Moreover, WTP variables are in log-form.

As is the case in a study by Moeltner and Layton (2002); Carlsson and Martinsson (2007), since there is many observations with zero WTP, we firstly recoded the WTP values before the log-transformation by adding the value 1 to all observations. Hence, a dependent variable then became $\ln(WTP + 1)$. Therefore censoring at 0 still is valid since $\ln(1) = 0$.

For data collection, two-hour and five-hour periods were chosen for the planned and unplanned outages. The five-hour period was chosen to cater for the worst-case scenario by including the block-connecting time of 30 minutes, and rounding it up to five hours. For seasonal outages, only summer and winter were chosen, even though there are four seasons. These two seasons contain the two extremes (hottest period and coldest period) of the four seasons. In addition, peak and off-peak periods are considered. In principle, electricity is used mostly during peak periods, and so it is interesting to see if this matters to household users. The intercept and the eight outage scenario coefficients are assumed to be normally distributed.

Due to the open-ended nature of the responses, a random parameter Tobit model is used to address the zero responses in the power outage scenarios. Table 2 below summarises the estimation results for WTP to avoid power outages from two models: the random parameter Tobit model, which is the main model of this study; and the standard Tobit model. The latter model is used to validate the results of the random parameter Tobit model. It is important to note that no multicollinearity was detected in the model. Our sample is randomly drawn from 695 households. We take 16 observations from each household.

With a few exceptions, all the outage scenarios' estimated parameters are significant at the one percent level, except for the off-peak scenario. As expected, most of the scenario parameters are significant and positive. All the slopes' coefficients are positive, meaning that costs are on average higher for planned outages, during winter, during peak hours, and on weekdays. WTP for unplanned outages is expected to differ from that for planned outages; because with planned outages, other options can be prepared to reduce the financial cost and inconvenience of the outage. On the other hand, unplanned outages may leave households desperate; hence they are also WTP for them, even though they do not think unplanned outages should occur. This contrast with Carlsson and Martinsson's (2004) findings, which showed households are more sensitive to unplanned outages; in our case, respondents state they would deal better with planned outages than unplanned ones.

In summer, demand for electricity falls, thanks to warmer weather (Eskom, 2014). However, summer outages can lead to food spoilage, especially outages of longer duration. For that reason, households may be prepared to pay for summer outages. But in winter the probability of WTP is higher, because of the low temperatures. This is evident from the magnitude of the summer and winter coefficients in Model 1 and Model 2; the winter coefficients are higher.

Peak periods are the busiest, and when electricity demand is highest; it is expected that households would be WTP to avoid an outage at this crucial time. There is a bit more resistance when it comes to off-peak outages, as can be seen on Model 1, which is only significant at 10 percent for off-peak outages, while Model 2 is not significant. This is not surprising; electricity usage is low during those times, so off-peak periods are not as important to households. Outages are even more detrimental during weekdays, as they disrupt preparations for work and school; while at weekends, most households remain at home. However, for some households it is important to have electricity on weekends for entertainment purposes, *because* they are not going out.

Although it is not shown in Table 2 above, we also assessed whether outage duration is also a significant determinant of WTP to avoid power outages. In the survey, we included all planned, unplanned, summer, and winter outages with durations of 2, 3, 4 and 5 hours. The results from this analysis indicate that WTP for outages - whether planned, unplanned, winter or summer - increases as duration increases, which is indicated by the signs of the coefficients changing from negative to positive.

The results of the random parameter Tobit model and the standard Tobit model are similar, to a large extent. The coefficients in the former model are marginally higher, which implies that not controlling for observed heterogeneity results in underestimation of the coefficients. But failure to control would not have resulted in major differences. A look at observed heterogeneity does not reveal any interesting findings. Surprisingly, the electricity bill, availability of back-up power, and medical equipment that uses electricity are not significant across all the models. Male respondents have higher WTP, and students also have significantly higher WTP. Older respondents have lower WTP.

The noticeable differences from model 1 and model 2 are in terms of demographics. More demographic parameters are significant in model 2 than in model 1. The Tobit model - model 2 - show that in addition to male dummy, age and student, which are significant in model 1, children under 18 years, education years, and employment are also significant. Respondents with children under 18 years old are WTP more than those without, and those who are employed are also WTP, although not as much as students. Education level does have a significant impact on WTP. This is consistent with the notion that individuals who are more educated have a higher probability of being WTP to avoid power outages.

We also present a spike model, which consists of a Probit model followed by a truncated regression model. This model is used as further validity for the random parameter Tobit model. The spike model that was proposed by Kriström (1997), is presented as an extension of the first two models presented in Table 2. Given the significant number of zero WTP responses, it is vital to analyse the probability of zero WTP. Here, we are looking at the mean WTP for the whole sample. We adopted a separate analysis approach, in which we first ran the probability of zero WTP using a Probit, followed by the analysis of the probability of a 'yes' response on the restricted sample, WTP>0 - model 2. A relevant model for the second stage is one that restricts

WTP to being non-negative.

Apart from the off-peak scenario, the other entire scenarios are negatively signed and significant. This result is logical, given that these respondents are bidding zero WTP for avoiding power outages overall. Males, households with children under 18 years old, education level and students are more unlikely to be WTP zero, which is consistent with findings in models in table 2. The finding that older respondents are more likely to be WTP zero is also consistent with model 1 and 2 results. The truncated results for model 2 show that households with children over 18 years are WTP significantly more than other households. This also applies to education years - that households with higher education are WTP significantly more - as well as students. Older households are also WTP significantly less than younger respondents.

In contrast to other models, household income, self-employment and retirement all matter for WTP>0. Since both WTP and income are in log form, income elasticity is equal to the marginal effect of the income variable on WTP. The income elasticity for WTP is around 25.16 percent, which suggests that a one-percent increase in household income increases WTP by 25.16 percent. Retired people are WTP significantly more than other occupations, followed by students and those who are self-employed.

Models in table 2 give the effect on WTP, while models table 3 give the effect on the decision to state a positive WTP or not, and the effect on WTP given that WTP is positive. Caution should be employed when interpreting coefficient magnitudes. To do that, we should instead look at marginal effects (i.e. the change in predicted probability, linked with changes in the explanatory variables).

The marginal effects capture the change in the dependent variable for a marginal change in an independent variable. For an OLS model, this would simply be the coefficient. For the censored and limited variable models, this is not the case. For this reason, it is wrong to interpret the results from a Probit model as marginal effects, for example. However, we can get marginal effects after running our models (Carlsson, 2008). Table 4 below shows the marginal effects post-random parameter Tobit analysis.

If planned outage increases by one unit, WTP increases by 0.04 units. If unplanned outage increases by one unit, WTP increases by 0.03 units. This shows that respondents are WTP more for planned versus unplanned outages. Respondents are WTP more in winter relative to summer. Their WTP will increase by 0.05 units to avoid winter cuts, compared to 0.03 during summer. The increase in WTP for peak versus off-peak is significantly higher, which was to be expected. Weekdays are also preferred over weekends. If number of students increases by one unit, WTP increases by 0.14 units. An older respondent WTP is 1 unit lower than for younger respondents.

In table 5 below, based on estimated WTP function we present WTP for power outages of different outage scenarios which. As with Carlsson and Martinsson (2007), we also calculate the predicted WTP for outages of different durations using the estimated relationship between the WTP and power outage duration by using sample means for all the other variables in the WTP functions. We calculate the predicted WTP for durations between 1 and 5 hours. To calculate predicted WTP, we need to firstly transform the expected latent log WTP into expected censored log WTP (see Greene, 2002). Thereafter we convert the log WTP into absolute WTP.

Note that simply taking the exponent of the expected log WTP would result in a log-transformation bias (Goldberger, 1968). In the case of this study, we follow Moeltner and Layton (2002) and Carlsson and Martinsson (2007) by multiplying the expected log WTP with a transformation term that is based on the actual observations of the WTP. The transformation term we make use of is the ratio between the actual WTP and the exponent of the expected log WTP.

The picture that emerges is that WTP increases with duration, which was expected. When making a comparison of planned and unplanned scenarios, the results from Table 4 above show that respondents prefer paying more for planned outages than for unplanned outages (i.e. in contrast with Carlsson and Martinsson, 2007). We argue that there are a number of relatively low-cost measures that can be implemented to mitigate economic and social costs of electricity blackouts such as improved planning and communication with households. Therefore, the relatively higher WTP for planned compared to unplanned outages reflects household's preference for a low-cost measure as a mitigating strategy towards the costs of blackouts. This suggests that households prefer effective communication channels prior to planned outages.

It is not surprising that WTP for peak periods is significantly more than for off-peak periods (more than double), because peak period is the time when electricity is used the most. The same applies to summer and winter outages: more power is used in winter. The finding that WTP is more for winter relative to summer is consistent with those in other studies (see Reichl, Schmidthaler, and Schneider, 2013). The share of zero WTP is slightly higher for summer outages than it is for winter outages. There is not a very big difference in WTP for weekends and weekdays. Having power on weekends and on weekdays has similar importance, though weekdays do have preference.

7 Conclusions

Using a contingent valuation survey, we elicited South African households' WTP to avoid load shedding. The panel type of data was generated, following a survey of 695 respondents interviewed face-to-face in Gauteng and the Eastern Cape province. A random parameter Tobit model was used in the first section of the study, while a spike model was used in the second analysis.

The specific challenge of the modelling exercise is to account for zero WTP answers to the scenarios. Besides open-ended contingent valuation, choice experiments have gained momentum over the last decade. In this respect, there are also econometric methods allowing to account for a zero WTP in choice experiments, such as Reichl and Fruehwirth-Schnatter 2012.

It is not surprising that households are WTP more to avoid power cuts between 18:00 to 22:00, as that is peak time for households. It is clear from household responses that important activities occur during peak periods, since the majority stated that 18:00 to 22:00 is both a peak period and the most disruptive time, therefore the 'outage cost' is high. Beside the inconvenience, most of the financial costs involved relate to damaged electrical appliances and food spoilage. However, if load-shedding is necessary to prevent the national power grid from collapsing, a notification beforehand is preferred as it enables households to plan of time to reduce the costs resulting from an outage. Thus, notification beforehand is deemed important to households.

The results are as expected, and consistent in the sense that households are WTP the most to avoid winter and weekday power outages. Due to the severity of winter and the higher demand compared to summer, it is not surprising that households are WTP relatively more to avoid winter outages than summer ones. This is closely followed by payment to avoid peak power cuts. The finding that households are WTP more for planned as opposed to unplanned power cuts is somewhat surprising; one would expect households to have more tolerance for planned cuts, as they can make alternative arrangements beforehand. Overall, duration and seasonality of power outages are the main drivers of WTP.

Power outages is a social good, hence it is imperative that the government becomes aware of public opinions and preferences about possible solutions to power outages or preferred energy technologies. South African households are generally WTP for improved reliability of power supply. Overall, South African households place a significant value towards avoiding the interruption. This study gives a snapshot of household WTP to avoid power outages. The study generates insight into welfare loss due to power outages. This WTP estimates in this study approximate the value of supply security.

The value that society places on avoiding electricity blackouts is an important first step in energy planning and policy. Although the level of electricity security has improved over time, maintaining this degree of reliability in future is going to be difficult. Efficient electricity infrastructure investments decisions are possible only if the values associated with electricity blackouts is determined. The findings in the study could have much more implications than for the pricing, for the investments in infrastructure and the quality assurance of the network.

The massive blackout has left millions of people without power. South Africa's power crisis has widespread effects on both social and economic development. South African households would like more investment on electricity infrastructure, and their WTP to avoid blackouts implies that they would not want to leave the future of the electricity grid to chance. Some argue that Smart Grids could help reduce the cost of outages. The electricity infrastructure must account for multiple objectives, including quality assurance of the network (i.e. reliability), affordability and security of power supply.

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List of Tables:

Pricing electricity blackouts among South African households

Table 1: General demographic information of respondents

Variables	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Male = 1 if male, otherwise 0	0.54	0.50	0.00	1.00
Age – age in years	35	12	21	78
Household size	4 people	1.89	1.00	14.00
Children under 18 = 1 if at least one child is < 18 years	0.57	0.50	0.00	1.00
Education years	4.6	3.58	0.00	20.00
Annual Household Income	R217 935 ($18 161)	R230 860 ($19 238)	R50 000 ($4 167)	R750 000 ($62 500)
Employed = 1 if working full time, otherwise 0	0.57	0.47	0.00	1.00
Student = 1 if student, otherwise 0	0.35	0.22	0.00	1.00
Self-employed = 1 if self-employed, otherwise 0	0.15	0.36	0.00	1.00
Retired= 1 if retired, otherwise 0	0.02	0.15	0.00	1.00
Bill amount – monthly electricity bill	R929 ($77)	R987 ($82)	R35 ($3)	R7 000 ($583)
Available backup = 1 has backup power, otherwise 0	0.15	0.36	0.00	1.00
Medical equipment = 1 use medical equipment that requires electricity, otherwise 0	0.14.	0.35	0.00	1.00

Table 2: Determinants of WTP to avoid power outages, using a random parameter Tobit model, and standard Tobit model

Dependent Variables	Random Parameter Tobit ln (WTP + 1)	Tobit ln (WTP+1)
Independent variables	Model 1	Model 2
Random parameters		
Constant	2.57 (2.06)	1.7 *** (0.45)
Planned	0.38 *** (0.02)	0.34 *** (0.03)
Unplanned	0.31 *** (0.02)	0.27 *** (0.04)
Summer	0.29 *** (0.02)	0.26 *** (0.04)
Winter	0.48 *** (0.02)	0.44 *** (0.04)
Peak	0.63 *** (0.03)	0.59 *** (0.06)
Off-peak	0.06 * (0.03)	0.02 (0.06)
Weekdays	0.95 *** (0.05)	0.87 *** (0.09)
Weekends	0.32 *** (0.02)	0.29 *** (0.04)
Fixed parameters		
Bill amount	0.00002 (0.00007)	0.00003 (0.0001)
Available back-up	0.004 (0.21)	-0.04 (0.37)
Medical equipment	0.27 (0.21)	0.14 (0.38)
Male dummy	0.30 ** (0.14)	0.29 *** (0.07)
Age	-0.07 *** (0.02)	-0.05 *** (0.003)
Household size	0.04 (0.09)	0.004 (0.02)
Children under 18 years	0.30 (0.34)	0.24 *** (0.07)
Education years	0.05 (0.05)	0.04 *** (0.01)
Log income	-0.16 (0.18)	-0.06 (0.04)
Employed	0.11 (0.57)	0.24 * (0.12)
Student	1.5 * (0.85)	1.16 *** (0.18)
Self-employed	-0.17 (0.69)	0.05 (0.15)
Retired	0.72 (1.23)	0.44 (0.27)
Log likelihood	-14 728.42	-20 596.55
Number of Households	690	690
Number of obs.	11 040	11 040
Prob. > chi2	0.00	0.00

Note: Standard errors in parentheses

* p < 0.10; ** p< 0.05; *** p < 0.01

Table 3: Determinants of WTP to avoid power outages, using a spike model, and truncated regression model

Dependent Variables	Spike Model (WTP = 0)	Truncated Regression (WTP>0)
Independent variables	Model 3	Model 4
Random parameters		
Constant	-1.12 *** (0.17)	-302.05 ***(29.18)
Planned	-0.05 *** (0.01)	27.3 *** (2.26)
Unplanned	-0.04 *** (0.01)	23.08 *** (2.32)
Summer	-0.04 *** (0.01)	20.56 *** (2.40)
Winter	-0.1 *** (0.01)	29.11 *** (2.36)
Peak	-0.15 *** (0.02)	29.97 *** (3.68)
Off-peak	0.03 (0.02)	17.27 *** (4.06)
Weekdays	-0.19 *** (0.03)	52.3 *** (5.58)
Weekends	-0.06 *** (0.01)	16.8 *** (2.25)
Fixed parameters		
Bill amount	0.00001 (0.00004)	0.003 (0.01)
Available back-up	0.01 (0.14)	3.69 (24.58)
Medical equipment	-0.01 (0.14)	22.77 (24.23)
Male dummy	-0.13 *** (0.03)	4.11 (4.70)
Age	0.02 *** (0.001)	-0.67 *** (0.22)
Household size	-0.01 (0.01)	-1.66 (1.18)
Children under 18 years	-0.08 *** (0.03)	15.39 *** (4.70)
Education years	-0.01 ** (0.00)	2.19 *** (0.70)
Log income	0.06 *** (0.01)	25.16 *** (2.53)
Employed	-0.03 (0.04)	2.82 (7.83)
Student	-0.37 *** (0.07)	25.81 ** (11.08)
Self-employed	0.08 (0.05)	18.46 * (9.54)
Retired	-0.09 (0.10)	107.4 *** (19.27)
Log likelihood	-7 171.70	-42 460.71
Number of Households	690	405
Number of obs.	11 040	6 479
Prob. > chi2	0.00	0.00

Note: Standard errors in parentheses

* p < 0.10; ** p< 0.05; *** p < 0.01

Table 4: Marginal effects post-random parameter Tobit model

Planned	0.04 *** (0.002)
Unplanned	0.03 *** (0.002)
Summer	0.03 *** (0.002)
Winter	0.05 *** (0.002)
Peak	0.06 *** (0.003)
Off-peak	0.01 ** (0.003)
Weekdays	0.09 *** (0.01)
Weekends	0.03 *** (0.002)
Bill amount	0.000002 (0.00001)
Available back-up	0.0004 (0.02)
Medical equipment	0.03 (0.02)
Male dummy	0.03 ** (0.01)
Age	-0.01 *** (0.002)
Household size	0.004 (0.01)
Children under 18 years	0.03 (0.03)
Education years	0.01 (0.005)
Log income	-0.02 (0.02)
Employed	0.01 (0.06)
Student	0.14 * (0.07)
Self employed	-0.02 (0.07)
Retired	0.07 (0.11)

Note: Standard errors in parentheses

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 5: WTP Results to avoid power outages

Scenario	Mean WTP	Standard Deviation	Median WTP	Minimum	Maximum	Share of Zero WTP
Planned	R64.21 ($5.35)	164.83	17.50	0.00	2 885.00	41.44%
2 Hours	R37.68 ($3.14)	85.63	10.00	0.00	1000.00	43.45%
3 Hours	R58.18 ($4.85)	182.02	15.00	0.00	3040.00	41.87%
4 Hours	R71.24 ($5.94)	175.07	20.00	0.00	3500.00	40.29%
5 Hours	R89.74 ($7.48)	216.60	25.00	0.00	4000.00	40.14%
Unplanned	R52.13 ($4.34)	110.48	12.50	0.00	1 425.00	43.92%
2 Hours	R31.31 ($2.61)	69.43	5.00	0.00	1 000.00	45.76%
3 Hours	R43.75 ($3.65)	87.60	10.00	0.00	1 200.00	44.03%
4 Hours	R60.51 ($5.04)	129.64	15.00	0.00	1 500.00	42.88%
5 Hours	R72.95 ($6.08)	155.26	20.00	0.00	2 000.00	43.02%
Summer	R48.80 ($4.07)	113.93	10.00	0.00	45.04%	45.04%
2 Hours	R28.06 ($2.34)	79.45	0.00	0.00	50.79%	50.79%
5 Hours	R69.53 ($5.79)	148.41	20.00	0.00	39.28%	39.28%
Winter	R76.17 ($6.35)	159.10	25.00	0.00	2 000.00	35.40%
2 Hours	R45.65 ($3.80)	107.92	10.00	0.00	1 000.00	38.85%
5 Hours	R106.68 ($8.89)	210.29	40.00	0.00	3000.00	31.94%
Peak	R69.36 ($5.78)	141.66	20.00	0.00	1 500.00	32.52%
Off-peak	R30.70 ($2.56)	85.26	0.00	0.00	1 200.00	53.09%
Weekdays	R76.31 ($6.36)	149.23	20.00	0.00	1 600.00	34.53%
Weekends	R61.11 ($5.09)	124.16	20.00	0.00	1 500.00	36.40%