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How Valuable is the Reliability of Residential Electricity Supply in Low-Income Countries?

Evidence from Nepal

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Abstract

This study uses a contingent valuation approach to value the willingness-to-pay (WTP) for improved service experienced by households in Nepal following the end of the country's load-shedding crisis of 2008-2016. Using a detailed survey of grid-connected Nepali households, the authors calculate the WTP per outage-day avoided and the residential value of lost (VoLL) and analyze their key drivers. Households are willing to pay, on average, 123.32 NR ($1.11) per month, or 65 percent of the actual average monthly bill for improved quality of power supply. The preferred estimates of the VoLL are in the range of 5 to 15 NR/kWh (¢4.7–¢14/kWh). These estimates are below the marginal cost of avoided load shedding, and virtually the same as valuations at the beginning of the load-shedding crisis.

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How Valuable is the Reliability of Residential Electricity Supply in Low-Income Countries? Evidence from Nepal

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1. Introduction

Access to reliable electricity services is essential for poverty reduction and economic growth (World Bank, 2017). However, many developing countries, particularly low-income countries of the South Asia and the Sub Saharan Africa regions, face severe electricity shortages, leading to frequent power shedding. Underpricing of public electricity services combined with high technical and commercial losses in these countries limits utilities' ability to recover capital and operational expenditures and affects the reliability of power supply (Blimpo and Cosgove-Davies, 2019; Zhang 2019). Valid estimates of the willingness to pay (WTP) for reliable power supply are thus critical for both power system planning decisions and regulatory policies aimed at improving the quality of electricity services. This is especially important for the residential sector, where low energy consumption and prevailing social norms make electricity cost recovery a challenging problem (Trimble et al., 2016; Burgess et al., 2020; Lee et al., 2020; Steinbuks and Sievert, 2020).

This paper estimates the value of lost residential electricity service in Nepal, a low-income country that has experienced chronic load shedding in the last decade. The load-shedding crisis over the period 2007 – 2017 has imposed high economic costs on Nepal's economy.[2] At the end of 2016, however, the daily load shedding of residential consumers ended due to improved electricity dispatch, increased electricity production, and imports from India, though households still experience some (unscheduled) outages (World Bank, 2019).

Assessing the value that households place on the reliable power supply is a difficult problem, due to a number of concurrent methodological challenges—especially in developing countries. First, because electricity can be essential for household leisure (e.g., watching TV),

[2] Timilsina et al., (2018), for example, estimates that load-shedding could have cost the country up to 7 percent of its GDP annually.

education (e.g., reading at nighttime), and health (e.g., clean cooking), the lost load has both direct and indirect values. Second, households can partially avoid power outages by investing in energy backup or storage (e.g., small diesel or solar generator, power inverters, and batteries) that often carry significant option value. Third, the data requirements for estimating a theoretically consistent system of electricity demand functions (Sanghvi, 1983) are exacting and unavailable in most locations. Fourth, the willingness to pay for reliable power supply is likely to be affected by unobserved heterogeneity in household preferences for electricity-using appliance choices (McRae, 2010). Fifth, in surveys, households may report lower (or even zero) willingness to pay for improved power supply even if they value it, in principle, because they object to the practices of the utility or disagree with certain aspects of the provision of the improved supply (Mitchell and Carson, 1989; Beenstock et al., 1998). Sixth, stated preference studies in developed economies (Layton and Moeltner, 2005; Carlsson and Martinsson, 2007, 2008; Hensher et al., 2014; Ozbafli and Jenkins, 2016) suffer from the problem that people have little experience with outages and with the arrangements that they would have to make to adjust to them. Finally, technical constraints and ethical considerations make it very difficult to randomly assign load-shedding schedules and prices, preventing experimental inference of the WTP increasingly common in other infrastructure settings (Berry et al., 2020; Do and Jacoby 2020; Grimm et al., 2020).[3] For these reasons, the literature on assessing the WTP from residential customers for electricity reliability in developing countries is comprised of only a

[3] One potential approach to experimentally elicit the WTP for reliable power supply is direct load management, where households voluntarily agree that utility takes control of some of the appliances (e.g., air conditioners) in critical peak hours (see Faruqui and Sergici, 2010, and references therein). This approach cannot work in Nepal due to technical unsophistication of national electricity grid and low power requirements of main electric appliances in Nepal. Additionally, one would expect a very high public distrust, which turned out a major obstacle to success of such experiments even in developed economies (Stenner et al., 2017).

handful of studies (Kateregga, 2009; Abdullah and Mariel, 2010; Karki et al., 2010; Twerefou, 2014; Oseni, 2017).

Our analysis is based on a nationally representative survey of Nepali households, collected as part of the World Bank Multi-Tier Framework for Assessing Energy Access Program. The survey was done less than a year since the residential load shedding had been eliminated, and the respondents were asked to indicate their willingness to pay to avoid the number of days with outages they had experienced before the termination of the load shedding schedule of October 2016. The uniqueness of our empirical setting yields several important advantages for using this contingent valuation approach. First, stated preferences allow us to get around the issue that it is not possible to estimate, and thus infer the value of lost electricity service from, a residential electricity demand function, as tariffs in Nepal are the same throughout the national territory, do not vary over the day, and have stayed the same for the last 7-8 years. Second, we take advantage of the respondents' *actual experience* with improved reliability of power supply, and by construction avoids a problem frequently faced in stated preference studies—namely unfamiliarity with the good to be valued (Mitchell and Carson, 1989). Finally, thanks to collected data on *actual outages* at the transformer substation-level, we can validate the quality of respondents' recall – an issue in contingent valuation studies, for which typically there is no easy solution (Hanemann, 1994).

Our analysis starts with calculating the WTP per kWh lost (i.e., the Value of Lost Load, VoLL) given assumptions about the load or exact information about the kWh used in a typical day. We then calculate the WTP per outage-day avoided, and analyze its key drivers, accounting for potential endogeneity between reported WTP for reduced outages and the choice of backup equipment. Finally, we assess the internal validity of our estimates by regressing the WTP on the number of outage-days reported by the respondents, controlling for the variety of households' characteristics. To our knowledge, our study is the first to address classical measurement error bias by instrumenting for the number of outage days using the frequency of all types of outages at the substation level.

The results from our study are striking for a number of reasons. First, we find that households, on average, attach meaningful value to a reliable power supply. The average WTP of 123.32 NR ($1.11) per month, or 65 percent of the actual average monthly bill, even though about 26 percent of the households are not willing to pay anything at all, and that respondents are likely *under*stating their WTP. Second, when we convert the WTP to a VoLL (i.e., the WTP per kWh lost), our preferred estimates are in the range of 5 to 15 NR/kWh (¢4.7 to ¢14/kWh), and thus bracket the average price per kWh from the grid paid by the respondents at the time of the survey. Even more surprising, these VoLLs do not seem to be any larger than those from a survey conducted more than a decade ago, when the load-shedding crisis started (Karki et al., 2010). However, when we adjust the VoLL of those with rechargeable batteries and solar equipment to the VoLL implicit in the purchase of such equipment, we obtain higher estimates ranging from 9 to 22 NR/kWh.

Third, for the sample as a whole, the VoLL is higher for service lost in unscheduled outages than for service lost during scheduled load shedding. But when we restrict the analysis to the "attentive" respondents—namely those who appear to have recollected exactly the number of outages in the month a year before the time of the survey—the VoLL is identical for unscheduled and scheduled lost electricity consumption. Fourth, households that use rechargeable batteries or solar equipment as backup equipment report systematically lower WTP. This is in sharp contrast with earlier studies, where households owing diesel generators with high running costs were willing to pay more for reliable power supply. Finally, although most households have economically meaningful willingness to pay for a reliable power supply, our VoLL figures appear to be below the marginal cost of avoided load shedding (i.e., utilizing high-cost operating reserves or importing electricity at times of high demand). These findings suggest that if the government's goal is to improve the quality of residential electricity consumption, it must find less expensive sources than the ones available at the time of the study.[4]

2. Background

A. Nepal's load shedding crisis, 2008-2016.

Nepal, like many other developing countries, is striving to provide reliable electricity to the population. Although the country has made significant progress in improving electricity access,[5] reliability of power supply has until very recently remained a major issue. Most of the electricity supplied by the Nepal Electricity Authority (NEA) is hydropower and is subject to seasonal fluctuations. Historically, inefficiencies and poor management issues have plagued the national grid, which in practice resulted in power supply lower than demand. As a result, households and other entities were subject to severe load shedding schedules.[6] The outage schedule was rotated across different service territories.

In October 2016, the NEA was able to resolve some of these issues, and the load shedding schedule was suspended (World Bank, 2019). Households may, however, still experience unscheduled outages.

[4] In 2018 the Nepali authorities have effectively eliminated all remaining scheduled outages after completing addition of low-cost generation capacity, while peak power demand remained flat.

[5] The World Bank Sustainable Energy for All (SE4ALL) database estimates that 93 percent of residential households had access to electricity in 2018.

[6] Shrestha (2014) reports that there were at most 2 hours daily of load shedding in 2005, and 3 in 2006. Starting in 2007 the situation appears to have worsened considerably, with 8 hours/day in 2007, 16 in 2008, 18 in 2009, 14 in 2010, 12 in 2011, 10 in 2012, and 12 and 8, respectively, in January and July 2014.

Figure 1 plots the hours with no electricity (as per the scheduled outages) each month from January to December 2016. In the early months of the year, people were without power for about half of the time. Load shedding occurred every single day between July and October 27, 2016. In July and the first half of August 2016, there was no electricity for about 9 hours a day. The load shedding lasted seven hours every day in the second half of August, September, and the first three weeks of October 2016. In late October 2016, the outage schedule was suspended indefinitely, bringing the load shedding hours to zero in November and December 2016.

B. VoLL definition and measurement

The value of avoided outages and lost consumption is often summarized into a metric known as the Value of Lost Load (VoLL). The VoLL can be expressed in dollars (or other currency) per hour of disruption, or dollars per kWh. It can be assessed separately for different classes of electricity customers. The VoLL has been traditionally used to assess the viability of projects aimed at adding capacity to the grid, and as of late, has been providing valuable information to capacity markets, balancing authorities, and aggregators seeking to help balance the market.[7]

The European Union defines the VoLL as "value attributed by consumers to unsupplied energy."[8] It is the willingness to pay to avoid the loss of one kWh in an outage, or—assuming no income effects—the willingness to accept the loss of one kWh in a service interruption.[9]

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[7] Most recently, much controversy arose when PG&E cut power to an estimated total of 2.5 million people in California in hopes of reducing the risk of wildfires sparked by power lines and electrical equipment (https://www.nytimes.com/2019/10/09/us/pge-shut-off-power-outage.html). The VOLL would have been an appropriate metric to quantify the costs and damages caused to the public by these service disruptions.

[8] See https://www.emissions-euets.com/internal-electricity-market-glossary/966-value-of-lost-load-voll

[9] The literature distinguishes between the direct and indirect damage costs of outages. Direct costs are the damages experienced directly from the subject or entity in question (e.g., production lost or delayed because of disrupted electricity service), while indirect costs are those borne by others (e.g., missed or delayed deliveries to other firms). Only the direct damage costs should enter in the calculation of the VoLL (Schoeder and Kuckshinrichs, 2015). The

The VoLL is generally expressed in dollars (or other currency) per kWh or per unit of time without electricity (Tol, 2007), and can be estimated in a number of ways—directly from the electricity demand function, using a macroeconomic approach, or by eliciting the public's willingness to pay to obtain a reduction in outages (or willingness to accept compensation to tolerate outages). The macroeconomic approach, for example, assumes that residential outages interfere with leisure, and values each hour of service lost at the value of leisure, which is equal to the wage rate or a fraction thereof (London Economics, 2013). Recent meta-analyses reveal that the VoLL can range between a few euro- (or dollar-) cents per kWh to several (and even hundred) euro (or dollar) per kWh, depending on the locale, the price of electricity, the type of customer and his or her ability to shift production activities to a different time (Cambridge Economic Policy Associates, 2018; London Economics International, 2013).

Sanghvi (1983) explains that a disruption in electricity service causes two types of economic consequences: Short-term costs and long-term adaptive response costs. When we restrict attention to residential electricity consumption, the former are caused by the loss of utility from temporarily halting household activities (reading, cooking, doing laundry, etc.) that must be resumed later, loss of data, or damage to household electrical equipment from an uncontrolled shutdown, etc. Long-term adaptive response costs refer to the purchase and operation of electrical-using equipment based on expectations about the reliability of electricity service in the future.

Sanghvi (1983) focuses on short-term costs, arguing that the only theoretically correct way to value, say, a one-hour loss of power, is to estimate a system of hourly demand functions, which accommodate, among other things, the household's ability (or inability) to shift

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damage costs should be kept separate from mitigation costs, namely the purchase and operation of equipment (e.g., generators) to make do in the event of an outage (Schoeder and Kuckshinrichs, 2015).

consumption to a different time. The consumer surplus under the corresponding one-hour demand curve provides an approximation to the compensating variation, the correct welfare loss from the supply interruption.

It is easy to see that the value of lost service varies with the time of the day, day of the week, and season of the year when it occurs, as well as the characteristics of the household and whether the household was given any warning about the impending outage.

It is also easy to see that it is extremely difficult to implement the theoretically correct approach described in Sanghvi (1983), given its exacting data requirements. Even we were to settle for an "average hourly demand function" or a "monthly demand function"—as discussed, and shown to be theoretically incorrect, in Sanghvi (1983)—we would be unable to fit such functions at our study locale, Nepal, where electricity tariffs are the same everywhere, haven't changed in 7-8 years, and are based on increasing monthly block rates, with no variation in tariffs throughout the day.

We also judge the alternate approach, which assumes that outages disrupt leisure solely and that the wage rate best approximates the value of lost leisure activities, inadequate in Nepal, where outages are extensive and where many households rely on remittances from its members who work abroad. Since neither of the abovementioned approaches is feasible or satisfactory, we turn to stated preference methods. For good measure, we also look at the cost of capital used to make do during outages.

3. The Data

A. Household Characteristics and their Experience with the Grid

The MTF survey data has extensive information about households, dwellings and housing tenure, expenditures on various consumption and durable items, cooking equipment and habits, access to electricity, experience with electricity outages, equipment used for lighting, or to powering appliances during outages, and sources of energy use. The survey was conducted between July and November 2017, and resulted in 6000 completed questionnaires, with almost 90% of the interviews completed in August and September.

A total of 4047 out of 6000 households reported that they were connected to the NEA grid. Some 640 households produced the most recent electricity bill, which displays the exact consumption in kWh during the latest billing cycle. The remaining households reported their typical bill in Nepalese Rupees (NR), and we are able to compute their monthly consumption in kWh by matching the bill amount with the NEA tariffs.[10] Figure 2 shows two histograms of the distribution of monthly electricity consumption. Figure 2.a is based on the exact consumption in kWh from the bill. Figure 2.b is based on either exact consumption, when available, or calculated consumption if the respondent merely reported the bill in NR. The two distributions are very similar: The average consumption is 61 kWh, and the median is 34 kWh for the sample with exact consumption data, and 38 KWh for the blended exact and calculated consumption sample, indicating that Nepali households use about 1-2 kWh/day.

The questionnaire asks respondents to indicate whether there were some periods during the year that were worse than most in terms of unscheduled electricity outages. Based on a total of 1543 responses, people experience, on average, 76.8 outages (median 40.5) and 92.38 hours (median 63) per month during the worst months. In practice, this means that there are unscheduled outages every day, for a total of 2-3 hours a day with electricity gone without

[10] At the time of the study the exchange rate of one United States dollar was 108 NR.

warning.[11] The situation appears to better in the "typical" month, when, as reported by the full sample, there are, on average, 40 outages (median 22.5) and some 30 hours (median 13.5) without electricity per month.

Table 1 shows that when there is no electricity, some households power their lights using rechargeable batteries, disposable batteries (used with flashlights and task lights), kerosene lamps, solar lanterns (i.e., lanterns powered by a photovoltaic cell), and solar lighting (somewhat more elaborate devices that are capable of charging cell phones and powering radios in addition to supplying lighting). Only 50 households in our sample have solar home systems on the premises. About 70 percent of grid-connected households have no back up for appliances. Only about 500 households use rechargeable batteries and storage to power their appliances during service outages.

The questionnaire also elicits households' opinions on a variety of issues, ranging from the quality and cost of electricity service to leisure and trust in the institutions. When asked whether they would be willing to pay higher tariffs for more reliable electricity supply, 61.37 percent of the surveyed households said that they would. When asked whether they agree with the statement that reliability can improve only if higher tariffs are charged, 33.12 percent indicated that they agreed with that statement. Finally, 63.17 percent said that they would be willing to pay more for electricity if the government used the revenue to subsidize poor households.

[11] We checked whether volunteering information about the worst months is significantly associated with location, income, and ownership of backup equipment. We fit linear probability models where the dependent variable is “volunteering worst month,” finding that this is significantly associated with the Province of residence, and with some of the simplest and least expensive backup equipment (disposable batteries, solar lanterns, solar lighting, kerosene lamp). Household income, which we proxy with expenditure for all consumption goods except electricity, is not important—whether or not we control for the backup equipment. When we regress the number of unscheduled outages per week or per month during the worst months, the association between them and the above mentioned regressors is generally weak, and results in regressions with R^2 no greater than 0.03.

B. Willingness to Pay for Improved Reliability

The questionnaire asks the respondents whether they still experience power outages at the time of the survey. Did these respondents also experience outages—scheduled *and* unscheduled — this month but a year ago (henceforth referred to as MONTH 2016)? If so, how many?

How much—the questionnaire continues—would the respondent be willing to pay each month, on top of the regular monthly electricity bill, to avoid going back to that situation? To make the respondent's valuation task easier, we suggested one amount drawn at random from an array of pre-selected figures (100, 200, 300, 400, and 500 NR). This was followed by inviting the respondent to indicate exactly how much he or she would be willing to pay.

A total of 2893 out of the 4047 respondents (about 71.5 percent) connected to the national electricity grid said that they still experienced outages at the time of the survey. Of these, 2725 had experienced outages in 2016. On average, they had experienced 20 days with outages "this month a year ago." About 36 percent of the respondents reported 30 or more outages, effectively telling us that a year earlier, there were outages every single day.

Figure 3.a displays the histogram of the number of days with outages, showing a small mode at low counts, a relatively uniform distribution from approximately 10 to 29 outage-days, and a spike at 30 or more. We note that, except for the respondents who were interviewed after October 27, 2017, only those who report 30 or more days provide accurate answers. We consider these respondents "attentive," because, even ignoring the unscheduled power interruptions, there were scheduled load shedding outages *every single day* in every part of the nation until October 27, 2016.[12]

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[12] We estimated a linear probability model relating 30 or 31 days of outages “this month last year” to a number of covariates. The likelihood that the respondents announces 30 or 31 days of outages varies meaningfully across

Based on enumerator debriefs and discussions with the local survey team, we believe that some respondents may have failed to notice that the survey questionnaire, which was previously focused on *un*scheduled outages, had now turned to both unscheduled *and* scheduled outages. NEA does not collect or provide information at the detailed local level about outages and other service disruptions in its territory that can be used to assess the quality of the respondent-reported data.

Fortunately, as shown in Figure 4, the respondent-reported number of days with outages 12 months earlier correlates well with the total frequency of outages—scheduled and unscheduled—reported by NEA over the same period at the 132 kV transformer substation that serves the municipality where the respondent resides.[13] The outages at the substation level may cause disruptions throughout the territory they serve (which neither the respondent nor the township where he or she resides have any control over), and additional outages may occur locally "downstream" from the substation, suggesting that the number of total outages at the substation level is a valid instrument for respondent-reported outage-days, should we need one in our regression analyses below.[14]

Regarding the WTP, as shown in Table 2, the share of respondents willing to pay the bid amount that was proposed to them declines systematically as the bid increases, as suggested by economic theory. "Open-ended" WTP responses—like the ones to our follow-up question—are

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Provinces, is (as expected) much lower when the survey took place in October or November 2017, and is negatively related to income. Subsequently entering education and dummies for lighting and backup equipment in the regression brings little additional explanatory power.

[13] There are a total of 35 132-kV substations in Nepali, which serve a total of 242 municipalities. One municipality is served by only one substation, but the same substation can supply more than one municipality. In 2016, the average substation experienced approximately 493 outages per month.

[14] We argue that outages at the substation level are correlated with (and often the cause of) the outages experienced at the respondent's residence, which determine his or her WTP to avoid them, but do not have an independent effect of the respondent's WTP, since the respondent is presumable unaware of where along the grid the failures occur and of the effects of substation-level outages at other locales.

generally interpreted as understating the true WTP (Welsh and Poe, 1998). Indeed, about 26 percent of the sample stated that they were not willing to pay at all. Yet, the data suggest that a reliable supply *is* valuable: The average WTP was 123.32 NR (or $1.11) per month, and represents on average, 65 percent of the actual monthly bill (median 25 percent). The median WTP is 100 NR, the 75th percentile 200 NR, and the 95th percentile 500 NR.

We wondered whether the zero WTP responses came primarily from the people that reported few outage-days. Figures 3.a and 3.b show that the distribution of respondent-reported outage-days is very similar across those who announced zero WTP and those with positive WTP. This comparison suggests that the zero WTP responses may include a number of "protest" responses on the part of subjects who actually do value grid electricity. It also helps dispel the concern that respondents might have had "selective memory" when reporting the number of days with outages from twelve months ago, i.e., that those who value electricity the most might also be reporting the most numerous outages (because they remember acutely something they regarded as very aggravating), and vice-versa. Also, we find that the number of outage days from a year ago does not vary much by equipment owned, although they do vary somewhat by Province, and, as shown in Figure 5, do not just affect the poor.

Tables A.1 and A.2 in Appendix A explore reasons for the zero WTP responses. The likelihood of announcing zero WTP varies with income, education, and the equipment owned by the household and the geographical area of residence, but its most important predictors appear to be beliefs about the cause, effects, and burden of outages. Monthly electricity consumption at the time of the survey does not have any additional explanatory power but suggests that the higher the consumption, the less likely it is the respondent to announce zero WTP.

4. Methods

A. Theoretical Model

We assume that the consumer derives utility from consuming goods, X, and energy services, S, powered by electricity. Grid electricity is rationed at $\bar{E}$ hours per day, forcing the consumer to use alternate equipment to supply the remainder they need (E*- $\bar{E}$). Let the energy services from off-grid energy sources be denoted as B: B=B(E* - $\bar{E}$). The consumer faces the following budget constraint:

(1) $$y = X + P_E \cdot \bar{E} + P_B \cdot (E^* - \bar{E}),$$

where y is income, and P_E and P_B, are, respectively, the prices of the grid and off-grid electricity (including storage devices and alternate energy sources, such as kerosene, required to produce the energy services *S*).

How much would the consumer be willing to pay for a small change in $\bar{E}$? To answer this question, we take the total differential of the Lagrangean with respect to y and $\bar{E}$, set that to zero, and solve to obtain

(2) $$\frac{dy}{d\bar{\bar{E}}} = -\frac{1}{\lambda}\left(\frac{\partial U}{\partial S}\frac{\partial S}{\partial \bar{\bar{E}}} - \frac{\partial U}{\partial B}\frac{\partial B}{\partial \bar{\bar{E}}^*}\right) + (P_E - P_B).$$

The first term in the right-hand side of (2) is the marginal utility differential between energy services produced from the grid and off-grid electricity sources, converted into Nepali rupees through dividing by the marginal utility of income. The second term is the price differential between the grid and off-grid electricity.

Expression (2), and hence the WTP for electricity beyond the rationed quantity, is zero when (i) the marginal utility from the energy services produced using grid electricity is approximately the same as that from the off-grid energy services, and (ii) the price of grid electricity is approximately the same as that of off-grid electricity (or the cost of producing a kWh using an alternate source of energy, such as kerosene or diesel and a generator).

The WTP will be positive when off-grid (or diesel-generator) electricity is a poor substitute for grid electricity, and/or when off-grid electricity is expensive compared to grid electricity.

B. Computing the VOLL

Our survey respondents announced their WTP to avoid the number of days with outages they had experienced in the MONTH 2016. To convert the WTP into a VOLL, we must divide it by an estimate of the kilowatt-hours lost to outages during that month. We proceed as follows. First, we compute an estimate of the number of hours without electricity in MONTH 2016. If, for example, the survey took place in July, and this respondent had listed July among the worst months in terms of electricity service, we take his or her estimate of the total duration of the unscheduled outages in the worst months. If the respondent did not flag July as one of the worst months, we take his or her estimate of the outage hours during a typical month. We then add the hours of scheduled load-shedding outages (in this example, those of July 2016), obtaining the total number of hours without electricity in MONTH 2016.

The kWhs lost are thus the total hours of service lost, times the household's average hourly consumption *now* (which is equal to monthly consumption, divided by 30 days, and divided again by 24, the number of hours in a day).[15] Finally, we compute the VOLL as the WTP divided by the kWhs lost. This results in respondent-specific VOLLs. About a quarter of them will be equal to zero if we take the respondent's WTP responses at face value.

[15] At the time of the survey the electricity supply situation in Nepal had much improved, and load-shedding outages had been discontinued, suggesting that electricity consumption was much closer to the desired level.

However, some respondents had invested in durable equipment to generate or store electricity. For these respondents, it is possible to impute an alternate VOLL—whether or not they announced zero WTP. Specifically, the value of a kWh lost must be the quantity V such that solves the equation:

(3) $$C = \frac{1-\exp(-\delta T)}{\delta} \cdot V \cdot E,$$

where C is the cost of the equipment, E is the annual consumption lost to outages (which presumably the equipment makes up for), T is the lifetime of the equipment, and δ is an appropriate discount rate.[16] The first term in the right-hand side of (3) is the discount factor, and equation (3) equalizes the discounted flow of electricity generated by the equipment with the price of the equipment.

C. VOLL for Scheduled and Unscheduled outages

Economic theory, and common sense, suggest that the value of lost electricity consumption should be greater for unannounced outages (Schroeder and Kuckshinrichs, 2015), as electricity customers can presumably avoid or mitigate some of the damages from power outages when sufficient warning of service interruption is given.

[16] The survey questionnaire elicits high-quality data about the cost, age and financing of solar lighting, solar lanterns and solar home systems, which we use to estimate a value per kWh-equivalent generated from this equipment. We assume a rate of return to the investment of 7%, which is appropriate for Nepal according to World Bank guidelines based on the Ramsey rule (Hepburn, 2007). We assume 12 years for solar home systems, 9 years for solar lighting systems, and 3 years for solar lanterns. Out of the 545 people who answered the WTP question and reported solar equipment type, cost and age, only 30 indicated that they had had made down payments and had paid (or were still paying) instalments. The remainder had paid in full (383 households) or had received the equipment for free (140 respondents). We used only the information from those who had paid in full to solve equation (3). All costs were converted to 2017 Nepalese Rupees. We were able to compute an implicit VOLL V for 312 respondents with solar equipment, plus for 734 respondents with rechargeable batteries with storage as backup for lighting or appliances. The questionnaire did not collect information about the cost of the rechargeable batteries (essentially, inverters that store grid electricity for later use), but it is reasonable to conservatively assume a price of 10,000 NR even and a lifetime of 5 years.

We empirically test this hypothesis in Nepal by regressing the WTP per outage-day on the estimate of the kWhs lost per day through unscheduled outages and the estimate of the kWhs lost per day as a result of the announced load shedding. We use WTP per outage-day (i.e., WTP divided by the number of outage-days reported by the respondent) because we prefer to avoid entering outage-days in the RHS of the regression, as we suspect this latter variable to be affected by measurement error.

Specifically, we fit the regression equation:

$$WTP\_DAY_i = \theta_1 \cdot kWh_{lost_{unsch\,i}} + \theta_2 \cdot kWh_{lost_{sched\,i}} + u_i, \quad (4)$$

where θ_1 and θ_2 are the VoLL per unscheduled kWh loss and unscheduled kWh lost, respectively.

Equation (4) is easily amended to control for equipment type, as the theoretical model of section 4.A suggests that equipment may be an important determinant of the WTP to reduce outages. It is, however, possible that unobserved taste for a stable, reliable, and abundant electricity supply influences both the WTP for reduced outages and the choice of generation or backup equipment, making them econometrically endogenous. We adopt Dubin and McFadden's framework (1984) to address this issue (see Appendix B for details). Briefly, we estimate a multinomial logit model for the choice of backup equipment, which we use to create predicted probabilities of adopting each possible backup option. We then use these predicted probabilities to form terms that are added to the RHS of the regression to capture and account for the endogeneity. Once these terms are entered, equipment is independent of the error term of the regression, and the coefficients on the equipment dummies from the least-squares regressions are asymptotically unbiased.

D. Internal Validity of the WTP Responses

We rely on answers to questions involving hypothetical transactions, so it is important to check that the WTP responses meet internal validity criteria (Bishop and Boyle, 2019). We wish to regress the WTP on the number of outage-days reported by the respondents, income and education, and other determinants. Formally,

$$WTP_i^* = \beta_0 + \beta_1 \cdot OUTDAYS_i + \beta_2 \cdot HHINC_i + \beta_3 \cdot EDUC_i + \mathbf{x}_i \boldsymbol{\beta}_4 + \varepsilon_i. \tag{5}$$

Economic theory suggests that the WTP should increase with the number of outage-days, income, and education and should depend on the equipment the respondent has invested in to generate and store electricity. Coefficient β_1, coupled with an estimate of the kWh lost in an outage-day, provides an additional estimate of the VOLL.

Fitting equation (5) is complicated for several reasons. First, about a quarter of the WTP responses are zero, and the remainder is positive. This would suggest fitting a Tobit model, but Tobit relies on an underlying normal distribution for WTP* in equation (5), which is a poor fit for the right-skewed, lumpy distribution of the WTP responses in our survey. We considered finite mixtures of zeros and distributions defined on the positive semi-axis, but, again, the fit was poor. For these reasons, we refrain from models that rely on a distributional assumption, and simply specify a linear regression.

Second, the number of outage-days is likely affected by measurement error, which, if classical, would render the OLS estimates inconsistent. We, therefore, instrument for the number of outage days using the frequency of all types of outages at the 132 kV substation serving the respondent's municipality in MONTH 2016. This approach should clean out the measurement error, but otherwise assumes all other terms in the right-hand side of equation (5) to be exogenous.

5. Results

A. VoLL Estimates

We compute that the average respondent lost approximately 269 hours of service in MONTH 2016, some 49 of which were due to unannounced outages. This translates into just under 1 kWh lost per outage-day (on average 0.80 kWh).

Table 3 presents a summary of the VoLL estimates. The figures in this table are striking. First, even though one-quarter of the sample stated that they would pay nothing at all, it is clear that people *are* willing to pay for improved service. For comparison, the average price per kWh from the grid paid by the respondents at the time of the survey is 7-8 NR/kWh. Second, there is considerable heterogeneity across respondents in the value they place on grid electricity.

In the first row of Table 3, we take the WTP responses at face value and use the full sample. The median and mean VoLL (5.09 NR and 15.25 NR, or 4.71 and 14.1 US cents, respectively) thus bracket the actual average price per kWh. These results are comparable to two recent studies of lower middle-income countries (Twerefou, 2014; Oseni, 2017), which report mean VoLL estimates of 14-16 US cents. As shown in Figure 6, the distribution of the VOLL is positively skewed.

Rows 2-5 of Table 3 summarize the VOLL among groups of respondents that rely on specific types of equipment during outages. Households with rechargeable batteries and storage appear to place a lower value on grid electricity than those that are forced to use disposable batteries. This is because they announce a zero WTP more often (30.96% of the times v. 23.80% for all others), report lower positive WTP amounts (on average 158.05 NR v. 170.19 for all others) and a lower WTP per outage-day (on average 12.10 NR v. 15.91 for all others), even though their monthly consumption is greater (mean 66.64 kWh v. 51.24 for all others) and they lost more kWhs to outages (mean 22.42 kWh v. 17.73).

When we "correct" the VOLL of those with rechargeable batteries and solar equipment, imputing the larger between the original VOLL and that implicit in the purchase of equipment (see section 4.B), households are prepared to pay on average 22.29 NR/kWh (median 9.37) (row 6 of Table 3).[17]

B. Scheduled- and Unscheduled-outage VOLL

Table 4 displays the results of regressions relating the WTP for an outage-day to the kWhs lost per outage-day from unscheduled outages and to KWhs lost per outage day from load shedding. Panels (A) and (B) both use the simplest possible specification but different samples. While Panel (A) uses all of the respondents who were administered the WTP question, panel (B) uses only those who correctly reported that outages occurred every day of the MONTH 2016.

The sample as a whole appears to place a higher value on consumption lost to unscheduled outages, whereas the "more attentive" sample (thirty or thirty-one outage days, as consistent with at least the load shedding schedule) appears to place virtually the same value on each kWh lost. Moreover, for the latter group, the value per kWh lost is considerably lower than either of the two coefficients from the full sample and is close to the lowest of the figures reported in table 7. A formal Wald test rejects the null that two VOLLs are the same for the full sample (Wald statistic 16.97, a p-value less than 0.0001), but fails to reject it for the sample of the panel (B).

[17] We note that the questionnaire does not mention or seek to distinguish between short-term damages from outages and long-term mitigation costs.

Adding controls for the type of the equipment owned by the respondents changes the point estimates of the VOLL (panels (C) and (D)), but not the substance of the findings: The VOLLs are different from each other in the full sample, but identical for the more "attentive" sample.

The regressions in panels (C) and (D) of table 4 are based on linear regressions that do not include Dubin-McFadden adjustment terms, because, in preliminary regressions, the latter were not found to be important. Since such terms are not included, we did not judge essential to use heteroskedasticity-robust standard errors and t statistics. For good measure, however, we also computed standard errors clustered at the municipality level (see Appendix Table A.3). This effectively doubled the standard errors around the VOLL in the full-sample regressions, to the point that one can no longer conclude that the two VOLLs are different. By contrast, clustering the standard errors did not change the standard errors much in the regressions for the subsample that reports 30 or 31 days with outages.

C. Internal Validity of the WTP

Our respondents stated that they were willing to pay, on average, 123.32 NR per month to avoid going back to the outage situation they faced in MONTH 2016. The reported WTP varies widely across the sample. Is this variation systematically linked to the respondent's experience with outages, the household's economic circumstances, and/or the households' behavioral attitudes?

To answer this question, we fit regressions where the dependent variable is the WTP, and the independent variables are the number of outage-days reported by the respondents, income, the highest educational attainment in the family, dummies for the equipment used to make do in the event of electricity outages, and dummies capturing attitudes regarding the electricity results. We instrument for the number of outage-days in the event as this variable may be affected by measurement errors. The excluded instrument is the number of outages (planned and unplanned) at the 132-kV substation level in MONTH 2016. We exclude from the sample households in the bottom and top 1% of the distribution of monthly consumption expenditures.

Table 5 displays the 2SLS results. The first two columns of Table 5 report first- and second stage estimates of the regression model (5), excluding the attitude questions. The last two columns of Table 5 report estimates, which also include the attitude questions. Regardless of whether or not the attitude questions are included, we see that the WTP increases by 6.87 – 6.97 NR for each additional day with outages. Since we estimate our respondents to lose on average 0.80 kWh per outage-day, this coefficient implies a VOLL of (6.92/0.80=) 8.65 NR/kWh, which is consistent with the results in section 5.A.

The WTP increases significantly—but slowly—with income: At the sample average, the WTP increases by 0.21-0.26 NR for each additional 1000 NR gain in households' income. This implies an income elasticity of 0.07. Education also has an important positive effect on WTP. Compared to the households with primary education (our reference category), the households with higher, graduate, and postgraduate education levels are, respectively, willing to pay 30, 40, 100 additional NR for improved reliability of power supply. These results are consistent with earlier studies emphasizing the role of income (Kateregga, 2009, Twerefou, 2014, Oseni 2017) and educational attainment (Twerefou, 2014) in explaining the WTP for improved power supply in developing countries.

The WTP for reliable power supply falls significantly if households own power back up equipment, such as a rechargeable or disposable batteries, and solar lighting, lanterns, or home systems. Depending on the type of the backup appliance owned and inclusion of attitude questions, households are willing to pay 25 – 75 NR *less* for a more reliable power supply. Owning a kerosene lamp also reduces the WTP by 65 NR. However, the economic and statistical significance of this estimate vanishes if attitude questions are removed.

These results differ significantly from a recent study on Nigeria (Oseni, 2017), where the households owing back up appliances were willing to pay *more* for better power supply. The notable difference between our study and Oseni (2017) is because, in Nigeria, households were mostly using diesel generators with high running costs. In our study, households rely on solar generation and storage, whose marginal running cost (net of grid electricity expenses for storage) is zero. The lower stated WTP, however, does not, however, imply the lower VoLL. As we show in section 5A, the owners of solar and battery backup have higher VoLL when the appliance cost is internalized in stated WTP for reliable power supply.

Finally, among the attitude variables, the indicator variables for if the respondent agrees that he or she would pay more for electricity if service were more reliable, or that higher prices would lead to better service, are both associated with higher WTP for the reliable power supply. This may or may not be especially useful to policymakers, but it is important for our purposes because it confirms the internal validity of the data.

6. Conclusions

Using a contingent valuation question that asked respondents to announce their WTP to avoid going back to the same number of days with power outages as they had experienced a year before, we have been able to place a value on the electricity service disruptions experienced by households in Nepal. Households are willing to pay, on average, 123.32 NR ($1.14) on top of their monthly electricity bill to avoid the outages experienced in the month one year before the survey.

However, when we divide the WTP amounts by the number of kWh lost due to unscheduled outages and load shedding, our preferred estimates of the resulting VoLL (5 – 15 NR/kWh, or ¢4.7 – ¢14/kWh) are low when compared with the marginal cost of adding capacity or delivering electricity when the demand is high. Imports from India have a marginal cost of approximately 30 cents per kWh during the times of highest demand. The highest marginal cost for the limited oil-based generation in Nepal is 20-30 cents/kWh. The cost of spinning reserve shortfall is likewise estimated at about 20 cents/kWh.[18] Each of these alternate estimates of the marginal cost of bringing additional electricity to the grid exceeds the VoLL.

It is even more striking that our estimates of the VOLL, based on data collected in 2017, is no larger than the figures obtained by Karki et al. (2008) in a survey in 2008. Furthermore, the respondents that we call "attentive" (because they appear to recollect the number of days with outage from the prior year correctly) are the ones that announce most often that they are not willing to pay at all to be rid of outages.

Economic theory and common sense suggest that the value of avoiding the loss of one kWh should be higher when the outage is unannounced, and we find evidence of this when we use the full sample of responses. But when attention is restrictive to the "attentive" respondents, it appears that the VoLL from unscheduled and scheduled outages is the same. Given the many daily hours without electricity before October 2016, it is likely that the notions of "intensive" and "extensive" margin (corresponding to one more kWh lost in scheduled and unscheduled outages, respectively) get blurred for such "attentive" respondents.

[18] Dr. Debabrata Chattopadhyay, head of the World Bank's Energy Planning Team, personal communication, 2 January 2020.

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Figure 1. Load shedding outages in Nepal in 2016.

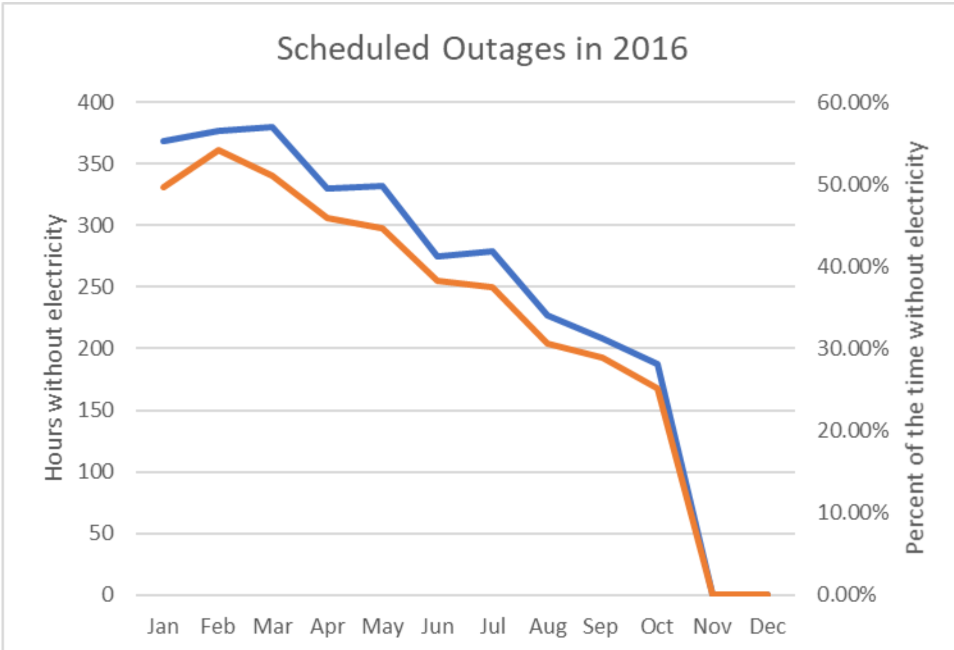

Figure 2.a. Distribution of monthly electricity consumption (exact household consumption, available for 638 households).

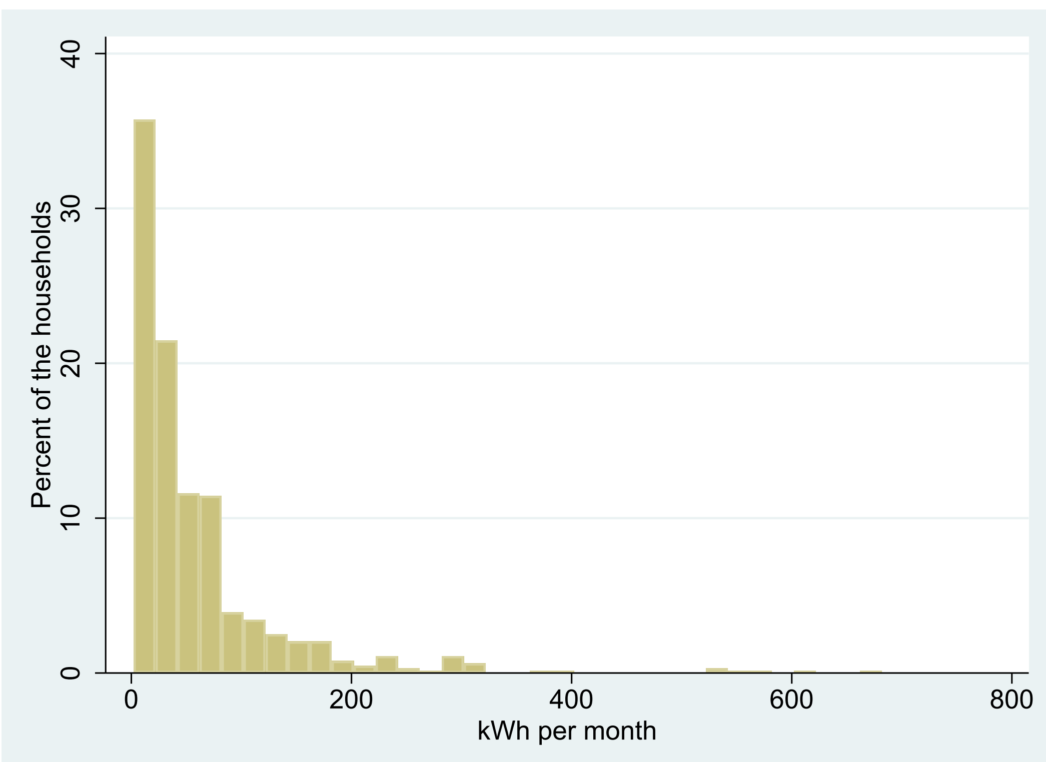

Figure 2.b. Distribution of exact or calculated monthly electricity consumption (N=2725).

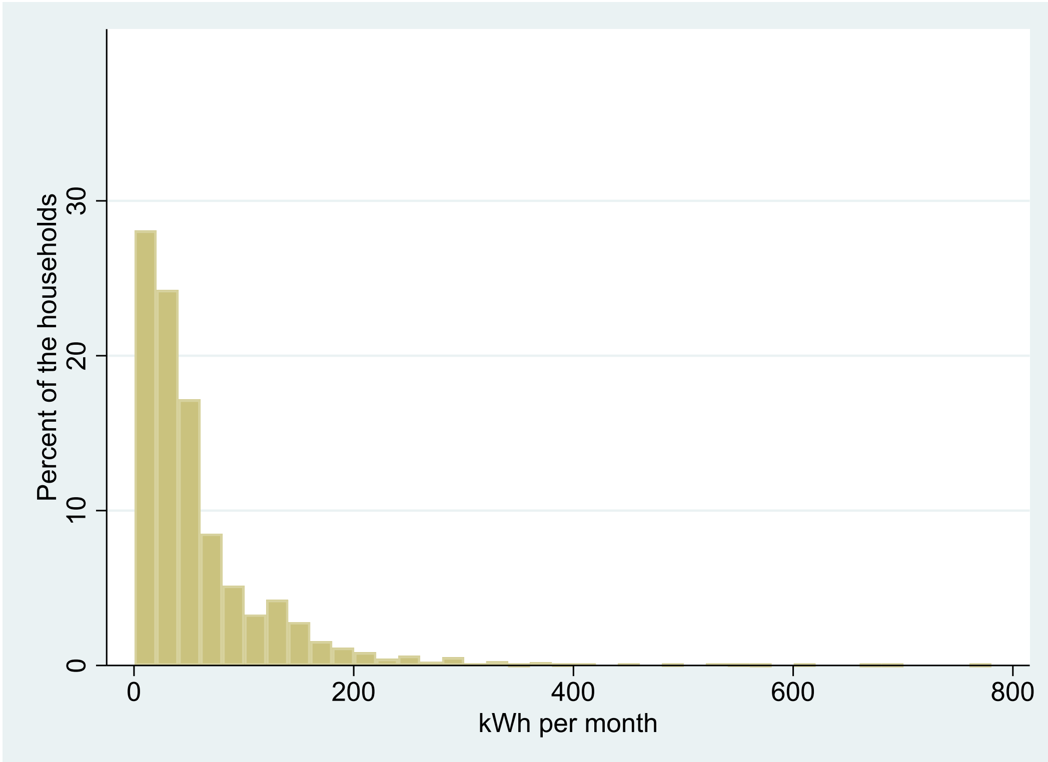

Figure 3.a Distribution of respondent-reported outage-days in MONTH 2016 (full sample, N=2723).

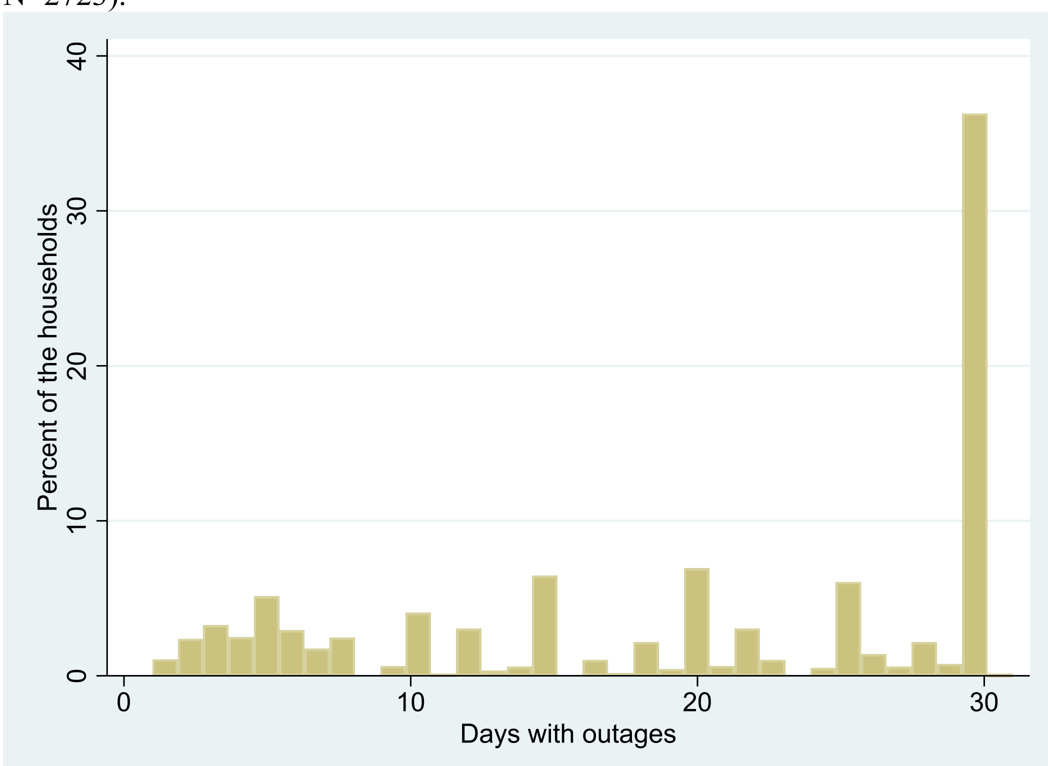

Figure 3.b Distribution of respondent-reported outage-days in MONTH 2016 (only respondents with zero WTP, N=709).

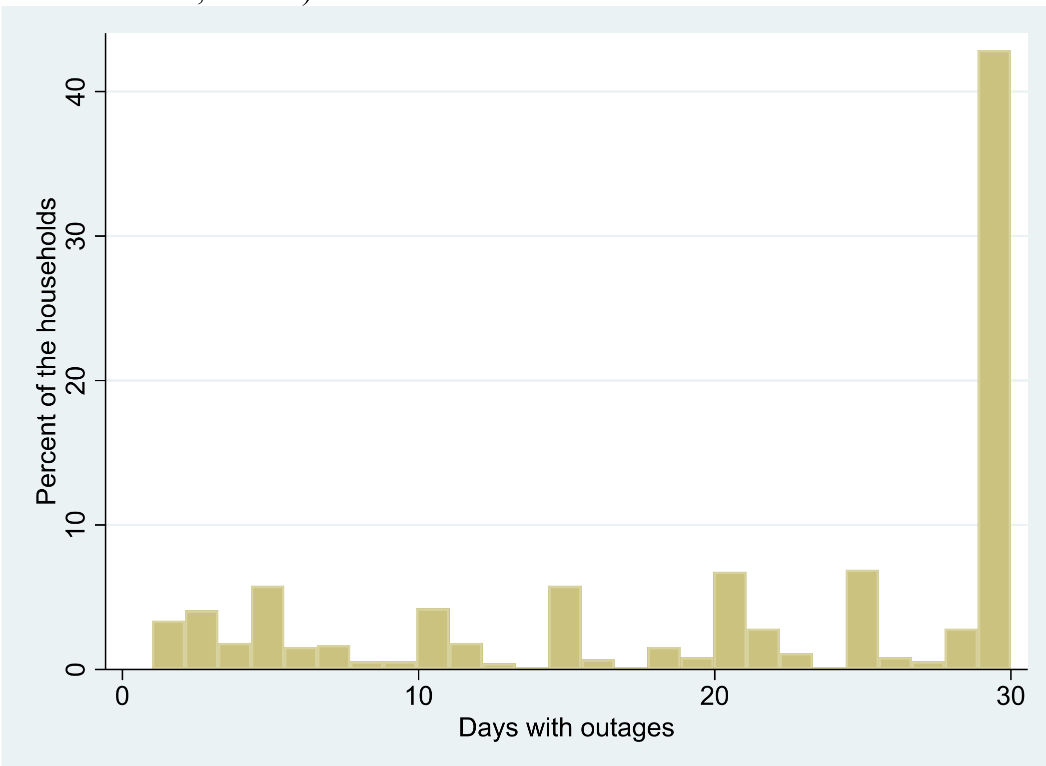

Figure 4. Total outages at the substation that serves the resident municipality v. respondent-reported outage-days.

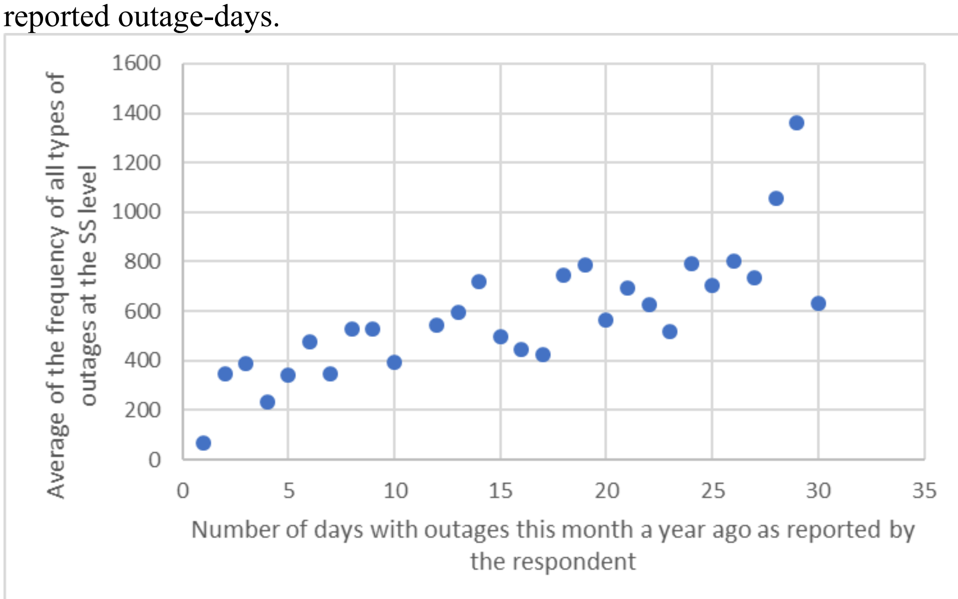

Figure 5. Average number of respondent-reported outage-days in MONTH 2016 by income quintile.

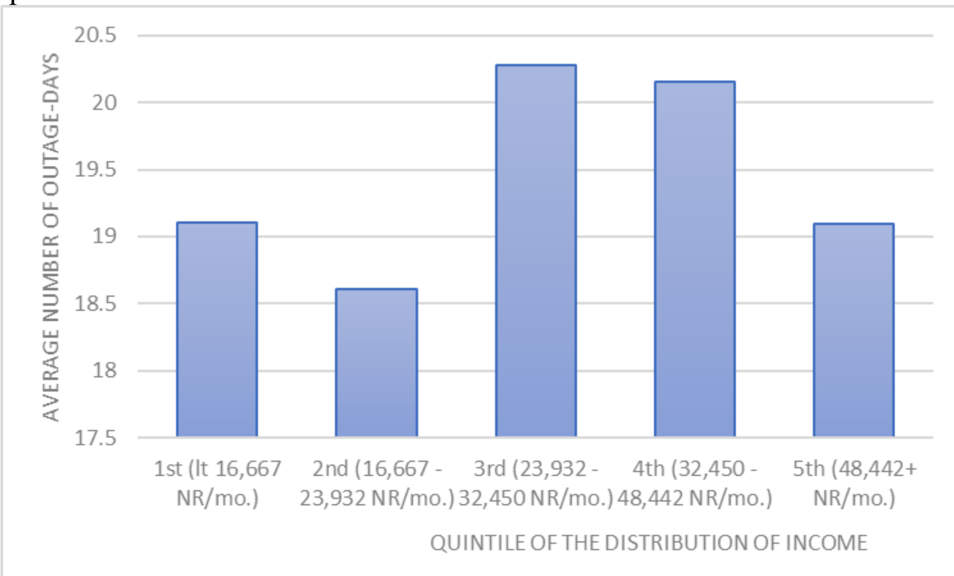

Figure 6. Distribution of VOLL in the sample.

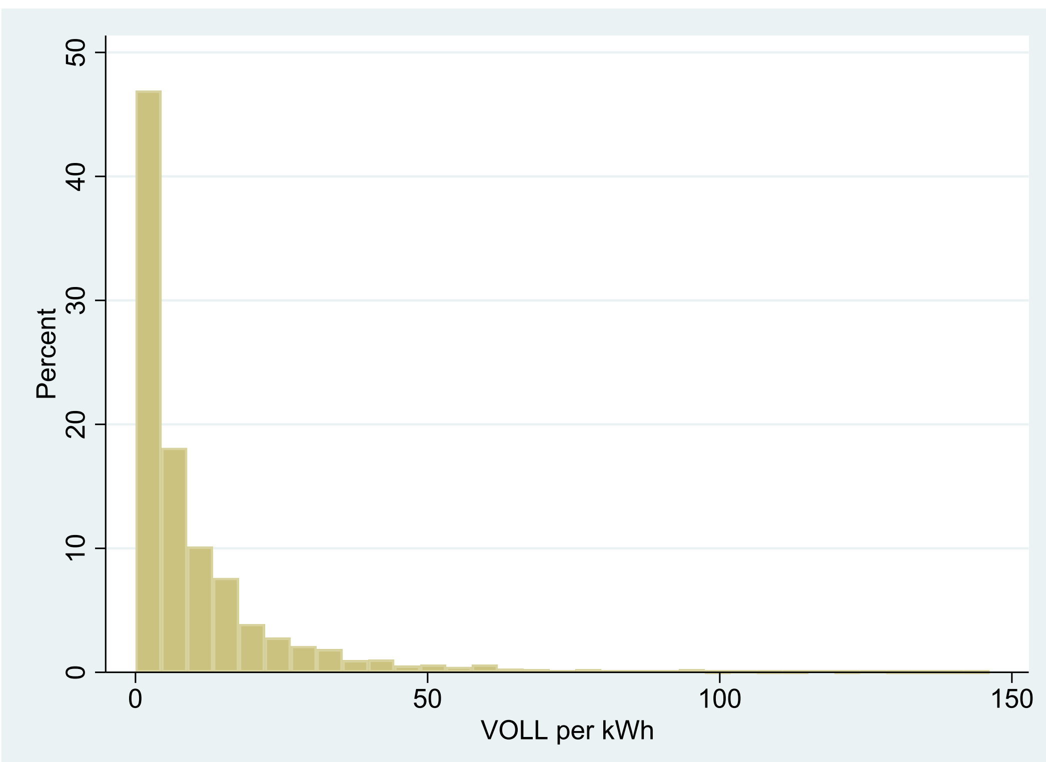

Table 1. Backup equipment used for lighting during outages.

Equipment used for lighting in case of an outage	Percent of the sample connected to the grid (N=4047)	Percent of the sample who still experience outages (N=2725)
Rechargeable batteries	29.06	30.04
Disposable batteries	14.46	15.23
Solar lantern	3.71%	3.60%
Solar lighting	17.79	16.0
Solar home system	1.43	1.14
Kerosene lamp	13.52	15.60
Has no backup for appliances	69.51	71.52

Table 2. Responses to the initial bid amount in the WTP question.

Bid amount (NR)	Percent willing to pay the indicated amount.
100	65.46
200	35.15
300	22.38
400	22.90
500	20.11

Table 3. Summary of calculated VOLL. All figures in NR/kWh.

	N	mean	25th perc.	median	75th perc.	90th perc.	95th perc.
VOLL	2281	15.25	0	5.10	13.85	29.03	48.08
VOLL if rechargeable batteries	734	12.08	0	3.77	10.77	23.09	40.57
VOLL if disposable batteries	311	18.29	3.43	8.88	18.71	37.40	67.05
VOLL if kerosene lamp	398	11.14	0	5.28	12.58	28.01	46.44
VOLL if any type of solar equipment	436	22.15	0	4.68	15.52	31.63	57.22
max (VOLL, implicit VOLL in the purchase of durable equipment)	2281	22.29	3.88	9.37	20.81	39.61	60.89

Table 4. Regression results. Dependent variable: WTP per outage-day.

	(1)	(2)	(3)	(4)
	All households	Thirtydays=1	All households	Thirtydays=1
kWh lost to	14.655***	4.057***	13.272***	1.868**
unscheduled outages	(1.054)	(0.966)	(1.035)	(0.897)
kWh lost to	8.527***	4.066***	3.759***	1.520***
uscheduled outages	(0.685)	(0.307)	(0.851)	(0.349)
Rechargeable batteries			-6.049***	-2.211***
and no backup (1 = Yes)			(1.612)	(0.589)
Rechargeable batteries			-5.888***	-1.554**
and backup (1 = Yes)			(1.903)	(0.661)
Disposable batteries			4.422**	1.061
(1 = Yes)			(1.792)	(0.739)
Solar lighting			-2.601	-1.901***
(1 = Yes)			(1.703)	(0.626)
Solar lantern			2.091	1.193
(1 = Yes)			(2.661)	(1.174)
Solar home system			-3.539	-0.472
(1=Yes)			(5.015)	(1.727)
Kerosene lamp			-7.011***	-1.111*
(1 = Yes)			(1.695)	(0.605)
Constant			9.311***	4.205***
			(1.292)	(0.537)
Observations	2,251	769	2,251	769
R-squared	0.215	0.343	0.125	0.093
Test: $\theta_1=\theta_2$ (p-value)	16.97 (0.00)	0.00 (0.99)		

Note. Standard errors in parentheses. "Thirtydays=1" means that the sample is restricted to those respondents who reported experiencing 30 or more days with outages "this month one year ago."

Table 5. Results from IV estimation of WTP equations.

Stage	I	II	I	II
Variables	Outages	WTP	Outages	WTP
Days of power outages		6.877***		6.967***
on a typical month		(2.508)		(2.500)
Monthly expenditures	-0.0122***	0.258***	-0.0108***	0.213***
(NR thousand)	(0.00354)	(0.0625)	(0.00355)	(0.0597)
Monthly expenditures not	4.521***	-46.70***	4.788***	-60.26***
reported (1 = Yes)	(0.709)	(18.10)	(0.717)	(18.43)
Hill Kathmandu region	-4.011***	0.559	-4.223***	21.40
(1 = Yes)	(0.837)	(18.13)	(0.838)	(18.11)
Maximum education:	0.890	23.62**	0.976	10.15
secondary (1 = Yes)	(0.644)	(11.02)	(0.644)	(10.74)
Maximum education:	1.147*	42.96***	1.228*	27.78**
higher (1 = Yes)	(0.679)	(11.70)	(0.681)	(11.43)
Maximum education:	3.219*	9.814	3.112	2.711
vocational (1 = Yes)	(1.940)	(33.25)	(1.933)	(32.07)
Maximum education:	0.407	51.72***	0.329	38.85***
graduate (1 = Yes)	(0.780)	(12.99)	(0.781)	(12.60)
Maximum education:	-0.826	114.6***	-0.832	92.87***
postgraduate (1 = Yes)	(1.164)	(19.46)	(1.165)	(18.88)
Rechargeable batteries	3.006***	-32.70**	4.200***	-77.55***
and no backup (1 = Yes)	(0.640)	(12.88)	(0.624)	(15.27)
Rechargeable batteries	-1.716	-7.962	5.031***	-50.60***
and backup (1 = Yes)	(1.085)	(18.76)	(0.708)	(17.32)
Disposable batteries	3.077*	-51.64*	2.002***	-23.46**
(1 = Yes)	(1.812)	(30.99)	(0.649)	(11.14)

Solar lighting (1 = Yes)	4.587***	-74.63***	3.010***	-32.22**
	(0.678)	(17.79)	(0.638)	(12.59)
Solar lantern (1 = Yes)	-0.0122***	0.258***	-1.592	-10.35
	(0.00354)	(0.0625)	(1.082)	(18.06)
Solar home system (1=Yes)	4.521***	-46.70***	2.942	-45.57
	(0.709)	(18.10)	(1.805)	(29.86)
Kerosene lamp (1 = Yes)	-4.011***	0.559	4.474***	-64.78***
	(0.837)	(18.13)	(0.677)	(17.25)
Attitude: Subsidies			-0.591	2.096
(1 = Yes)			(0.427)	(7.034)
Attitude: Reliability I			0.518	83.10***
(1 = Yes)			(0.444)	(7.283)
Attitude: Reliability II			-1.949***	23.57***
(1 = Yes)			(0.427)	(8.591)
Substation-level	0.00350***		0.00343***	
Outages	(0.000596)		(0.000593)	
Substation-level	0.738		0.793	
Outages Missing	(0.520)		(0.519)	
Constant	15.15***	-8.087	15.74***	-62.66
	(0.785)	(42.42)	(0.829)	(43.86)
Observations	2,598	2,598	2,598	2,598
R-squared	0.107		0.115	
IV F-stat		22		20.77

Notes. (i) Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

(ii) Attitude questions are as follows. Subsidies: "Would pay more if the government used the revenue to subsidize the poor." Reliability I: "Would pay more if the supply was more reliable." Reliability II: "Agrees that higher prices would lead to better service."

Appendix A.

Table A.1. Percentage of zero WTP responses by equipment, attitudes, and ecological region. N=2725.

A. by equipment

Equipment used for lighting in case of an outage	Percent of respondents
Rechargeable batteries and backup for appliances	25.87
Rechargeable batteries and no backup for appliances	34.03
Disposable batteries	14.84
Solar lantern	22.68
Solar lighting	26.40
Solar home system	25.81
Kerosene lamp	29.41
Other types of backup lighting	24.29

B. by attitudes

Attitude	Percent of respondents
Subsidies (would pay more if the government used the revenue to subsidize the poor)	21.80
Reliable 1 (would pay more if the supply was more reliable)	11.14
Reliable 2 (agrees that higher prices would lead to better service)	22.89

C. by ecological region of residence

Ecological region of residence	Percent of respondents
Mountain	25.25
Hill	20.40
Terai	30.35
Hill Kathmandu Region	25.00

Table A.2. Probit models of the zero WTP responses.

Variables	(1) zeroWTP	(2) zeroWTP	(3) zeroWTP	(4) zeroWTP
Monthly expenditures	-0.004***	-0.004***	-0.004***	-0.003***
(NR thousand)	(0.001)	(0.001)	(0.001)	(0.001)
Monthly expenditures	-0.074	-0.063	-0.077	0.038
not reported	(0.100)	(0.101)	(0.103)	(0.113)
Maximum education:	-0.297***	-0.290***	-0.263***	-0.164*
secondary (1 = Yes)	(0.089)	(0.089)	(0.090)	(0.097)
Maximum education:	-0.310***	-0.289***	-0.261***	-0.116
higher (1 = Yes)	(0.094)	(0.095)	(0.098)	(0.104)
Maximum education:	0.103	0.150	0.179	0.310
vocational (1 = Yes)	(0.270)	(0.272)	(0.275)	(0.295)
Maximum education:	-0.457***	-0.427***	-0.394***	-0.319***
graduate (1 = Yes)	(0.110)	(0.112)	(0.117)	(0.124)
Maximum education:	-0.300*	-0.246	-0.199	0.055
postgraduate (1 = Yes)	(0.164)	(0.168)	(0.172)	(0.182)
Monthly electricity		-0.001	-0.001	-0.001*
consumption (kWh)		(0.000)	(0.001)	(0.001)
Rechargeable batteries			0.192**	
and no backup (1 = Yes)			(0.088)	
Rechargeable batteries			0.163	
and backup (1 = Yes)			(0.103)	
Disposable batteries			-0.388***	
(1 = Yes)			(0.102)	
Solar lighting			-0.076	
(1 = Yes)			(0.160)	

Solar lantern			0.123	
(1 = Yes)			(0.092)	
Solar home system			0.331	
(1=Yes)			(0.259)	
Kerosene lamp			0.061	
(1 = Yes)			(0.096)	
Own a Fridge			-0.111	
(1 = Yes)			(0.074)	
Attitude: Subsidies				0.153**
(1 = Yes)				(0.068)
Attitude: Reliability I				-1.540***
(1 = Yes)				(0.071)
Attitude: Reliability II				0.429***
(1 = Yes)				(0.071)
Constant	-0.256***	-0.236***	-0.264**	0.271***
	(0.083)	(0.084)	(0.103)	(0.096)
Observations	2,568	2,568	2,568	2,568
Pseudo R-squared	0.018	0.019	0.035	0.214

Notes. (i) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

(ii) Attitude questions are as follows. Subsidies: "Would pay more if the government used the revenue to subsidize the poor." Reliability I: "Would pay more if the supply was more reliable." Reliability II: "Agrees that higher prices would lead to better service."

Table A.3. Dependent variable: WTP per outage-day.

	(1)	(2)	(3)	(4)
	All households	Thirtydays=1	All households	Thirtydays=1
kWh lost to	14.655**	4.057**	13.272**	1.868
unscheduled outages	(7.080)	(1.802)	(6.116)	(1.591)
kWh lost to	8.527**	4.066***	3.759	1.520***
unscheduled outages	(3.585)	(0.444)	(4.291)	(0.400)
Rechargeable batteries			-6.049***	-2.211**
and no backup (1 = Yes)			(2.032)	(0.962)
Rechargeable batteries			-5.888***	-1.554
and backup (1 = Yes)			(2.148)	(0.990)
Disposable batteries			4.422	1.061
(1 = Yes)			(2.887)	(1.258)
Solar lighting			-2.601	-1.901**
(1 = Yes)			(2.522)	(0.941)
Solar lantern			2.091	1.193
(1 = Yes)			(3.623)	(1.373)
Solar home system			-3.539	-0.472
(1=Yes)			(4.670)	(2.253)
Kerosene lamp			-7.011***	-1.111
(1 = Yes)			(1.814)	(0.791)
Constant			9.311***	4.205***
			(1.840)	(0.940)
Observations				
R-squared	2,251	769	2,251	769
Test: $\theta_1=\theta_2$ (p-value)	0.44 (0.51)	0.00 (0.99)		

Note. Standard errors clustered at the municipality level in parentheses. "Thirtydays=1" means that the sample is restricted to those respondents who reported experiencing 30 or more days with outages "this month one year ago."

Appendix B. Dubin-McFadden approach.

Formally,

(B.1) $$WTP\_DAY_i = \mathbf{w}_i\boldsymbol{\beta} + u_i$$

(B.2) $$y_{ij}^* = \mathbf{z}_i\gamma_j + \eta_{ij} \qquad \text{j=1, 2,…, J}$$

As in Bourguignon et al. (2007), we assume that the model is non-parametrically identified from the exclusion of some of the variables in **z** from those in **w**. We do not observe the y_{ij}^*s, but we do observe that equipment k is selected, which means that $y_{ik}^* > \max\,(y_{ij}^*)$ for k≠j. Assuming that the ηs are i.i.d. from a type I extreme value distribution, we obtain a multinomial logit specification:

(B.3) $$\Pr\,(k) = \exp\,(z_i\gamma_k)/\textstyle\sum_{j=1}^{J}\exp\,(z_i\gamma_j)\ .$$

How can β be estimated, taking into account the correlation between u and the ηs? Dubin and McFadden assume that $\mathrm{E}\big(\mathrm{u}\big|\eta_1,..,\eta_J\big) = \sigma\frac{\sqrt{6}}{\pi}\sum_{j=1}^{J} r_j(\eta_j - E(\eta_j))$. With the multinomial logit model, $\mathrm{E}\big(\eta_j - E(\eta_j)\big|k\ chosen\big) = -\ln\,(P_k)$ for j=k, and $\mathrm{E}\big(\eta_j - E(\eta_j)\big|k\ chosen\big) = \frac{P_j\ln\,(P_j)}{1-P_j}$ for j≠k. This results in the regression:

(B.4) $$WTP\_DAY = x\beta + \sigma\frac{\sqrt{6}}{\pi}\left[\sum_{j=1}^{J} r_j\frac{P_j\ln\,(P_j)}{1-P_j} - r_j\ln\,(P_j)\right] + w$$

which can be estimated by least squares after the P_j terms have been replaced with their estimates from the multinomial logit. Care must be taken to use robust standard errors and t statistics, as *w* is heteroskedastic, and the heteroskedasticity is made even worse by plugging in estimated probabilities.

References:

Bourguignon, François, Martin Fournier, and Marc Gurgand. 2007. Selection Bias Corrections Based on the Multinomial Logit Model: Monte Carlo Comparisons. *Journal of Economic Surveys* 21(1), 174-205.