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Bigerna, Simona and Choudhary, Piyush and Kumar Jain, Nikunj and Micheli, Silvia and Polinori, Paolo

Department of Economics, University of Perugia, Oil and Natural Gas Corporation Ltd., Ministry of Petroleum Natural Gas, Government of India, Indian Institute of Management Nagpur, Department of Economics, University of Perugia, Department of Economics, University of Perugia

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Households' willingness to pay in India

Simona Bigerna[a*], Piyush Choudhary[b], Nikunj Kumar Jain[c], Silvia Micheli[a], Paolo Polinori[a]

[a] Department of Economics, University of Perugia, Via A. Pascoli, 20, 06100, Perugia, Italy

[b] Oil and Natural Gas Corporation Ltd., Ministry of Petroleum & Natural Gas, Government of India, New Delhi, India

[c] Indian Institute of Management Nagpur, Nagpur 441108, India

* Corresponding author: simona.bigerna@unipg.it

Abstract

Reliable electricity is a key factor in improving the living conditions of households and sustainable development of the country. Power outages restrict economic and social welfare of developing countries. This study used contingent valuation survey to elicit the factors affecting Indian household's willingness to pay to avoid unanticipated power outages. The survey was outlined to ensure that a household gives preferences considering multiple aspects of the outages. The households were asked to state their willingness to pay for five different types of outages. Empirical data from 1043 Indian households were analyzed using double hurdle approach. The econometric results indicate that the households' willingness to pay to avoid power outage strictly depend on the length of outages ranging, on average, from 30.2 INR (2 hours) to INR. 245.6 (12 hours). Further income and environmental attitude of respondents positively influence higher WTP to avoid power outages. Our findings provide useful insights for policy makers and utility companies to design more reliable and customer centric energy generation and distribution models.

Keywords: Power outages; contingent valuation; willingness to pay; residential electricity

JEL-Code: C24, C93, D12, Q41,

1. Introduction

Lack of reliable electricity is one of the major obstacles for economic growth of developing countries. Electrification, in particular in rural areas, helps reduce poverty increasing labor supply, schooling of boys and girls, household per capita income and expenditure (Sedai et al., 2022; Khandker et al., 2014). Thus, the provision of reliable electricity is a priority for many governments and development organizations. The absence of adequate and affordable electrical power in India is one of the significant obstacles of the country's economic development in today's digital society where reliability becomes highly crucial (Tiewsoh et al., 2019). Power outages characterize the service across India. On average, urban households face two hours of power outages at least once a day, while rural households, in particular in northern and eastern states face unanticipated supply interruptions for six or more hours per day (Agrawal et al., 2020). The situation was then exacerbated during 2021 due to the Indian energy crisis linked to the shortage of coal, which makes up around 70% of India's electricity mix (International Energy Agency, 2021). India is the world's second largest importer of coal, and its imports fell drastically due to the global coal prices increased by 40%. Thus, from 2021, major cities faced power outages for hours over the weekend, with several parts across India remaining without power for several hours a day. The government is facing an important challenge to achieve a balance between meeting demand for electricity from its almost 1.4bn people and the wish to both provide reliable power of adequate quality regularly to the population and reduce India's dependence on a polluting fossil source. However, in recent years, Indian government is developing renewable energies, led by solar power, to achieve the Sustainable Development Goals set by the 2030 Agenda for Sustainable Development. Actually, solar accounts for around 4% of India's electricity generation, but the country aims at reaching 450 GW of renewable capacity by 2030. Such ambitious targets act as a spur in the power sector. The Covid-19 crisis has complicated efforts to resolve the problems, among others, of reliable electricity supply for millions of Indian households. Despite the shock from Covid-19, India's electricity demand is still projected to grow by almost 5% per year to 2040 (International Energy Agency, 2021).

Although it is in customers' interest to pay low electricity tariffs, it is crucial to analyze whether Indian consumers would be willing to pay more for improvements in the reliability of power supply. Some literature suggests that investigating the demand side is crucial to explain the current gaps in electricity access. The analysis of the social needs of the population with respect to the reduction, up to the cancellation, of power outages, supports the decisions of investments in physical infrastructures (Agrawal et al., 2019). Thus, it is necessary to understand the factors that influence the attitudes and decisions of consumers with respect to electricity connections, which are typically not free, and for the level of continuity of the electricity service.

The aim of this paper is to measure the willingness to pay (WTP) of urban consumers for having a continuous supply of electricity for residential avoiding unanticipated power outages in India. The WTP is a monetary indicator that captures the perceived value of power outages for final consumers, that is, in a sense, the cost of outages. This information allows policy makers to make important considerations on investments to upgrade and modernize electricity infrastructures. This information provides policy makers with a list of issues to consider for enhancing investments in electricity infrastructure. We use a contingent valuation (CV) method, which is one of the most popular methods used by economists to value environmental goods and services (Deutschmann et al., 2021; Guo et al., 2014). In particular, we investigate the WTP for avoiding several types of outages differing in terms of duration. To elicit consumers’ WTP, we have conducted a web-based anonymous survey using an online questionnaire in Delhi, the capital city of India. The survey was conducted between October 1-20, 2021, and sample size was 1043. To capture the relationship between the WTP and the duration of the outages, we implement both equations system and the selection models (Heckman, 1979), which is an innovative methodological approach.

Our main findings are that both approaches used provide WTP estimated which are close, and the magnitude of the welfare measures are in line with the literature results, showing an evident monotonicity accordingly to the outages lengths. Results are also robust given that the WTP to avoid an hour of outage fall in a tight range. Our findings also highlight that zero responses represent an important issue in CV approach zeros in underestimate the aggregate WTP.

Our study is in line with previous literature investigating the WTP for avoiding unanticipated power outages and in relation to several possible characteristics of an outage, such as the duration, time of the week and time of the year. We contribute to existing literature by estimating preferences for avoiding unanticipated power outages among urban population using a large representative sample in Delhi. Given the insights from our findings, we provide key policy implications for improving power supply.

The remainder of the paper is organized as follows. Section 2 describes the related literature on the stated preferences method applied to the outages assessment. Section 3 shows method and econometric approaches. Section 4 provides empirical results including welfare analysis. Section 5 concludes.

2. Literature review

The cost of reducing power outages is an important information for power system planning and regulation mechanism designs. Basically, there are three approaches to estimate the value of power outages for consumers, i.e., direct methods, case specific applications, and survey-based approaches, such as CV (Carlsson and Martinsson, 2007). The latter is the most frequent option as it relies on primary data collection. Indeed, the first two approaches require, on the one hand, readily available statistical information that can typically be provided by companies, and on the other hand, applications that may not be feasible due to lack of data. Furthermore, survey-based approaches are the only ones that also consider all welfare effects by including non-market effects, e.g., during power outages individuals cannot watch their favorite TV show. This event certainly has a negative impact on people's welfare (Amoah et al., 2019).

The CV method is applied by interviewing a statistical sample of the population, and it provides a methodological way to ask WTP questions and values for goods, typically energy and environmental goods. Specifically, the method creates a realistic but still hypothetical scenario which details out the description of the good to be valued, it describes the payment method, and allows respondents to indicate how much they will be willing to pay for the good under investigation. Although the CV is a very popular method, the technique remains controversial. Indeed, although it aims at generating precise statistical estimates of WTP, concerns arise about the fact that respondents may not have all the information and incentives they need to fully research their preferences (MacMillan et al., 2006). However, the research highlights that if respondents are given with more information and time during the interview, and, in some cases, if the can join group discussions, they may form coherent and consistent values during the CV (Champ et al., 2002). Thus, CV is still widely utilized among researchers to measure nonmarket values.

Several studies analyze the WTP for improving electricity services in high-income countries (Carlsson et al., 2021; Wethal, 2020; Cohen et al., 2018; Morrissey et al., 2018; Cohen et al., 2016; Ozbafli and Jenkins, 2015; Hensher et al., 2014). A relatively smaller part of the literature analyzes the WTP for improving electricity services in developing countries for residential users (Chindarkar et al., 2021; Bakkensen and Schuler, 2020; Smith and Urpelainen, 2016; Oseni, 2017; Khandker et al., 2012; Abdullah and Mariel, 2010). Kennedy et al. (2019) find that in Indian rural communities where daily hours of electricity availability are high and outages or voltage fluctuation rare, households are willing to pay higher amounts on the electricity bill between 13% and 48%. Blankenship et al. (2019) conducted a survey on popular WTP for better service with data from Uttar Pradesh, India's most populous state, and results show that, although the WTP is generally low, it also varies substantially across households and situations, with trust as a powerful and robust predictor of the WTP.

Meles (2020) show that households in Ethiopia are willing to pay 20%–23% above their monthly bill to improve electricity reliability, on top of their regular monthly electricity bill. Taale and Kyeremeh (2016) find that monthly income, business ownership, household size and education significantly affect WTP for reliable electricity services in Ghana, and, on average, households are willing to increase their monthly electricity bill by approximately 44% to avoid power outages. Alberini et al. (2022) show that in Nepal households are willing to pay 65% more than their current bill to completely eliminate the electricity outages. Twerefou (2014), through a CV survey, assess households' WTP for improved electricity supply as well as the factors that influence WTP in Ghana. Results show that Ghanaian are willing to pay about one and a half times more than what they are paying now if they will be provided with improved electricity supply, and household income, sex, the level of education of the household head and household size are significant factors that affect households' WTP for improved electricity.

3. Methodology

3.1. Survey method and questionnaire

Our CV study was administered online the Delhi areas which has a population of 28 million of inhabitants and, roughly 3 million of households (Census, 2018) with 95% of the population that lives in urban areas. In this paper we have directly asked Indian households about their WTP to avoid power outages by using a stated preference approach (SPA). How it is highlighted by Carlsson et al. (2021), this is one out of three[1] different available approaches in order to assess the cost of power outages to households. SPA suffers of the several criticisms due to the required market simulation associated to the elicitation process, but it is able to capture the welfare changes due to both market and non-market effects. Consequently, SPA have often provided useful insights to regulate the electricity industry, helping to define the optimal level of maintains and investment in the power grid. Among the SPA methods the contingent valuation (CV) is one of the most used in the empirical literature on the electricity and energy sector. (Oerlemans et al., 2016; Sundt and Rehdanz, 2015; Ma

[1] The others two (Carlsson et al., 2021) refer to the direct cost of the outages or to the household's expenditure to mitigate outage effects.

et al., 2015). In the CV method a hypothetical market is used in order to trade and place a value on the non-market good analyzed (Mitchell and Carson, 1989). Both the current state of reference and the target state to be valued have to be clearly define in order to apply the CV method.

Consequently, the survey method and both the microeconomic theory and the econometric technique associated to the elicitation format used have to be explained in order to guarantee the readers understanding. To derive estimates of households' WTP for the value of electricity supply security, a rapid online survey[2] was conducted in October 2021, using Google Forms. We asked 1043 respondents a variety of energy-related questions, such as their experience with power outages, and about their socioeconomic characteristics (Table 1).

As experience with power outages might matter for the preferences on power supply security (e.g. Carlsson et al., 2011), we asked several questions pertaining to this issue.

A preliminary analysis was conducted in June 2021 by a focus group composed by energy managers, experts, members of energy authorities and consumers associations. Their knowledge permit to avoid value judgments and consumer confusion that typically affect non market evaluation e.g., in the case of outages economic assessment. Focus groups allowed us to properly construct the final questionnaire, describing several outages scenarios. Further, we administered the pilot survey (around 100 questionnaires) in order to check whether the proposed questions, related to the unanticipated outage characteristics were understandable, and to assess the pros and cons of scenario proposed. Validity test[3] questions (Soderqvist and Soutukorva, 2006) are also used to assess the goodness and

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[2] The full raw data set obtained was directly managed by authors for this research, so, on principle, no hidden non-stochastic distortions (such as recoding mistakes) affect the results. 1043 respondents have been interviewed with a sample frequency with is aligned with other research on outages assessment (See Table A1).

[3] Validity questions are also used to construct variables that concerns the accuracy of the answers provided by respondents about the scenario proposed. For example, focusing on the degree of RES knowledge if the respondent answered “yes” to the question on the RES knowledge and then correctly identified the different types of RES in the following question, the dummy variable is equal to one, zero otherwise.

the understanding of the scenarios descriptions also evaluating how respondents are directly or indirectly affected by the outages simulated. Finally, it is well known that in CV studies a divergence between stated and actual consumer behavior exists (Diaz-Rainey and Ashton, 2008). To reduce this divergence, a cheap talk script[4] is directly introduced in the elicitation format.

The final version of the questionnaire comprises three sections containing both close and open-ended questions.

The first section was designed to collect socioeconomic characteristics, their opinions concerning several issues linking India energy situation, a focus on renewables and main energy consumption activities.

In the second section several potential solutions for power outages are provided to the respondents, jointly with some assessment of the national energy policies.

The final section of the questionnaire includes the elicitation format, then the WTP[5] for different power outages durations are detected. The answers of this section of questions were also designed for the verification of valid responses.

3.2. Elicitation format

For the WTP questions, a payment card has been used with several bids for planned power outages. Formally, for the scenario described the maximum amount that respondents are willing to pay to

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[4] The cheap-talk script aims to decrease the potential hypothetical bias due to the respondents that claim to pay a higher or lower amount in CV context than they would do in a real payment situation. Specifically, among ex-ante methods, we have adopted a cheap talk script (Cummings and Taylor, 1999) in order to explicitly warn participants about hypothetical bias. Furthermore, participants are asked to respond to valuation questions as if the payment were actual. The script used is similar to that of Cummings and Taylor (1999) that was appropriately modified to be consistent with our scenarios.

[5] To construct a reliable WTP scenario, respondents were first asked to state the amount of their last bill and the outage suffered on average in the last year.

avoid unanticipated outage is asked[6] for each outage duration using as price vector a surcharge on electricity bill. Mitchell and Carson (1984) have first introduced the payment card approach that allow to identify a values' interval. Indeed, respondents are asked to choose the value, which represents their maximum WTP values that lies above the indicated value and below the next higher one. The advantages and the disadvantages of the payment card approach are well known (e.g., Mitchell and Carson, 1986; Cameron and Huppert, 1989; Ready et al., 2001; Hu, 2006; Kateregga, 2009). Summarizing, this approach is not affected by starting point bias and the original data allow to directly determine the WTP further, the estimated WTP is more robust. Finally, this approach guarantees a higher flexibility in finding the lower and upper bounds of the estimated WTP. However other type of bias[7] can affect this approach (e.g., range, centering, and end point bias). Furthermore, the WTP estimated value is affected both by the design of elicitation format and the estimation technique used to assess the welfare measure.

3.3. Econometric models

To analyze responses obtained requires to handle data that imply some econometric challenges to address. First, equations systems have been employed to jointly assess the WTP referring to different length of the outage. Formally, providing a payment card elicitation format for outages with different length we are dealing with the well-known problem of the relationship between WTP and the proposed quantity change (see among others Chilton and Hutchinson, 2003). To manage the scope sensitivity issue, we employ the equations system approach in order to properly take into in account

[6] Formally: *"Let consider that you will suffer power cut of various duration. If you DO NOT know in ADVANCE the schedule of such power cuts, how much maximum amount are you willing to pay in order to avoid power cut of 2 hours, similarly some maximum amount for each 4, 8, and 12 hours."*.

[7] A limitation of the payment card approach is the dependence on the bids offered to the respondents. The range chosen in this research was based on a presurvey Range obtained also considers the average cost for direct energy prices to households.

respondents' preferences for different lengths of the outages. Consequently, we wish to allow for the possibility that the decisions about WTP for different outages duration are not made independently using several equations systems to avoid the 2-, 4-, 8- and 12-hours outages as a single censored equation. The second and third points are strictly related referring to the double step procedure and the "zeros typologies". One could conjecture that the respondents' decision-making process can purposely be divided in two steps. First, respondent decides whether to respond to the questionnaire and only subsequently express her preferences with respect to the issues investigated.

A two steps decision process requires other two specifications. It is necessary to: i) verify if the two choices are correlated or not; ii) account for several censoring mechanisms that could affect data meaning. In other words, one has to test for two different types of zeros[8].

We safely assume that elicited zero values can belong to two different typologies: protest zeros and true zeros. The first type of zeros comes from respondents that do not accept or consider the scenario proposed as unrealistic. For instance, respondents with favorable attitudes towards such service but, at the same time, think that others should pay for avoid power cut might well respond with a protest zero. The second type of zeros comes from those respondents that do not value such service.

Formally, the two steps are considered separately, assuming that different determinants could influence participation and the subsequent outcome (stated WTP amount). This implies modelling the event using two latent variables and two latent equations. Furthermore, we use two separate

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[8] Accordingly, to Lindsey (1994) protests may occur if elicited WTP by respondents is different from their true WTP. Typically, even if respondent has a positive WTP (i) a zero WTP or (ii) much higher WTP are stated. Three main reasons usually explain this behavior (Boyle, 2003). First, respondent answers to the WTP question even if he does not understand what he is asked to do in the survey. Second, respondent act strategically hopping that the change proposed in the CV scenario will be paid by others. Third (Mitchell and Carson, 1989), respondents protest against some component of the CV survey refusing to "participate" in the "experiment" proposed. In order to differentiate between true and protest zeros a set of debriefing questions are proposed to respondents who are unwilling to pay for scenario proposed.

different samples a full sample with both types of zero and a second sample with only true zeros. Formally, using a panel card on one hand we apply the equations systems approach:

$y_i(WTP_{ah}) = X_{ia}\beta_{ia} + \varepsilon_{ia}$ (1a)

$y_i(WTP_{bh}) = X_{ib}\beta_{ib} + \varepsilon_{ib}$ (1b)

$y_i(WTP_{ch}) = X_{ic}\beta_{ic} + \varepsilon_{ic}$ (1c)

where *a, b, c* are equals to 2-*(4-)*, 4-*(8-)*, 8-*(12-)* hours in the short-medium (medium-long) outages model. Following Rodman (2011) the SUR model used to estimate the systems of equations is:

$$\underset{1xj}{\boldsymbol{y}^{*\prime}} = \underset{1xj}{\boldsymbol{\theta}'} + \underset{1xj}{\varepsilon'}$$

$$\underset{1xj}{\boldsymbol{\theta}'} = \underset{1xk}{x'} + \underset{kxj}{\boldsymbol{B}} \tag{2}$$

$$\boldsymbol{y} = \{g_1(\boldsymbol{y}^*), \dots\dots, g_j(\boldsymbol{y}^*)\}'$$

$$\varepsilon|x \sim i.i.d\ \mathrm{N}(\boldsymbol{0}, \boldsymbol{\Sigma})$$

where *B* is a matrix of coefficients, *y* and *ε* are random vectors, *x* is a vector of predetermined random variables *(x1, ..., xk)'* and we set $g_j(y^*)$ as truncated regression assuming that the dependent variable is bound between the lower $[T_i^{LO}]$ and upper $[T_i^{UP}]$ truncation points. Consequently, the *LL* must be normalized by the total probability over the observable range as follows:

$$LL_i\left(\beta, \sigma^2, T_i^{LO}, T_i^{UP}; y_i|x_i\right) = \frac{\phi(y_i - \theta_i; \sigma^2)}{\Phi\left(T_i^{UP} - \theta_i; \sigma^2\right) - \Phi\left(T_i^{LO} - \theta_i; \sigma^2\right)} \tag{3}$$

$$LL_i\left(\beta, \sigma^2, T_i^{LO}, T_i^{UP}; y_i|x_i\right) = \int_{h^{-1}(y_i)} f_\varepsilon(\varepsilon)d\varepsilon \Big/ \int_T f_\varepsilon(\varepsilon)d\varepsilon \tag{4}$$

with $T = \left[T_i^{LO} - \theta_i, T_i^{UP} - \theta_i\right]$ and $\Phi(\cdot)$, that is, the cumulative normal distribution.

On the other hand, following Cragg (1971), one can simultaneously take into account two stochastic processes and the two types of zeros.

Combining equations two stochastic processes and binary censoring data type are accounted for:

$$y_i = \begin{cases} y_i^* \text{if } d_i^* > 0 \text{ and } y_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{5}$$

The associated likelihood function depends on the relationship type assumed between the two error terms. Assuming independence one obtains:

$$logL = \sum_{y=o} ln\left[1 - \Phi(z_i\delta)\left(\frac{x_i\beta}{\sigma}\right)\right] + \sum_{y\in R^+} ln\left\{\Phi(z_i\delta)\frac{1}{\sigma}\phi\left[\frac{y_i - x_i\beta}{\sigma}\right]\right\} \quad (6)$$

And that the associated likelihood function with the Double Hurdle model with dependent errors (Cragg, 1971) is:

$$logL = \sum_{y=o} \ln\left[1 - \Phi\left(z_i\delta, \frac{x_i\beta}{\sigma}, \rho\right)\right] + \sum_{y\in R^+} \ln\left\{\Phi\left[\frac{z_i\delta + \frac{\rho}{\sigma}(y_i - x_i\beta)}{\sqrt{1-\rho^2}}\right]\frac{1}{\sigma}\phi\left[\frac{y_i - x_i\beta}{\sigma}\right]\right\} \quad (7)$$

4. Results and discussion

The findings obtained with the two different econometric models are reported in this section, considering the two samples, both the complete one and the one including only the true zeros. Initially, we briefly discuss the descriptive results. Table 1 shows stated WTP amounts accordingly to the several scenarios proposed. Using all 1043 observations, WTP to avoid unanticipated outages strictly depend on the outages' lengths proposed even if WTPs range between 0 INR and 1200 INR for all durations considered. Mean and median computed are strictly increasing moving from 2- to 12-hours with the mean that ranges from 15.38 INR to 194.58 INR Considering only the true zeros the remaining 833 observations included into the sample exhibit higher mean WTP values that range from 19.24 INR to 242.86 INR.

Table 1 here

Female exhibit lower WTP compared to male, especially for the short outages (10.6 INR vs. 16.1 INR for 2-hours and 21.9 INR vs. 29.1 INR for 4-hours) and the differences are statistically significant. For medium and long outages, the stated WTPs by male and female are instead closer each other's. WTPs are also negatively correlated with the family size. Respondents belonging to high-income classes show, on average, a higher WTP. Particularly the higher is the income the higher is the WTP with the only exception of long outages (12 hours) that, however, are significantly different compared to medium (8-hours) outages. Furthermore, WTPs are also highly related to the amount of the electricity bill. Pro-environmental behavior also emphasizes the difference between the mean WTP values among the sample. Indeed, respondents characterized by pro-environmental behavior (respondents those believe in renewable projects to mitigate outages) show a higher WTP compared to others. Finally, respondents mainly prefer to avoid outage from 7 to 14.

4.1. Equations' systems approach

In accordance with the estimated models, Table 2 shows results for both types of samples, divided into short-medium term and medium-long term. From Table 2 it emerges that the statistically significant parameters do not vary significantly with the variation of the model, and show signs consistent with theoretical expectations. Furthermore, within each model, these parameters are robust even by comparing the individual equations. Generally, the parameters relating to medium-long term models have a greater magnitude than those of medium-short term, highlighting how the duration of the outage affects the WTP. As expected, (Meyerhoff and Liebe, 2006) the elimination of the observations relating to non-true zeros produces an increase in the magnitude of the significant parameters for both models estimated[9]. Estimates show that the significant parameters in all models and in all equations are income, age, knowledge of the cost of one's electricity bill, and the duration of the outages experienced. In addition, the preferences towards the time when the outage is not desired are constantly significant, i.e. the time slot 11:00-14:00, as well as the degree of knowledge of RES.

With regard to age, the older respondents have a lower WTP. Higher-income people have a higher WTP, as do people who pay a higher electricity bill, and suffer from longer outages. Those who indicate 11:00-14:00 as a time slot guaranteed by the electricity service have a lower WTP. The higher

[9] This procedure is coherent with the current main approach that is to delete protest zeros from the sample (Morrison et al., 2000).

knowledge of RES concurs to form a higher WTP. RES as a tool to limit outages contribute to increasing the respondents' WTP, even if in four equations this variable is not significant.

With regard to the time bands to be guaranteed, an appreciable heterogeneity emerges, with the band from 14:00 to 17:00 which reduces the WTP, although in two equations in the full sample it is not significant. With reference to the professional status, only self-employed workers exhibit a positive effect on WTP, albeit limited to a few equations, while businesses have a lower WTP.

Table 2 here

4.2. Double hurdle approach

These models were estimated assuming respondents state their WTP through a two-step decision, this entails that the two steps could either be dependent or independent. Double Hurdle was estimated (Table 3) assuming that the decision to participate and WTP intensity is handled as correlated[10]. It is well known that the correct model identification requires that at least one variable has to be used only in the participation equation.

Table 3 here

Variables related to the energy scenario were tested as participation factor jointly to the variables proxies of the environmental attitude and, among them, Cl_EnProbl and City_pwrCut provide best results. This is not surprising given that environmental attitude is widely considered as an important precursor of green services consumption from a theoretical point of view (Barr and Gilg, 2007). It is also important to underline that gender variable is significant only in the participation equation exhibiting opposite signs in the intensity equation. Indeed, meanwhile it is positive in the in the

[10] The assumption of independence is tested estimating separately the two steps equations: probit and OLS. See Polinori et al. (2018) for further details. Independence was tested comparing model with the corresponding decomposed model and the hypothesis of independence was rejected using the likelihood ratio test; results are available upon request.

participation equation it is negative in the intensity equation meaning that females are more willing to participate even if they could exhibit a lower WTP to avoid outage compared to males.

Focusing on the WTP equations parameters confirm previous econometrics results. The medium-long parameters exhibit a greater magnitude compared to medium-short ones highlighting that outage length affects the WTP. In details the amount of the electricity bills is positively related to the stated WTP confirming that higher the expenditure for electricity is, higher is the WTP to avoid unanticipated outages. The same result arises for the outages experienced by respondents, confirming that who have experienced long outages provide higher WTP. Finally, both the degree of RES knowledge and the belief that RES might concur to mitigate outages arise as positive predictors of WTP to avoid outages. These results are counterintuitive given that usually renewables are expected to have a negative impact on electricity supply security stressing the transmission and distribution grids due to intermittent generation. However, if renewables are associated to local projects that do not involve the national grid transmission, green energy sources are perceived as a useful tool to reduce number and lengths of the outages. Negative impacts on stated WTP are due to the age and to the timing of the outage accordingly to the equation systems approach results.

4.3. Welfare analysis

Econometric results suggest that among respondents of New Delhi the WTP to avoid power outage strictly depend on the outages lengths ranging, on average, from 30.2 INR to 245.6 INR. Figure 1 reports results obtained estimating short-medium and medium-long systems using both full sample and true-zeros sample.

Results obtained by equations systems approach exhibit a well-defined pattern of estimated values. First, WTP to avoid unanticipated outages which is highly sensitive to the zeros treatment, second parameters associated to different outages systems are not statistically different inside the same sample. WTP to avoid 4-hours outages is around 70 INR increasing to 84 INR for 8-hours outages using the full sample. Excluding the no-true zeros the estimated WTP noticeable increase by more than 30% considering *4-hours* outages and by more than 50% referring to *8-hours* outages.

Figure 1 here

Finally, WTP for extreme outages lengths confirm the monotonicity of the welfare measures. In order to avoid *2-hours* outages WTP stated by respondents ranges from 30 to 45 INR meanwhile the WTP to avoid *12-hours* outages lies between 107 and 179 INR depending on sample considered.

Figure 2, shows WTP associated with different outages lengths obtained by double hurdle approach.

Figure 2 here

Also in this case, results exhibit an evident monotonicity with the WTP that increase form 31.5 INR to 245 INR. Overall, WTP obtained are comparable with some literature results. For example, Graber et al. (2018) fund an average stated WTP for one hour of additional hour of electricity equal to 42.1 INR in Uttar Pradesh. Kennedy et al. (2019) found that a 1 hour increase in total hours available would increase WTP by about 52 INR in six states in rural India. Others study fund lower WTP. For example, Gunatilake et al. (2012) computed a WTP of 38 INR to avoid 12-hours outages in Madhya Pradesh. It is not surprising that an overall variation in the WTP estimated can occur. Indeed, it is well known in literature that several sources of heterogeneity exist such as the observed heterogeneity in housing and socio-economic variables rather than the outages characteristics.

However, in our study computing the WTP to avoid hourly outage, results show an appreciable homogeneity with the amounts that lie between 15 INR and 26 INR confirming the robustness of the analysis.

4.4. Protest answers analysis

Zero responses represent an important issue in CV approach, particularly due to the economic meaning linked to the two main zeros' typologies: trues and protest ones. As expected, a large number of responses are around zero values. This is a common phenomenon in demand analysis (e.g., Yu and Abler, 2010). Accordingly, with the literature (e.g., Jakobsson and Dragun, 2001; Strazzera et al.,

2003) in order to differentiate between a true zero and a protest response we have used a set of debriefing questions shown in table 4.

Table 4 here

In detail, 435 out of 1043 responded they would be willing to pay zero for the service proposed, with 48.3% protest and 51.7% true zeros. Female respondents show higher participation rates, indeed only 63 out of 435 zeros belong to female respondents (40 are true zeros). True zero are firstly associated to the budget constraint of respondents. 33% of zeros are due to household income levels compared to the intervention vector prices, indeed respondents frequently could consider unfair to pay given their budget constraints. 11% of respondents do not put value on the service proposed and, finally, other true zeros are associated with service quality and environmental values.

Protest answers are mainly associated to a negative attitude of respondents towards the change proposed (30%), meanwhile others respondents protested against some component of the CV survey which have been evaluated as unsatisfactory such as: i) how service proposed could be ensured (16%) and ii) degree of information provided (1.5%). Finally, only 1% of protest answers have been caused by free riding behaviour.

5. Conclusions and policy implications

It is well known that power outages cause welfare losses for the society producing economic cost and social harm for citizens, households, firms and governments. In this paper we have focused on short and local electric unanticipated power outages that in India occur often guaranteeing respondents are familiar with the scenarios regarding which they are asked to express their preferences and their WTP. Indeed, this ensure that citizens are able to fully consider the several aspects and consequences of the outages.

Firstly, aggregate benefit computation confirms the importance of the protest zeros in underestimate the aggregate WTP. This is an important result given that a reliable outages impact assessment requires a robust estimate of the economic and social value that citizens place on resilient electric services and robustness requires the identification of the respondents that “accept to participate in the CV study” without lying about their preferences. WTP estimated both with equations systems with reduced sample and the double-hurdle approach are similar and the magnitude of the welfare measures are in line with the literature results.

Focusing on the main WTP drivers two techniques underline the importance of the outages duration that is positively correlated with the WTP values. Furthermore, respondents’ preferences are positively related to income and RES knowledge confirming the importance of the environmental attitude also in a BRICS country. This confirms that as citizens have satisfied their material needs, they tend to increase their environmental attitude that is an important precursor of green services consumption. Double-hurdle approach also supports this result given that variables associated to the environmental attitude: i) are important participation factors; ii) positively affect the WTP specially to avoid longer outages. Finally, the experience of the lengths of the outages strongly determines the magnitude of the WTP.

Our results have three major implications. First, those with and without previous outage experiences were different in their WTP and only those who have prior experience with long outages express reliable preferences over scenarios proposed. Second, respondents were willing to pay to avoid outages and, in this process, environmental attitude plays a crucial role. However, this is particularly true for higher income respondents and without further study, it is not possible to say how and if these findings might be extended towards more vulnerable segments of the population. Third, focusing on an hourly outage, respondents seem did not respond differently based on the length of outages; indeed, values based on different scenarios are quite similar. Finally, it is difficult to directly compare our estimates to literature results given that each study, using different assumptions, have employed different design or different elicitation techniques and in many cases different outage length scenarios and last but least respondents are often characterized by different degree of outages experiences. The needed of homogenize these characteristics represents a future research direction.

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Table 1. Sample answers' descriptive statistics

Variables	Typology	UoM	Acronyms	Obs	Mean	Q50	Std. Dev.	Min	Max	Skewness	Kurtosis
WTP to avoid unexpected outages of 2, 4, 8, 12 h	Continuous	Rupje	WTP_2h_Noknw	1,043	15.38	10.00	61.79	0.00	1200.00	15.70	285.07
				833	19.24	10.00	68.61	0.00	1200.00	14.20	231.71
			WTP_4h_Noknw	1,043	28.18	20.00	72.50	0.00	1200.00	10.32	148.10
				833	35.22	20.00	79.58	0.00	1200.00	9.51	124.37
			WTP_8h_Noknw	1,043	88.94	50.00	139.77	0.00	1200.00	3.52	22.01
				833	111.12	50.00	148.24	0.00	1200.00	3.30	19.65
			WTP_12h_Noknw	1,043	194.58	100.00	264.56	0.00	1200.00	1.80	5.97
				833	242.68	100.00	274.57	0.00	1200.00	1.56	5.08
Individual income	Continuous	Rupje	incomeM_INR	1,043	133389.30	125000.00	98800.84	25000.00	350000.00	1.25	3.54
				833	131602.60	125000.00	97126.29	25000.00	350000.00	1.28	3.71
Age of respondents	Continuous	#	age	1,043	38.85	38.00	9.75	16.00	78.00	0.61	3.42
				833	38.56	38.00	9.48	16.00	78.00	0.59	3.48
Electricity bill amounts (on average)	Continuous	Rupje	elbill	1,043	2144.86	1750.00	1799.41	0.00	25000.00	4.50	38.30
				833	2186.03	1700.00	1905.24	0.00	25000.00	4.53	37.18
Outages duration	Continuous	Hours/day	elPwrCt_C1	1,043	2.61	2.00	2.18	0.00	18.00	2.17	14.85
				833	2.61	2.00	2.23	0.00	18.00	2.17	14.22
Preferences to avoid unexpected outages in several hourly intervals	Dummy	#	D_HAvoid_pwrCt_711	1,043	0.40	0.00	0.49	0.00	1.00	0.40	1.16
				833	0.42	0.00	0.49	0.00	1.00	0.33	1.11
	Dummy	#	D_HAvoid_pwrCt_1114	1,043	0.40	0.00	0.49	0.00	1.00	0.42	1.18
				833	0.38	0.00	0.49	0.00	1.00	0.50	1.25
	Dummy	#	D_HAvoid_pwrCt_1417	1,043	0.09	0.00	0.28	0.00	1.00	2.97	9.81
				833	0.08	0.00	0.28	0.00	1.00	3.03	10.16
	Dummy	#	D_HAvoid_pwrCt_1720	1,043	0.04	0.00	0.20	0.00	1.00	4.56	21.75
				833	0.04	0.00	0.20	0.00	1.00	4.49	21.18
Internet usage	Ordinal	#	Cl_InterUse	1,043	2.90	3.00	0.35	1.00	3.00	-3.67	16.71
				833	2.91	3.00	0.32	1.00	3.00	-4.03	19.72
Gender dummy	Dummy	#	D_Female	1,043	0.16	0.00	0.37	0.00	1.00	1.82	4.30
				833	0.18	0.00	0.38	0.00	1.00	1.67	3.77
Profession status of respondent	Dummy	#	D_Business	1,043	0.04	0.00	0.21	0.00	1.00	4.44	20.72
				833	0.04	0.00	0.20	0.00	1.00	4.64	22.54
	Dummy	#	D_SelfEmplo	1,043	0.04	0.00	0.20	0.00	1.00	4.50	21.22
				833	0.04	0.00	0.20	0.00	1.00	4.72	23.28
Geographical dummy	Dummy	#	D_Urban	1,043	0.84	0.75	0.48	0.00	1.00	0.59	1.35
				833	0.88	0.75	0.48	0.00	1.00	0.57	1.33
Respondent belives in RES to mitigate outages in the short run	Dummy	#	D_PrjRES_outag	1,043	0.96	1.00	0.19	0.00	1.00	-4.74	23.48
				833	0.97	1.00	0.17	0.00	1.00	-5.39	30.07
Respondent perception of India Energy scenario due to fossil fuels reserves depletation	Ordinal	#	Cl_EnProbl	1,043	3.26	3.00	0.88	0.00	4.00	-1.27	4.25
				833	3.28	3.00	0.87	0.00	4.00	-1.28	4.22
Respondent degree of RES knowledge	Dummy	#	RES_knw_degree	1,043	0.58	0.63	0.17	0.00	1.00	-0.93	3.95
				833	0.58	0.63	0.17	0.00	1.00	-0.93	3.98
Respondent believes in RES project to mitigate outages in the long run	Ordinal	#	Cl_REPrj	1,043	4.74	5.00	0.49	2.00	5.00	-1.74	5.47
				833	4.77	5.00	0.46	2.00	5.00	-1.72	5.00
Most of the city in India are facing power cut crating dependence upon fossil fuels.	Ordinal	#	City_pwrCu	1,043	2.83	3.00	0.91	0.00	4.00	-0.39	2.59
				833	2.83	3.00	0.92	0.00	4.00	-0.44	2.67

Table 2. Equations systems estimates: short-medium and medium-long run

Variables	Equations							
	Full sample				True Zeros sample			
	Short-Medium period		Medium-Long Period		Short-Medium period		Medium-Long Period	
	WTP_2h_NOknw		WTP_4h_NOknw		WTP_2h_NOknw		WTP_4h_NOknw	
incomeM_INR	0.00004	**	0.00008	***	0.00005	**	0.00011	***
	(0.00001)		*(0.00001)*		*(0.00002)*		*(0.00002)*	
age	-1.009	***	-1.301	***	-1.129	***	-1.457	***
	(0.164)		*(0.183)*		*(0.202)*		*(0.220)*	
elbill	0.020	***	0.024	**	0.022	***	0.026	***
	(0.000)		*(0.001)*		*(0.001)*		*(0.001)*	
elPwrCt_C1	1.381	*	3.037	***	1.071	**	2.915	***
	(0.715)		*(0.796)*		*(0.451)*		*(0.923)*	
D_HAvoid_pwrCt_711	-6.967		-13.155	*	-5.986		-12.204	*
	(6.269)		*(6.979)*		*(7.401)*		*(8.038)*	
D_HAvoid_pwrCt_1114	-9.290	*	-19.185	***	-7.527	*	-16.969	**
	(5.245)		*(6.953)*		*(4.397)*		*(8.034)*	
D_HAvoid_pwrCt_1417	-9.674		-18.930	**	-5.977		-14.249	*
	(7.724)		*(8.599)*		*(9.245)*		*(10.094)*	
D_HAvoid_pwrCt_1720	3.169		-1.661		7.623		4.021	
	(9.366)		*(8.421)*		*(11.910)*		*(12.062)*	
Cl_InterUse	-9.067	**	-9.755	*	-12.315	**	-14.738	**
	(4.508)		*(5.019)*		*(5.854)*		*(6.358)*	
D_Female	-6.706	*	-8.335	*	-7.473	*	-10.198	**
	(3.850)		*(4.620)*		*(4.301)*		*(5.214)*	
D_Business	-11.560	*	-14.960	*	-15.341	*	-19.570	*
	(6.500)		*(8.351)*		*(9.317)*		*(10.181)*	
D_SelfEmplo	13.485	*	6.378		13.218	*	4.583	
	(7.835)		*(8.723)*		*(7.801)*		*(10.684)*	
D_Urban	-2.474		-1.288		-3.236		-1.550	
	(3.234)		*(3.601)*		*(3.893)*		*(4.228)*	
D_PrjRES_outag	2.673		4.438		2.982		-3.981	
	(8.154)		*(9.079)*		*(10.716)*		*(11.169)*	
Cl_EnProbl	2.247		-0.488		3.230		-0.131	
	(1.772)		*(1.973)*		*(2.163)*		*(2.349)*	
RES_knw_degree	11.516	*	17.772	*	15.142	*	22.982	*
	(8.434)		*(10.503)*		*(9.483)*		*(12.466)*	
_cons	22.431	**	40.914	**	33.405	**	62.122	***
	(9.899)		*(18.814)*		*(11.715)*		*(23.639)*	
	WTP_4h_NOknw		WTP_8h_NOknw		WTP_4h_NOknw		WTP_8h_NOknw	
incomeM_INR	0.00008	***	0.00018	***	0.00011	***	0.00026	***
	(0.00001)		*(0.00003)*		*(0.00002)*		*(0.00004)*	
age	-1.301	***	-1.863	***	-1.457	***	-1.871	***
	(0.183)		*(0.379)*		*(0.220)*		*(0.439)*	
elbill	0.024	***	0.033	***	0.026	***	0.033	***
	(0.001)		*(0.002)*		*(0.001)*		*(0.002)*	

elPwrCt_C1	3.037	***	19.851	***	2.915	***	22.908	***
	(0.798)		*(1.649)*		*(0.923)*		*(1.842)*	
D_HAvoid_pwrCt_711	-13.155	*	-18.318		-12.204	*	-17.175	
	(7.003)		*(14.45)*		*(7.038)*		*(16.103)*	
D_HAvoid_pwrCt_1114	-19.185	***	-28.973	**	-16.969	***	-19.400	**
	(6.976)		*(14.39)*		*(8.034)*		*(6.012)*	
D_HAvoid_pwrCt_1417	-18.930	**	-48.597	***	-14.249	*	-37.277	*
	(8.628)		*(17.80)*		*(9.014)*		*(20.013)*	
D_HAvoid_pwrCt_1720	-1.661		-24.193		4.021		-15.176	
	(10.46)		*(21.59)*		*(12.06)*		*(24.062)*	
Cl_InterUse	-9.755	**	-5.410		-14.738	**	-10.120	
	(5.001)		*(10.309)*		*(6.358)*		*(12.680)*	
D_Female	-8.335	*	2.260		-10.198	*	-4.922	
	(4.635)		*(9.568)*		*(5.214)*		*(9.040)*	
D_Business	-14.960	*	-2.065		-19.570	*	-2.413	
	(8.378)		*(17.129)*		*(10.111)*		*(20.118)*	
D_SelfEmplo	6.378		-14.881		4.583		-14.762	
	(8.752)		*(18.016)*		*(10.614)*		*(21.123)*	
D_Urban	-1.288		-6.263		-1.550		-4.763	
	(3.613)		*(7.458)*		*(4.228)*		*(8.434)*	
D_PrjRES_outag	4.438	**	34.955	*	3.981	*	32.541	*
	(2.109)		*(18.810)*		*(1.391)*		*(15.331)*	
Cl_EnProbl	-0.488		-5.786		-0.131		-6.516	
	(1.980)		*(4.086)*		*(2.349)*		*(4.686)*	
RES_knw_degree	17.772	**	18.693	*	22.982	**	19.572	*
	(7.53)		*(8.175)*		*(12.46)*		*(9.187)*	
_cons	40.914	**	33.960	**	62.122	***	47.785	**
	(18.816)		*(18.914)*		*(23.613)*		*(27.114)*	
	WTP_8h_NOknw		WTP_12h_NOknw		WTP_8h_NOknw		WTP_12h_NOknw	
incomeM_INR	0.00018	***	0.00032	***	0.00026	***	0.00047	***
	(0.00003)		*(0.00007)*		*(0.00004)*		*(0.00008)*	
age	-1.863	***	-2.314	**	-1.871	***	-2.021	**
	(0.380)		*(0.772)*		*(0.439)*		*(0.888)*	
elbill	0.033	***	0.043	***	0.033	***	0.041	***
	(0.002)		*(0.004)*		*(0.002)*		*(0.004)*	
elPwrCt_C1	19.851	***	38.108	***	22.908	***	44.294	***
	(1.653)		*(3.355)*		*(1.840)*		*(3.722)*	
D_HAvoid_pwrCt_711	-18.318		-34.570		-17.175		-29.122	
	(14.491)		*(29.411)*		*(16.012)*		*(32.410)*	
D_HAvoid_pwrCt_1114	-28.973	**	-55.144	**	-19.400	*	-30.295	*
	(14.430)		*(29.301)*		*(11.601)*		*(13.238)*	
D_HAvoid_pwrCt_1417	-48.597	***	-106.920	***	-37.277		-84.726	**
	(17.185)		*(36.243)*		*(20.011)*		*(40.437)*	
D_HAvoid_pwrCt_1720	-24.193	*	-71.126	*	-15.176	*	-57.374	*
	(16.614)		*(38.914)*		*(7.104)*		*(38.162)*	
Cl_InterUse	-5.410		2.666		-10.120		-7.652	
	(10.421)		*(21.115)*		*(12.67)*		*(25.632)*	

D_Female	2.260	*	35.310	*	4.922	**	21.833	*
	(0.992)		*(19.417)*		*(1.319)*		*(11.101)*	
D_Business	-2.065		-3.233		-2.413		-0.949	
	(17.313)		*(35.119)*		*(20.161)*		*(40.783)*	
D_SelfEmplo	-14.881		-41.807		-14.762		-35.075	
	(18.111)		*(36.716)*		*(21.211)*		*(42.191)*	
D_Urban	-6.263		-2.683		-4.763		4.054	
	(7.476)		*(15.117)*		*(8.427)*		*(17.014)*	
D_PrjRES_outag	34.955	*	70.727	*	32.541	*	84.228	*
	(18.814)		*(38.126)*		*(13.301)*		*(47.114)*	
Cl_EnProbl	-5.786		-4.648		-6.516		-5.610	
	(4.096)		*(8.316)*		*(4.682)*		*(9.470)*	
RES_knw_degree	18.693	*	17.044	**	19.572	*	17.816	**
	(10.80)		*(9.269)*		*(10.185)*		*(9.295)*	
_cons	33.960	**	25.841	**	47.785	**	31.186	**
	(11.104)		*(9.205)*		*(21.110)*		*(15.261)*	
/lnsig_1	3.886	***	3.993	***	3.955	***	4.038	***
	(0.021)		*(0.021)*		*(0.024)*		*(0.024)*	
/lnsig_2	3.996	***	4.721	***	4.038	***	4.728	***
	(0.021)		*(0.028)*		*(0.024)*		*(0.024)*	
/lnsig_3	4.723	***	5.431	***	4.727	***	5.432	***
	(0.021)		*(0.021)*		*(0.024)*		*(0.024)*	
/atanhrho_12	1.460	***	0.750	***	1.442	***	0.690	***
	(0.030)		*(0.030)*		*(0.034)*		*(0.034)*	
/atanhrho_13	0.453	***	0.460	***	0.413	***	0.383	***
	(0.031)		*(0.030)*		*(0.034)*		*(0.034)*	
/atanhrho_23	0.750	***	1.299	***	0.689	***	1.198	***
	(0.031)		*(0.030)*		*(0.034)*		*(0.034)*	
sig_1	48.697	***	54.217	***	52.203	***	56.697	***
	(1.067)		*(1.184)*		*(1.278)*		*(1.388)*	
sig_2	54.397	***	112.275	***	56.700	***	113.106	***
	(1.193)		*(2.454)*		*(1.389)*		*(2.772)*	
sig_3	112.554	***	228.490	***	113.008	***	228.544	***
	(2.467)		*(4.992)*		*(2.766)*		*(5.600)*	
rho_12	0.898	***	0.635	***	0.894	***	0.598	***
	(0.006)		*(0.018)*		*(0.006)*		*(0.022)*	
rho_13	0.425	***	0.430	***	0.391	***	0.365	***
	(0.025)		*(0.025)*		*(0.029)*		*(0.029)*	
rho_23	0.635	***	0.861	***	0.598	***	0.833	***
	(0.018)		*(0.007)*		*(0.022)*		*(0.010)*	
Number of obs	1043		1043		833		833	
LR chi2(48)	825.23		798.96		804.10		777.62	
Prob > chi2	0.000		0.000		0.000		0.000	
Log likelihood	-16357.206		-18177.080		-13224.223		-14662.020	
Pseudo R2	0.1230		0.1075		0.1475		0.1292	
AIC	32828.41		36468.16		26562.45		29438.05	
BIC	33110.55		36750.30		26831.77		29707.37	

Reps	*2000*		*2000*		*2000*		*2000*	
Wald chi2(16)	*39.10*		*68.25*		*45.17*		*76.28*	
Prob > chi2	*0.0011*		*0.0000*		*0.0001*		*0.0000*	
Mean WTP (2h)	30.201	**			45.147	***		
	(17.472)				*(12.740)*			
Mean WTP (4h)	69.071	**	70.555	**	95.860	***	106.788	***
	(30.909)		*(15.648)*		*(22.141)*		*(22.141)*	
Mean WTP (8h)	84.282	**	84.888	**	135.492	*	136.273	***
	(30.331)		*(30.231)*		*(42.945)*		*(40.564)*	
Mean WTP (12h)			107.428	*			179.259	*
			(56.185)				*(90.672)*	

Cmp command has used assuming truncated distribution of LHS variables to estimate equations systems.
Estimates obtained by 2000 reps: observed coefficients and bootstrapped standard errors, in brackets, are provided.
Mean WTP is computed using *nlcom* and the average of each significant variable.
***, **, * statistically significant at 1%, 5% and 10% respectively.

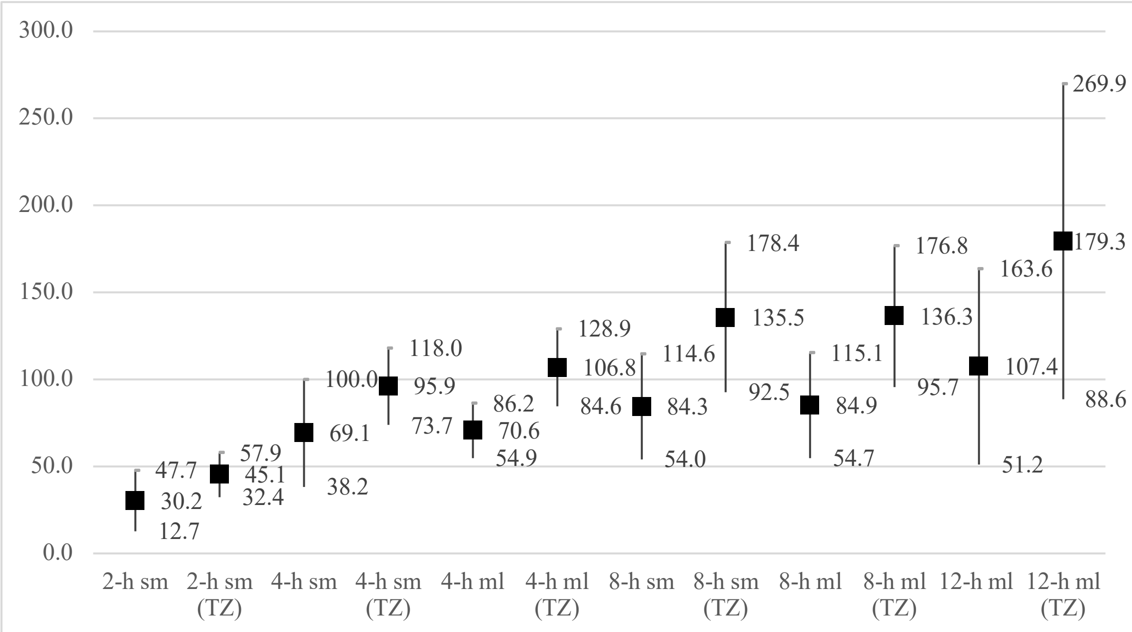
Table 3. WTP estimates using a double hurdle approach

Variables	WTP_2h_NOknw		WTP_4h_NOknw		WTP_8h_NOknw		WTP_12h_NOknw	
WTP equation								
incomeM_INR	0.00004	**	0.00009	***	0.00030	***	0.00062	***
	(0.00002)		*(0.00002)*		*(0.00006)*		*(0.00011)*	
age	-1.482	***	-1.888	***	-2.029	***	-0.991	**
	(0.239)		*(0.273)*		*(0.606)*		*(0.211)*	
elbill	0.025	***	0.031	***	0.037	***	0.040	***
	(0.001)		*(0.001)*		*(0.003)*		*(0.005)*	
elPwrCt_C1	2.084	**	3.411	***	30.286	***	62.313	***
	(1.021)		*(1.189)*		*(2.924)*		*(5.758)*	
D_HAvoid_pwrCt_711	-16.104	*	-21.050	**	-40.725	*	-75.865	*
	(8.937)		*(10.216)*		*(21.751)*		*(43.035)*	
D_HAvoid_pwrCt_1114	-24.174	***	-34.161	***	-48.859	**	-66.727	
	(8.969)		*(10.124)*		*(22.106)*		*(44.037)*	
D_HAvoid_pwrCt_1417	-15.615		-24.092	*	-60.578	**	-135.394	**
	(11.109)		*(12.679)*		*(26.774)*		*(53.904)*	
D_HAvoid_pwrCt_1720	-1.244		-2.413		-9.843		-52.974	
	(3.310)		*(2.153)*		*(8.310)*		*(43.170)*	
Cl_InterUse	-5.205		-5.767		3.613		23.076	
	(6.532)		*(7.550)*		*(3.173)*		*(20.101)*	
D_Female	-4.728		-5.763		-10.661		1.612	
	(5.943)		*(6.719)*		*(11.049)*		*(1.131)*	
D_Business	-12.612		-15.118		7.441		20.142	
	(11.150)		*(12.409)*		*(7.068)*		*(17.160)*	
D_SelfEmplo	15.417	*	5.449	*	-17.029		-55.340	
	(8.382)		*(1.316)*		*(11.734)*		*(53.134)*	
D_Urban	1.368		3.202		2.866		13.734	
	(2.678)		*(5.310)*		*(2.166)*		*(13.164)*	
D_PrjRES_outag	22.876	*	4.684	*	118.290	***	279.966	***
	(12.84)		*(1.199)*		*(30.65)*		*(62.99)*	
Cl_EnProbl	1.683		-2.199		-1.501		19.159	
	(2.540)		*(2.923)*		*(6.954)*		*(14.415)*	
RES_knw_degree	11.585	*	19.241	*	38.977	*	71.014	*
	(6.159)		*(8.544)*		*(14.193)*		*(33.244)*	
_cons	-17.579	***	-22.633	**	-45.149	***	-43.417	**
	(4.617)		*(11.081)*		*(21.078)*		*(12.229)*	
Partecipation equation								
elPwrCt_C1	0.332	*	0.308	*	-0.090	***	-0.071	***
	(0.197)		*(0.160)*		*(0.029)*		*(0.026)*	
Cl_EnProbl	-0.377	*	-0.633	**	-0.245	**	-0.260	***
	(0.119)		*(0.187)*		*(0.117)*		*(0.091)*	
Cl_REPrj	0.168		0.180		0.282		0.154	
	(0.398)		*(0.320)*		*(0.190)*		*(0.140)*	
City_pwrCu	0.215	*	0.207	*	0.121	*	0.160	*
	(0.078)		*(0.044)*		*(0.059)*		*(0.084)*	
RES_knw_degree	1.180		0.573		-0.625		-0.484	
	(1.070)		*(0.946)*		*(0.573)*		*(0.446)*	
D_PrjRES_outag	1.700	***	1.829	***	3.671	***	5.159	***
	(0.446)		*(0.515)*		*(1.256)*		*(2.495)*	
D_Female	0.200	**	0.154	**	0.771	**	0.470	**
	(0.069)		*(0.037)*		*(0.391)*		*(0.170)*	
_cons	3.548	**	1.811	***	4.347	**	5.961	**
	(1.665)		*(0.377)*		*(2.494)*		*(2.557)*	
/sigma	63.050	***	71.106	***	140.786	***	265.609	***
	(1.886)		*(2.237)*		*(5.772)*		*(12.46)*	
/covariance	45.204	***	36.681	**	10.280	***	26.664	***
	(13.196)		*(19.495)*		*(3.173)*		*(6.188)*	
Number of obs	1043		1043		1043		1043	
LR chi2(16)	632.8235		650.624		503.936		373.710	
Prob > chi2	0.0000		0.0000		0.0000		0.0000	
LR chi2(7)	33.439		46.958		36.371		45.945	
Prob > chi2	0.0007		0.0003		0.0001		0.0000	
LR chi2(23)	582.3586		599.541		432.694		334.505	
Prob > chi2	0.0000		0.0000		0.0000		0.0000	
Log likelihood	-3655.062		-3761.62		-4280.563		-4731.370	
AIC	7364.123		7577.240		8615.126		9516.739	
BIC	7497.769		7710.886		8748.772		9650.386	
Mean WTP	31.501	**	83.768	**	145.093	**	245.564	**

	(16.986)	*(58.985)*	*(71.158)*	*(100.222)*

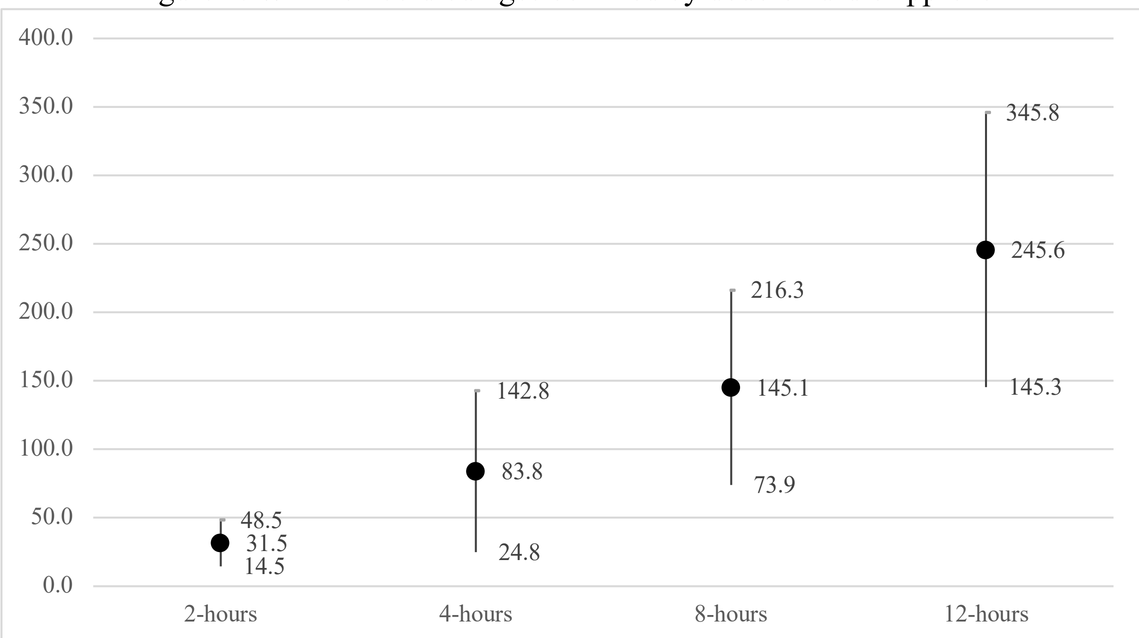
Estimates obtained by 2000 reps: observed coefficients and bootstrapped standard errors, in brackets, are provided.
Mean WTP is computed using *nlcom* and the average of each significant variable.
***, **, * statistically significant at 1%, 5% and 10% respectively.

Figure 1: WTP to avoid outages obtained by equations system approach



N.B.: WTP are in INR 2019; sm = short-medium outages system; ml = medium-long outages system; TZ = true zeros sample; interval of confidence (95%) obtained by bootstrap of 2000 replications

Figure 2: WTP to avoid outages obtained by double hurdle approach



N.B.: WTP are in INR 2019; interval of confidence (95%) obtained by bootstrap of 2000 replications

Table 4. Debriefing questions to identify protest answers

Responses	Freq.	Perc.	Cum.	Female	PA
I can't afford to pay these amounts	144	0.331	0.331	34	
This service should be free of charge	129	0.297	0.628	11	X
It is not clear to me how this service could be ensured	69	0.159	0.786	10	X
I don't face Power cuts or PWC are not a problem	46	0.106	0.892	3	
This service was not enough to warrant any payment.	21	0.048	0.940	1	
I would only pay if the energy used to avoid power cut would be green	14	0.032	0.972	2	
Not enough information is given.	6	0.014	0.986	1	X
I would pay only if I am sure that all users will pay for it	4	0.009	0.995	1	X
Others protest	2	0.005	1.000	-	X
Total	435	1.000		63	

N.B. Freq. = frequency, Perc. = percentage, Cum. = cumulative function, PA protest answers.

Appendix

Table A1. Sampling rate in other power cut-off assessment studies

Authors	Year	State/region	Sample	Population	%sample
Kim & Yoo	2020	South Korea	1000	51780000	0.0019%
Amoah et al	2019	Ghana Greater Accra Region	504	4000000	0.0126%
Hotaling et al	2021	NY State	940	19500000	0.0048%
Woo et al	2014	Honk Kong	1876	7500000	0.0250%
Radmehr et al	2014	North Cyprus	264	326000	0.0810%
Abdullah & Mariel	2010	Kisumu, Kenya	202	390000	0.0518%
Bakkensen & Schuler	2020	Vietnam	14000	97000000	0.0144%
Kennedy et al	2019	India (714 villages)	2348	2680356	0.0876%
Jang et al	2014	South Korea	1000	51780000	0.0019%
Carlsson et al	2021 (2007)	Sweden	1650	10500000	0.0157%
Carlsson et al	2021 (2014)	Sweden	1547	10500000	0.0147%
Carlsson et al	2011	Sweden	1518	10500000	0.0145%
Morrissey et al	2018	NW England	283	7300000	0.0039%
Amador et al	2013	Canary Islands	376	2207000	0.0170%
Meles et al	2021	Ethiopia (Major cities)	2180	5698233	0.0383%
Frondel et al	2019	Germany	5640	83240000	0.0068%
Our study	2021	Delhi In INDIA	1043	28,000,000	0.0037%

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