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Research paper

Consumers' willingness to pay for electricity service attributes: A discrete choice experiment in urban Indonesia

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A B S T R A C T

In developing countries like Indonesia, the challenge of providing electricity services is often about how to combine commercial and development objectives optimally. In this context, good knowledge of consumers' willingness to pay (WTP) and trade-offs among electricity service attributes is of strategic value, especially when achieving development objectives involve raising electricity tariffs to consumers. This study uses a discrete choice experiment (DCE) and two estimation methods, mixed logit (MXL) and latent class logit (LCL), in order to better understand the preferences of electricity customers. Specifically, the objective of the experiment is to understand how consumers balance the trade-off among four electricity service attributes: the duration of the outage, source of electricity generated, rural electrification ratio, and tariffs. The DCE survey was conducted in Bandung (Indonesia) with 1600 questionnaires were distributed. The analysis demonstrates that consumers are willing to pay for the proposed condition, away from status-quo. For example, using MXL method to reduce the outage duration to be 2 hours/year, the WTP is ranging from IDR5,000 (USD1.18) to IDR61,500 (USD14.49) per month, depending on the size of the installed capacity. While for the increase of rural electrification ratio to 100%, it ranges from IDR17,600 (USD4.15) to IDR215,000 (USD50.64) per month. The analysis emphasizes that there is significant heterogeneity in preferences for electricity service attributes.

1. Introduction

Scaling up electricity services is crucial for both economic and social development in any country. Moreover, satisfying consumers' needs and gaining competitive advantage through improved service and product quality is a common objective of all firms, and electricity service firms are no exceptions. Therefore, to offer better electricity services that can be beneficial for economic and social development, as well as satisfying consumers, individual's preferences and willingness to pay (WTP) for improved electricity services should be clearly understood.

To address the issue above, especially in the context of urban consumers, we conducted a discrete choice experiment (DCE) study in Bandung, Indonesia, one of the fastest-growing cities in Southeast Asia to evaluate the relative importance of product-specific attributes. The DCE[1] was developed by Louviere and Woodworth (1983), and its theoretical foundation lies in the work of Lancaster (1966), who argued that consumer utility is obtained not from the product itself but from the attributes or characteristics of the product. Since its development, DCE has been improved and applied in various disciplines because, theoretically, the method has the ability to imitate almost any choice situation in our everyday lives.

The DCE is a survey-based valuation method that describes goods or services as a collection of attributes. By varying the attribute levels, namely, rural electrification ratio, outage duration, mix energy composition, and monthly electricity bill, this study creates different 'goods (or alternatives)' presented to the respondents. We can see how they change their decisions accordingly. The overall findings suggest that urban consumers' demand for electricity service improvements is motivated more by the increase of rural electrification ratio than by the reduction of outage duration per year or having more environmentally friendly electricity source, or paying higher prices.

The rest of this paper is organized as follows: Section 2 gives a brief overview of the Indonesian electricity service condition. Section 3 describes the methodology used in this study. Section 4 presents results from data analysis, including the models estimated from the DCE data. Finally, Section 5 concludes the present study.

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[1] DCE is also known as choice experiments, choice-based conjoint analysis, stated choice method, or attribute-based SP method, however, this study refers to them as DCEs as per Louviere et al. (2010).

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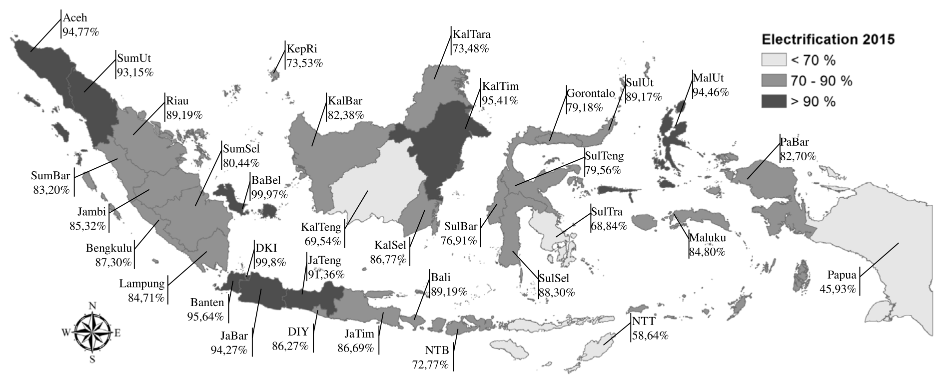

Fig. 1. 2015 Electrification Rates in Indonesian Provinces.
Source: Ministry of Energy and Mineral Resources, 2015.

2. Overview of Indonesian electricity sector

According to the World Development Indicator (WDI) 2016, Indonesia's per capita consumption of electricity is only around a quarter of the world's per capita consumption. Electricity contributed 11% of final energy use in Indonesia in 2015 (in oil equivalent terms), which is much less than the contribution of electricity to final energy use in China (22%). Besides, Indonesia has a higher reliance on coal for the generation of electricity oil-based fuels (International Energy Agency, 2017). This heavy reliance on coal makes Indonesia the 11th-largest emitter of carbon dioxide emissions from the generation of electricity and heat International Energy Agency (2017). Renewable sources of energy are looking increasingly attractive in Indonesia, not only to support environmental policy around CO2 emissions but also on account of their improving cost profile and ability to be deployed in a more decentralized manner. The current power generation fuel mix includes coal (56%), gas (24.9%), oil (8.6%) and renewables (10.5%).

There is substantial geographical variation in electricity use within Indonesia. Java, home to 57% of Indonesia's population, accounted for 72% of electricity sales in 2016 (PT PLN (Persero), 2016). From Fig. 1, the household electrification rate is also the highest in Java, although with some variation between provinces. Papua has the lowest electrification rate among Indonesia's provinces, at less than 50% in 2015. The national household electrification rate had risen to 87% as of 2016 (PT PLN (Persero), 2016,?)), up from 64% in 2009 (PT PLN (Persero), 2009), and 53% in 1995 (Asian Development Bank, 2016). However, with 87% national electrification ratio, it still leaves over 61 million people without access to electricity. Most of them live in the rural area (current rural electrification is 68% in Java and less in outer Java) (Ministry of Energy and Mineral Resources, 2015). The Government of Indonesia has the aim of reaching a national household electrification rate of 97% by 2019 as mandated in Medium National Development Plan.

Another electricity service issue is the threat of electricity outages. The average electricity user in Indonesia faced 81 h without electricity in 2008 (PT PLN (Persero), 2011) as a result of rolling blackouts from a supply system that was struggling to meet demand. A Report by Ministry of Energy and Mineral Resources (2015), for example, suggests that only less than 60% area of operations of the electricity providers in Indonesia are considered adequate in meeting its demand. The rest is either on the deficit or on alert. This has put a large number of consumers at high risk of having blackouts.

The government sets residential electricity prices in Indonesia. The tariff varies by consumer group based on the in-house installed power connections, measured in volt–ampere (VA): 450 VA, 900 VA, 1300 VA, and 2200 VA. Consumers are billed monthly and face both fixed charges and utilization tariffs. These are typically higher for consumers with larger power connections. Many consumers face increasing block tariff structures, meaning that they pay a higher marginal per kilowatt-hour (kWh) tariff at higher usage levels. Electricity prices were raised after the Asian financial crisis of the late 1990s as part of the fiscal reforms. However, for residential electricity prices, the rise is only applied for consumers with power connections of 1300 VA and 2200 VA and leaving most of the residential consumers paid the subsidized price. As of 2016, it was calculated that more than 70% of households received subsidized electricity (Initiative, 2016), with the official poverty rate of only 11% (BPS, 2016), this only suggests that there are so many people received electricity subsidies even though they were not poor.

Looking at the current condition, the Government of Indonesia, through State Electricity Company (*Perusahaan Listrik Negara*/PLN), has set the target of electricity coverage of 99.7% while reducing greenhouse gas emissions by 26% by the year 2025 and improving the quality of electricity supply. One way to achieve such an objective is by prioritizing the development of renewable resources, especially to relieve pressure on the PLN grid. Hydropower is currently the largest single source of renewable power in Indonesia. In 2017, PLN planned for hydro to account for 6.4% of national power generation, and this is expected to grow to 12.3% in 2026, even though Indonesia has approximately 75 GW of hydropower potential. In summary, to improve electricity service, Indonesia electricity providers need to at least cover three essential attributes, namely, rural electrification, the use of hydropower for electricity generation, and the duration of an unplanned power outage.

To summary, despite many improvements in certain areas, such as the overall electrification rate, the Indonesian electricity sector is still facing at least three following challenges. First, the quality of access, such as the frequency of outage, is still considered below standard. High frequency of outage does not only cause discomfort to household electricity customers but can also create a high cost to industries, which is not in line with the country's aspiration to achieve higher economic growth. Secondly, despite high access on average, there is still a large disparity of access among regions, particularly between urban and rural areas. Thirdly, Indonesia aspires to diverse its electricity mix to include more renewable energy sources. This understandably needs an extra financial resource for investments. Currently, the price of electricity charged to certain customers, including the non-poor, is still subsidized. Diverting these financial resources into renewable energy investment can be a viable alternative. Nevertheless, this kind of diversion will involve raising the price

Table 1
Review of several DCE studies on electricity service attributes.

Author(s)	Study site	Key findings
Goett et al. (2000)	USA	(1) Consumers, on average, are willing to pay extra for supplier that has 25% hydro power relative to a supplier with no renewables. (2) Consumers only focus on the use of hydro in the electricity generation rather than the impact of hydro on the environment.
Abdullah and Mariel (2010)	Kenya	(1) There is a demand for electricity service reliability. (2) Reliability is measured by the number of planned blackouts and duration of outage. (3) The importance of identifying socio-economic and demographic characteristics to explain the preference heterogeneities.
Amador et al. (2013)	Spain	(1) WTP to reduce outage frequency is positively correlated with customers experiences on serious outages. (2) WTP for renewable energies is positively correlated with customers education level and concern for the greenhouse gases (GHG) emissions.
Sagebiel and Rommel (2014)	India	(1) Household preferences are highly heterogeneous. (2) Limited preparedness of domestic users to pay for improved electricity quality and renewable energy. (3) Households prefer state owned distribution companies to private enterprises or cooperative societies.
Huh et al. (2015)	Korea	(1) Electricity bill and electricity mix are the two most important attributes in electricity service. (2) Customers WTP for a significant increase in the share of renewable energy is far less than the actual cost of achieving it.
Ozbafli and Jenkins (2016)	Turkey	(1) There is a demand for electricity service reliability. (2) Reliability is measured by the frequency, duration, time, and prior notification of outage. (3) The annualized economic benefits would justify an investment in additional generation capacity to eliminate the service reliability problem.
Kalkbrenner et al. (2017)	Germany	(1) Electricity bill and electricity mix are the two most important attributes in electricity service. (2) There is no indication that consumers are willing to pay for higher shares of regional generation.

to customers. Understanding the willingness of customers to tolerate such an increase is valuable information for policymakers. These three urgent issues are exactly the problems that we intend to address from the findings of this research.

3. Literature review

A growing number of studies have used DCE to value preferences for electricity service improvement in the residential sector. Table 1 provides an overview of the key findings of various DCE studies on electricity service attributes for both developed and developing countries. These studies use consumer's willingness to pay (WTP) of electricity service attributes to value preferences for electricity service improvement. In some of these studies, the WTP was expressed in relative or absolute terms. In others, it was expressed as an increase in the amount of an electricity bill or an increase in the price per kWh of electricity supplied. Across all studies cited here, generally, people are willing to pay for the improvement of electricity service attributes and outage attribute is the most common attribute found.

One of the earliest studies using DCE in the energy sector is the study by Goett et al. (2000) in the United States (US). They used five attributes in their study: (1) price and contract terms; (2) green energy attributes; (3) customer services; (4) value-added services; and (5) community presence. Focusing on green energy attributes, they found that the majority of consumers prefer hydro or a mix of sources to the wind. Consumers, on average, are willing to pay USD 1.46 per kWh extra for a supplier that can provide them with 25% hydropower relative to a supplier with no renewables. However, the WTP for a supplier that has 50% hydropower is only USD 0.18 cents, suggesting that consumers only focus on the use of hydro in the electricity generation rather than the impact of hydro on the environment.

Abdullah and Mariel (2010), one of the first studies conducted in a developing country, investigate the cost of reliable electricity services in Kenya. The attributes used in their study are (1) price, (2) type of distribution provider; (3) number of planned blackouts; and (4) duration of the outage. Using the mixed-logit method, they found that the duration of the outage is the attribute with the highest WTP (KSh 61.87). Moreover, they also found that several socio-economic and demographic characteristics may explain the preference heterogeneities. This kind of understanding of costumers characteristics can assist service differentiation to accommodate the diverse households' preferences towards the improvement of the electricity service.

One of more recent studies conducted in a developing country is a study by Sagebiel and Rommel (2014). In their study, conducted in Hyderabad, India, each respondent faced nine choice sets, and each choice set contains two alternatives to choose from (no status-quo alternative). Each alternative consists of six attributes with different attribute levels, namely duration of scheduled power cuts, duration of unscheduled power cuts, renewable energy in the energy mix, institutional setup, and additional cost per month. Using conditional logit and latent-class logit model, they show that additional monthly electricity bill, institutional set up of suppliers, and scheduled power cuts per day influence the household choice between different electricity alternatives. While unscheduled power cuts and renewable energy in the energy mix do not have any effect on the respondent's decision-making process. Their results imply that increased domestic tariffs cannot finance improvements in reliability and increases in renewable energies.

Amador et al. (2013) used a choice experiment method to explore customers' preferences for electricity service attributes in Spain. In the choice experiment, each respondent was presented with nine choice scenarios, resulting in a total of 3,384 observations. While Abdullah and Mariel (2010) only focus on the frequency of outages and the duration of the outage, in Amador et al. (2013) study, they also consider renewable energy mix and energy audit attributes. Results from the choice experiment show that the price attribute is not the only attribute that influences the household choice between different electricity bundles. The customers' WTP to reduce outage frequency tends to move with the customer's experiences on severe outages.

In contrast to the result from Goett et al. (2000) study, WTP for renewable energies is positively correlated with customers' education level and concern for greenhouse gases (GHG) emissions. Similarly, Ozbafli and Jenkins (2016) also investigated reliable electricity services with five electricity service attributes used: (i) frequency of outages; (ii) duration of outages; (iii) time of outages; (iv) prior notification; and (v) percentage change in monthly electricity bill. Their results indicate that households are willing to pay extra 3.6% (equivalent to 0.28 Turkish Lira) and a 13.9% (equivalent to 1.08 Turkish Lira) increase in their monthly

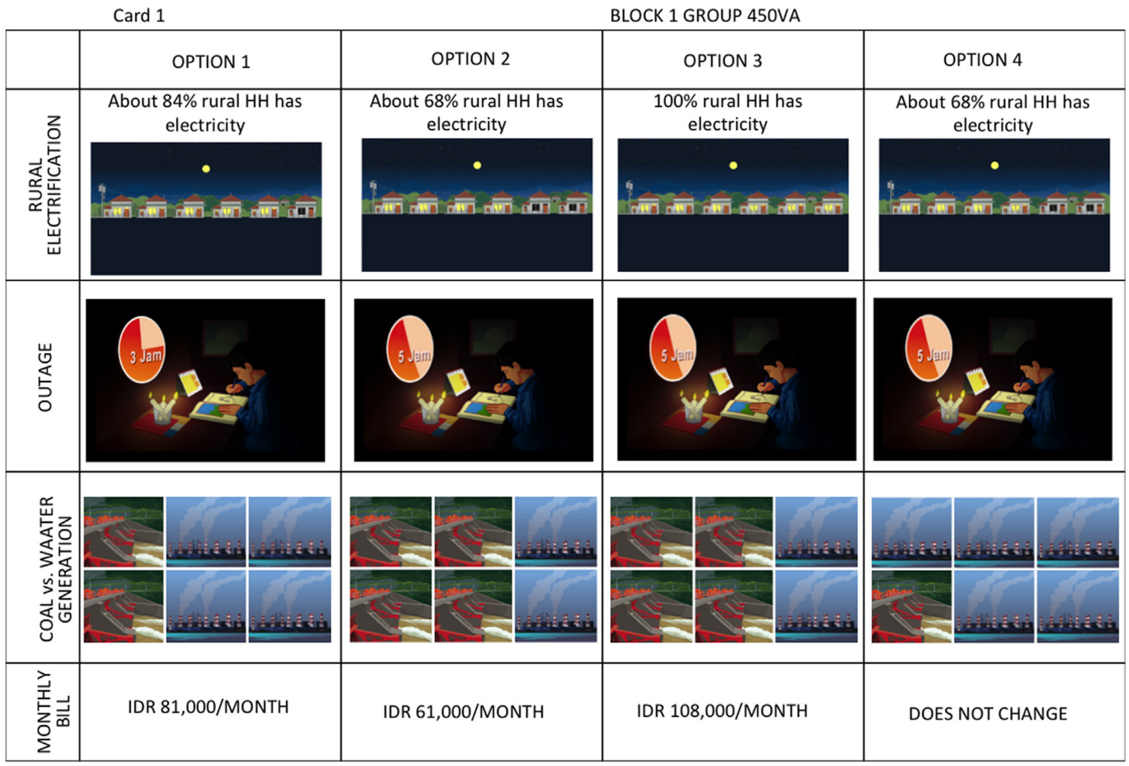

Fig. 2. Sample of Choice Set. HH stands for household and the word 'jam' in Indonesian language is 'hour' in English.

electricity bill for summer and winter, respectively, in order to avoid the cost of outages.

Huh et al. (2015) have used choice experiments method to find household preferences for electricity service improvement in South Korea. There are five non-monetary attributes used for hypothetical residential electricity service: (1) electricity mix; (2) smart meter installation; (3) number of blackouts (yearly); (4) duration of each blackout; and (5) Social contribution of the electric power company. Their study found that the consumers are willing to pay 2.2% higher electricity bills (for a significant increase in the share of renewable energy, which, according to their study, is far less than the actual cost of achieving this renewable target. While to reduce a minute of unplanned power cuts, the consumers are willing to pay KRW 64/year (USD 0.06/year). Although there is an apparent demand for electricity mix, as opposed to the results of Sagebiel and Rommel (2014), customers WTP for a significant increase in the share of renewable energy is far less than the actual cost of achieving it.

This study also investigates the value that consumers place on electricity service attributes. It defines electricity service using four attributes: (1) frequency of outage per year; (2) hydropower for electricity generation; (3) rural electrification; and (4) monthly electricity bill. The rural electrification ratio is the attribute that is of relevance to the current condition in Indonesia and can also be regarded as the social attribute, a type of attribute that has been neglected in previous studies, except for Huh et al. (2015).

4. Methodology

4.1. Discrete choice experiment

DCE is a preference elicitation method introduced by Louviere and Hensher (1982) and commonly used in the valuation of the public good. In a DCE survey, respondents are generally asked to choose between two or more alternatives described by attributes. At least one attribute of the alternative is systematically varied across respondents so that preference parameters of an indirect utility function can be inferred (Carson and Louviere, 2011). This characteristic makes DCEs is commonly used in understanding the trade-offs and willingness to pay for different product attributes.

According to Johnston et al. (2017), the success of conducting a DCE study requires proper survey development and implementation. The survey development includes: (a) designing a survey instrument that clearly explains the baseline (or status quo) conditions and poses a consequential valuation question; (b) selecting samples from the potentially affected population; and (c) choosing a survey mode with desired properties. Specifically for the survey instrument design, it is a cyclical process that involves four steps (Hoyos, 2010): (1) definition of attributes and its levels; (2) experimental design; (3) questionnaire development; and (4) sampling strategy.

In the survey, respondents had to hypothetically choose between four unlabeled electricity service alternatives (Fig. 2). As mentioned earlier, the alternatives vary according to the level of these four attributes: rural electrification, duration of outage, electricity mix, and monthly electricity bill. For the electricity mix attribute, the study only included the combination of coal and hydro generations since coal is currently the primary source of electricity, and this condition is unlikely to change in the foreseeable future. While for hydro, it is the most utilized source of renewable energy at present, and potential hydropower sites are spread out across the country (Ministry of Energy and Mineral Resources, 2015). The use of electricity bill as one of the attributes is necessary for finding the marginal price of other attributes (Amador et al., 2013) as well as a payment vehicle.

Another important note regarding the attributes used in the present study is on the price attribute. In standard DCE studies, there is usually one price attribute of which its level is systematically varied across respondents. However, in our study, it is

Table 2
Attributes and Levels.

Attributes	Unit	Level 1	Level 2	Level 3
Rural electrification	%	68	84	100
Outage	hours/year	2	3	5
Hydro-power	hydro:coal	1:5	2:4	4:2
Electricity bill for 450 VA	IDR/month	IDR 61,00	IDR 81,000	IDR 108,000
900 VA	IDR/month	IDR 95,00	IDR 162,000	IDR 237,000
1300 VA	IDR/month	IDR 704,00	IDR 962,000	IDR 1,490,000
2200 VA	IDR/month	IDR 1,100,000	IDR 1,600,000	IDR 2,000,000

not the case since the electricity price (per kWh) in Indonesia depends on in-house installed power. There are four pricing categories for residential consumers, depending on their size of installed capacity, i.e., 450 VA (volt–ampere), 900 VA, 1300 VA, and 2200 VA. The prices of the first two categories are heavily subsidized. Consequently, the present study has four different price attributes for each type of consumer. The following Table 2 presents the attributes and its levels used in the study.

All four 3-level attributes can produce 81 ($=3^4$) possible alternatives (known as the full factorial experimental design). Requiring respondents to choose among so many alternatives would be cumbersome and cognitively demanding. Therefore, the study uses a D-optimal main-effects fractional factorial design (Louviere et al., 2000) to obtain 36 choice sets. In each choice set, the fourth alternative is always the status-quo option; hence it remains constant across all choice sets. These choice sets are subsequently split into six blocks of 6 choice sets. Respondents are randomly allocated to one of the six blocks. The design and block definition steps are performed using R software and following the guide found in Aizaki et al. (2014).

4.2. Data collection

The data were collected using a face-to-face structured interview from October until November 2016. A survey research company recruited the respondents and conducted the survey. The target population of the study consisted of citizens who are in charge of energy-related and financial decisions in their respective households. A total of 1600 respondents were contacted. However, there were 98 frivolous respondents excluded. The final sample consisted of 1502 respondents divided into four categories based on the in-house installed power capacity. The survey instrument and choice experiment was the same across categories, except for the price attribute.

4.3. Estimation strategy

To model the choice-probability of different alternatives, an assumption regarding the probability distribution of the error terms is necessary. Traditionally, the choice is modeled using conditional logit (CL) formulation, in which the error terms are assumed to be independently and identically distributed according to Gumbel distribution. In other words, the choice is independent of irrelevant alternatives (IIA). As a result, the CL is not capable of capturing unobserved heterogeneity. Instead, this study uses models that have more flexible formulation, the mixed logit, and the latent class logit models. These two models are deemed to be more realistic than CL since both models introduce the heterogeneity in respondents' preferences on attributes. Although both models introduce heterogeneity, as shown later, they have a different approach to introduce such heterogeneity.

The analysis of the choices made in DCEs is based on random utility theory, developed by Mcfadden (1974). Specifically, it assumes that the utility of individual i who chooses repeatedly in t situations between several alternatives n is written as a linear function of electricity service attributes (observable components) and a random error (unobservable component). That is:

$$U_{in} = \alpha_1 + \beta_0 PRICE_{in} + \sum_{k=1}^{K} \beta_{ik} A_{ink} + \epsilon_{in} \tag{1}$$

where A_{ink} is the level of attribute k for alternative n and β_{ik} the corresponding utility coefficient.

Using standard logit method, the probability that individual i will select alternative m in T sequence of choices is:

$$Pr_{im} = \prod_{t=1}^{T} \frac{exp(\alpha_1 + \beta_0 PRICE_{in} + \sum_{k=1}^{K} \beta_{ik} A_{ink})}{\sum_{k=1}^{K} exp(\alpha_1 + \beta_0 PRICE_{in} + \sum_{n=1}^{N} \beta_{ik} A_{ink})} \tag{2}$$

The traditional conditional logit model analyzes customers' preferences based on the assumption of a homogeneous preference structure, or in other words, the parameters are fixed and take the same value for all respondents.

The mixed logit (MXL) method introduces heterogeneity in the parameters by assuming that the coefficient vector of attributes, β_{ik}, follows a particular probability distribution. By doing this, the MXL method can reflect the heterogeneity of consumers' preferences (Train, 2009). Therefore the probability that individual i will select alternative m in T sequence of choices can be expressed as follows:

$$Pr_{im} = \int \cdots \int \left(\prod_{t=1}^{T} \frac{exp(\alpha_1 + \beta_0 PRICE_{in} + \sum_{k=1}^{K} \beta_{ik} A_{ink})}{\sum_{k=1}^{K} exp(\alpha_1 + \beta_0 PRICE_{in} + \sum_{n=1}^{N} \beta_{ik} A_{ink})} \right) dF(\theta_{i0}) \cdots dF(\theta_{iK}) \tag{3}$$

where $F(\cdot)$ is the cumulative standard normal distribution, and θ_{ik} is normally distributed terms designed to account for any unobserved heterogeneity in the marginal utility. However, different distributions can be assumed according to attributes' effects on consumers' preferences (Train and Sonnier, 2005).[2]

While MXL method introduces the heterogeneity by assuming that coefficient vector of attributes follows a certain probability distribution, the latent class logit (LCL) method assumes that coefficient vector of attributes takes a finite number of value S ($\beta_{k|0}, \beta_{k|1}, \ldots, \beta_{k|S}$) with corresponding probabilities ($h_1, h_2, \ldots, h_S$). Hence, the probability that individual i will select alternative m in T sequence of choices can be expressed as follows:

$$Pr_{im|s} = \sum_{s=1}^{S} h_s \left(\prod_{t=1}^{T} \frac{exp(\alpha_1 + \beta_0 PRICE_{in} + \sum_{k=1}^{K} \beta_{ik} A_{ink})}{\sum_{k=1}^{K} exp(\alpha_1 + \beta_0 PRICE_{in} + \sum_{n=1}^{N} \beta_{ik} A_{ink})} \right) \tag{4}$$

h_s are unknown but can be estimated with a multinomial logit method (Sagebiel and Rommel, 2014). The goodness-of-fit statistics like the Akaike information criterion (AIC) or the Bayesian

2 The MXL model can only be solved using maximum simulated likelihood estimation (MSLE) method due to its computational complexity (Train, 2009).

Table 3
Goodness-of-fit Statistics.

Classes	LLF	AIC	BIC
2	−7950.425	15946.85	16069.08
3	−7131.978	14333.96	14519.97
4	−7003.708	14101.42	14351.2
5	−6799.914	13717.83	14031.39
6	−6686.486	13514.97	13892.31
7	−6672.709	13511.42	13952.53

information criterion (BIC) are used to identify the most appropriate number of classes statistically. However, one should also make sure that the parameters of the classes are valid in a behavioral sense (Scarpa and Thiene, 2005). As presented in Table 3, the AIC and BIC support the model with six classes. However, we choose to pursue the LCL analysis with three classes, as a model based on six classes presented a high number of insignificant variables and was making certain classes hardly interpretable.

Both methods use the following equation to calculate the willingness to pay:

$$WTP = -\frac{\beta_{ik}}{\beta_{i0}} \tag{5}$$

The study uses Stata's mixlogit command, developed by Hole (2007), to estimate the MXL model. In order to increase the computational speed and efficiency of the estimation, it uses 2500 Halton draws for realizations of each of θ_k (Hole, 2007). While for the LCL model, it uses Stata's lclogit command, developed by Pacifico and Yoo (2012). To derive the WTP value for each attribute, either from mixed logit or latent class logit, it uses Stata's WTP command, developed by Hole (2007).

5. Results

5.1. Descriptive statistics

Before any analysis of the consumers' preferences for improved electricity service, it is necessary to examine their socioeconomic characteristics. As mentioned before, the final sample consists of 1502 respondents. As each respondent had to make six choices sequence – and in each choice set, there are three new alternatives and one status-quo alternative – the survey produced 36,048 observations in total. Table 4 presents selected socioeconomic characteristics of our sample.

Overall, there are positive correlations between income, education, employment status, and house ownership with the size of in-house installed power categories. In contrast, gender, marital status, age, and household size are statistically indistinguishable across groups. Since the survey was conducted during the daytime, when most of the male households members were outside the house, female respondents, as expected, are overrepresented across all groups, except for group 2200 VA.[3]

Most respondents range in income from IDR 7,000-IDR 9,999 (37%) and IDR 1,000-IDR 3,999 (19.9%); 85.4% were married. The final sample was predominantly employed respondents (55.5%) who were the owner of the establishment during the survey (63.8%). The educational background of respondents was as follows: primary education (19.1%), Secondary (63%), and college and university (17.9%). Consistent with expectations, most respondents were working-age adult (Mean: 40.3 years old; SD: 11.7 years old) and belong to a 4-member household, a typical urban household (Mean 4.2; SD: 1.6).

3 In Indonesia, it against the social norm to conduct a survey interview in the night time.

5.2. Estimation results

This subsection presents the results from MXL model and then followed with the results from LCL model. To analyze consumers' preferences for improved electricity services, the econometric specification for the utility function of consumer i choosing alternative n is represented as follows:

$$\begin{aligned} V_{in} = {} & asc_n + \beta_1 \text{doutage2}_{in} + \beta_2 \text{doutage3}_{in} + \beta_3 \text{dmix2}_{in} \\ & + \beta_4 \text{dmix3}_{in} + \beta_5 \text{drural2}_{in} \\ & + \beta_6 \text{drural3}_{in} + \gamma_1 \text{price450}_{in} + \gamma_2 \text{price900}_{in} + \gamma_3 \text{price1300}_{in} \\ & + \gamma_4 \text{price2200}_{in} \end{aligned} \tag{6}$$

where *asc* is a variable to capture consumers' preferences towards proposed conditions; *doutage*2 and *doutage*3 are dummy variables representing the 3- and 2-hours yearly outage duration, respectively; *dmix*2 and *dmix*3 are dummy variables representing the 2/6- and 4/6-hydro power contribution in the electricity generation; *drural*2 and *drural*3 are dummy variables representing the 84%- and 100% rural electrification ratio. Finally, *price*450, *price*900, *price*1300, and *price*2200 are monthly electricity bill for each in-house installed power category. These price variables are included in order to capture the different in the nominal value of price attribute for each in-house installed power category. Furthermore, the constructed econometric specification above are allowing us to evaluate the marginal utilities associated with changes in the levels of the attributes, and as a result, changes in the probability of selecting an alternative.

The overall findings suggest that the electricity consumers are willing to pay a higher electricity price to have better quality in all three attributes studied here. However, if the GoI can only improve one, out of three, attribute, then reducing the disparity of electricity access, particularly between urban and rural areas, is the first attribute that should be pursued.

5.2.1. Mixed logit model

The MXL was estimated with all attributes parameters being random and normally distributed. There are three underlying motivations why it assumes a normal distribution for all attributes parameters, even though it might be misleading since normal distribution allows for positive and negative values. First, the normal distribution assumption has been widely used and comprises some convenience features (Sagebiel, 2017). Second, Sillano and de Dios Ortúzar (2005) and Meijer and Rouwendal (2006) argue that the normal distribution can still be a good approximation in a case that there are high parameter values; hence the probability of having a counterintuitive value is very low. Third, using different distributions that force the parameter to have a positive sign only lead to further difficulties with estimation and interpretation (Sillano and de Dios Ortúzar, 2005).

The MXL results are reported in Table 5. The coefficients represent the utility corresponding to each level of attributes used in the choice experiment. The standard deviations reflect the heterogeneity of preferences. Statistically significant standard deviations show that respondents value certain aspects to varying degrees. Table 5 shows that the ASC term is positive and significant, which suggests that respondents are positively willing to pay for the proposed condition, away from status-quo. All four estimated price parameters are highly significant and negative at the 1% level since consumers prefer lower monthly electricity bills over the higher ones regardless of their in-house installed power. However, the price coefficients tend to diminish with the in-house installed power, indicating that the respondents who belong to the low installed power capacity are more responsive to the price change. They are more likely to stay with the status-quo option at a higher price. Furthermore, we also find that the

Table 4
Sample characteristics.

Variable	Total sample ($N = 1502$)	450 VA ($N = 375$)	900 VA ($N = 379$)	1300 VA ($N = 377$)	2200 VA ($N = 371$)
	Frequency (%)				
Income (in IDR 000)					
≤1000	2.4	5.9	3.2	0.5	–
1000–3999	19.9	30.1	21.1	18.8	9.4
4000–6999	13	12.8	12.7	11.4	15.1
7000–9999	37	41.6	47.8	36.9	21.3
10,000–12,999	12.7	6.4	10.8	14.6	18.9
13,000–15,999	8.7	1.9	3.4	9.8	19.7
16,000–18,999	2.3	0.8	0.5	3.2	4.9
19,000–22,999	2.7	0.3	0.5	2.9	7.3
≥23,000	1.4	0.3	–	1.9	3.5
Gender					
Female	60	67.2	64.6	62.3	45.6
Male	40	32.8	35.4	37.7	54.5
Marital status					
Not married	14.6	16.8	11.4	13.3	17
Married	85.4	83.2	88.7	86.7	83
Education					
Primary (≤grade 9)	19.1	29.3	23.2	17.2	6.5
Secondary (grade 10 - grade 12)	63	64.3	68.1	65.3	54.2
Tertiary (≥grade 12)	17.9	6.4	8.7	17.5	39.4
Employment status					
Employed	55.5	49.3	52	53.9	66.9
Unemployed	44.5	50.7	48	46.2	33.2
House ownership					
Owned	63.8	32.3	70.2	76.4	76.3
Others	36.2	67.7	29.8	23.6	22.7
	Mean (SD)				
Age	40.3 (11.7)	37.6 (12.3)	40 (10.5)	41.9 (12.2)	41.6 (11.2)
HH size	4.2 (1.6)	3.6 (1.6)	4.2 (1.5)	4.4 (1.7)	4.4 (1.6)

price coefficient is less heterogeneous with the in-house installed power. This can be related to the higher standard deviation in income in the lower in-house installed power.

The coefficients of the outage duration are positive and significant (at the 1% level), indicating that consumers show a positive preference for the shorter duration of the outage (3 or 2 h) as compared to the current level of 5 h per year. The coefficients increase significantly with the lower outage duration (from 0.249 to 0.768), suggesting that consumers do not only value the outage duration, but they are also sensitive to the specific outage reduction. The study finds heterogeneous preferences regarding outage duration per year.

Parameter estimates of electricity mix are highly significant at the 1% level, indicating that consumers generally prefer higher content of hydropower (2:4 or 4:2) in the electricity generation as compared to the current level of hydropower (1:5). We find the parameter for the higher content of hydropower (4:2) has the highest standard deviation across all parameters estimated. This suggests that some consumers value the higher hydropower in the electricity generation, while others do not.

Lastly, the study also finds that parameter estimates of rural electrification using MXL model are significant at 1%. Coefficients for both 84% and 100% rural electrification ratio are positive, which suggests that consumers prefer better rural electrification ratio over the current ratio. This result is in line with the recent studies on ethical consumerism that suggests that consumers increasingly care about social components of products as much as environmental components (Auger et al., 2007; Lerro et al., 2017; Miller et al., 2017). Furthermore, the MXL result also shows that the rural electrification attribute gives the highest utility, relative to the outage and energy-mix attributes. This result is unsurprising since it is common in Indonesia to have relatives that live in the rural area.

5.2.2. Latent class logit model

Next is the results of a five-preference-class LCL model. The model shows meaningful results that are in line with MXL findings. The pseudo R^2 comes to 0.326, and the overall model is highly significant, and the probabilities of being a member in each class are relatively similar. Class 3 and Class 1 are the largest and the second largest, with a share of 24.1% and 20.2%, respectively. Next is Class 2 with a share of 19.2% and the last two are Classes 4 and 5 with both classes have 18.2% share. Across all five classes, we observe that the ASC is insignificant only in Class 4, suggesting that these respondents are indifferent about the attributes for the improved electricity service. Furthermore, across non-monetary attributes, rural electrification is the most important attribute in influencing the choice decision, followed by energy-mix attribute and then the outage duration attribute. This result is identical with the result from MXL specification.

A closer look into the four preference classes indicates the structure of heterogeneity. Across all five classes, all price parameters are negative and significant at the 1% level, which is identical with the MXL specification but with different degrees of sensitivity across classes and in-house installed power. For 450 VA, 900 VA, 1300 VA, and 2200 VA group, respondents who belong to the Class 1, Class 3, Class 4, and Class 5 are significantly more sensitive relative to other respondents in other classes, respectively. Having a relatively high price parameter implies that these respondents are less likely to want a deviation from the status quo if it is related to the increase in the price and hence displays low WTP values for the attributes.

Both coefficients of outage attributes are negative and statistically significant in most of the classes, except for Class 2 and 5. For members of Class 2, they do not regard the reduction of the unplanned outage duration as an essential attribute for the electricity service improvement whatsoever. While for members of Class 5, the unplanned outage duration is an essential attribute for the electricity service improvement if the outage duration

Table 5
Estimation results.

	Mixed logit		5-class latent class logit				
	Mean	SD	Class 1	Class 2	Class 3	Class 4	Class 5
asc	1.397***		6.41***	−6.52***	4.752***	0.041	1.094***
	(0.114)		(0.96)	(1.204)	(0.295)	(0.316)	(0.264)
price450	−0.153***	0.127***	−0.707***	−0.072***	−0.105***	−0.012**	−0.123***
	(0.009)	(0.009)	(0.094)	(0.024)	(0.006)	(0.005)	(0.008)
price900	−0.053***	0.037***	−0.06***	−0.075***	−0.102***	−0.033***	−0.007***
	(0.003)	(0.002)	(0.006)	(0.027)	(0.006)	(0.004)	(0.002)
price1300	−0.03***	0.026***	−0.003***	−0.016***	−0.017***	−0.044***	−0.018***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.005)	(0.001)
price2200	−0.013***	0.013***	−0.002***	−0.003***	−0.009***	−0.008***	−0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
doutage2	0.249***	0.727***	0.287**	−0.798	0.426***	0.384***	0.14
	(0.071)	(0.133)	(0.127)	(0.533)	(0.105)	(0.141)	(0.128)
doutage3	0.768***	1.295***	1.03***	−0.803	0.738***	1.035***	0.459***
	(0.082)	(0.111)	(0.136)	(0.658)	(0.115)	(0.16)	(0.132)
dmix2	0.858***	1.431***	0.743***	1.221**	1.111***	0.711***	1.177***
	(0.087)	(0.123)	(0.148)	(0.608)	(0.144)	(0.151)	(0.154)
dmix3	1.942***	2.345***	2.08***	0.268	1.774***	1.73***	1.794***
	(0.111)	(0.138)	(0.171)	(0.704)	(0.157)	(0.168)	(0.16)
delect2	1.004***	1.561***	1.617***	2.179**	0.599***	1.203***	0.66***
	(0.093)	(0.124)	(0.176)	(1.102)	(0.14)	(0.184)	(0.153)
delect3	2.687***	2.262***	2.905***	2.804**	2.044***	2.421***	2.003***
	(0.116)	(0.132)	(0.198)	(1.11)	(0.177)	(0.222)	(0.153)
Class shares			0.202	0.192	0.241	0.182	0.182
Log likelihood	−7716.7				−6799.9		
McFadden R^2	0.186				0.326		

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

is reduced to 2 h per year. The estimated coefficients for the share of hydropower in the electricity generation are significant and positive across all classes when the hydro-coal ratio is 2:4. However, when the ratio is 4:2, members of Class 2 are indifferent about the share of hydropower share in the electricity generation. Finally, for the rural electrification attribute, its coefficients are the only coefficients that are positive and significant across all classes. When the level of rural electrification is 84%, members of Class 2 have the highest estimated coefficient, while when the rural electrification at 100% level, it is the members of Class 1 who have the highest estimated coefficient.

5.3. Willingness to pay calculation

Estimated models are also used to compute consumers' WTP for attributes of improved electricity services. The WTP is the marginal rate of substitution between an attribute and the cost attribute, or in other words, the WTP is the compensation value in monetary terms for a one-unit deterioration of an attribute to remain at the same level of utility. Table 6 shows those WTP estimates and their corresponding 95% confidence intervals calculated using Krinsky and Robb (1986) bootstrapping procedure with 5,000 replications. Estimates based on MXL Model and all five classes from LCL Model indicate that households are willing to pay a significant increment for each attribute of improved electricity services. Table 6 presents the WTP results.

In the MXL model, respondents WTP for each attribute is increasing with the attribute level and in-house installed power. The WTP for rural electrification attribute is the highest compared to the other two attributes, which corresponds with the estimation results presented in Table 5. For 2 h outage per year, the WTP ranging from IDR5,000 (IDR3,900-IDR6,200) for respondents belongs to 450 VA group to IDR61,500 (IDR47,800-IDR76,100) for respondents belong to 2200 VA group. While for the 4:2 hydro-coal ratio, the WTP of respondents belong to 450 VA is about IDR12,700 (IDR11,100-IDR14,800) and increased to IDR155,400 (IDR133,900-IDR182,600) from respondents belong to 2200 VA group. Respondents would be willing to pay IDR17,600 (IDR15,700-IDR20,100) to increase the rural electrification ratio at 100% level for 450 VA group, and it increases to IDR215,000 (IDR189,500-IDR249,200) for respondents who belong to 2200 VA group.

The LCL model presents WTP results that diverge substantially across classes. Class 1 and 3 produce WTP results that have a similar pattern with MXL specification such that the WTP for each attribute is increasing with the attribute level and in-house installed power group. Class 2 respondents show no support for the reduction of outage duration and the hydro-coal ratio at the level of 4:2. Class 4 shows that respondents from 450 VA and 2200 VA have very high WTP for each attribute of electricity service improvement. On the contrary, Class 5 shows that respondents from 900 VA and 1300 VA have very high WTP for each attribute, except for the outage duration at the level of 3 h per year. Although it is not presented here, however, we can obtain WTP estimates that correct for all different groups of preferences by weighting the WTP figures obtained for each class according to their corresponding class share probability.

6. Conclusions

This paper reports a discrete choice experiment (DCE) study to value the improvement of electricity service in Indonesia, with the City of Bandung as the study site. Our study surveyed 1502 households using a stratified random sample. There are three non-monetary and one monetary service attributes considered in the study: unplanned power outage, hydro power in electricity generation, rural electrification ratio, and monthly electricity bill. Each attribute has three different levels. Currently, this is the first DCE study on electricity sector in Indonesia. Reasonable WTP estimates suggest that respondents are capable in understanding the choice scenarios well and responding to them reasonably.

The consumers' WTP estimates are based on two different econometric methods that can capture the heterogeneity in consumers' preferences on attributes. The econometric estimations and WTP results indicate that the respondents understand that

Table 6
Mean WTP (in IDR 000).

Attributes	Mixed logit	Latent class logit				
		Class-1	Class-2	Class-3	Class-4	Class-5
450 VA						
Outage: 3 h per year	1.6 [0.7–2.6]	0.4 [0.1–0.8]	–	4.1 [2.1–6]	32.4 [6.4–140.2]	–
Outage: 2 h per year	5 [3.9–6.2]	1.5 [1–2]	–	7 [4.9–9.2]	87.4 [45.6–319.9]	3.7 [1.6–5.9]
Hydro-coal mix: 2:4	5.6 [4.5–6.8]	1.1 [0.6–1.6]	16.9 [0.8–56.4]	10.6 [8.2–13.1]	60.1 [27.2–246]	9.5 [7.1–12]
Hydro-coal mix: 4:2	12.7 [11.1–14.8]	2.9 [2.3–3.9]	–	16.9 [14.3–20]	146.2 [79.6–572.5]	14.5 [12.1–17.5]
Rural electrification: 84%	6.6 [5.4–8]	2.3 [1.8–3.1]	30.2 [2–95.3]	5.7 [3.1–8.5]	101.7 [53.5–389.3]	5.4 [3–8.1]
Rural electrification: 100%	17.6 [15.7–20.1]	4.1 [3.3–5.4]	38.9 [10.6–121.9]	19.5 [16.2–23.2]	204.6 [116–797.8]	16.2 [13.6–19.4]
900 VA						
Outage: 3 h per year	4.7 [2.1–7.4]	4.8 [0.6–9.3]	–	4.2 [2.2–6.2]	11.6 [3.1–20.8]	–
Outage: 2 h per year	14.5 [11.3–17.7]	17.2 [12.6–22.3]	–	7.2 [5.1–9.5]	31.2 [21.8–41.4]	63.2 [26.9–116.9]
Hydro-coal mix: 2:4	16.2 [13.1–19.5]	12.4 [7.6–17.5]	16.2 [0.8–63]	10.9 [8.3–13.6]	21.4 [12.7–32.1]	162.2 [104.5–293.8]
Hydro-coal mix: 4:2	36.7 [32.2–42.1]	34.7 [28.8–42.8]	–	17.4 [14.6–20.7]	52.1 [40.6–68.9]	247.2 [168.1–435]
Rural electrification: 84%	19 [15.5–22.9]	27 [21.5–34.1]	28.9 [2.2–102.8]	5.9 [3.2–8.6]	36.3 [26.9–48.2]	91 [47.7–173.2]
Rural electrification: 100%	50.7 [45.7–57.1]	48.4 [41.1–59.4]	37.3 [9.8–130.7]	20 [16.7–23.5]	72 [61.7–90]	276 [193.1–497]
1300 VA						
Outage: 3 h per year	8.4 [3.7–13.1]	103 [12.16–333.29]	–	25.7 [13.4–38.8]	8.7 [2.4–16]	–
Outage: 2 h per year	25.8 [20.1–31.8]	370 [207.43–1,067]	–	44.5 [30.4–59.3]	23.4 [15.4–33.5]	25.9 [11.1–41.2]
Hydro-coal mix: 2:4	28.8 [22.9–35.1]	266.6 [129.9–839.4]	78.2 [3.3–158.3]	67 [50.8–85.3]	16.1 [9.1–24.8]	66.5 [49.7–84.5]
Hydro-coal mix: 4:2	65.1 [56.6–75.6]	746.9 [430.9–2.,268.6]	–	106.9 [88.1–131.3]	39.2 [29.4–54]	101.3 [83.3–123.6]
Rural electrification: 84%	33.7 [27.5–41]	580.7 [332.5–1.,879.8]	139.6 [15.2–317.2]	36.1 [19.5–53.7]	27.3 [18.6 −39.9]	37.3 [21.2–56.4]
Rural electrification: 100%	90 [80–103]	1.,043.1 [635.8–3,177.2]	179.7 [46.5- 365.6]	123.1 [100.9–152.1]	54.9 [41.7–76.1]	113.1 [94.4–137.5]
2200 VA						
Outage: 3 h per year	19.9 [8.7–31.4]	175.4 [20.2–543.1]	–	47.6 [25.3–70.8]	50.7[14.7–88.3]	–
Outage: 2 h per year	61.5 [47.8–76.1]	630.3 [357.6–1.695]	–	82.4 [57.6–108.6]	136.7[96.6–179.3]	20.3 [8.8–32.5]
Hydro-coal mix: 2:4	68.7 [54–85.2]	454.2 [232.1–1,264.6]	349 [162.9–887.5]	124.1 [95.6–155]	93.9 [56.5–134.8]	52 [38.1–68.6]
Hydro-coal mix: 4:2	155.4 [133.9–182.6]	1.272.4 [753.5–3,508.5]	–	198 [167.6–234.8]	228.6 [184.9–284.2]	79.3 [63.1–100.9]
Rural electrification: 84%	80.3 [65.5–98.7]	989.2 [564.3–2,973]	623.1 [47.5–1,663]	66.9 [36.1–100]	159 [114.1–213.3]	29.2 [16.6–44.5]
Rural electrification: 100%	215 [189.5–249.2]	1,777.1 [1,087.4–5,133.3]	801.9 [216.7–1,912.1]	228.2 [187–278.6]	319.8 [261.3–392.8]	88.5 [72.2–112.1]

low quality of electricity service can be expected to cause disutility, even though the disutility level varies from one consumer to another depending on the characteristics of the consumer him/herself.

Information on consumers' preferences for improved electricity service attributes can serve many purposes. At an aggregate level, consumer-level information can be used by policymakers and other stakeholders in the power sector to evaluate the investment feasibility for service improvement. Capturing heterogeneity at the consumer level is also important as it makes it possible to offer a menu of improvement structures based on consumer willingness to pay. Our analysis seems promising for policymakers because the share of consumers who are willing to pay for electricity improvement is rather high. The majority of our respondents consider all non-monetary attributes are important. For example, using MXL method, they are willing to pay to reduce the outage duration to be 2 hours/year, the WTP is ranging from IDR5,000 (USD1.18) to IDR61,500 (USD14.49) per month, depending on the size of the installed capacity. While for the increase of rural electrification ratio to 100%, it ranges from IDR17,600 (USD4.15) to IDR215,000 (USD50.64) per month. This means that increased monthly electricity bills can potentially finance improvements in electricity service. A detailed cost–benefit analysis would go beyond the scope of this paper. Yet, the hypothesis that the marginal benefits were larger than the marginal costs of such improvements seems realistic. As expected, our analysis also reveal that a low economic status group has rather low WTP for such improvements, and most of them can be identified by the size of their in-house installed power. Hence, our results can be a scoping basis for financing improvements through residential consumers, without significantly reduce social welfare.

To conclude, this study provides an evidence that even among urban consumers, there is heterogeneity in preferences for electricity service attributes. Taking the engineer-dominated supply side approach while neglecting the nature of consumers' needs in designing national electricity policy might result in failed project and frustration at both electricity consumers and providers ends. Further research is required to better understand consumer preferences including industrial and commercial users, and to compare the costs and the benefits of improved electricity service.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Martin Siyaranamual: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Mia Amalia:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing - original draft, Writing - review & editing. **Arief Yusuf:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Visualization, Writing - original draft, Writing - review & editing. **Armida Alisjahbana:** Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Writing - original draft.

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