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Power Outages, Increasing Block Tariffs and Billing Knowledge

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To my Parents and Brothers

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I am solely responsible for any shortcoming and error found in this PhD thesis.

Tensay Hadush Meles
Gothenburg, August 2017

Contents

Introduction

In developing countries, access to electricity is limited in terms of both connections to a grid and, for those who are connected, benefiting from a regular supply without outages. According to the International Energy Agency (2016), more than 95% of the estimated 1.2 billion people who live without electricity are in countries in Sub-Saharan Africa (SSA) and developing Asia, and predominantly in rural areas. Two-thirds of the population in SSA lack access to electricity and the 35% electrification rate in SSA countries is the lowest in the world (International Energy Agency, 2016). The lack of access to electricity has long been recognized as a fundamental challenge for development. Thus, providing access to electricity is a key objective of developing countries and is part of recent global action plans that define goals and targets for 2030 and beyond.[1] For example, the 7th Sustainable Development Goal sets an agenda for 2030 to ensure universal access to affordable, reliable and modern energy services and the Sustainable Energy for All (SE4All) initiative has been established to ensure fulfillment of this goal. Likewise, the Power Africa initiative in 2013 sets the goal to add 60 million new connections in Africa. Similar national goals are set, and of relevance for this thesis, the Government of Ethiopia in its first Growth and Transformation Plan (GTP I, 2010-2015) aimed to increase electricity coverage to 75% of the population, and in the GTP II the goal is to reach 90% of the population by 2020.

Access to electricity services is important to human welfare and economic development (Toman and Jemelkova, 2002). Recent empirical evidences document the benefits of access to electricity at household level. For example, electrification significantly increases female employment (Dinkelman, 2011). Children also benefit from electricity as it reduces the time needed to collect biofuels, making more time available for school and other activities (Khandker et al., 2012, 2013). Furthermore, electricity use reduces indoor air pollution from solid fuel use (Baron and Torero, 2017).

While access to electricity has received a great deal of attention, its reliability has been given less focus in terms of project funding and research, though it is equally important. In low-income developing countries like SSA, many of those with access to electricity experience frequent power outages (Andersen and Dalgaard, 2013). For instance, according to the World Bank Enterprise Surveys for the period 2010–2016, power outages in SSA

[1] Those without access to electricity rely on traditional biomass such as the use of firewood, charcoal, crop residue, and animal waste for energy, which leads to environmental issues and health problems associated with indoor pollution. In view of the negative effects of using traditional fuels for cooking, increasing attention has also been given to improved cook stoves (see, e.g., Jeuland and Pattanayak, 2012).

occurred 8.5 times in a typical month, each with average duration of 4.1 hours. The poor quality of the electricity supply can undermine the expected benefits of electricity services. For instance, evidence from a World Bank survey shows that power outages constitute the most critical bottleneck for Ethiopian manufacturing firms (World Bank Enterprise Surveys, 2015). The poor electricity supply can also slow down the energy transition from solid fuels to electricity. Moreover, the unreliable power supply generates both direct costs, e.g., for alternative sources of energy and indirect costs such as the inconvenience experienced during power outages. In **Chapter I** of this thesis, we use available tools and information to analyze preferences for improved electricity services from the perspective of households.

Ensuring universal access to affordable, reliable and modern energy is a tall order in its own right. To do this in countries that are also experiencing rapid economic growth at the same time as the population is still growing fast, such as in Ethiopia, is even a greater challenge. Increase in power generation capacity and extension of grids will therefore need to be accompanied by carefully designed tariff structures. Tariffs typically play the role of combining a number of objectives, such as recovering costs of supply, signaling to consumers not to waste electricity and often also distributional objectives.

In developing countries, increasing block tariff (IBT) is the most popular tariff structure for electricity pricing (Briceño-Garmendia and Shkaratan, 2011; Whittington et al., 2015). In an IBT structure, a different price per unit is charged for different blocks of consumption and the price rises with each successive consumption block. The conventional wisdom is that IBT is designed so that the lowest – the 'lifeline' – block, which covers the subsistence consumption, is subsidized to promote equity while the pricing of the higher consumption blocks encourages conservation and recovers costs of providing the service. However, the overall small response to the additional prices (Labaderia et al., 2017) and the presence of shared connections could challenge the policy objectives of the IBT structure. For instance, IBT might not provide the intended subsidy to the poor, as poor households either are not connected to the service or share a connection (see, e.g., Whittington et al., 2015).

The IBT structure hinges on the assumption that consumers respond to changes in marginal prices for each consumption block. In reality, however, consumers might make their consumption decisions with limited information, attention and cognitive abilities. It is therefore not clear whether consumers in fact respond as intended to marginal prices in a complicated tariff structures like IBT. In **Chapters II and III** of this thesis, we discuss consumers' responses to marginal prices in an IBT structure and the effect of educating consumers about how their monthly bill is computed in an IBT on electricity consumption behavior.

Regarding the different issues discussed above, Ethiopia is an ideal setting for a case study. In Ethiopia, more than 90% of the total energy consumed still comes from traditional sources such as fuel wood, charcoal, animal dung, and crop residues (Samuel, 2014). The country's huge renewable energy potential from hydropower, wind, geothermal, and solar provides an opportunity to expand its clean renewable energy base. In recent years, a significant achievement has been observed in terms of access to electricity and power generation capacity. Access to electricity services in the country had reached 54% of the population in 2014. Also, the power generation capacity mainly from hydropower has tripled in just a decade from about 850 MW to above 2,000 MW. The 4,260 MW capacity in 2016 is expected to reach 10,000 MW in the coming few years when the construction of the Grand Ethiopian Renaissance Dam is completed (Ethiopian Electric Power, 2016). Furthermore, the country has started exporting electricity to neighboring countries like Djibouti, Sudan, and Kenya while establishing grid links to South Sudan, Uganda, Rwanda, Tanzania and Yemen with the aim of becoming a renewable energy hub in east Africa (GTP I, 2010–2015).

The energy sector in Ethiopia has recently experienced a sharp increase in power demand due to the rising demand from existing connections and grid expansions to new areas of the country. Like many other utilities in developing countries, the state-owned single electric utility, the Ethiopian Electric Utility, uses an IBT structure for residential customers as a tool to subsidize low income consumers, promote electricity conservation, and recover costs. The current electricity tariffs have remained unchanged since 2006 despite inflation. In July 2008, for example, the country's inflation in food prices soared to 92% (Central Statistics Agency, 2008). The existing average consumer tariff of 0.49 birr/kWh (0.025 USD/kWh) is much lower than the average tariff of 2.93 birr/kWh (0.15 USD/kWh) that would be required to fully cover the costs of supply (Addis Ababa Distribution Master plan, 2015).

This dissertation comprises three self-contained but related empirical studies on residential electricity services in the case of Ethiopia. The three essays are based on data collected from a household survey in Addis Ababa (the capital of Ethiopia) and monthly billing records from the Ethiopian Electric Utility. The first chapter analyzes households' preferences for improved electricity services using data on households' defensive expenditures and willingness to pay. The second chapter investigates whether consumers respond to marginal prices in an IBT structure. The last chapter assesses a related issue – the effect of educating consumers about how their monthly bill is computed in an increasing block tariff structure on monthly electricity consumption behavior.

Chapter I, *Preferences for Improved Electricity Services in Developing Countries: Households' Defensive Behavior and Willingness to Pay*, uses data on households' defensive expenditures and willingness to pay (WTP) to analyze households' preferences for improved electricity supply. The aim of the study is to understand preferences for improved electricity supply from the households' perspective using the available tools and information. We provide an estimate of average monthly defensive expenditures at different monthly hours of power outages using the generalized propensity score method – a continuous treatment matching method. Furthermore, we elicit households' willingness to pay for improved electricity services using the contingent valuation method. To this end, we use field survey data from 1,152 sample households in Addis Ababa, Ethiopia.

Poor electricity supply imposes a direct cost on households for example in the form of extra expenditures on alternative sources for lighting, cooking, baking, and water heating during power outages. In our defensive behavior approach, we use survey data on the extra expenditures for alternative sources to reveal how much households are willing to pay for a higher quality of electricity supply. Results from the generalized propensity score (GPS) method show that the estimated average monthly defensive expenditures vary with monthly number of hours of power outages. At the average monthly hours of power outages, the estimated average monthly defensive expenditures total US$3.3 for the full sample. This is equivalent to 50% of the existing average monthly electricity bill of $6.6, implying a significant cost of outages to households in Ethiopia. The estimates from the defensive expenditure approach provide insights to look for ways to improve reliability. However, they are not net measures, as a fraction of the defensive expenditures would have been paid on electricity service had it been available. Also, the survey data could be affected by issues such as reporting and recollection problems.

In addition to the direct costs, power outages generate indirect costs such as inconvenience. Thus, in this study, we also elicit households' WTP for improved electricity services using the contingent valuation method. Results from the contingent valuation study show that households are willing to pay US $1.3–$1.6 monthly on top of their electricity bills (19%–25% of the existing average monthly bill) for improved electricity services. The estimated mean WTP is lower than the estimated average defensive expenditures at the average monthly hours of power outages, though the WTP elicited using the contingent valuation method is expected to be higher as it includes more values. In developing countries, the low degree of public trust in existing institutions (World Values Survey, 2005–2010) possibly contributes to a low WTP for public service improvements of e.g., the power supply. Decisions based on low WTP estimates could leave the electricity service provider in a vicious circle. Overall, it is important to focus not only on access to electricity but also on the reliability of the service in order to have a sustainable energy transition from traditional fuels to electricity and for people to be able to enjoy the benefits of having access to electricity.

In **Chapter II**, *Do Consumers Respond to Marginal Prices of Electricity under Increasing Block Tariffs*, we provide empirical evidence that residential consumers do not respond to marginal price in an IBT structure. By combining administrative monthly electricity bill records with a detailed survey of sample households, we investigate whether marginal prices in an IBT scheme affect residential electricity consumption. Our empirical approach is based on a non-parametric approach (bunching analysis) and a parametric approach (the Arellano-Bond estimator, which is also called the difference generalized method of moments). The availability of a large number of administrative monthly electricity billing records allows us to estimate bunching around the kink points and to compare the results with demand model estimates. In contrast to the standard economics prediction of piecewise linear budget sets, we find no bunching of consumers around the kink points in the distribution of monthly electricity consumption. Similarly, the estimated price elasticity of demand from the Arellano-Bond estimator is statistically insignificant, though it keeps its expected sign and magnitude. These results imply that the existing electricity price does not affect monthly electricity consumption.

A possible explanation for the lack of a significant effect of the marginal price on electricity consumption is the existing low prices. The real prices of the consumption blocks as of 2016 are about 20 times lower than what they were in 2006. Because the prices are low, consumers may not pay attention to their electricity use. Another explanation could be consumers' lack of tariff knowledge and difficulties in understanding how their monthly bills are computed in the block-based price scheme. The survey evidence supports the idea of consumers lacking knowledge about the existing tariff schedules. Our survey shows that a majority of the respondents (79.30 %) do not know that the existing price structure is increasing block price and only 13.85% of the households regularly check the details of their monthly electricity bills, while the rest (86.15%) check only the amount due. Lack of tariff knowledge, inattention, and cognitive limitations are not unique to Ethiopian households. For example, Ito (2014) finds consumer inattention to a complex pricing structure in residential electricity consumption in the U.S. Also, de Bartolome (1995) documents subjects' cognitive difficulties in understanding a non-linear price structure in a laboratory experiment. Moreover, the presence of shared electricity connections, billing irregularities, and power outages might also be distorting households' response to electricity prices.

Our study provides essential information on why the policy objectives of the IBT structure may not be achieved. With multiple households per shared connection exceeding the consumption allowed for a single household, these households pay at the higher rate for consumption in the higher block and therefore do not receive the subsidy intended for them. The distortion of the subsidy could be worse, as low-income households are more likely than richer ones to have a shared connection. In addition, the utility may not achieve its policies of electricity conservation and generation of enough revenue for operation, maintenance, and investment, since the existing electricity prices are low and do not affect electricity demand. Following the findings, we suggest that the Ethiopian Electric Utility consider revising the existing low electricity tariff while taking into account the cooking needs for energy transition from solid fuels to electricity.

Finally, we explore whether educating consumers about their monthly bill affects their consumption behavior. **Chapter III**, *Billing Knowledge and Consumption Behavior: Experimental Evidence from Nonlinear Electricity Tariffs,* examines whether educating consumers about how their monthly electricity bill is calculated in an IBT structure affects their electricity consumption. To evaluate the effect of the treatment, we conduct a field experiment with residential electricity consumers in Ethiopia, where electricity prices are heavily subsidized and shared connections are common.

The rationale for this study is that the increasing block tariff (IBT) structure for electricity pricing is popular in developing countries, yet consumers may not know the marginal price they face and might not fully understand how their bill is computed. Thus, could educating consumers about how their monthly bill is computed in the IBT scheme affect their monthly electricity consumption behavior?

Using monthly consumption data from the electric meters, we find no statistically significant effect after six months in response to the treatment. Our findings suggest that it is not the lack of billing information that makes residential electricity consumers insensitive to the IBT structure. Alternative reasons, such as the low electricity prices, are provided.

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Chapter I

Preferences for Improved Electricity Services in Developing Countries: Households' Defensive Behavior and Willingness to Pay

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Abstract

Access to electricity has received much attention but its reliability has been given less focus. Thus, uninterrupted power supply remains a critical challenge facing households in low-income developing countries. In this paper, we use data on household defensive expenditures and willingness to pay (WTP) to analyze households' preference for improved electricity supply. We provide an estimate of average monthly defensive expenditures at different monthly hours of power outages using the generalized propensity score method – a continuous treatment matching method. Furthermore, we elicit households' willingness to pay for improved electricity supply using the contingent valuation method. To this end, we use a field survey data from 1,152 sample households in Addis Ababa, Ethiopia. Our results show that the estimated average monthly defensive expenditure is substantial and vary by the monthly hours of power outages. Also, results from the stated preference study show that households are willing to pay 19%–25% of the existing average monthly bill for improved electricity supply.

JEL Classification: C21, D12, L94, N77, Q41, Q51

Key-words: Power outages, defensive behavior, willingness to pay, Ethiopia, generalized propensity score

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1. Introduction

In this paper, we use data on defensive expenditures and willingness to pay (WTP) to analyze households' preferences for improved electricity services in Ethiopia. Lack of access to electricity has long been recognized as a main challenge for development. As a result, it has become an increasingly important issue on both international and national agendas (see, e.g., the 7th Sustainable Development Goal, the Sustainable Energy for All (SE4All), the Power Africa initiative, and Ethiopia's Growth and Transformation Plans, 2010–2015, and 2015–2020). Having access to electricity services provides a number of benefits. For instance, it increases female labor supply (Dinkelman, 2011), decreases the time spent collecting biofuels (Khandker et al., 2013), increases school enrollment (Khandker et al., 2012), and reduces indoor air pollution (Baron and Torero, 2017).

While access to electricity has received a great deal of attention, its reliability has been given less focus in terms of project funding and research, though it is equally important. In low-income developing countries like Sub-Saharan Africa, many of those with access to electricity experience frequent power outages (Andersen and Dalgaard, 2013). For instance, according to the World Bank Enterprise Surveys for the period 2010–2016, power outages in SSA occurred 8.5 times in a typical month, each with an average duration of 4.1 hours.[1] In Ethiopia, as in other sub-Saharan African countries, power outages are common. For example, daily hours of electricity interruption data from the Ethiopian Electric Utility for the period July 2015–June 2016 shows that the average duration of a power outage at the distribution line level in Ethiopia's capital Addis Ababa is 1 hour and 9 minutes. The main reason behind the frequent power outages is low capacity and poor physical condition of the transmission and distribution lines.[2]

Given that electricity is a clean source of energy and cheap in Ethiopia, having access to it is expected to improve the welfare of households.[3] However, the poor quality of the electricity supply undermines the potential benefits of electricity services to individual households and to the country overall. For instance, Engeda et al. (2011) found a 3.1% loss in GDP as a result

[1] http://www.enterprisesurveys.org

[2] For the same period (July 2015–June 2016), the duration of a given power outage at the distribution lines (medium voltage lines, MV), which carry electricity from the sub-station to the transformers, has a standard deviation of 2 hours and 53 minutes and a maximum duration of 23 hours and 58 minutes. Technical problems at the transmission and distribution lines (earth fault and short circuit) account for 98% of the power outages. The rest is caused by overload (1.99%) and by request from customers (0.01%). This is the author's own computation using data from the Ethiopian Electric Utility.

[3] For instance, the average marginal price of the increasing block tariff for residential consumers is 0.50 birr/kWh. 1 U.S. dollar = 21 birr in May 2016.

of power outages. The unreliable power supply could also slow down the adoption of electricity and thus, the anticipated energy transition from solid fuels to electricity. Moreover, it imposes direct costs to households for example in the form of additional expenditures on alternative sources of energy such as candles and stand-by generators for lighting and kerosene, charcoal, firewood, and liquefied petroleum gas (LPG) for cooking, baking, and heating water during power outages. The poor supply also generates indirect costs such as fear of walking in unlit neighborhoods, loss of leisure time, and the inconvenience of using alternative energy sources and the resulting adverse environmental and health effects.[4]

Quantification of the consequences of power outages in monetary terms is important in order to make optimal policy decisions. For instance, it is useful when analyzing the tradeoff between the negative welfare effects of power outages and the costs of reducing power outages by maintaining the network grid lines and investing in new power plants. The information is also useful in policy decisions regarding whether to improve electricity services on the existing grid or add new connections. However, such quantification requires knowledge of the value that society places on a reliable power supply. This value goes beyond a direct market value, and it is difficult to obtain all the necessary information. Thus, in the present study, we use available tools and information to understand preferences for improved electricity services from the perspective of households.[5] We use data on households' defensive expenditures, i.e., the costs of actions taken to mitigate the consequences of power outages, and WTP from a household survey in Ethiopia.

The empirical approaches used to assess households' preferences for improved electricity services are based on the defensive behavior and contingent valuation methods. The defensive behavior method, also referred to as the averting behavior method, is a revealed preference approach that uses observed market transactions to infer the value of non-marketed goods (Grossman, 1972; Cropper, 1981; Harrington and Portney, 1987). In our case, it is the extra expenditures on alternative energy sources for lighting, cooking, baking and heating water during power outages. Our defensive behavior method is based on the idea that the extra expenditures on alternative energy sources during power outages provide information about

[4] The use of traditional fuels causes deforestation and environmental degradation (Allen and Barnes, 1985; Hofstad et al., 2009; Köhlin et al., 2011), as well as pre-mature deaths due to indoor air pollution (WHO, 2009). It also contributes to global warming (e.g., Sagar and Kartha, 2007; Grieshop et al., 2011).

[5] Recent studies have also examined the effect of power outages from the perspective of firms (see, e.g., Foster and Steinbuks, 2009; Andersen and Dalgaard, 2013; Allcott, 2016; Fisher-Vanden et al., 2015; Grainger and Zhang, 2017).

the value households place on service quality improvements. A primary challenge in this empirical analysis is that the defensive expenditures and number of hours of power outages are likely to be endogenous. For instance, multiple fuel use in developing countries (Masera et al., 2000) could affect both electricity-dependent services and the choice of averting action. Similarly, in survey data such as those used in the present study, respondents could have a tendency of over-reporting their households' defensive expenditures and number of hours of power outages to stress the severity of the unreliable electric power supply. To control for potential endogeneity, we apply the generalized propensity score (GPS) method – a continuous treatment matching method.

We estimate average causal effects of monthly number of hours of power outages on monthly defensive expenditures using generalized propensity score method under the assumption that the monthly number of hours of power outages to household is random conditional on set of covariates. In our sample data, the total monthly duration of outages varies greatly with an average of 55 hours, standard deviation of 50 hours, and interdecile range of 110 hours.

In the contingent valuation method (CVM), we elicit households' WTP for improved electricity services. In this approach, we develop a hypothetical scenario of electricity service improvement and elicit households' WTP using a double-bounded dichotomous choice format, where respondents were asked if they support a payment of a certain amount for improved service and then, depending on the response to the first question, a follow-up question was asked.[6] We apply an interval data model (Hanemann et al., 1991) to estimate households' WTP for improved electricity services.

Our analysis is based on field survey data collected from 1,152 sample households that use electricity from 715 randomly selected electric meters in Addis Ababa, Ethiopia. Due to the presence of shared electricity connections, other households that share a connection are also

[6] In the literature (see, e.g., Venkatachalam, 2004), there are four major types of elicitation techniques for contingent valuation studies: bidding game, payment card, and open-ended and dichotomous choice (close-ended). The dichotomous choice approach is further divided into single-bounded and double-bounded dichotomous choices. In the bidding game approach, a respondent is randomly assigned a particular bid from a range of pre-determined bids and is then asked a yes/no question for that particular bid, and the process continues until the highest positive response is recorded. In the payment card approach, the respondents are presented with a range of WTP values from which they choose their maximum WTP values. The open-ended elicitation technique involves asking about the maximum amount that an individual is willing to pay for the good under consideration. In a dichotomous choice question, the respondent is asked a yes/no question about a payment of a certain amount for the good under consideration. The latter technique was mentioned as the most adequate by the National Oceanic and Atmospheric Administration (Arrow et al., 1993). All mentioned elicitation techniques have their respective pros and cons.

included in the survey. In the analysis, we split the total sample (1,152 households) into households that have a private connection and are responsible for the monthly electricity bill (N=509), households that share a connection and are responsible for the monthly electricity bill (N=206), and households that share a connection but that are not responsible for the monthly electricity bill (N=437)[7].

Our findings show that the estimated average monthly defensive expenditures vary with the monthly number of hours of power outages. At the average monthly number of hours of power outages, the average monthly defensive expenditures for the various groups of sample households range from 60 to 77 birr (US \$2.9–\$3.7).[8] Also, results from the contingent valuation method show that households are willing to pay 27–34 birr/month (or \$1.3–\$1.6) on top of their regular monthly electricity bills (19–25% of the existing monthly electricity bill) for improved electricity services. When looking at the estimates of the two approaches within each subset of sample households, households that share a connection but are not responsible for the monthly electricity bill have the lowest estimated defensive expenditures and WTP. The estimated mean WTP is lower than the estimated average defensive expenditures at the average monthly number of hours of power outages though the WTP elicited from the contingent valuation method is expected to be larger as it includes more values.

Our study is related to the literature that uses stated preference and revealed preference techniques to estimate the economic value of non-marketed environmental goods and services (Adamowicz et al., 1994; Mitchell and Carson, 1989; Braden and Kolstad, 1991; Louviere et al., 2000; Haab and McConnell, 2002). The defensive behavior method has been applied to valuation of air quality (Bartik, 1988; Courant and Porter, 1981; Deschenes et al., 2017) and water services (Abdalla et al., 1992; Pattanayak et al., 2012). To our knowledge, no previous studies have used a defensive behavior method for electricity services. Therefore, we provide a first revealed preference estimates for improved electricity services. However, other studies have applied a stated preference approach (CVM and choice experiments) in valuations of electricity services (see, e.g., Beenstock et al., 1998; Carlsson and Martinsson, 2008; Abdullah and Mariel, 2010; Ozbafli and Jenkins, 2016). Thus, our study contributes to the existing literature by simultaneously using two different approaches – a revealed preference approach (defensive behavior) and a stated preference approach (contingent valuation, or "CV") – to estimate households' preferences for improved electricity service. The study also

[7] For this last category of households, the electricity payment is included in their house rent, or they share the bill or pay a flat rate.

[8] Birr is the Ethiopian currency. At the time of the survey (May 2016), 1 USD ≈ 21 birr.

contributes to the existing literature by analyzing households' preferences for a reliable power supply in the context of Ethiopia. The study highlights that it is important to focus not only on access to electricity but also on the reliability of the service in order to have a sustainable energy transition from traditional fuels to electricity and for people to be able to enjoy the benefits of having access to electricity.

The rest of the paper is organized as follow. Section 2 provides the theoretical framework and model estimations. Section 3 describes the survey design and data collection. Section 4 presents the descriptive statistics. Section 5 presents the results and, finally, Section 6 concludes the paper.

2. Theoretical Framework and Model Estimation

2.1 Defensive Expenditures (Averting Behavior) Approach

Household production theory is a relevant theoretical approach that explains households' averting behavior in relation to power outages (Becker, 1965; Deaton and Muellbauer, 1980; Courant and Porter, 1981; Bartik, 1988). A well behaved household utility function is represented by:

$$U = U(E, X; Z), \tag{1}$$

where E denotes consumption of home produced good, X represents consumption of a private market good, Z is a vector of exogenous variables that determine the household's preferences, and $\partial U/\partial E > 0$, $\partial U/\partial X > 0$. Good E is the output (in our case electricity-dependent services like lighting, cooking, and heating) of the household production function:

$$E = f(A, R). \tag{2}$$

In this case, A denotes the averting behavior that a household takes to offset the effect of poor electricity supply, R represents the reliability of the service provided by the electric utility, and $\partial f/\partial A > 0$, $\partial f/\partial R > 0$. The household budget constraint is given by:

$$P_A A + X = M, \tag{3}$$

where the price of the private good is normalized to unity, P_A denotes the price of averting action taken, and M is the household's income. The household maximizes the utility function:

$$\begin{aligned} &Max\ U = U(f(A, R), X; Z\ ) \\ &subject\ to: P_A A + X = M. \end{aligned} \tag{4}$$

Solving the optimization problem and rearranging the terms in the first-order necessary conditions provides the following expression:

$$\frac{\partial U/\partial E}{\partial U/\partial X} = \frac{\partial U/\partial E}{\lambda} = \frac{P_A}{\partial f/\partial A}, \tag{5}$$

where λ denotes the lagrange multiplier (marginal utility of income). Equation (5) indicates that the household allocates resources so that the marginal benefit of electricity-dependent services equals to the marginal cost of producing it. The first-order condition could be solved for the optimal values of the private market good X^* and averting action taken A^* as a function of the price of the defensive behavior, reliability of electricity service, household income, and other household characteristics as follows:

$$X^* = X(P_A, R, M; Z)$$
$$A^* = A(P_A, R, M; Z). \tag{6}$$

The household expenditure (D) on the levels of averting actions chosen by the utility-maximizing household at a given $P_A, R, M,$ and Z is provided as follow:

$$D = P_A \, A^*. \tag{7}$$

Equation (7) guides the empirical estimation. However, directly estimating the households' defensive expenditures could lead to biased estimates due to joint production and unknown prices of averting actions (Dickie, 2017).[9]

To address potential endogeneity and selection biases, we apply the generalized propensity score method proposed by Hirano and Imbens (2004) and estimate the average defensive expenditures at different numbers of hours of power outages. This estimation method is an extension of Rosenbaum and Rubin's (1983) binary treatment propensity score method in a continuous treatment setting.

Borrowing notation from Hirano and Imbens (2004), we index the households in our sample by $i = 1, \dots, N$ and denoted by $Y_i(t)$ the potential outcome of household i under treatment level $t \in \mathrm{T}$, where T is an interval $[t_0, t_1]$. In our application, t denotes number of hours of monthly power outages and $Y_i(t)$ represents households' monthly defensive expenditures. Our goal is to estimate the average dose-response function (DRF) denoted by $\mu(t) = E[Y_i(t)]$. For each unit i, we observe a vector of covariates X_i, the level of treatment T_i, and the potential outcome corresponding to the treatment level, $Y_i = Y_i(T_i)$. For notational simplicity, the subscript i is omitted in the remainder of this section.

The key identification assumption to estimate the DRF is weak unconfoundedness (Hirano and Imbens, 2004):

$$Y(t) \perp T | X \text{ for all } t \in \mathrm{T}. \tag{8}$$

[9] Joint production occurs when averting actions jointly produce additional benefits or costs beyond their mitigation of power outages.

The assumption in Equation (8) states that, conditional on observed covariates X, the level of treatment (T) is independent of the potential outcome $Y(t)$. This is an extension of the unconfoundedness assumption for binary treatment made by Rosenbaum and Rubin (1983), though in the case of a continuous treatment it only requires conditional independence for each value of the treatment rather than joint independence of all potential outcomes.[10]

Suppose $r(t,x) = f_{T|X}(t|X = x)$ is the conditional density of the treatment given the covariates. Then the generalized propensity score (GPS), which is the conditional density of a particular level of treatment $t = \mathrm{T}$, is:[11]

$$R = r(T,X). \tag{9}$$

The GPS has a balancing property as in the case of the standard propensity score. Within strata with the same value of $r(t,X)$, the probability of $t = \mathrm{T}$ does not depend on the value of X:

$$X \perp= \{\mathrm{T} = t\} |\, r(t,X). \tag{10}$$

In combination with unconfoundedness, Equation (10) implies that assignment to treatment is also weakly unconfounded given the Generalized Propensity Score (Hirano and Imbens, 2004). This allows the estimation of the average dose-response function using the GPS to remove selection bias.

Implementation of the GPS comprises three main steps. In the first step, the conditional distribution of the treatment variable given the covariates is estimated. We assume that the treatment (or its transformation) is normally distributed conditioning on the covariates:

$$f(T_i)|X_i \sim N\{g(\beta,X),\sigma^2\}. \tag{11}$$

After estimating Equation (11) using maximum likelihood, the estimated GPS is obtained as:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left[-\frac{1}{2\hat{\sigma}^2}\{f(T_i) - g(\hat{\beta},X)\}\right]. \tag{12}$$

The test for the balancing property is carried out by dividing the treatment values into intervals (groups) based on the sampling distribution of the treatment variable. Within each group, we evaluate the GPS at the median of the treatment variable. We then further divide each group into five blocks by the quintiles of the GPS using the GPS distribution of households in that particular group. Within each block, we compute the difference-in-means of covariates of households that have a GPS such that they belong to that block but have a different treatment level (i.e., households belong to the other groups). A weighted average

[10] The unconfoundedness assumption rules out any systematic selection into treatment levels based on unobservable characteristics.
[11] The function $r(.,.)$ defines both the GPS, $r(T,X)$ – a single random variable at level T of the treatment and X – and a family of random variables indexed by t, $r(t,X)$.

over the five blocks in each treatment group is then used to calculate the t-statistics of the differences-in-means between the particular treatment group and the other groups. The differences-in-means of each covariate at various treatment levels should not be statistically different from zero if adjustment for GPS properly balances the covariates.

In the second step of implementing the GPS, the conditional expectation of the outcome given the observed treatment level and the estimated GPS is modeled as a flexible function of its two arguments. Following Bia and Mattei's (2008) suggestion, our empirical approach uses the following cubic specification:

$$E[Y_i|T_i,\hat{R}_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 {T_i}^2 + \alpha_3 {T_i}^3 + \alpha_4 \hat{R}_i + \alpha_5 {\hat{R}_i}^2 + \alpha_6 {\hat{R}_i}^3 + \alpha_7 T_i . \hat{R}_i. \qquad (13)$$

Equation (13) is estimated by OLS. As Hirano and Imbens (2004) point out, the estimated regression coefficients $\hat{\alpha}$ do not have any direct meaning.

In the final step, the value of the dose-response function (average potential outcome) at treatment level t is estimated by averaging Equation (13) over the distribution of the GPS (holding constant the treatment level t):

$$\widehat{E[Y(t)]} = \frac{1}{N}\sum_{1=1}^{N}[\hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 t^3 + \hat{\alpha}_4 \hat{r}(t,X_i) +$$

$$\hat{\alpha}_5 \hat{r}(t,X_i)^2 + \hat{\alpha}_6 \hat{r}(t,X_i)^3 + \hat{\alpha}_7 t . \hat{r}(t,X_i)]. \qquad (14)$$

The entire dose-response function (DRF) can then be obtained by repeating Equation (14) at different levels of the treatment.[12] We use bootstrap methods to compute standard errors and confidence intervals. The estimated dose-response function shows the average potential outcome at each level of the treatment and how the average response varies along the interval $\mathrm{T} = [t_0, t_1]$. From this, we can compare the average outcome at one particular treatment level with the average outcome at any other treatment level. Since the GPS model controls for differences in observed covariates, the differences in average outcomes can be interpreted as a causal effect of varying the dose of the continuous treatment variable.

2.2 Contingent Valuation Method: Willingness to Pay (WTP)

We use a random utility theory to model the decision of a household for improved electricity services. The random utility theory model assumes that choices are made by comparing the utility between available alternatives and the alternative with the highest utility is preferred (McFadden, 1974; Louviere et al., 2000). In the random utility theory, the indirect

[12] Since the flexible parametric forms could make the DRF sensitive to model specification, alternatively non-parametric approach (e.g. an inverse weighting kernel estimator) by Flores et al. (2012) has been applied.

utility function $V_i(.)$ comprises a deterministic component that is a function of covariates and a random component ε_i. A household's maximum WTP^* for a change in electricity service from the status quo R^0 to an improved level R^1 is the maximum amount of money that is taken from the household's income while keeping the utility unchanged. Formally, it can be expressed as follows:

$$V_{1i}(M_i - WTP_i{}^*, Z_i, R^1, \varepsilon_{1i}) = V_{0i}(M_i, Z_i, R^0, \varepsilon_{0i}), \tag{15}$$

where M is household income and Z is a vector of covariates. Assuming a linear functional form and solving Equation (15) for WTP^* provides the following econometric model:

$$WTP_i{}^* = X_i{}'\theta + u_i. \tag{16}$$

In Equation (16), $WTP_i{}^*$ is the latent WTP for household i, X_i is a vector of explanatory variables, θ is a vector of parameters, and u_i is the stochastic error term, which is normally distributed (i.e., $u_i \sim N(0, \sigma^2)$).

In a double-bounded dichotomous choice, respondents are presented with two bid levels, where the second bid is contingent upon a response to an initial bid (B_i). If the response to the initial bid is yes, the second bid is higher (B_H); otherwise, it is lower (B_L). Thus, there are four possible outcomes: yes-yes, no-no, yes-no, and no-yes. Following Hanemann et al. (1991), the likelihoods of these outcomes are denoted by π^{yy}, π^{nn}, π^{yn} and π^{ny} respectively.

$$\pi^{yy}(B_i, B_H) = P_r.(B_i \leq WTP^* \; and \; B_H \leq WTP^*) = P_r.(B_H \leq WTP^*) = 1 - G_{WTP^*}(B_H; \theta) \tag{17}$$

$$\pi^{nn}(B_i, B_L) = P_r.(B_i \geq WTP^* \; and \; B_L \geq WTP^*) = P_r.(B_L \geq WTP^*) = G_{WTP^*}(B_L; \theta) \tag{18}$$

$$\pi^{yn}(B_i, B_H) = P_r.(B_i \leq WTP^* \leq B_H) = G_{WTP^*}(B_H; \theta) - G_{WTP^*}(B_i; \theta) \tag{19}$$

$$\pi^{ny}(B_i, B_H) = P_r.(B_i \geq WTP^* \geq B_L) = G_{WTP^*}(B_i; \theta) - G_{WTP^*}(B_L; \theta) \tag{20}$$

$G_{WTP^*}(.)$ is the cumulative distribution function of the WTP^*. In Equations (19) and (20), the second bid allows to limit both an upper and a lower bound on the WTP^*. Similarly, in Equations (17) and (18), the follow-up bid refines the lower and upper bounds in a single bounded dichotomous choice format.

Given a sample of n respondents and the bids $B_i, B_L,$ and B_H, the log-likelihood function of the double-bounded model (also called interval data model) takes the following form:

$$\ln L(\theta) = \sum_{i=1}^{n} \{I_i{}^{yy} ln\pi^{yy}(B_i, B_H) + I_i{}^{nn} ln\pi^{nn}(B_i, B_L) + I_i{}^{yn} ln\pi^{yn}(B_i, B_H) + I_i{}^{ny} ln\pi^{yny}(B_i, B_L)\}, \tag{21}$$

where $I_i{}^{yy}, I_i{}^{nn}, I_i{}^{yn},$ and $I_i{}^{ny}$ are binary variables and θ is a vector of parameters of interest. The maximum likelihood estimator for the interval data model is the solution to the equation

$\frac{\partial \ln L(\theta)}{\partial \theta} = 0$ subject to $\frac{\partial^2 \ln L(\theta)}{\partial^2 \theta} < 0$. In the interval data model, the maximum likelihood estimation directly estimates the parameters of interest.[13] Once the estimated parameters are obtained, we can estimate households' WTP. In the case with no covariates, the mean WTP is equal to the coefficient of the constant. In the presence of covariates, we can also estimate the WTP depending on the values we assign to each covariate.

The interval data model is based on the assumption that the respondents' true distribution of WTP is identical across the initial and follow-up bids (Hanemann et al., 1991). For comparison, we also consider a bivariate probit model that assumes the underlying WTP distribution changes between the first and second bids (Cameron and Quiggin, 1994). In addition, we employ a probit model for the first response to compare WTP between a single-bounded and a double-bounded dichotomous choice format.

3. Survey Design and Data Collection

The study is based on a field survey conducted in April and May 2016 in Ethiopia, a country where power outages occur frequently mainly due to the low capacity and poor physical condition of the transmission and distribution lines. As more than 90% of the electricity in the country is generated from hydropower, a shortage of reserve water in the dams also caused severe power interruptions in 2010 and consequently electricity rationing was applied to mitigate the problem (Endgida et al., 2011).[14] To address the power outages, the Ethiopian government and the state-owned Ethiopian Electric Utility have recently undertaken various short- and long-term measures. The measures include upgrading and rehabilitating the transmission and distribution lines, replacing outdated transformers, a huge investment in new generation capacity, and diversifying from the main source of electricity (hydropower) to other renewable sources, such as wind, geothermal, and solar (GTP I, 2010–2015; GTP II, 2015–2020).

Electricity services for residential, commercial, and industrial consumers are provided by a single state-owned utility: Ethiopian Electric Utility. The present study focuses on residential electricity services in the case of Addis Ababa – the capital of Ethiopia. For the purpose of our study, we first obtained a list of all residential electric meters in Addis Ababa from the

[13] The *doubleb* command in Stata directly estimates the coefficients using maximum likelihood. This is equivalent to the results of interval regression model in which the dependent variable is the lower and upper bounds of the bids.

[14] Additional causes of power outages are overload (excess demand) during peak hours and other natural or man-made causes. During our discussions with the utility's staff, we learned that most of the power outages in 2016 were unplanned and not caused by power shortages. Rather, there were problems with the transmission and distribution lines and failures of old transformers.

utility's office. We then randomly selected 715 electric meters using a stratified random sampling technique with a proportional allocation of the sample size across strata.[15] Due to the presence of shared connections, our sampling units were electric meters rather than households. Thus, in the case of shared connections, other households that use electricity from the shared connection were also included in the survey. Consequently, the sample consists of 1,152 households that use electricity from the 715 randomly selected electric meters. Of these households, 509 have a private connection and are responsible for the monthly electricity bill, 206 share a connection and are responsible for the monthly electricity bill, and the remaining 437 share a connection but are not responsible for the monthly electricity bill.

All households that are responsible for the monthly bill agreed to take part in the survey unless the neighborhood had been demolished for urban development or the households had moved to other areas for other reasons. Only five households of those that share a connection and are not responsible for the bill refused to participate in the survey. Also, a few other households that share a connection were not interviewed, either due to language problems or because they were away from home during the survey period. In the cases where households responsible for the bill were not available, they were replaced with households from the reserve list, which were selected randomly from the same neighborhood. The survey was conducted through face-to-face interviews with the household head, spouse, or other adult household member who had good knowledge of the household.

This study is part of a survey about household electricity and water use in Addis Ababa, Ethiopia. The survey data contains detailed information on socio-demographic characteristics of households, the stock of electric appliances, sources of energy, electric power outages, and other variables of interest. In addition, we had access to monthly electricity bill records from the utility for the period May 2015 to April 2016 as well as daily hours of power outages at the distribution line level (i.e., medium voltage lines) from July 2015 to June 2016. For our analysis, we matched the survey data with the monthly bill records.

Before the main survey, two pre-tests were undertaken. The first was aimed at understanding the prevailing electricity services in Addis Ababa, examining households' WTP for reliable electricity services, and assessing the prevalence of shared electricity connections. It was conducted with households that use electricity from 220 sample electric meters (not necessarily random, though from different districts of the electricity distribution) with the help of meter readers. In the second pilot, we tested the entire final version of the

[15] For details of the sampling process, see Hadush, T. (2017). "Do Consumers Respond to Marginal Prices of Electricity under Increasing Block Tariff?"

entire questionnaire and the CV scenario for improved electricity service with a total of 74 households from 64 randomly selected electric meters. The stated preference scenario was presented in Amharic, which is the local language. The interviewers were instructed to simply read the scenario as it is and give explanations to the respondents if asked (see CV scenario in Appendix).

The main field survey was conducted with a group of 24 professional fieldworkers, consisting of 21 enumerators under close supervision of three supervisors. The fieldworkers were chosen from a list of applicants based on their experience of urban surveys and their skills in collecting data using tablets. Then they were provided three days of training on the survey questionnaire and one day of debriefing on the pilot test before the main survey. Electric meter readers guided the fieldworkers to locate the sample households. Once the households had been located, the meter readers introduced the fieldworkers to the households. Then the enumerators introduced themselves as being involved in the field research that was being conducted by a semi-autonomous government research think-tank – the Ethiopian Development Research Institute.[16] After the enumerators explained the study and its purpose, the respondents were asked about their willingness to participate in the study. If they were willing to participate, the meter readers left and the interview began.

3.1 Households' Defensive Behavior

In Ethiopia, households have adopted various strategies to cope with the existing poor electricity supply. Some adjust by using candles, battery lamps, and chargeable batteries for lighting, and kerosene, charcoal, firewood and liquefied petroleum gas (LPG) for cooking, baking, and heating water. Others install solar panels or connect to a stand-by generator. To estimate the monthly household defensive expenditures, we compute household expenses for various mitigating actions. During the survey, respondents were asked if their households use a backup mechanism from a list of options for lighting, cooking, and other activities during power outages. If used, the associated extra expenditures during power interruptions in the previous 30 days were elicited. Since some of the coping costs involve capital expenditures, e.g., the cost of a chargeable battery, solar panel, and stand-by generator, the respondents were asked about the cost and expected lifespan of the equipment, and this was then converted into monthly cost. This monthly cost of equipment is gross and hence not adjusted

[16] The research survey was conducted by the University of Gothenburg (Sweden) in collaboration with the Ethiopian Development Research Institute (EDRI), The World Bank, and the University of North Carolina at Chapel Hill (USA).

for depreciation and inflation. Moreover, respondents were asked separate questions about their households' typical monthly expenses for alternative fuels, e.g., kerosene, charcoal, firewood, and LPG.

The household monthly defensive expenditures approach has some limitations in measuring the welfare effects of power outages. For instance, the mitigating actions do not perfectly substitute for electricity services, i.e., they do not provide benefits that are perfectly comparable to the benefits of reliable electricity services that are void of power outages. It also ignores costs such as the inconvenience of candle lighting; indoor pollution from cooking with charcoal, LPG, kerosene and firewood; noise from stand-by generators; and storage and transaction costs of alternative fuels. In addition, a fraction of the defensive expenditures would have been paid in the form of an equivalent expenditure on electricity service had it been available, so the defensive expenditure is not a net measure. In a survey setting, it is also possible that respondents could have problems with recollection when distinguishing the expenses for alternative fuels during power outages from the typical monthly fuel expenses (see, e.g., Deaton, 1997).[17]

In the present paper, we crosscheck the validity of the self-reported data using three different approaches. First, we check whether respondents have problems with recollection by comparing a reported typical monthly electricity bill with the average of the recorded 12-months electricity bill from the utility. Figure 2 shows the cumulative distribution of self-reported typical monthly electricity bill and the average of the recorded monthly bills for 12 months (May 2015–April 2016). Of all respondents from the households that are responsible to pay the electric bills for the 715 randomly selected electric meters, 698 reported their typical monthly electricity bills. The averages of the reported and recorded monthly bills are the same (137 birr) and the pair-wise average difference is close to zero (0.08 birr). However, we observe a very small variation in the distribution for the large percentiles. This could partly be due to a majority of the respondents reporting typical bills rounded up to values that are easy to state as well as due to recorded billing errors related to electric meter reading, recording, and technical problems with the electric meters. We formally test the null hypothesis that both distributions are the same using the Wilcoxon matched pairs signed-rank test. We fail to reject the null hypothesis at p-value equals to 0.92.

Second, we compare the self-reported hours of power outages at a shared connection between the main households and the shared households; see the box plot in Figure 3 for the

[17] We check the share of the expenses on alternative fuels during power outages with the typical monthly expenses of those fuels. It is a small portion of the typical monthly expenses.

results. The two groups of households show almost identical distributions of number of hours of power outages. They have equal medians of 40 hours but the average is 2.5 hours higher (52 hours) for the main households than for the shared households. Using an unpaired t-test, we do not find this difference statistically significant (p-value= 0.49).

Third, we assess whether the self-reported monthly hours of power outages are within the possible ranges of the recorded figures for the distribution lines, which carry electricity from the sub-station to transformers (i.e. medium voltage lines), from the utility. Thus, this does not include the power outages that could happen at the lines between the transformers and the household premises (i.e., low voltage lines). To this end, we use the daily hours of power outage records for around 200 lines in the entire city (Addis Ababa) to determine the total number of monthly hours of power outages for the period July 2015 to June 2016. Figure 4 presents the cumulative monthly hours of power outages at the households' level and at the distribution lines' level. While the hours of power outages at households level is reported for one month prior to the survey period, the outages at distribution lines level is an average of 12 months. As shown in Figure 4, about 90% of the self-reported hours of outages are within the possible ranges of the recorded figures for the distribution (medium voltage) lines. It is plausible that the additional hours reported by households are due to outages at the level of the low voltage lines. Overall, the data from the three different approaches suggest good validity of the self-reported data for our analysis though do not completely rule out problems of recollection.

3.2 Contingent Valuation (CV) Scenario

Before explaining the CV scenario and asking the WTP questions, respondents were asked about the frequency of power interruptions in their neighborhood; the frequency and duration of power outages at their homes in the last 7 and 30 days, respectively; in which part of the day they experienced the most electricity service interruptions affecting their households; major concerns of their households during power outages; mitigating actions and corresponding costs in the last 30 days; and their perceptions regarding possible future improvement of the service. This helped us understand how familiar respondents were with the existing electricity services and made the respondents more involved in the scenario of improved electricity services.

Then the respondents were orally reminded about the prevailing unplanned interruptions in electricity service, the costs and major concerns of their households, and the main causes of power outages in the study area, before the planned improvement in electricity service was presented. The main causes of the ongoing power outages were explained as low capacity of the transmission and distribution lines, aged and poor physical condition of transformers, and wastage of power due to high loss along these lines. The proposed project was described as *improving the reliability of electricity delivery along the transmission and distribution lines* through a government program aiming to rehabilitate, upgrade and replace equipment in poor physical condition, so that you and other households will not face unplanned electricity interruptions due to problems related to the transmission and distribution lines. In the scenario, it was stated that implementing the project involves costs to the government and that one way to recover them would be to charge households a fixed monthly amount for this project. The payment vehicle used is the monthly electricity bill, with which respondents are familiar. It was stated that every household would pay a fixed amount every month if the project were to be implemented. It was also stated that the project would be implemented if a majority of the people supported it.

The respondents were reminded about their household income and that, if the project would be implemented, their household would not experience power interruptions and would not incur costs for alternative energy sources to cope with power outages. This helps to reduce a possible hypothetical bias when using the contingent valuation method.

The WTP question is a double-bounded dichotomous choice format (Hanemann et al., 1991). The respondents were first asked the question:

> *"Do you support the project, if* ***every household*** *in Addis Ababa including your household has to pay* **______***birr* ***monthly*** *for improving the electricity services?"*

Following the initial response, the respondents were again asked the same question but with a different bid (higher or lower than the initial bid). After these two questions, the respondents were asked to give reasons why they were willing or not willing to pay for the improved electricity service.

The double-bounded dichotomous choice approach is statistically more efficient than the single-bounded approach of asking only the first question (Kanninen, 1993; Hanemann et al., 1991), but it is criticized for its starting point bias and yea-saying (Ready et al., 1996; Herriges and Shogren, 1994).[18] To minimize the strategic behavior when responding to the

[18] Starting point bias occurs when the response to the follow-up question is affected by the presence of the first question. Yea-saying bias is the tendency of respondents to agree with questions regardless of the content. Yea-saying may be due to social pressure or a desire for warm glow and the moral satisfaction of contributing to public goods.

follow-up bid, respondents were provided information in advance about the presence of two bids (Aravena et al., 2015). The statements used for this study were:

> "*Because the exact cost of the project (improving quality of electricity service) is not presently known, we will ask you to vote on two different costs for the project. These costs represent the range within which the actual cost should fall. In what follows, you will vote for or against each alternative costs.*"

The respondents were not told whether the second bid would be higher or lower. Such withholding of information helps to avoid anchoring on the first bid in a double-bounded approach.

Since there was no prior information on the distribution of the true WTP, we carried out two pre-tests to design a vector of bids. In a first pilot, completed in December 2015, with households that use electricity from 220 sample electric meters (not necessarily random though from different districts of the electricity distribution) with the help of meter readers, respondents were asked an open-ended question: *At what times of day is electricity service important for your household and what is the maximum additional amount (on top of the typical monthly electricity bill) that your household would be willing to pay in order to have reliable electricity service for the stated times of day?* The responses varied from 0 to 600 birr, with a high proportion (70.3%) of zeros. The large share of zeros could be due partly to the news by that time that the electricity price would go up by 50% and partly to the fact that meter readers were involved in the interviews. In the second pilot, we developed a scenario almost identical to the final version and conducted interviews with the help of experienced and trained fieldworkers who would also conduct interviews for the main survey. The second pre-study involved 74 households that use electricity from 64 randomly selected electric meters in different neighborhoods of the city where the main survey was conducted, but these households were excluded from the main survey.

Based on the findings of the pilot studies, a bid vector was designed for the main survey following the approach by Scarpa and Bateman (2000) and Hutchinson et al. (2001). The bid vector consisted of six bids (measured in birr):10, 20, 35, 65, 150, and 225. These bids were taken from various points (lower, middle, and higher) of the WTP distribution from the second pilot. Respondents were first randomly assigned to any of the four bids in the middle. In the follow-up questions, the bid was increased to the next larger bid if the response to the initial bid was "yes" and reduced to the next lower bid if the response to the initial bid was "no."

4. Descriptive Statistics

< *Table 1 here* >

Table 1 displays the summary statistics for the 1,152 sample households in our study. A majority of the respondents are head of households (54%) and female (65%). The average age of the respondents is 39.7 years and the typical family size is 3.95 persons, which is close to the national figure of 3.7 persons per household in urban areas (Central Statistics Agency, 2011). Regarding marital status, 23.59% of the respondents are single, 56.81% are married, and 19.60% are either divorced or widowed. In terms of house ownership, around 37% live in their own houses and the rest live either in a rented house or in a relative's house. As for education, 46.88% have completed primary school or less, 43.23% high school, and 9.90% a bachelor's degree or more. When it comes to electricity services, 56% of the households share a connection with at least one other household.

The mean monthly electricity bill is 138 birr at the electric meter level and the average reported monthly household income is about 5,477 birr. This average monthly electricity bill is about 2% of the monthly average household income of those households that are financially responsible for the bill. The monthly electricity bill is positively and significantly correlated with monthly income ($\rho = 0.22$). When we split the monthly bills across connections, the average monthly electricity bill is 162.50 birr for shared connections and about 128 birr for private connections.[19]

A majority of the respondents (76%) believe that the reliability of electricity services will improve in the coming five years. Respondents were asked whether they had experienced power outages at home in the last 30 days. All but 11 respondents answered yes. When the respondents were asked about their main concern during power interruption, 47.74% stated darkness and resulting security issues, 37.33% reported inability to cook as their main concern, and the remainder reported other issues, such as being unable to watch TV, food spoilage, and damage to electric appliances.

< *Figure 1 here* >

Figure 1 demonstrates the density of the self-reported monthly number of hours of power outages at household level. To keep the estimated results (average defensive expenditures) from being driven by outliers, we drop observations in the top 1%, i.e., more than 244 hours of monthly power outages and defensive expenditures above 925 birr. This leaves us with

[19] The average reported monthly income (5357.88 birr) is higher for households in a shared connection that are financially responsible for the monthly bill than for those that are not responsible (3528.83 birr), but it is less than the monthly income (7198.10 birr) of the households in a private connection.

1,132 sample households. As displayed in Figure 1, the power outage distribution shows large variation. The average monthly duration is 53 hours and the standard deviation and interdecile ranges are 43 hours and 106 hours, respectively.[20] In Table 2 Panel A, we provide the summary statistics of monthly hours of power outages across sample groups. Shared households, i.e., households that share a connection but are not responsible for the monthly bill, reported relatively fewer hours of power outages.

< *Table 2 here* >

Table 2 Panel B, Columns (1)–(3) present average monthly defensive expenditures and their components for the full sample, for the main households, i.e., households responsible for the monthly bills, and for the shared households, respectively. The monthly defensive expenditures include monthly lighting costs, costs of equipment, and monthly costs of alternative fuels such as firewood, charcoal, kerosene, and LPG for cooking, baking, and heating during power outages. The average monthly defensive expenditures range from 103.37 to 147.37 birr. The cost of alternative fuels is the largest portion of the defensive expenditures. Furthermore, we assess pairwise correlation among hours of power outages, monthly electricity bills, and defensive expenditures. Monthly defensive expenditures are positively and significantly associated with number of hours of outages ($\rho = 0.09$), with monthly bill ($\rho = 0.15$), and with monthly household income ($\rho = 0.35$). Nevertheless, the correlation between hours of power outages and monthly bill is close to zero ($\rho = 0.01$) and statistically insignificant. This could partly be due to higher usage when the service is available.

< *Figure 5 here* >

Figure 5 shows the proportion of "yes" responses across the four initial bids (20, 35, 65, and 150 birr). 51.60% of the respondents who were randomly assigned to 20 birr and 39.81% of those assigned to 35 birr said "yes." Similarly, 19.51% and 8.65% of the respondents assigned to 65 birr and 150 birr, respectively, said "yes." The share of "yes" responses to a given bid decreases when the size of the bid increases. The share of "yes" responses to the lowest initial bid (20 birr) is very low. This is probably related to the bid design.[21] The reasons from the debriefing questions: the stated amount is higher, and do not have enough

[20] For the full sample (N=1,152), the average monthly number of hours of power outages and the average monthly household defensive expenditures are 55.29 hours and 143.55 birr, respectively.

[21] In designing the lowest initial bid, we considered the cost of covering the project in case the government implemented it. Our presumption was that amounts lower than 20 birr might not be sufficient to cover the cost. Similarly, the scenario that power outages will be reduced permanently was initially aimed at comparing the WTP estimates with the amount of defensive expenditures that would be saved if no power outages occurred.

income, support the explanation. It could be also related to respondents' strategic behavior and respondents believe on the scenario that power outages will be permanently reduced.

< *Table 3 here* >

Table 3 presents the distribution of the responses to the initial and follow-up bid. It consists of four possible response outcomes: no-no, no-yes, yes-no, and yes-yes. For instance, the value of 23.84% for no-no responses to the initial bid of 20 birr implies that, of the total 281 respondents randomly assigned to 20 birr, 23.84% said "no" to both the 20 birr and the lower follow-up bid of 10 birr. As seen in Table 3, the share of respondents who said "no" to both the first and the second bid increases with bid size.

Of the total 1,152 respondents, 516 (44.75%) answered "no" to both the first and the follow-up question. From the debriefing questions, they are not willing to pay for improved electricity services because they do not have enough income (40.31%), the stated amount is higher than what they can pay (39.53%), the cost should be covered by the monthly bill paid (8.91%), they do not believe power outages will be reduced to the level stated (7.95%), and for other reasons (3.19%). Some of the reasons, such as that the cost should be covered by the monthly bill and they do not believe outages will be reduced to the level stated, are protests to the scenario (Meyerhoff and Liebe, 2006, 2010). When we estimate the mean WTP, we include and exclude these protest responses to check whether the estimated WTP is under or overestimated.

We also explore the distribution of the reasons – why respondents are not willing to pay – across the initial bids. Using chi-squared, we formally test whether there is a significant difference in the distribution of the reasons across the initial bids. We reject the null hypothesis that the distribution is independent at the 1% level of significance. When we look specifically at the raw distribution of the two main reasons, the percentage rises with bid sizes. Furthermore, we estimate a simple probit model to check for any systematic relationship between the no-no responses and household and respondent characteristics. What we find is that households with higher monthly incomes, larger households, younger respondents, respondents with higher education (i.e. high school completed or above), and respondents who believe service will be improved in the future are less likely to respond no-no. Perhaps as expected, the probability of responding no-no is higher at higher bid levels. However, the estimated coefficients for hours of power outages, shared connection, gender, and household head are not statistically significant.[22]

[22] The probit results are available from the author upon request.

5. Results

5.1 Households' Defensive Behavior

We begin our empirical analysis by presenting the results from the generalized propensity score matching and the estimated dose-response functions (DRFs). Since the distribution of power outages is highly skewed (see Figure 1), we use a zero skewedness Box-Cox transformation of the treatment to satisfy the normality condition and apply maximum likelihood to obtain the GPS (Bia and Mattie, 2008). To test for balancing property, following Hirano and Imbens (2004) and Kluve et al. (2012) we split the sample into three groups according to the distribution of hours of monthly power outages, cutting at the 30th and 70th percentiles (26 and 62 hours, respectively).

< Table 4 here >

Table 4 reports t-statistics for the difference-in-means of each covariate in one group compared with the other two groups. With 13 covariates, we calculate 39 t-statistics and assess, at the 90 and 95% confidence levels, the null-hypothesis that the mean difference in covariates is zero. Having adjusted for the GPS, out of the 39 tests conducted only one t-statistic is higher than 1.645. This implies that the estimated GPS satisfied the desired property of balancing the covariates.

< Table 5 here >

Next, to estimate the dose-response function we first regress the outcome variable (monthly defensive expenditures) on the treatment (monthly hours of power outages) and the GPS; see Equation (13). Due to skewedness of the monthly defensive expenditures, we use its logarithmic specification. Table 5 presents the estimated coefficients. As Hirano and Imbens (2004) pointed out, the estimated coefficients do not have direct meaning but are rather utilized in computation of the DRFs.

< Figure 6 here >

Finally, we estimate the average effects for different values of the treatment to construct the dose-response function (DRF). Figure 6 shows the DRF for various sample households: the full sample, the main households, and the shared households. The DRF plots are obtained with nine different values of the treatment that correspond to the deciles of the empirical distribution.[23] For each of the DRFs, we provide 95% confidence intervals obtained with 200 bootstrap replications. As displayed in Panel A of Figure 6, the DRF increases at lower

[23] We also cross-check the DRF using a non-parametric approach, but the results remain similar (not reported here).

monthly hours of outages, reaches a maximum around the median values, and declines somewhat at higher numbers of hours of power outages. The estimated DRF can be interpreted as a counterfactual fact how households would respond to a given monthly hours of power outages had they received a different level of power outages. For instance, the average monthly defensive expenditures at 10 outage hours (10th percentile) is 55 birr (=*exp*(4)), but 73 birr (=*exp*(4.29)) at 62 hours (80th percentile).

< *Table 6 here* >

Table 6 reports the estimated average monthly defensive expenditures at selected percentiles of the distribution of the treatment (hours of power outages). By fixing the levels of the treatment at the 25th, 50th, and 75th percentile as well as at the mean (i.e., 22 hours, 42 hours, 72 hours and 53 hours of power outages, respectively), we obtain the corresponding values of the average monthly defensive expenditures. We observe differences in average outcomes across sample groups. Households that share a connection but that are not responsible for the monthly electricity bill have the lowest average defensive expenditures at the different hours of power outages. For instance, at the mean hours of power outages, the corresponding average monthly defensive expenditures are 60, 70, and 77 birr for the shared households, all households, and main households, respectively. The low value for the shared households is possibly associated with lower monthly income, fewer household members, and smaller stock of electric appliances.

5.2 Households' Willingness to Pay

In this sub-section, we present regression results of the models employed to estimate households' WTP for improved electricity services. The interval data model is our standard model applied to estimate WTP from the double-bounded choice format. Therefore, we base the estimated mean WTP on this model in explaining the main results.

< *Table 7 here* >

Table 7 shows the estimated results of the interval data model with no control variable (only with constant) and the corresponding WTP and its confidence interval for the different sample groups. Columns 1 and 2 are for the full sample, but the protest responses (87 observations) are excluded in Column 2. Column 3 is for households that are responsible for the monthly electricity bill (N=715), whereas Column 4 provides results for households that share a connection but are not responsible for the monthly electricity bill (N=437). Since the interval model directly estimates the coefficients, in the case with no control variables the mean WTP is simply the constant. The estimated WTP ranges from 27 birr for the shared households to 34 birr for the main households. This is equivalent to 19%–25% of the existing average monthly electricity bill. Given the average monthly power outages of 55 hours, households are willing to pay 0.5–0.6 birr more than the existing bill to enjoy an additional hour improvement in power supply.

< *Table 8 here* >

We alternatively run a bivariate probit model and a probit model in order to compare the results of the interval model with results of other models and with results from a single-bounded. Table 8 reports regression results of the probit model and bivariate probit model for the full sample using bid as the only covariate. Column 1 presents probit results for the first response and Columns (2)–(3) are bivariate model estimates for the first and second responses, respectively. Since the value from a Box-Cox transformation test strongly rejects the linear specification for the bid but fails to reject for the logarithmic specification, we use a logarithmic specification in our regression models.[24] As expected, the coefficients on the bid variables are significant and negative. This implies that, as the bid amount increases, the respondents are less likely to pay for electricity service improvement, all else equal. The correlation coefficient for the first and second responses from the bivariate probit model is very small and statistically insignificant. This indicates independence of the responses and justifies the use of the interval data model in our study.

Table 8 also presents the estimated WTP and its confidence interval from each model using a delta method (Cameron, 1991).[25] Bid is the only covariate included in the estimation of the WTP. The estimated mean WTP for improved electricity services from the single-bounded (using probit model) is 57 birr per month for the full sample (N=1,152). In the bivariate model, since the mean differs between the first and second responses, following Haab and McConnell (2002), we choose the mean WTP for the first response, which is less noisy and appears to be a better candidate. The estimated mean WTP is 57 birr per month for the full sample. This is the same as the estimates from the probit model for the single bound. The estimated mean WTP from the double-bounded (using the interval data model) is more efficient (has a tighter confidence interval) than the single-bounded (using the probit model). This supports the use of the double-bounded choice format. However, the estimated mean WTP is lower for the double-bounded than for the single-bounded choice format. This could

[24] For the linear specification: LR statistic chi2 =25.78 and p-value=0.00. For the logarithmic specification: LR statistic chi2 =2.17 and p-value=0.14. The logarithmic specification can predict unrealistically large estimates of mean WTP (Haab and McConnell (2002).

[25] We also applied Krinsky and Robb procedures (Krinsky and Robb, 1986; Haab and McConnell, 2002) to estimate mean WTP, but the results remained the same.

be explained by the tendency for initial “yes” respondents to answer “no” to the second question, regardless of the amount (Haab and McConnell, 2002; Hanemann et al., 1991). As a term of comparison, we also use a distribution-free non-parametric estimation, i.e., the Kaplan-Meier-Turnbull (KMT) estimator, for the first responses (Haab and McConnell, 1997). This estimator is robust to miss-specification errors and yields a conservative WTP estimate of 29.54 birr for the full sample.[26]

WTP estimate from the contingent valuation method is expected to be larger than the revealed preference estimates since it includes more values. However, our findings show the opposite. For instance, at the average monthly number of hours of power outages (53), the corresponding average monthly defensive expenditures are 2 times greater than the monthly WTP. As displayed in Table 7, the confidence interval for the estimated mean WTP from the interval data model does not include the estimated average monthly defensive expenditures at the mean value of the monthly hours of power outages.[27] This indicates that we do not find evidence that defensive expenditures are a lower bound of WTP, even after excluding the protest responses in the contingent valuation method.

The contingent valuation method has been widely applied in developed countries (Freeman, 2003) and also increasingly used in developing countries (Whittington, 2002). However, its application has been criticized with reference to the reliability and validity of its results in general (Carson et al., 2001; Bateman et al., 2002; Venkatachalam, 2004) and problems related to posing a hypothetical question to low-income and poorly educated respondents in developing countries in particular (Whittington, 1996). In developing countries, a low degree of public trust in government (World Values Survey, 2005–2010) could also influence contributions to the service improvement under consideration. A study by Whittington (2010) documents that in developing countries, households’ WTP for a wide range of goods and services offered in stated preference scenarios is low, in both relative and absolute terms and compared with the costs of service provision. This indicates that relying on

[26] The Kaplan-Meier-Turnbull (KMT) estimator provides a conservative estimate and does not allow for negative WTP. The lowest end point is set equal to the observed yes proportion for the lowest bid. The higher end point is also set conservatively by assuming that at any higher bid level the proportion of yes responses would be zero. The estimated mean WTP is given by the formula: $E(WTP)=\sum_{j=1}^{k} B_j\,(Y_j - Y_{j+1})$, where Y_j and Y_{j+1} are the proportion of yes responses to bid B_j and the next higher bid, respectively. In our case (see Table 3), the estimated mean WTP is 20(.516-.398)+35(.398-.195)+65(.195-0.087)+150(.087-0)=29.54.

[27] Since the coefficient (positive) on monthly hours of power outages is not statistically significant, we do not compute WTP at different hours of power outages. However, we find a positive and significant relationship between monthly defensive expenditures and WTP estimate from the interval data model.

WTP estimates from stated preference studies in cost-benefit analyses of proposed service improvements could be misleading.

6. Conclusion

Access to electricity is expected to improve people's living standards. However, the potential benefits are likely to be undermined if a connected consumer does not receive an adequate level of service due to an unreliable electricity supply. Power outages are a concern particularly in developing countries like Ethiopia. In order to compute the socially optimal levels of power interruption, it is important to know the value that society places on a reliable power supply. It is, however, difficult to obtain all the necessary information in this respect. Then, what are the tools and information available to analyze how relevant an uninterrupted electricity supply is to people?

In this paper, we use data on defensive expenditures and willingness to pay (WTP) to understand preferences for improved electricity supply from perspective of households. Poor electricity supply imposes a direct cost on households, for example in the form of extra expenditures on alternative sources for lighting, cooking, baking, and water heating during power outages. In our defensive behavior approach, we use survey data on the extra expenditures for alternative sources to reveal how much households are willing to pay for a higher quality of electricity supply. Our results from the generalized propensity score (GPS) method show that the estimated average monthly defensive expenditures vary with monthly number of hours of power outages. At the average monthly hours of power outages, the estimated average monthly defensive expenditure is US$3.3 for the full sample. This is equivalent to 50% of the existing average monthly electricity bill of $6.6, implying a significant cost of outages to households in Ethiopia. Similarly, evidence from a survey shows that power outage is the most critical bottleneck for Ethiopian manufacturing firms (World Bank Enterprise Survey, 2015). The estimated results from the defensive expenditure approach provides insights to look for ways to improve reliability, but they are not net measures since a fraction of the defensive expenditures would have been paid on electricity service had it been available. Also, the survey data could be affected by issues such as reporting and recollection problems.

In addition to the direct costs, power outages generate indirect costs such as inconvenience. Thus, in this paper, we also elicit households' WTP for improved electricity services using the contingent valuation method. Results from the contingent valuation study show that households are willing to pay US $1.3–$1.6 monthly on top of their electricity bills (19%–

25% of the existing average monthly bill) for improved electricity services. The estimated mean WTP is lower than the estimated average defensive expenditures at the average monthly hours of power outages though the WTP elicited from the contingent valuation method is expected to be higher as it includes more values. In developing countries, the low degree of public trust in existing institutions (World Values Survey, 2005–2010) possibly contributes to a low WTP for public service improvement of e.g., the power supply. Decisions based on low WTP estimates could leave the electricity service provider in a vicious circle. A lack of adequate funds to expand and improve the existing services leads to underinvestment, which in turn, leads to poor service levels. With a poor electricity supply, people are less willing to pay, which worsens the funding situation even more.

Overall, it is important to focus not only on access to electricity but also on the reliability of the service in order to have a sustainable energy transition from traditional fuels to electricity and for people to be able to enjoy the benefits of having access to electricity. The present study provides insights on the importance of a reliable electricity supply. Given the findings, we would propose that future research should put even more effort for a better understanding of the welfare implication of power outages in low-income developing countries and thus, provide more inputs to policies and investments in the energy sector.

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Appendix A: List of Tables

Table 1. Variable description and summary statistics

Definition	Mean	Std. dev.	Median
Average monthly electricity bill over a year (in birr)	137.93	124.74	110.01
Reported household monthly income in birr	5477.13	6362.71	3597.50
Self-reported relative economic status of household (= 0 if poor,=1 if medium ,=2 if rich)	.52	.56	0
Index for stock of electric appliances in kW	4.75	4.30	4.53
Who pays the monthly electricity bill: (=0 my HH and a private connection, =1 my HH but shared connection, =2 other HHs pay the bill)	.94	.90	1
=1 if shared connection, 0 otherwise	.56	.50	1
=1 if respondent believes reliability of electricity services will improve in the coming 5 years, 0 otherwise	.76	.43	1
=1 if respondent is male, 0 otherwise	.35	.48	0
Age of respondent in years	39.66	15.57	35
Marital status of the respondent (=0 if single, =1 if married, =2 if widowed or separated)	.96	.66	1
=1 if respondent is household head, 0 otherwise	.54	.50	1
Respondent's level of education (=0 if primary and below, =1 secondary and =2 if bachelor's degree or higher)	0.63	0.66	1
=1 if respondent has job, 0 otherwise	.55	.49	1
Total number of household members	3.95	2.04	4
=1 if at least one household member stays at home during day time	.73	.44	1
=1 if lives in own home, 0 otherwise	.37	.48	0

Table 2 presents summary statistics for the full sample (N=1,152). However, the monthly electricity bill is computed at the 715 sample electric meters.

Table 2. Average monthly hours of power outages and defensive expenditures

Variable description	Full sample	Main HH	Shared HH
Panel A: Power outages			
Monthly hours of power outages	52.99	55.18	49.50
	(43.41)	(43.20)	(43.57)
Panel B: Monthly defensive expenditures (in birr)			
Lighting costs	20.68	23.20	16.64
	(24.03)	(28.29)	(13.98)
Fuel costs (for cooking, baking, and heating)	102.02	113.45	83.76
	(142.63)	(154.35)	(119.54)
Cost of equipment	7.73	10.71	2.97
	(26.18)	(31.39)	(13.05)
Total defensive expenditures	130.42	147.37	103.37
	(154.06)	(167.84)	(124.55)
Observations	1,132	696	436

Table 2 presents the mean monthly hours of power outages, household defensive expenditures and their components for the full sample (Column 1), main households (Column 2), and shared household (Column 3) after excluding the outliers. Standard deviations are in parentheses.

Table 3. Distribution of the first and second responses

Initial bids	Second bids		Number of respondents				Total
	Higher	Lower	NO-NO	NO-YES	YES-NO	YES-YES	
20	35	10	67	69	85	60	281
			(23.84%)	(24.56%)	(30.25%)	(21.35%)	
35	65	20	112	80	101	26	319
			(35.11%)	(25.08)	(31.66%)	(8.15%)	
65	150	35	147	84	46	10	287
			(51.22%)	(29.27%)	(16.03%)	(3.48%)	
150	225	65	190	52	18	5	265
			(71.70%)	(19.62%)	(6.80%)	(1.89%)	
Total			516	285	250	101	1,152

Table 4. Balance in covariates: t-statistics for equality of means

Variables	(1)	(2)	(3)
	Hours of power outages interval		
	[0, 26]	(26, 62]	(62, 244]
Household characteristics:			
Monthly household income	-395.47	248.51	126.98
Index for stock of electric appliances in kW	-.020	.219	-.007
Household bakes *injera* at home (1=yes, 0= no)	.002	.001	.011
Number of household members	.038	.012	.061
Lives in own home (1=yes, 0= no)	.013	.007	-.014
Shared connection (1=yes, 0= no)	-.021	-.023	.008
Member(s) stay home during day time (1=yes, 0= no)	-.002	.0242	-.014
Respondent characteristics:			
Household head (1=yes, 0= no)	.012	.014	-.033
Male (1=yes, 0= no)	.031	-.026	-.007
Age in years	-.487	1.559**	-.986
Primary school or below (1=yes, 0= no)	.002	-.027	.023
High school (1=yes, 0= no)	-.007	.028	-.019
Bachelor's degree or higher (1=yes, 0= no)	.005	-.001	-.003

Table 4, Columns 1–3 reports the t-tests of mean differences of each covariate between observation in group i and observations in the other two groups of the monthly hours of power outages distribution for the full sample.

Table 5. Parameter estimates of conditional expectation of outcome given treatment and GPS

	(1)	(2)
Variables	Coeff.	Std. Error
Hours of outages	-.046**	.022
Hours of outages^2	.001**	.000
Hours of outages^3	.000**	.000
GPS	21.819***	4.454
GPS^2	-50.145***	12.491
GPS^3	38.275***	10.475
Hours of outages *GPS	.0246**	.015
Constant	1.338***	.430
Adjusted R-squared	0.054	
Number of households	1,132	

Table 5 presents the parameter estimates of conditional expectation of household defensive expenditures given hours of power outages and GPS. The outcome variable is natural logarithm of monthly household defensive expenditures. ***, **, and * stand for significance level at 1%, 5%, and 10%, respectively.

Table 6. Estimated DRF for selected percentiles of the distribution of the treatment

Hours of power outages	Average monthly defensive expenditures (in birr)		
	Full sample	Main households	Shared households
22 hours (25th percentile)	53.82	75.24	38.14
42 hours (50th percentile)	77.26	81.90	66.99
72 hours (75th percentile)	59.61	70.47	47.07
53 hours (mean)	70.34	77.13	60.50

Table 6 shows the dose-response function at selected monthly hours of power outages for different sample groups.

Table 7. Results of the interval data model and the corresponding mean WTP

Variables	(1)	(2)	(3)	(4)
Constant	29.624***	33.995***	31.174***	27.422***
	(1.699)	(1.658)	(2.244)	(2.546)
Observations	1,152	1,065	715	437
Mean WTP	29.62	34.00	31.17	27.42
Confidenc interval	[26.29, 32.95]	[30.75, 37.24]	[26.77, 35.57]	[22.43, 32.41]

Table 7 displays regression results of the interval data model with only constant and the corresponding mean WTP and its confidence intervals for the full sample (Column 1 and Column 2–excluding protest responses), for the main households (Column 3), and for the shared households (Column 4). Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 8. Results of probit model and bivariate probit model

Variables	Probit model	Bivariate probit model	
	(1)	(2)	(3)
log of initial bid	-0.726***	-0.727***	
	(0.061)	(0.062)	
log of follow up bid			-0.472***
			(0.080)
Constant	2.249***	2.255***	1.267***
	(0.235)	(0 .234)	(0.291)
ρ (correlation coefficient)		0.111	
		(0.083)	
Observations	1,152	1,152	
Mean WTP	57.17	57.01	116.38
Confidence interval	[43.59, 70.76]	[43.61, 70.41]	[4.6, 228.07]

Table 8 reports regression results of the probit model and bivariate probit model for the full sample with only bid as a covariate. Column 1 presents probit results for the first response and Columns 2–3 are bivariate model estimates for the first and second responses, respectively. Robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: List of Figures

Figure 1. Density of self-reported monthly hours of power outages

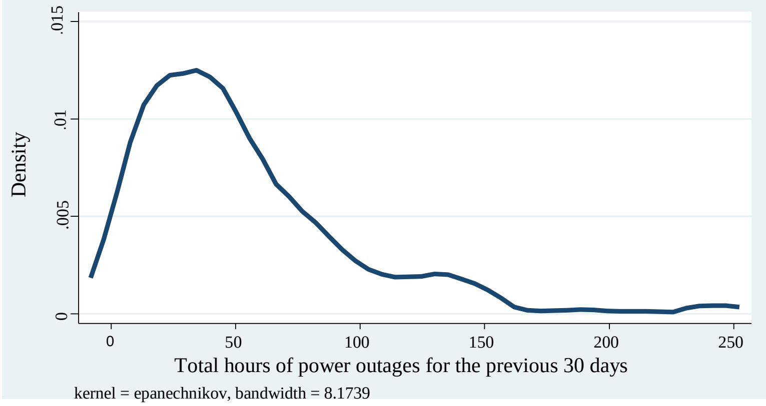


Figure 2. Cumulative distribution of actual and reported monthly

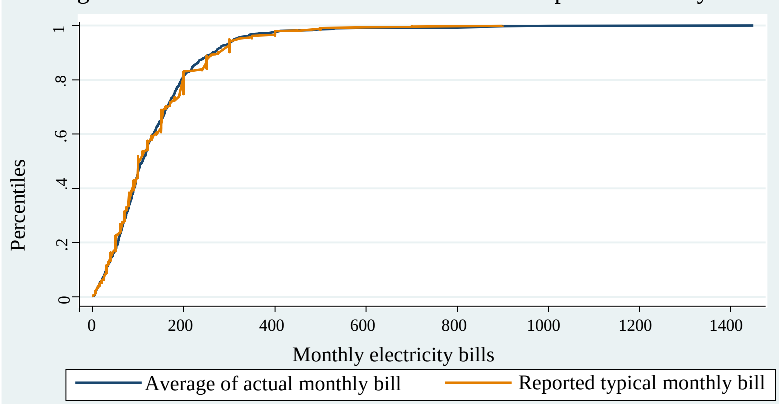


Figure 3. Box plot of self-reported monthly hours of power outages

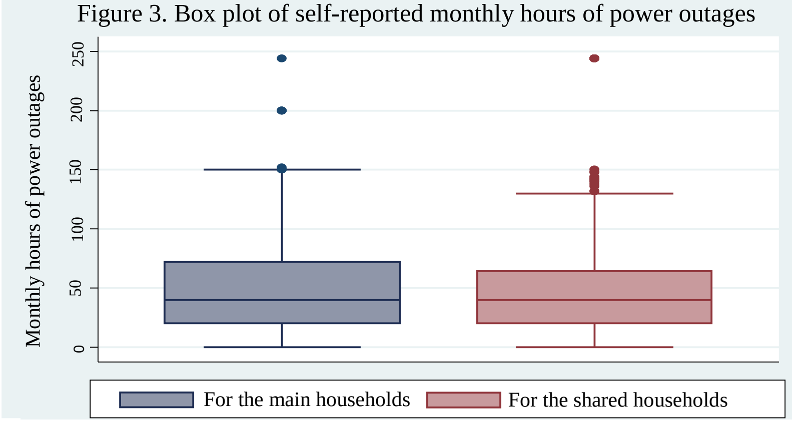


Figure 4. Cumulative distribution of monthly hours of power outages

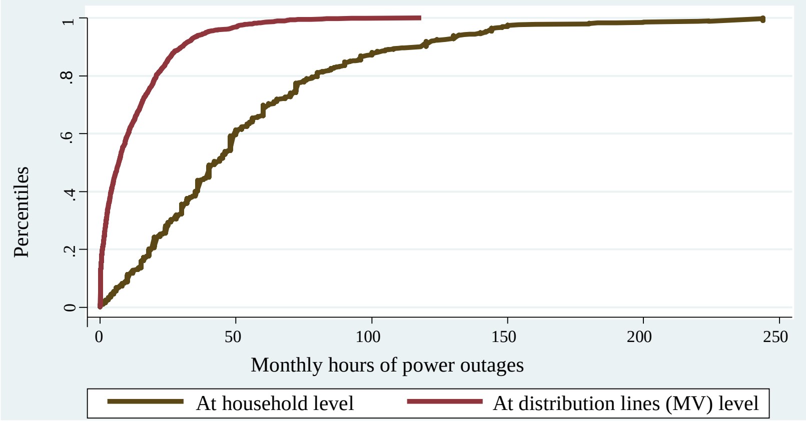


Figure 5. Response to the initial bids

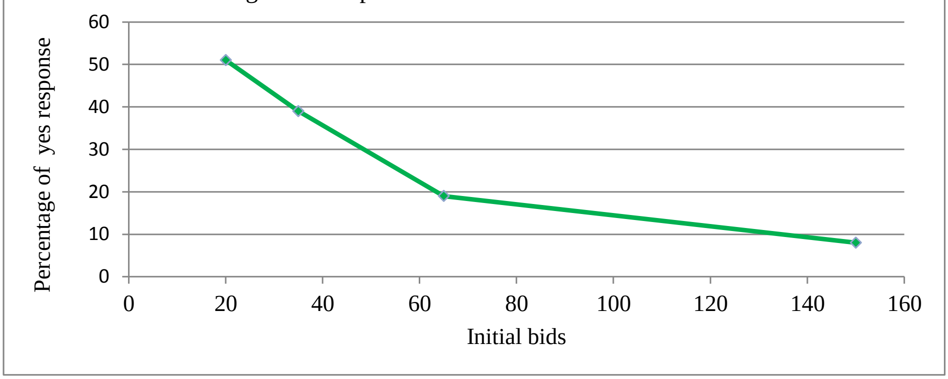
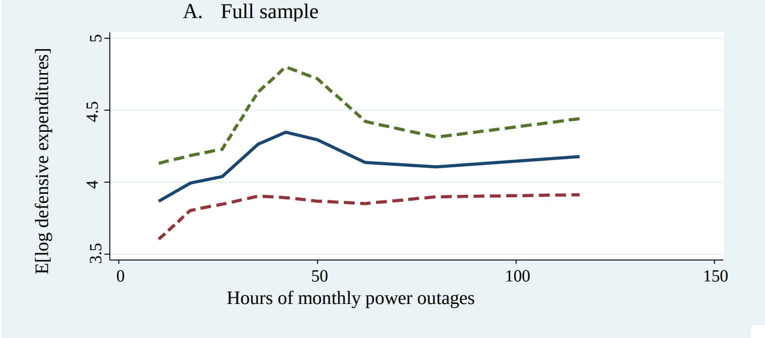
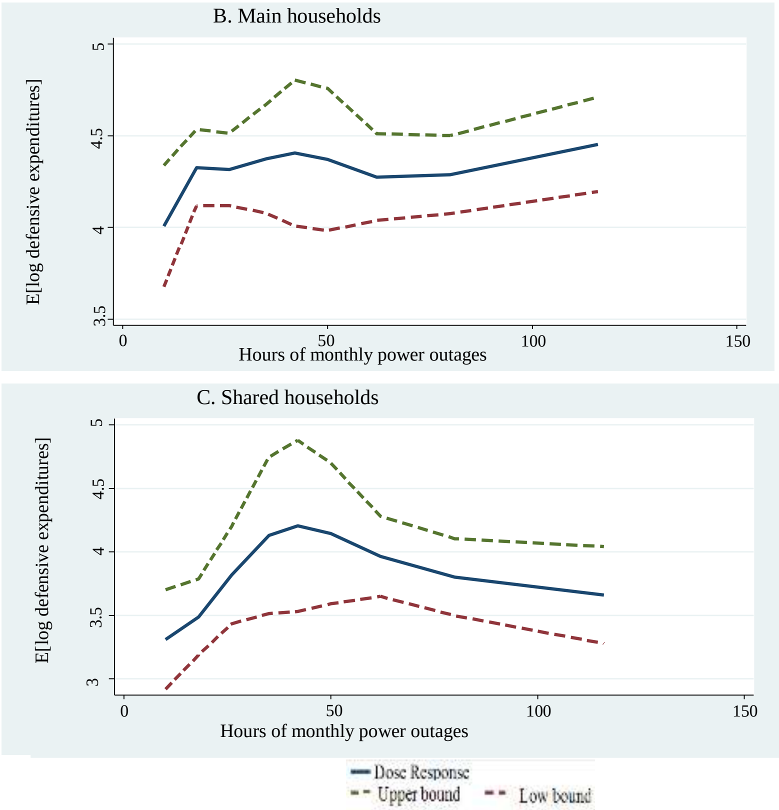


Figure 6. Dose-response functions (DRF)

A. Full sample





Confidence bounds at 0.95 % level

Appendix C: CV Scenario

WTP for improved electricity services (Amharic Version)

ኣሁን ሰለተሻሻለና በኣግባቡ ያለመቆራረጥ የሚደርስ የኤሌክትሪክ ሃይል ኣገልገሎት ለእርስዎ ቤተሰብ ያለው ጠቀሜታ እናወራለን።

እርስዎ ኣስትውለዉት እንደሆነ በተለያዩ የሀገራችን ክፍሎች ኣዲሳኣበባን ጨምሮ የኤሌክትሪክ ሃይል ኣገልገሎት መጥፋትና መቆራረጥ ኣለ። ቅድም እንደገለፁልኝ ይህ የመብራት መጥፋትና መቆራረጥ ስያጋጥም እርስዎና ቤተሰብዎን በዋናነት ከሚያሳስቦዎት ጉዳዮች **(the 1st, 2nd and 3rd responses to Q-5.5)** እንደሆኑ ነግሮውኛል። በተጨማሪ ይህ መብራት ያለኣግባብ መጥፋትና መቆራረጥ የሚፈጥረውን ችግር ለመቋቋም እርስዎና ቤተሰብዎ ሌሎች የሃይል ኣማርጮች በመፈለግ ለተለያዩ ያልተፈለጉ ወጪዎች እየተዳረጋችሁ ነው።

ለኤሌክትሪክ ሃይል ኣገልገሎት ያለኣግባብ መጥፋትና መቆራረጥ ዋነኛ ምክንያቶች የሚባሉ ያረጁና የተበላሹ ትራንስፎርመሮች መኖራቸው፤ የሃይል ማስተላለፊያና ማሳራጫ መስመሮች ሃይል የመሸከም ኣቅማቸው በማነስ ምክንያት የሚፈጠረው የቴክኒክ ብልሽትና በነዚህ መስመሮች ያለው ከፍተኛ የሆነ የሃይል ብክነት ነው።

ይህ ያልታሰበና ያልታቀደ የመብራት መቆራረጥና መጥፋት ችግር እንዲፈታና የኤሌክትሪክ ሃይል ኣገልገሎት በኣግባቡና በተፈለገው ግዜ ለሁሉም የኤሌክትሪክ ሃይል ኣገልገሎት ተጠቃሚ እንዲደርስ መንግስት የሚከተለውን ፕሮጀክት ለመተግበር ኣስቧል።

> ***"የተበላሹና ያረጁ ትራንስፎርመሮች በሌሎች ኣዳዲስ ትራንስፎርመርች እንዲተኩ፤ የሃይል ማስተላለፊያና ማሳራጫ መስመሮች ኣቅማቸውን ለማሳደግና እድሳት የሚያስፈልጋቸውን ለማሳደስ ኣስቧል።"***

ይሁንእንጂ ይህን ፕሮጀክት ለማስፈፀም ብዙ ወጪ ይጠይቃል። የዚሁ ፕሮጀክት ወጪ ለሸፈንበት የሚችል ኣንዱ መንገድ ሁሉም የኤሌክትሪክ ሃይል ኣገልገሎት ተጠቃሚ በየወሩ የተወሰነ ብር ለነዚህ የሃይል ማስተላለፍያና ማሳራጫ መስመሮች ማሻሻያ የሚሆን ከኤሌክትሪክ ሃይል ፍጆታ ክፍያ ጋር ኣብሮ እንዲከፍል ማድረግ ነው።

ይህ ክፍያ ተግባራዊ የሚሆነው መንግስት ፕሮጀክቱን በእርግጠኝነት የሚተገብረው ከሆነና ኣብዛኛው የኤሌክትሪክ ሃይል ኣገልገሎት ተጠቃሚ የፕሮጀክቱን ጠቀሜታ ኣይቶ በክፍያው ከተስማማ ብቻ ነው።

ለዚሁ ለተሻሻለና በኣግባቡ ለሚደርስ የኤሌክትሪክ ሃይል ኣገልገሎት የሚከፈለው **<u>የብር መጠን ኣብዛኛው ተጠቃሚ ሊከፍለው የሚችል ወይም ለመክፈል የተስማማው የብር መጠን</u>** ሁኖ **ለሁሉም ተጠቃሚ ተመሳሳይና <u>በየወሩ ኣንድ ኣይነት የገንዘብ መጠን</u>** ይሆናል። ይህ ክፍያ ለኤሌክትሪክ ሃይል ፍጆታ ከሚከፈለው ክፍያ የተለየ ሁኖ ግን በየወሩ በኣንድ ላይ ይከፈላሉ።

የዚህ ጥናት ዋና ኣላማ ኣዲሳኣባባ ያሉ የኤሌክትሪክ ሃይል ተጠቃሚዎች ለተሻሻለና በኣግባቡ ለሚደርስ የኤሌክትሪክ ሃይል ኣገልገሎት ያላቸውን ኣስተያየትና ፕሮጀክቱ ለተጠቃሚዎች ያለውን ጠቀሜታ ግንዛቤ ለማግኘት ነው። ልክ ቅድም እንደገለፅኩት ፕሮጀክቱ የሚተገበረው ይህ የተሻሻለና በኣግባቡ የሚደርስ የኤሌክትሪክ ሃይል ኣገልገሎት ለተጠቃሚዎች ያለውን ጠቀሜታና ፕሮጀክቱ ለማስፈፀም የሚያስፈልገው ወጪ ታይቶ ነው።

እርስዎ ሊገነዘቡት የሚገባው የገለፅኩትን ፕሮጀክት የሚተገበር ከሆነ **ላለፉት 30 ቀናት የእርስዎ ቤተሰብ ያጋጠሞት ያልታሰበና ያልታቀደ የመብራት መጥፋትና መቆራረጥ ኣይኖርም።** በተጨማሪ የእርስዎ ቤተሰብ ባልታሰበና ባልታቀደ የመብራት መቆራረጥና መጥፋቱ ምክንያት ለሌሎች የሃይል ኣማራጮች የሚያወጡት ወጪ ኣይኖርም።

7.1 እስከሁን የገለፅኩት የኤሌክትሪክ ሃይል ኣገልገሎት በተሻሻለና በኣግባቡ ለሁሉም ተጠቃሚ እንዲዳረስ የሚያደርግ ፕሮጀክት በተመለከተ ጥይቄ ኣሉዎት?

1) ኣዎ   (**Enumerator**: Ask what the question is and provide an explanation for it)
2) የለኝም

በኣሁኑ ሳዓት የፕሮጀክቱ ወጪ በእርግጠኝነት ኣይታወቅም። ስለዚህ እኔ ፕሮጀክቱ ለማስፈፀም የሚያስችልና እያንዳንዱ የኤሌክትሪክ ሃይል ኣገልገሎት ተጠቃሚ እርስዎን ጨምሮ በየወሩ ልትከፍሉት የታሰበው የገንዘብ መጠን በሁለት የወጪ ኣማራጮች እጠይቆዎታለሁ። ቀጥሎ እርስዎ በያንዳንዱ ወጪ ፕሮጀክቱ እንዲተገበር የሚደግፉት ወይም የማይደግፉት መሆኑዎን ይመልሳሉ። እነዚህ ሁለት የተለያዩ የወጪ ኣማራጮች ፕሮጀክቱን እንዲተገበር የሚያስችል ወጪ ሊሆኑ ይችላሉ ተብሎ ይታሰባል።

የሚከተሉትን ጥያቄዎች ሲመልሱ የቤተሰብዎን የወር ገቢና የተሻሻለና በአግባቡ የሚደርስ የኤሌክትሪክ ሃይል አገልገሎት ለእርስዎ ቤተሰብ ያለውን ጠቀሜታ ግምት ውስጥ ማስገባት ይኖርቦታል።

7.2 እያንዳንዱ የኤሌክትሪክ ሃይል አገልገሎት ተጠቃሚ ቤተሰብ የእርስዎን ጨምሮ **በየወሩ _______ብር** ለተሻሻለና በአግባቡ ለሚደርስ የኤሌክትሪክ ሃይል አገልገሎት የሚዉል ክፍያ የምትከፍሉ ከሆናችሁ ፕሮጀክቱ እንዲተገበር እርስዎ ይደግፉታል?

1) አዎ
2) አልደግፈዉም (**SKIP TO Q-7.4)**

7.3 እያንዳንዱ የኤሌክትሪክ ሃይል አገልገሎት ተጠቃሚ ቤተሰብ የእርስዎን ጨምሮ **በየወሩ _______ብር** ለተሻሻለና በአግባቡ ለሚደርስ የኤሌክትሪክ ሃይል አገልገሎት የሚዉል ክፍያ የምትከፍሉ ከሆናችሁ ፕሮጀክቱ እንዲተገበር እርስዎ ይደግፉታል?

1) አዎ (**SKIP TO Q-7.6)**
2) አልደግፈዉም (**SKIP TO Q-7.6)**

7.4 እያንዳንዱ የኤሌክትሪክ ሃይል አገልገሎት ተጠቃሚ ቤተሰብ የእርስዎን ጨምሮ **በየወሩ _______ብር** ለተሻሻለና በአግባቡ ለሚደርስ የኤሌክትሪክ ሃይል አገልገሎት የሚዉል ክፍያ የምትከፍሉ ከሆናችሁ ፕሮጀክቱ እንዲተገበር እርስዎ ይደግፉታል?

1) አዎ (**SKIP TO Q-7.6)**
2) አልደግፈዉም

WTP for improved electricity services (English Version)

Now we will discuss how valuable an improved electricity service is to your household.

As you may be aware of, there are electric power outages in many parts of Ethiopia, including in Addis Ababa. Previously, you explained to me that your household's major concerns when power outages occur are: **(the 1st, 2nd and 3rd responses to Q-5.5).** And, due to the electric power outages, you or other members of your household spend your resources on alternative sources of energy to cope with the poor electricity service.

The main causes of power outages are low capacity of the transmission and distribution lines, aged and poor physical conditions of transformers, and wastage of power due to high loss along these lines. To improve the reliability of electricity services at the transmission and distribution lines, the Ethiopian government aims to rehabilitate, upgrade, and replace equipment that is in poor physical condition so that you and other households will not face unplanned electricity outages due to problems related to the transmission and distribution lines.

However, implementing this project will involve costs to the government. One way to cover these costs is to charge households a fixed monthly amount for rehabilitating and upgrading the transmission and distribution lines so that every household can enjoy improved electricity services. Please note that the payment for upgrading the transmission and distribution lines will be fixed and different from what you pay for the monthly electricity consumption, though both will be paid together monthly.

The objective of this study is to assess whether people in Addis Ababa support the project. Implementation of the project depends on how much value households place on improved electricity services assuming that the government would make a commitment to permanently reduce the service interruption due to problems at the transmission and distribution lines. It will be implemented by the government if a majority of the people in Addis Ababa support it. The fixed monthly amount will be the amount that a majority support and will be the same for all households.

Also, remember that if the project is implemented, the Q**- 5.3.3** hours of power interruptions that your household experienced in the last 30 days will be zero and your household will **not** incur any costs for on alternative sources of energy to cope with the power outages.

7.1 Do you have any questions regarding the situation I have described so far?

1) Yes (**Enumerator**: Ask what the question is and provide an explanation for it)
2) No

- *Because the exact cost of the project is not presently known, we will ask you to vote on two different costs for the project. These costs represent the range within which the actual cost should fall. In what follows, you will vote for or against each alternative. You are asked how you would* *vote if the good could be provided at one of the two costs. This is followed directly by a second question about how you would vote if the good could be provided at the second of the two costs*.

- *When answering the following questions, consider your household income and how your household would value an improved electricity service.*

7.2 Do you support implementation of the project if **every household** in Addis Ababa, including your household, has to pay (*initial bid*) birr **monthly** for improving the electricity services?

1) Yes
2) No (**SKIP TO Q-7.4)**

7.3 If **yes to Q-7.2**, do you support implementation of the program if **every household** in Addis Ababa, including your household, has to pay *(higher second bid)* birr **monthly** for improving the electricity services?

1) Yes (**SKIP TO Q-7.6)**
2) No (**SKIP TO Q-7.6)**

7.4 If **No to Q-7.2**, do you support implementation of the program if **every household** in Addis Ababa, including your household, has to pay *(lower second bid)* birr **monthly** for improving the electricity services?

1) Yes (**SKIP TO Q-7.6)**
2) No

Chapter II

Do Consumers Respond to Marginal Prices of Electricity under Increasing Block Tariff?

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Abstract

In developing countries, electric and water utilities commonly use increasing block tariff (IBT) as a tool to encourage resource conservation, recover costs, and subsidize low-income consumers. However, it is not clear whether consumers actually respond to marginal prices under IBT. We empirically analyze whether marginal price in an IBT influences residential electricity demand, by combining administrative monthly electricity bill records with a detailed survey of sample households. Results from a bunching analysis and an Arellano-Bond estimator show that prices of electricity do not significantly affect monthly electricity consumption. The finding highlights that consumers do not respond to marginal prices under IBT when electricity price is low or if they are unaware of the pricing schedules and have difficulty in understanding how their bills are computed in such tariff structures. This, in turn, has severe implications for the efficacy of the policy objectives of IBT.

JEL Classification: C23, D12, L11, L94, Q21

Key-words: Residential electricity demand, shared connections, increasing block tariff, bunching analysis, panel data

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1. Introduction

Prices of electricity can convey essential information regarding scarcity, affordability and sustainability. In developing countries, increasing block tariff (IBT) is the most popular tariff structure for pricing electricity (Boland and Whittington, 2000; Briceño-Garmendia and Shkaratan, 2011; Whittington et al., 2015).[1] In an IBT, the unit price rises with each sequentially defined consumption block.[2] This tariff scheme is designed with the intention that the lower prices will provide subsidies to the poor while the higher prices will encourage conservation and recover costs of providing the services. However, the IBT might not provide the intended subsidy to the poor, because poor households either are not connected to the service or share a connection (see, e.g. Whittington et al., 2015; Nauges and Whittington, 2017).

The IBT structure hinges on the assumption that consumers respond to changes in marginal prices for each consumption block. In reality, however, consumers might make their consumption decisions with limited information, attention and cognitive abilities. Empirical evidence regarding behavior under non-linear pricing schedules of electricity, water, and income tax rates indicate that people respond to average price or other perceived price, instead of marginal price, because obtaining and using information is costly (see, e.g., Shin, 1985; Nieswiadomy and Molina, 1991; de Bartolome, 1995; Saez, 1999; Liebman and Zeckhauser, 2004; Borenstein, 2009; Binet et al., 2013; Ito, 2014). This response to average or perceived price, rather than to marginal price, could make the increasing block tariff unsuccessful in achieving its policy objectives. Some of the studies (e.g., Ito, 2014; Shin, 1985; Binet et al., 2014) suggest providing consumers with information about the marginal prices they pay on their service bills to check whether they respond to the correct marginal prices.

The key question remaining, then, is whether consumers respond to marginal price if they receive marginal price information in their bill. In this paper, we investigate whether marginal prices in an increasing block tariff affect residential electricity demand, using micro-level data in a context where consumers receive marginal price information in their bill. We further probe the main correlates of residential electricity demand and compare monthly electricity consumption between shared and private connections.

[1] IBTs also have been widely used in the United States, Japan and other developed countries for electricity and water in the residential sector (Whittington, 1992; Monteiro and Roseta-Palma, 2011; Sibly and Tooth, 2014; Suárez-Varela et al., 2015). See also Banerjee et al. (2010) for water tariffs in Africa.
[2] We use block tariffs, block pricing schedules and non-linear pricing schedules interchangeably in this paper.

Understanding consumers' response to change in electricity prices is crucial in designing appropriate pricing policy, forecasting demand and planning future generating capacity. Consequently, many studies have estimated electricity demand. The economic literature for electricity demand dates back at least to the work of Houthakker (1951), who analyzed residential electricity consumption in the United Kingdom. Empirical estimation of residential electricity demand, however, has received much attention since the 1970s energy crisis, with rising concerns for electricity conservation and global warming (see, e.g., Halvorsen, 1975; Espey and Espey, 2004; Shi et al., 2012). Although there is a general consensus in the literature that price elasticity of demand for electricity is negative and inelastic, its magnitude varies from -2.5 to -0.004 with different functional forms and estimation methods, country and period of analysis (short-run and long-run). For review literature, see Espey and Espey (2004) and Labandeira et al. (2017).

The present study analyzes response to marginal prices under IBT in a developing country context, in this case, Ethiopia. Despite the growing demand and huge government investment in the power sector in Ethiopia, studies that investigate electricity demand using micro-level data are scarce. Most of the studies emphasize household energy choice and energy demand in general (see, e.g., Gamtessa, 2003; Alem et al., 2013). The only relevant published studies of which we are aware are Guta et al. (2015) and Gabreyohannes (2010), who analyze the demand for residential electricity at the macro level using time series models. The studies find price elasticity of demand within the range of -1.14 to -0.173. Because residential electricity consumers are heterogeneous, using micro-level data can better reflect consumers' behavior and can add detailed understanding of consumers' responses. As Dubin and McFadden (1984) indicate, micro-level data avoids misspecification error that is caused by aggregation bias from using aggregate electricity consumption and prices.

An important feature of the present study is that the consumers in our study receive unusually detailed information about consumption and prices. The electric utility provides detailed billing information to its consumers in their monthly bill, including marginal prices along with quantity consumed and how consumption in each block translates into the monthly bill (see Figure 1). However, there is no previous evidence on whether or not the consumers respond to their marginal prices. Another important feature is the presence of many shared electricity connections. This could make it difficult to control for aggregate consumption by multiple households. Moreover, the consumption block prices, which range from 0.27 birr to 0.69 birr per kWh, have been stable in nominal terms since 2006 despite the high inflation, particularly in 2008.[3] The real prices of the consumption blocks as of 2016 had declined by about 20 times from what they were in 2006 (see Figure 3).[4] If price is low, households may not find it worthwhile to adjust their electricity use to the prices. Also, this stable nominal electricity price has significant welfare implications given that a large portion of households in the country are still using alternative fuels (e.g., kerosene, Liquefied Petroleum Gas, charcoal, and firewood) whose prices increased during the same period. Overall, examining sensitivity to marginal prices in the context of Ethiopia has interesting implications for the policy objectives of IBT: electricity conservation, distribution of subsidies, and generating sufficient revenue for operation, maintenance and investment.

Our empirical approach to analyzing consumers' responses to marginal price is based on a non-parametric approach (bunching analysis) and a parametric approach (the Arellano-Bond estimator, which is also called the Difference Generalized Method of Moments). The availability of a large number of administrative monthly electricity billing records allows us to estimate bunching around the kink points and to compare the results with demand model estimates. The general idea of the bunching estimation is to construct a measure of excess mass locally at the kink points by comparing this to the counterfactual density that would have occurred in the absence of the kink points.[5] According to the bunching approach (Saez, 2010; Chetty et al., 2011), we should find households bunching in consumption distribution at the kink points if marginal price in an increasing block tariff affects monthly electricity consumption behavior. However, perfect bunching may not be observed, because households might not perfectly control their consumption, e.g., when connections are shared or when consumers are subject to power outages.[6] In the absence of perfect control, a kink point in the increasing block pricing should generate a hump in the consumption distribution or a clustering around the kink points. On the other hand, there might not be evidence of bunching if households are inattentive and fail to understand the non-linear pricing schedule and, instead, respond to other perceived prices, such as average prices, or if they respond to marginal prices with near-zero elasticity (Ito, 2014).

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[3] Birr is the Ethiopian currency, with an exchange rate of 1 USD to approximately 21 Ethiopian birr in May 2016 (at the time of the survey).

[4] In July 2008, for example, food price inflation in Ethiopia soared to 92% (Central Statistics Agency, 2008).

[5] A kink point is the amount of electricity use/consumption at which the marginal price changes discretely, marking the end of one tariff bracket and the beginning of the next.

[6] Power outages are common in Ethiopia. For instance, daily hours of electricity interruption data from the Ethiopian Electric Utility for the period July 2015 to June 2016 shows an average duration of 1 hour and 9 minutes for a given power outage at the distribution lines level in Addis Ababa – the capital city of Ethiopia.

In the parametric approach, we estimate demand for residential electricity using a Difference Generalized Method of Moments (Difference GMM). Our demand estimation follows the Nordin (1976) marginal price specification. Since the work of Taylor (1975) and Nordin (1976), the marginal price specification has been modified to incorporate a *difference* variable in order to account for the fact that not every unit is charged at the marginal price in a block tariff rate. The difference variable (also called the rate structure premium) is the actual bill paid by a consumer minus what the consumer would have paid if all the electricity use had been charged at the marginal price. A key challenge in estimating residential electricity demand under IBT is the endogeneity of the price variables. The marginal price and the difference variable are endogenous due to the nature of the price structure itself. Both the block price and the quantity of use are simultaneously determined. To address the endogeneity problem, we apply the Difference GMM estimator (Arellano-Bond estimator). For robustness checks of our results, we use average price and total bill as alternative price information to which consumers could possibly respond. In addition, we use a static panel data model with an instrumental variable approach.

The analysis combines monthly electricity bills from the Ethiopian Electric Utility (EEU) with a detailed survey of households that use electricity from 715 randomly selected sample electric meters in Addis Ababa (the capital city of Ethiopia). Due to the presence of a high number of shared electricity connections, all of the variables of interest in the demand analysis are measured and aggregated at the electric meter level instead of at the household level. Survey data are also collected at the electric meter level. In our demand model, we treat all individuals who use electricity from a given electric meter as a household unit for purposes of decisions regarding electricity consumption. Furthermore, we had access to the entire residential electricity billing records of the city – over 348,000 customers – which is primarily used for the bunching analysis.

Our findings show a lack of evidence of bunching at the kink points of the monthly electricity consumption distribution. Similarly, the estimated coefficient on marginal price from the regression model is insignificant, though it keeps its expected negative sign and magnitude. This reveals that marginal price in an increasing block tariff does not significantly affect monthly electricity consumption. The size of the stock of electric appliances owned, income, price of alternative fuels (mainly firewood and LPG), and number of individuals who use electricity from a given connection are significantly associated with monthly electricity consumption. We also find significant differences in monthly electricity consumption between private and shared connections. The absence of a significant effect of marginal price on monthly electricity consumption is likely due to the heavily subsidized electricity prices. Another possible explanation is that households might be unaware of the existing block price structure or might have cognitive difficulty in understanding the block price and how their monthly electricity consumption translates into monthly bills in such a pricing structure. It is also likely that the presence of shared electricity connections and power outages are preventing consumers from responding to the marginal prices.

Our study contributes to the empirical literature on estimation of residential electricity demand under block tariff which aims at analyzing the relevance of this pricing policy. We note the discussion in that literature concerning whether average price or marginal price should be used in the demand analysis.[7] In addition, there are issues related to identification due to the price structure itself. Considering the methodological issues, our study uses a non-parametric approach – bunching analysis – as a supplementary approach to identify behavioral responses to marginal price and to estimate the price elasticity of demand, and then compares the bunching estimates with results from the demand model estimates.

The remaining parts of the paper are organized as follow. Section 2 describes the theoretical framework and the estimation methodology. Section 3 provides institutional background and the data. Section 4 presents the empirical results. Section 5 concludes the chapter.

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[7] In the literature, there is an ongoing discussion on whether marginal price or average price specification should be used in estimating demand under block pricing schedules. Some studies use a marginal price specification (e.g., Henson, 1984; Garbacz, 1984). Other studies use an average price specification (e.g., Tiwari, 2000; Boogen et al., 2014). This is based on the argument that a consumer's choice depends on limited information rather than on the full information that is assumed in the marginal price specification. If consumers are unaware of the pricing structure or have difficulty in understanding the structure and how their consumption translates into the electricity bill, they may be more likely to respond to average price, which requires only knowledge of the total bill and consumption. In that case, average price should be used in estimating the demand for electricity (see, e.g., Ito, 2014; Shin, 1985; Binet et al., 2014). Still other literature (see, e.g., Shin, 1985; Nieswiadomy and Molina, 1991; Binet and Carlevaro, 2013) uses a perceived price specification, which is a function of both marginal and average prices. According to Shin (1985), the perceived price (P_i) to which an imperfectly informed consumer responds could be expressed by the formula: $P_i = MP_i\left(\frac{AP_i}{MP_i}\right)^k$. The ratio $\frac{AP_i}{MP_i}$ is designed to capture the effect of the difference variable on price perception and k is expected to be non-negative. The consumer responds to marginal price MP_i when the perception parameter k is equal to zero and to average price AP_i when $k = 1$. As $MP_i > AP_i$ under increasing block tariff, the perceived price lies between average and marginal price if $0 < k < 1$. The case $k > 1$ corresponds to a perceived price above the average price. The perceived price can be re-written as: $\ln(P_i) = (1-k)\ln(MP_i) + kln(AP_i)$. A meta-analysis of residential electricity demand by Espey and Espey (2004) shows that marginal price is by far the most common choice of researchers.

2. Theoretical Framework and Estimation Method

2.1 Bunching Analysis

We analyze households' response to marginal prices in an increasing block pricing schedule using the bunching technique developed by Saez (2010) and Chetty et al. (2011). Following Saez (2010), we assume that, with a constant marginal price of electricity τ_1 (without kink points), electricity consumption is distributed according to a smooth density distribution $h_0(E)$. The presence of a kink point at a consumption level, K, where the marginal price increases from τ_1 to τ_2, such that the marginal price is τ_2 for consumption $E > K$ and τ_1 for $E \leq K$, transforms the consumption distribution into $h(E)$ as households adjust their electricity use to the increase in marginal price. This kink point produces bunching (a spike) in the consumption distribution at K for households whose consumption was falling into a segment $[K, K + \Delta E]$ under the constant marginal price scenario. That is, the households given by $B(\Delta E) = \int_K^{K+\Delta E} h_0(E)dE$, which were in the dominated region $[K, K + \Delta E]$, are better off moving to the bunching point K after the marginal price increases. However, households farther up in the consumption distribution, $E > K + \Delta E$, do not move to the kink point and households originally located at or below the kink point do not change their behavior, i.e., the consumption distribution for $E \leq K$ remains unaffected, $h(E) = h_0(E)$.

Following the formula by Saez (2010) and Chetty et al. (2011), we use the number of households bunching at the kink point to identify the price elasticity. The price elasticity of demand for electricity is defined as the percentage of electricity consumption E that is due to a one percent increase in marginal price locally at K.

$$e(K) = \frac{\%\Delta E}{\%\Delta \tau} = \frac{\Delta E / K}{\Delta \tau / \tau_1}. \tag{2.1}$$

Now it is possible to relate price elasticity $e(K)$ to the number of households bunching at the kink point:

$$B(\Delta E) = \int_K^{K+\Delta E} h_0(E)dE = \Delta E h_0(\xi) \quad for\ some\ \xi \in [K, K + \Delta E]. \tag{2.2}$$

Inserting Equation (2.2) into (2.1) and rearranging the terms gives:

$$e(K) = \frac{B(\Delta E)}{h_0(\xi)\ K\ \Delta \tau / \tau_1}. \tag{2.3}$$

For small marginal price changes ($\Delta\tau = d\tau \ and \ \Delta E = dE$), where $\xi \to K$, the number of households that bunch around the kink are $B(dE) = dEh_0(K)$. Thus, we have[8]

$$\lim_{\Delta\tau,\Delta E\to 0} e(K) = \frac{B(dE)}{h_0(K)\,K\log(\tau_2/\tau_1)} \tag{2.4}$$

In Equation (2.4), the kink point (K) and the marginal prices for consumption below the kink (τ_1) and above the kink (τ_2) are directly observable. However, the mass of households bunching at the kink (B) and the counterfactual density $h_0(K)$ – the density in the absence of any kink – need to be estimated.

The key to bunching estimation is to construct the counterfactual distribution of the monthly electricity consumption. The counterfactual density is estimated by excluding the data near the kink – the omitted region – and then estimating a smooth function through the values of the other data. In other words, the number of observations surrounding the threshold is compared to a counterfactual that is constructed using observations farther away from the threshold. Saez (2010) uses the actual (observed) distribution to the left and to the right of the kink to construct a counterfactual for the amount of mass that should be at the kink. However, Chetty et al. (2011) estimate the counterfactual density directly by local polynomial regression. The two approaches provide similar results. In this paper, we follow the approach developed by Saez (2010) to estimate the excess mass B at the kink points and the counterfactual density $h_0(K)$.

For a given empirical distribution $h(E)$, we construct an electricity consumption band around the kink $[K-\delta, K+\delta]$ and two surrounding consumption bands: $[K-2\delta, K-\delta]$ and $[K+\delta, K+2\delta]$. The parameter δ measures bandwidth, which is chosen by visually looking at the graph. This is needed to capture bunching and can be moved around for robustness checks. Then, the estimate of excess bunching is given by:

$$\begin{aligned} B &= \int_{K-\delta}^{K+\delta} h(E)dE - \int_{K-2\delta}^{K-\delta} h(E)dE - \int_{K+\delta}^{K+2\delta} h(E)dE \\ &= H - H_- - H_+. \end{aligned} \tag{2.5}$$

Empirically, the density of the lower band $h(K)_-$ can be estimated as a fraction of households in $[K-2\delta, K-\delta]$ divided by δ. Similarly, the density of the upper band $h(K)_+$ can be estimated as the fraction of households in $[K-2\delta, K-\delta]$ divided by δ. The number of households in each of the three bands denoted by $\widehat{H}$, $\widehat{H_-}$ and $\widehat{H_+}$ is estimated by regressing (simultaneously) a dummy variable for belonging to each band on a constant in the

[8] When $\Delta\tau$ is small, $\frac{\Delta\tau}{\tau_1} \approx \log\left(1+\frac{\Delta\tau}{\tau_1}\right) = \log\left(1+\frac{\tau_2-\tau_1}{\tau_1}\right) = \log\left(\frac{\tau_2}{\tau_1}\right)$.

sample of households belonging to any of those three bands. We then calculate $\widehat{h}\,(K)_{-} = \frac{\widehat{H_{-}}}{\delta}$, $\widehat{h}\,(K)_{+} = \frac{\widehat{H_{+}}}{\delta}$, and $\widehat{B} = \widehat{H} - (\widehat{H_{-}} + \widehat{H_{+}})$ to estimate price elasticity.

The standard errors of the price elasticity of demand are estimated using a delta method. Alternatively, a bootstrap method can be used to compute the standard errors. The choice of the bandwidth δ matters when estimating bunching. Too small (large) δ underestimates (overestimates) the amount of bunching at the kink points; hence, it affects the magnitude of the price elasticity accordingly.

2.2 Residential Electricity Demand Model

In this sub-section, we discuss a theoretical framework for residential electricity demand analysis based on household production theory (Becker, 1965; Deaton and Muellbauer, 1980). We specifically follow the application of household production theory to electricity demand analysis by Dubin (1985) and Filippini (1999). According to the household production theory, households purchase goods from the market to serve as an input in the production process of a commodity that enters the household utility function. In the case of electricity demand analysis, a household purchases both electricity and a stock of electric appliances to produce a composite electricity service commodity, which includes lighting, cooking, heating, etc. The production function of the composite commodity for electricity services (ES) can be expressed as:

$$ES = f(kWh, App), \tag{2.6}$$

where kWh is electricity use in kWh and App is stock of electric appliances. The amount of electricity services produced depends on the amount of electricity purchased and the quantity of the stock of electric appliances.

The composite commodity for electricity services (ES) appears as an argument in the household utility function together with the numeraire good X and a vector of other variables (Z) that determine the household's preference. The household maximizes the following utility function:

$$\begin{aligned} &Max\ U = U(ES, X; Z\ ) \\ &subject\ to{:}\ P_{ES}ES + X = M. \end{aligned} \tag{2.7}$$

In this case, M is household income; P_{ES} is the price of the composite electricity services; and the price of the numeraire good X is set to one. The household is assumed to have a utility function with the usual properties of differentiability and curvature. Solving the optimization problem provides the following derived demand for electricity and stock of electric appliances.

$$Kwh^{*} = g\left(P_E, P_{App}, M; Z\right) \quad (2.8)$$

$$App^{*} = h\left(P_E, P_{App}, M; Z\right), \quad (2.9)$$

where P_E is the price of electricity and P_{App} is the price of the stock of electric appliances.

Demand for residential electricity is derived from the demand for services such as lighting, cooking, heating and cooling using electric appliances. In the short run, the demand for electricity is constrained by the existing stock of electric appliances. Therefore, electricity demand in the short run depends on the already available stock of electric appliances and the utilization rate (intensity and frequency of use) of the appliances, which in turn hinge on the price of electricity, income, price of alternative fuels and some household socio-demographic variables. On the other hand, in a long-run demand analysis, households adjust their stock of appliances to more electricity-efficient appliances. In this paper, we estimate residential electricity demand from a short-run perspective in which the stock of electric appliances is fixed. This is because we have data on households' stock of electric appliances at only one point in time during the survey period. We do not have data on the profile of the stock of appliances either before or after the survey period.

In Equation (2.8), the price of electricity (P_E) enters as an argument in the demand function. The price under a block pricing schedule, in which households face a piecewise linear budget constraint, is related to the standard budget constraint as follows. A household budget constraint in increasing block rate pricing with j blocks, $j-1$ kink points (switching points), P_j block price and F fixed charge (services charge) can be written as:

$$\begin{cases} F + P_1\text{kWh} + \text{X} = \text{M} & \text{if } 0 < \text{kWh} < K_1 \\ F + P_1K_1 + P_2\text{kWh} + \text{X} = \text{M} & \text{if } K_1 < \text{kWh} < K_2 \\ \vdots & \\ F + P_1K_1 + P_2(K_2 - K_1) + \cdots + P_{j-1}\left(\text{kWh} - K_{j-2}\right) + \text{X} = \text{M} & \text{if } K_{j-2} < \text{kWh} < K_{j-1} \\ F + P_1K_1 + P_2(K_2 - K_1) + \cdots + P_{j-1}\left(K_{j-1} - K_{j-2}\right) + P_j\left(\text{kWh} - K_{j-1}\right) + \text{X} = \text{M} & \text{if } kW\text{h} > K_{j-1}, \end{cases} \quad (2.10)$$

where kWh is quantity of electricity used, the composite good X is a numeraire good such that its price is set to one, $(K_1, \dots, K_{j-1})$ are the kink points or quantities at which change in marginal prices occurs, and M is household income.

According to Nordin (1976), Equation (2.10) can be rewritten in a compact form similar to the standard budget constraint:

$$P_j\text{kWh} - \left\{(P_2 - P_1)K_1 + (P_3 - P_2)K_2 + \cdots + \left(P_{j-1} - P_{j-2}\right)K_{j-2} + \left(P_j - P_{j-1}\right)K_{j-1}\right\} + \text{X} = \text{M} - \text{F}. \quad (2.11)$$

Again, Equation (2.11) is equivalent to the following more compact expression.

$$P_j\, kWh \;+\; X = (M - F) - Diff = \widetilde{M}. \tag{2.12}$$

$$Diff = -\sum_{i=2}^{j} (P_i - P_{i-1})K_{i-1} = Bill - P_j \text{ kWh}, \tag{2.13}$$

where P_j is marginal price of electricity (the price of the last unit, which is equivalent to the price of the block where the consumption ends up), while $Bill$ is electricity bill (excluding fixed charge) for a given period of consumption.

The term $Diff$ is referred to as the *Nordin's difference* or the *rate of structure premium*, which is defined as the actual bill paid by a household minus what the household would have paid if all consumption units had been charged at the marginal price. In an increasing block pricing schedule, the difference takes a negative value. It represents an implicit subsidy (an in-kind electricity subsidy). As the infra-marginal rate increases, the difference becomes a larger negative value (i.e., a smaller positive value). This causes a reduction in the implicit subsidy, which in turn causes a decrease in electricity use.[9] $\widetilde{M}$ is the virtual income, which is the actual household's income plus the implicit subsidy from consuming at higher consumption blocks. Using Equation (2.13), we can also derive the relationship between marginal price (P_j=MP) and average price (AP), which is the amount of the bill divided by the quantity consumed. Formally, it is expressed as follows:

$$AP = \frac{Bill}{kWh} = \; MP + \frac{Diff}{kWh} \tag{2.14}$$

In a block pricing structure, not every unit consumed is charged at the marginal price. The Nordin's difference is therefore introduced to account for this. The average price in a block pricing schedule differs from the marginal price by the rate structure premium. It is lower than the marginal price in increasing block pricing because $Diff < 0$. Because we are interested in response to marginal prices, we focus our analysis on the marginal price specification, which includes the Nordin's difference. However, for comparison, we use the average price and the monthly bill alternatively in our regression estimations.[10]

Our econometrics approach for the demand model is based on panel data analysis. Following the literature on demand for electricity (see, e.g., Houthakket et al., 1974, Shin,

[9] In the case of a declining block rate, the difference has positive values, representing an implicit lump sum tax which must be paid to purchase an additional unit at lower marginal price.

[10] In our data, marginal price is strongly correlated with the Nordin's difference ($\rho = -0.83$), average price ($\rho = 0.91$), and monthly electricity bill ($\rho = 0.61$).

1985; Alberini and Filippini, 2011), we employ a dynamic panel data model specification.[11] We use the most commonly used double logarithmic functional form to compare our findings with other studies. This functional form also makes it easy to interpret the price elasticity of demand in terms of percentage.

The dynamic panel data model assumes a simple partial adjustment process such that the change in actual demand between any two periods t, $\ln(kWh_{it})$, and $t-1$, $\ln(kWh_{it-1})$, is some fraction (λ) of the difference between the actual demand in period $t-1$ and the optimal demand in period t, $\ln(kWh^{*}{}_{it})$. This can be formally expressed as:

$$\ln(kWh_{it}) - \ln(kWh_{it-1}) = \lambda[lnkWh^{*}{}_{it} - \ln(kWh_{it-1})], \qquad 0 < \lambda < 1, \quad (2.15)$$

where λ represents the speed of adjustment toward the optimal (desired) consumption and $\ln(kWh_{it-1})$ provides information on persistence of the consumption habit.

The optimal level of monthly electricity consumption is unobservable, whereas the current $\ln(kWh_{it})$ and previous $\ln(kWh_{it-1})$ monthly consumption levels are observable. Following Equation (2.8) and expressing the natural logarithm of the optimal consumption level as a linear function of own price $ln(P_{it})$, income $ln(M_{it})$ and a vector of other explantory variables Z_{it}, and then substituting this function for the optimal consumption level and rearranging the terms in Equation (2.15), provides the following dynamic regression equation.

$$\ln(kWh_{it}) = \beta_0 + \beta_1\ln(kWh_{it-1}) + \beta_2\ln(P_{it}) + \beta_3 ln(M_{it}) + Z_{it}\gamma + \eta_i + \theta_t + \varepsilon_{it}, (2.16)$$

where β_0, β_1, β_2, β_3, γ are parameters to be estimated; η_i and θ_t are electric meters and time fixed effects; and ε_{it} is the error term, which could be serially correlated.

In the present study, variables except price and monthly electricity consumption are time invariant because they are collected only once during the survey period. We use lagged price variables rather than contemporaneous prices based on the assumption that, if households monitor their electricity consumption, it is most likely through the monthly bills that they receive at the end of the consumption period. Besides, our price specification includes both marginal price and the Nordin's difference. Therefore, the dynamic panel data model in Equation (2.16) is modified to the following expression:

$$\ln(kWh_{it}) = \alpha_0 + \alpha_1\ln(kWh_{it-1}) + \alpha_2\ln(MP_{it-1}) + \alpha_3 diff_{it-1} + Z_i\delta + \theta_t + v_{it}, \quad (2.17)$$

[11] In non-linear pricing contexts, a discrete/continuous choice (DCC) model also has been applied to labor supply under non-linear taxation (Burtless and Hausman, 1978; Hausman, 1985; Moffitt, 1986) and water demand under block pricing (Hewitt and Haneman, 1995; Olmstead et al., 2007; Szabo, 2015). The model accounts for joint choice of block pricing and the amount consumed within that block. It is based on the assumption that consumers know their marginal prices.

where $v_{it} = \eta_i + \varepsilon_{it}$.

The lagged consumption $\ln(kWh_{it-1})$ is correlated with the composite error term $v_{it,}$ which contains the unobservable heterogeneity, by construction. As a result, the standard linear panel data model (ordinary least squares, random effects, and fixed effects) estimators lead to biased and inconsistent estimates.[12] To address the problem, we apply an instrumental variable approach that exploits the panel dimension of the data and used two period lagged values of the endogenous explanatory variables as instruments. This is what is known in the literature as the Arellano and Bond estimator or Difference GMM estimator (Arellano and Bond, 1991). This estimation approach takes the first differences of Equation (2.17) to eliminate the individual effects and time-invariant observable variables and provides the following specification:

$$\Delta\ln(kWh_{it}) = \alpha_1\Delta\ln(kWh_{it-1}) + \alpha_2\Delta\ln(MP_{it-1}) + \alpha_3\Delta diff_{it-1} + \Delta\theta_t + \Delta v_{it}. \qquad (2.18)$$

In the case of highly persistent data, lagged variables in levels are likely to be weak instruments for contemporaneous differences and potentially lead to biased estimates (Blundell and Bond, 1998).[13] In this paper, following the approach in Bond (2002), we check for persistence of the key variables: monthly electricity consumption and lagged price variables. However, we do not find highly persistent estimates (see Table 6). We therefore apply the Difference GMM estimator that uses two period lagged levels as instruments for the contemporaneous differences. The validity of the instruments can be verified using Hansen's Test. Since the lagged price variables could be endogenous, we instrumented them by their two period lagged values.

3. Institutional Background and Data

In Ethiopia, electricity services for various activities are provided by a single public enterprise – the Ethiopian Electric Utility (EEU).[14] As of 2016, the country has a total of 4260

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[12] Because, by construction, $\ln(kWh_{it})$ is correlated with η_i, $\ln(kWh_{it-1})$ is also correlated with η_i. As a result, OLS is biased and inconsistent. Though the within transformation (fixed effects) eliminates η_i, $\ln(kWh_{it-1}) - \ln(kWh_{i,-1})$ is correlated with $\varepsilon_{it} - \varepsilon_i$ through ε_i. It is consistent when $T \to \infty$ but not when $N \to \infty$, where $\ln(kWh_{i,-1}) = \sum_{t=2}^{T} \frac{\ln(kWh_{it-1})}{T-1}$ and $\varepsilon_i = \sum_{t=1}^{T} \frac{\varepsilon_{it}}{T}$.

[13] If the coefficients are highly persistent (close to one or random walk), the lagged levels are weak instruments. In such a case, it is appropriate to apply the System GMM estimator by Blundell and Bond (1998), which uses lags of the endogenous explanatory variables expressed in first differences as instruments for contemporaneous levels and lags of the variables in levels as instruments for contemporaneous differences.

[14] In 2013, the Ethiopian Electric Power Corporation (EEPCo) was unbundled into two public enterprises – Ethiopian Electric Power (EEP) and the Ethiopian Electric Utility (EEU) – with the aim of providing efficient, reliable and quality services. EEP is responsible for construction and operation of power generation and

MW installed power generating capacity, mainly from hydropower, and the capacity is expected to reach 10,000 MW in the coming few years when the construction of the Grand Ethiopian Renaissance Dam is completed (Ethiopian Electric Power, 2016). Given the country's large potential of renewable sources of energy (hydropower, geothermal, wind and solar), the Ethiopian government is undertaking huge investments in the power sector to meet the growing domestic demand, for energy transition, and for export to neighboring countries. Access to electricity services in the country has increased from 41% of the population in 2010 to 54% in 2014 and is planned to reach 90% in 2020 as part of the Growth and Transformation Plan (GTP-II, 2015-2020).[15] This figure indicates that most of the energy needs in Ethiopia still are fulfilled by other fuels, mainly traditional biomass (firewood, charcoal, crop residues and animal dung).

As of 2015, the Ethiopian Electric Utility had around 2.58 million customers, including residential, commercial and industrial electricity customers. A customer is equivalent to a unit receiving electricity services from an electric meter. The majority of the customers are residential customers and are concentrated around the capital, Addis Ababa. Residential electricity customers use electricity for household activities. This accounts for about 33% of total electricity consumption in the country (EEU, 2015). Residential customers pay their consumption bills monthly at the end of their consumption periods.[16] This follows a process of bill preparation that involves meter reading at the premise of the customer, recording the reading into a database, and preparing and sending out the monthly bill to local offices where customers collect and pay their bills at predefined dates. This post-paid billing system is prone to billing irregularities and unpaid bills (Smith, 2004).

The residential monthly electricity bill contains detailed information such as consumption period, total consumption in kWh, consumption in each block and the corresponding prices, service charge, and the total amount to be paid. It also shows how consumption in each block and total consumption translates into the monthly bill (see Figure 1).

< Table 1 here >

Table 1 displays the increasing block price schedule of residential electricity service in Ethiopia. The increasing block tariff consists of consumption block based tariff and service charges. Table 1, Panel A presents the seven consumption blocks and their corresponding unit

transmission, while the EEU is responsible for construction and operation of power distribution and for electricity sales.

[15] The connection fee, which involves labor and material cost of wiring to the house and installation of an electric meter, is not fixed. It depends on the distance to the nearest distribution line and can go up to 1,700 birr.

[16] The utility also has residential and commercial customers in Addis Ababa with pre-paid electric meters.

prices. The unit price of electricity ranges from 0.273 birr per kWh for the first consumption bracket to around 0.6943 birr per kWh for the seventh and last consumption block. Panel B shows the service charges which depends on the type of electric meters. In the case of single-phase meters, the service charge depends on the amount of the monthly electricity consumption whereas the service charges for three-phase and active-reactive meters are fixed amounts. Almost all (99.33%) of the residential electric meters in Addis Ababa City are single-phase.[17] Combining the consumption blocks with the service charges provides eight kink points for the monthly electricity consumption of the single-phase electric meters. The kink points at the 25 kWh and the 105 kWh are created due to a change in service charges whereas the kink points at 50 kWh and 300 kWh are due to a change in prices of consumption blocks and service charges. The rest kink points are as a result of a change in prices of consumption blocks.

To obtain the marginal prices at the kink points, we first calculate the total bill at the kink point and then compute the price of the additional unit from the kink point. The marginal prices jump at the kink points to a higher price and immediately get back to the prices of the consumption blocks. For instance, the marginal price at the first kink point (i.e. at 25 kWh) jumps from 0.273 birr to 2.273 birr due to a change in the service charge from 1.40 birr to 3.40 birr and then gets back to 0.273 birr for consumption up to 50 kWh. At the 50 kWh, the marginal price increases from 0.273 birr to 3.776 birr due to a change in both price of the consumption block and the service charge. This is a 1283% increase in marginal price and is the largest jump in marginal price. The second and third largest jumps happen at the 25 kWh and 105 kWh. Marginal prices increase from 0.273 birr to 2.273 birr and from 0.4993 birr to 3.919 birr at the 25 kWh and 105 kWh, respectively. These are 732% and 685% increases in marginal prices. At the highest kink point (at 500 kWh), the marginal price changes from 0.588 birr to 0.6943 birr. [18] At the kink points, marginal price is larger than average price. For consumption outside the kink points, the marginal and the average prices are very close to each other albeit the average price is larger for monthly consumption below 100 kWh (see Figure 2 for details). The marginal prices for the three-phase and active-reactive meters are the same as the prices in each of the consumption blocks.

[17] Monthly billings data from the Ethiopian Electric Utility shows that 99.33% of the residential electric meters are single-phase, 0.64% are three-phase and the rest 0.02% are active-reactive.

[18] The marginal prices at the kink points: 100 kWh, 200 kWh, 300 kWh, and 400 kWh, jumps from 0.3564 birr to 0.4993 birr, 0.4993 birr to 0.55 birr, 0.55 birr to 3.977 birr, and 0.5666 birr to 0.588 birr, respectively.

The current electricity price has not changed since 2006 despite the high inflation in 2008. The real electricity prices of the consumption blocks in 2016 were about 20 times lower than what they were in 2006 (see Figure 3). In Figure 3, the dashed lines represent the existing price for the first consumption block and the last block. The real price for the first (lowest) block (0.54 birr) in 2006 is higher than the real price for the highest (seventh) block in 2016 (0.31 birr).[19] Having recognized the gap between the cost of providing electricity and the existing tariff, the utility has been contemplating revising the tariff to a cost-recovery level, though as yet no change has been made.[20]

3.1 Sampling and Data Collection

The study is based on a field survey conducted in April and May 2016 with a total of 1,152 sample households that use electricity from 715 randomly selected electric meters in Addis Ababa. Given the large presence of shared electricity connections, our sampling units were electric meters rather than households. In the case of shared connections, other households that use electricity from the shared connection were also interviewed. Of the 1,152 sample households, 509 households have a private connection and are responsible for the monthly electricity bill; 206 of the sample households share a connection and are financially responsible for the monthly electricity bill; and the remaining 437 households share a connection but are not directly responsible for the monthly electricity bill. For the last category of households, the electricity payment is included in their house rent, or they share the monthly bill or pay a flat rate.

Our sampling technique is stratified random sampling with a proportional allocation of the sample size across strata. Electric power distribution in Addis Ababa comprises four districts (North, South, West and East). Within each district, there are a number of smaller administrative units called centers. Customers in a given center are grouped into a smaller unit called books. A book is a list for use by meter readers. A standard book contains a list of about 400 electric meters that are located in a nearby neighborhood. The number of centers varies from district to district and the number of books differs from center to center.

For our sample, we first obtained a list of all residential electricity customers in Addis Ababa from the utility. After that, we assigned the number of electric meters to be sampled (out of the total of 715) to each of the four districts in proportion to their number of electric

[19] Author's own computation using consumer price index (annual average) data from the World Bank (http://data.worldbank.org/indicator/FP.CPI.TOTL?locations=ET). The base year used is 2010.

[20] As of 2015, the average cost of generating electricity was nine US cents per kWh compared to the selling price of five US cents (*The Ethiopian Herald*, 2015).

meters for residential electricity customers. Next, we randomly chose half of the centers from each district. This provides 18 centers from a total of 35 centers. Then, in proportion to the number of electric meters in each center and based on the assumption that five or six electric meters per book would be representative, 3 to 13 books per center were randomly picked. Finally, from each book, five or six electric meters were selected randomly.[21] To identify households in a shared connection, the survey asked the household that is responsible for the monthly bill for a list of other households that share the connection. Our sampling process provides a large enough sample size and at the same time includes various types of residential electricity customers from a wide area of the city. The data was collected using tablets, with a total of 24 fieldworkers (3 supervisors and 21 enumerators) who have experience in urban surveys. The author has been fully monitoring the field survey.

The survey data has detailed information on the stock of electric appliances, socio-demographic characteristics of households, different sources of energy, electric power outages and other variables of interest. In addition, we had access to monthly electricity billing records from the utility for the period May 2015 to April 2016. In this study, we use monthly billing data for both the 715 sample residential electricity customers (electric meters) and all residential electricity customers in Addis Ababa. In our demand analysis, we match the survey data with the monthly billing records.

3.2 Descriptive Statistics

This section presents summary statistics of the monthly electricity consumption for all residential electricity customers in the study area (more than 348,000 electric meters) and the sample customers (715 electric meters). In addition, it provides summary statistics of the variables of interest in the demand model.

< *Figure 4 here* >

The kernel density in Figure 4 plots average monthly electricity consumption over 12 months for all residential electricity customers in the study area and for the sample customers. The two distributions have almost the same pattern. In both, a majority of the monthly quantities of electricity consumption are concentrated around the third consumption block (100 kWh-200 kWh). Similarly, Table 2 shows that the majority of the customers (about 27%) are concentrated around a monthly electricity consumption of 100-200 kWh and the distribution of customers across the consumption blocks is more or less the same for all

[21] In case a customer was not willing to participate in the survey or was not available during the survey, the customer was replaced by another consumer in the same book using sampling with replacement.

customers and for the sample customers. We also formally test whether the average monthly electricity consumption for all residential electricity customers (260 kWh) is significantly different from that of the sample customers (266 kWh). We fail to reject the null hypothesis that the two average monthly electricity levels of consumption are equal (with *p-value*=0.775). This raw evidence indicates that the random samples of the electric meters for the survey are representative of residential electricity customers in Addis Ababa city.

< Table 3 here >

Table 3 presents descriptive statistics of the sample electric meters. As displayed in Table 3, the average monthly electricity consumption over 12 months is 266 kWh. The large standard deviation (289 kWh) of the monthly consumption indicates heterogeneity in monthly consumption among households. The average per capita monthly electricity consumption is about 53 Kwh. The mean reported monthly income at electric-meter level is 8,824 Birr. The average monthly electricity bill (138 birr) accounts for about 2% of the reported average monthly income of the households that are financially responsible for the monthly bill.[22] Around 28.8% of the sample electric meters are shared with at least one other household. The typical number of individuals who use electricity at a given electric meter is 6. Households spend a substantial amount on alternative fuels such as firewood, charcoal, LPG and kerosene. The average monthly expense on these alternative fuels is around 537 birr for all households at given electricity meter.

The median number of households sharing a connection with a financially responsible household is 2. The monthly electricity consumption in a shared connection (306 kWh) is higher than in a private connection (249 kWh) (see the density in Figure 5). We formally test the null hypothesis that the average monthly electricity consumption is equivalent in the two connections, using a paired two-sided t-test. The result shows a statistically significant difference in monthly electricity consumption between a shared and a private connection. The difference remains significant at all the conventional levels of significance, as well as with a non-parametric Wilcoxon rank-sum test. However, our raw data shows that the per capita monthly electricity consumption for a shared connection is 20 kWh lower than that of a private connection. This is statistically significant at the 1% level of significance. This is possibly due to the presence of a larger number of individuals in a shared connection.

[22] The average reported monthly income for households with a private connection (N=509) is 7198.10 birr, whereas the average is 5357.88 birr for households in a shared connection who are financially responsible for the monthly bill (N=206). Households in a shared connection who are not responsible for the bill payment (N=437) reported an average monthly income of 3528.83 birr.

< Table 4 here >

Table 4 compares average monthly electricity consumption for different covariates. We identify a set of variables that could affect monthly electricity consumption. Each variable of interest is categorized into two groups. For continuous variables such as income, stock of electric appliances, number of individuals and monthly hours of power outages, a dummy variable is constructed based on the median value of the variables; see Table 3. The value equals zero if it is less than the median value; otherwise, it is one. The other variables are categorical variables. In Table 4, the average monthly electricity consumption for the dummy with values equal to zero is shown in Column 1 and, for the dummy values equal to one, the average consumption is shown in Column 2. Column 3 presents the difference in average monthly electricity consumption between these two categories. The raw results show significant variation in monthly electricity consumption across groups. For instance, the average monthly electricity consumption is significantly higher than the comparison groups for households that have cooking stoves, *injera*[23] stoves, or both; those who bake injera at home; and those who share a connection. Similarly, individuals below the median value and households with monthly income and stock of electric appliances below the median value have lower monthly electricity consumption than their counterparts. However, we do not find significant differences in monthly electricity consumption for power outages.

4. Empirical Analysis and Results

4.1 Bunching at the Kink Points of the Increasing Block Pricing Schedule

We begin our empirical analysis by examining bunching of households at the kink points of the increasing block pricing schedule, using the bunching approach developed by Saez (2010). Our bunching analysis is based on monthly electricity consumption for all residential electricity customers in Addis Ababa for the period May 2015 to April 2016. In these monthly bill records from the utility, we observe a negative or zero kWh record in at least one month for about 36% of the entire electric meters. This is possibly due to errors in reading and recording to database, and due to technical defects at the electric meter. In the presence of such billing problems, it is difficult to identify behavioral response around the kink points. Thus, customers with a negative or zero monthly consumption record for at least one month are excluded.[24] This leaves us with about 221,000 residential electric meters.

[23] Injera is the main Ethiopian staple food.
[24] This does not mean that there is no problem with the positive monthly kWh records, but it is not easy to identify errors in electric meters with positive records.

To detect bunching at the kink points, we plot a histogram of the distribution of monthly electricity consumption. Due to imperfect bunching, we might only observe clustering or humps around the kink points. In this case, we use kernel density estimates to smooth noisy histograms and visually detect excess bunching.[25]

< *Figure 6 and Figure 7 here* >

Figure 6 shows a histogram of the monthly electricity consumption distribution pooled over 12 months from May 2015 to April 2016. We do not observe any significant spike of monthly electricity consumption at the kink points. Relative to the other kink points, the spike in the fifth kink point (200 kWh) is slightly visible. The kernel density (with bandwidth of 8 kWh)[26] of the pooled monthly electricity consumption in Figure 7 shows evidence similar to the histogram. There is no significant evidence of bunching at the kink points, even at the kink points where marginal price jumps by 1283% (at the 50 kWh) and at the highest kink point (at the 500 kWh). We further examine bunching around the kink points with different bandwidths because, with a large bandwidth, small clusters would smooth out and disappear completely, while, with a small bandwidth, random clusters could be wrongly interpreted as clustering around the kink points (see Figure 8).[27] We also check whether the bunching evidence changes over months (see Figure 9). Nevertheless, results remain almost the same. Moreover, we investigate bunching evidence locally around the kink points where the largest jump in marginal price occurs (at 50 kWh), at the 105 kWh, at the fifth kink point (200 kWh) and at the highest kink point (500 kWh) using two different bandwidths (2.5 kWh and 8 kWh). However, as displayed in Figure 10, we do not find any systematic clustering around the kink points.

< *Table 5 here* >

Table 5 reports price elasticity estimates based on bunching evidence, standard errors and the number of observations in the bands surrounding the kink ($\widehat{H}$, $\widehat{H_-}$ and $\widehat{H_+}$). The price elasticity of demand for residential electricity is computed locally around each kink point. Following Saez (2010), observations farther away from the bandwidths on both sides of the kink point, are used to construct the counterfactual density of monthly electricity

[25] At each electricity consumption level Kwh, the kernel density method computes local averages of the number of observations around Kwh, using decreasing weights as the observations get farther away from Kwh. The bandwidth δ determines how quickly the weights decrease as we move away from Kwh.

[26] The bandwidth of 8 kWh is an approximation of the default bandwidth (7.713) for the kernel density. The bandwidth could be also chosen based on visual inspection from the graphical presentations (histogram and kernel density).

[27] The bandwidth is decreased to 2.5and 5, and increased to 10 and 15.

consumption. To compare the estimated results, we use two different bandwidths (8 kWh and 12 kWh).[28]The standard errors are calculated using the delta method. The estimated results are very small, close to zero. This is in line with the graphical evidence. Our findings from the bunching estimation indicate that households are not sensitive to the marginal price of electricity in the neighborhood of the kink points.

4.2 Demand Model Results

< Table 7 here >

Table 7 presents regression results of the dynamic panel data model specifications in Equations (2.17) and (2.18). Columns (1)–(2) are OLS and fixed effects estimates of Equation (2.17), respectively. Though we observe positive and statistically significant coefficients of the OLS estimates on the lagged monthly electricity consumption and marginal prices, all the coefficients are biased and inconsistent due to the correlation between the composite error terms and lagged monthly electricity consumption. The same is true for the fixed effects estimates.[29] Instead, we turn to the Difference GMM estimation results. Columns (3)–(9) provide Difference GMM estimates controlling for the individual fixed effects and using two-period lagged values of the endogenous explanatory variables as instruments for contemporaneous differences. The results are one-step GMM estimates.[30] The coefficient on the lagged monthly electricity consumption has the expected sign and magnitude. In Column (3), it is statistically significant at the 10% level of significance. The estimated parameter of the lagged monthly electricity consumption from the Difference GMM lies between the OLS and fixed effects estimates.

In Table 7, Column 3, the estimated coefficient on marginal price is negative and is within the expected range (i.e., between zero and one) but it is statistically insignificant at all the conventional levels of significance. The estimated parameter for the Nordin's difference is almost zero and statistically insignificant. Our results indicate that marginal price does not affect monthly electricity consumption. The finding supports the lack of evidence of bunching around the kink points of monthly electricity consumption.

[28] The kink points at 100 kWh and 105 kWh are very close to each other. To avoid overlapping, we compute the price elasticity at 105 kWh which shows larger marginal price jump than the 100 kWh. When we alternatively compute at 100kWh, results remain more or less the same.

[29] In the OLS regression, the lagged monthly consumption is positively correlated with the error terms and provides a coefficient that is biased upward. However, the coefficient on the fixed effects regression is biased downward due to the negative sign on the transformed error. Given the opposite direction of the bias in the two estimates, it is useful to check that consistent estimates lie between those values.

[30] The asymptotic standard errors in two-step GMM estimators tend to be too small and downward biased in finite samples (Arellano and Bond, 1991).

4.3 Robustness Checks

For robustness checks of the demand model results, we replace the marginal price specification with alternative price specifications such as average prices and monthly electricity bill. The estimated coefficient from the Difference GMM for the average price specification is provided in Table 7, Column (4), and that for the monthly electricity bill in Column (5). Although coefficients on average price and monthly electricity bill are negative as expected, they are insignificant. This indicates that residential electricity consumers in our sample do not respond to average price or monthly electricity bill. We also check results of the marginal price specification for different sub-sample sets. In Table 7, Column (6) displays results for a private connection and Column (7) for sample electric meters excluding with at least one month non-positive kWh record. Column (8) shows estimated results for samples of households that experience more monthly hours of power outages (i.e. above the median of the sample) and Column (9) for samples of households that do have knowledge of the existing tariff structure. The coefficients on the marginal price remain insignificant throughout except the estimated coefficient for the samples of households that experience more hours of power outages.

Furthermore, we check robustness of the estimated results using a linear panel data model with an instrumental variable approach. In this case, in addition to the price variables, we control for other explanatory variables, such as an index for stock of electric appliances, income, type of connection, number of individuals at a connection, and price of alternative fuels, mainly firewood, charcoal, LPG and kerosene.[31] We do not include weather variables as explanatory variables because the study area does not have much variation in weather conditions throughout the year, due to the highland tropical climate. We assume that the additional observable right-hand side variables are constant across months for one year because data on those variables is collected only once during the survey period.[32]

To address the price endogeneity, we apply the standard instrumental variable approach used in the block pricing literature for electricity services (e.g., Hausman et al., 1979; McFadden et al., 1977; Barnes et al.; 1981; Henson, 1984; Terza, 1986), for labor supply

[31] We consider only four of the alternative fuels, which are used by at least 5% of the households using the sample electric meters. Firewood is typically used for baking injera, while charcoal, LPG and kerosene are commonly used for cooking. Though the average prices of LPG and kerosene are easy to compute per liter, measuring the average price for firewood and charcoal in terms of common units is difficult due to the presence of various local units, which are difficult to convert to one another. Therefore, we simply use the total monthly expenses for firewood and charcoal.

[32] The additional explanatory variables could be endogenous. In that case, our estimated results are better interpreted as correlation rather than causation.

(Hausman and Wise, 1976; Rosen, 1976), and for water services (e.g., Deller et al., 1986; Nieswiadomy and Molina, 1989; Barkatullah, 2002; Jansen and Schulz, 2006). In the first stage, observed electricity consumption is regressed on observable time-invariant explanatory variables and on the actual marginal price that would be faced by each individual at the typical consumption level (266 kWh) from the empirical distribution of residential electricity consumption for our sample. That means the marginal price for the typical monthly consumption is pre-determined. In the second stage, the actual rate schedule is used to obtain the predicted marginal price that corresponds to the predicted electricity consumption in stage one. The feedback of quantity on price is eliminated by using an instrumental price which is constant for all households subject to the same price schedule; any variation in the instrumental price variable is only over the price schedule, not over the quantity consumed. In other words, the block rate schedule is linearized to one price schedule.[33] McFadden et al. (1977) and Terza (1986) show that this procedure improves reliability of the estimates and produces consistent estimates.

< Table 8 here >

Table 8 reports the regression results of the residential electricity demand for a linear panel data model specification of Equation (2.17).[34] The demand model is estimated using different alternative specifications: pooled OLS, random effects (*RE*), fixed effects (*FE*) and panel corrected standard error (*xtpcse*) models. Results of the regression models in Table 8 show that the estimated coefficients for pooled OLS with IV, random effects with IV, and panel corrected standard errors models with IV are similar but the R^2 for *xtpcse* is high.

Column (1) in Table 8 displays the pooled OLS regression results. In contrast to what is expected, the estimated price elasticity coefficient is positive and significant. This is due to the endogeneity of marginal price, in which the OLS estimation provides biased and

[33] The instrumental variables approach is based on the following procedures. For a known rate schedule pricing function $P_j = f(kWh_{it})$, let W be observations on exogenous price variables calculated at predetermined consumption levels. In our case, this is the marginal price at the typical monthly consumption level of 266 kWh, letting X_{it} be all the other observable time-variant and time-invariant exogenous variables in the model. Then the procedure can be expressed as follows.

Step 1: Run OLS on the reduced form equation: $kWh_{it} = \pi W + X'_{it}\delta + v_{it}$

Step 2: Compute predicted values: $k\widehat{Wh_{\iota t}} = \hat{\pi}\, W + X'_{it}\hat{\delta}$

Step 3: Compute price instruments using the actual rate: $\widehat{P_j} = f(k\widehat{Wh_{\iota t}})$

Step 4: Estimate coefficients of the model using $(\widehat{P_j}, X)$

[34] We report regression results with contemporaneous price variables to relate our results with other studies that employ a similar instrumental variable approach. However, results remain similar with lagged price variables.

inconsistent coefficients. The high R^2 (0.859) indicates the model is good at predicting the variation in monthly electricity consumption. Unlike the pooled OLS estimates, results under instrumental variable (IV) estimates (Columns 2–5 of Table 8) support the demand theory that the coefficient on the marginal price is negative. The magnitude of the price elasticity is within the range of what is in the literature (Espey and Espey, 2004). In our case, the marginal price coefficient of the IV estimates is negative and similar under the different specifications but it is insignificant at all the conventional levels of significance. In Column (6), we further check robustness of our results by excluding the marginal price and the Nordin's difference from the regression models. The coefficients on the other variables remain more or less stable regardless of the exclusion of the price variables from the regression model. This supports the argument that marginal price does not affect monthly electricity consumption. The result is consistent with the findings from the bunching analysis and the Difference GMM estimates. Results regarding the difference variable are weak, though the sign is as expected.

Size of stock of electric appliances, income per capita, price of alternative fuels (firewood and LPG), and number of individuals at the electric meter are significantly correlated with monthly electricity consumption. See details of the results in Table 8. We also find that the coefficient on the dummy for a shared connection is positive and significant. This supports the raw results in the descriptive statistics: monthly electricity consumption for shared connections is significantly higher than monthly consumption for private connections. This highlights the relevance of private connections in monitoring electricity usage.

5. Conclusion

Pricing policy, particularly increasing block tariff (IBT), has been commonly used by electric and water utilities in developing countries as a tool for resource conservation, for cost recovery, and to ensure access to the services for low-income consumers. However, it is not clear whether consumers actually respond to marginal price under increasing block pricing. In the present study, we empirically investigate whether marginal price in an IBT affects residential electricity demand, by combining administrative monthly electricity bill records with a detailed survey of sample households. We further analyze the main correlates of residential electricity demand and compare monthly electricity consumption between shared and private connections.

Our results from the bunching analysis show that households do not bunch around the kink points of the monthly electricity consumption distribution. Similarly, the estimated price elasticity of demand from the Arellano-Bond estimator is statistically insignificant, though it keeps its expected sign and magnitude. These results imply that the existing electricity price does not affect monthly electricity consumption. Size of stock of electric appliances owned, income, price of alternative fuels (mainly firewood and LPG) and number of individuals who use electricity from a given connection are significantly correlated with monthly electricity consumption. We also find significant differences in monthly electricity consumption between private and shared connections. This result highlights a policy intervention that encourages private connection, such as subsidizing connection fees, so that consumers can monitor their own consumption and then reduce their consumption.

A possible explanation for the lack of significant effect of the marginal price on electricity consumption is the existing low prices. The real prices of the consumption blocks as of 2016 are about 20 times lower than what they were in 2006. Because the prices are low, consumers may not pay attention to their electricity use. Another explanation could be consumer's lack of tariff knowledge and difficulty in understanding how their monthly bills are computed in the block-based price scheme. The survey evidence supports consumer's lack of knowledge about the existing tariff schedules. Our survey shows that a majority of the respondents (79.30 %) do not know that the existing price structure is increasing block price and only 13.85% of the households regularly check the details of their monthly electricity bills, while the rest (86.15%) check only the amount to pay. Lack of tariff knowledge, inattention and cognitive limitations are not peculiar to Ethiopian households. For example, Ito (2014) finds consumer inattention to complex pricing structure in residential electricity consumption in the USA. Also, de Bartolome (1995) documents subjects' cognitive difficulty in understanding a non-linear price structure in a laboratory experiment. Similarly, McRae and Meeks (2016) report consumers' lack of knowledge of a new tariff structure, from a survey conducted three months after an electricity tariff reform in Kyrgyzstan. Moreover, the presence of shared electricity connections, billing irregularities and power outages might also be distorting households' response to electricity prices.

Our study provides essential information on why the policy objectives of the IBT may not be achieved. With multiple households per shared connection exceeding the consumption allowed for a single household, these households pay at the higher rate for the higher block, and therefore do not receive the subsidy intended for them. The distortion of the subsidy could be worse, because low-income households are more likely than richer households to have a shared connection. In addition, the utility may not achieve its policies of electricity conservation and generating enough revenue for operation, maintenance, and investment, because the existing electricity prices are low and do not affect electricity demand.

Our results are relevant for proper design and implementation of electricity pricing policy. Following the findings, we suggest that the Ethiopian Electric Utility consider revising the existing low electricity tariff while still taking into account the cooking needs for energy transition. One option is to revise the existing long list of consumption blocks with small price changes across blocks into a few blocks with strong price signals. However, in the presence of shared connections, the policy of subsidizing poor consumers might still not be achieved. Therefore, an alternative option is to introduce a flat tariff structure, similar to the existing tariff for the industrial sector, and provide a subsidy for purchasing electric appliances. In addition, graphical presentation of the billing information – consumption and the corresponding prices – could be easier to understand and more appealing, thus encouraging consumers to be attentive.

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Appendix A: List of Tables

Table 1. The increasing block tariff structure for residential electricity service in Ethiopia

Panel A: Consumption block price			
Tariff Blocks	Consumption blocks (in kWh)	Tariff per kWh (in birr)	% change in tariff
1st	(0 , 50]	.273	-
2nd	(50 , 100]	.3564	30.54%
3rd	(100 , 200]	.4993	40.10%
4th	(200, 300]	.55	10.15%
5th	(300, 400]	.5666	2.91%
6th	(400 , 500]	.588	3.89%
7th	>500	.6943	18.08%

Panel B: Service charges		
Electric-meter type	Monthly consumption (in kWh)	Total service charge (in birr)
Single-phase	[0 , 25]	1.40
	(25 , 50]	3.40
	(50 , 105]	6.82
	(105, 300]	10.24
	>300	13.65
Three-phase	-	17.06
Active-Reactive	-	37.56

Table 2. Distribution of customers across the consumption blocks

Blocks	Consumption blocks (in kWh)	All customers		Sample customers	
		Percent (%)	Cum.	Percent (%)	Cum.
1st	(0 , 50]	8.63	8.63	7.03	7.03
2nd	(50 , 100]	11.01	19.65	9.43	16.46
3rd	(100 , 200]	26.74	46.38	27.54	44.00
4th	(200, 300]	20.76	67.15	21.54	65.54
5th	(300, 400]	12.82	79.97	14.67	80.21
6th	(400 , 500]	7.54	87.51	8.27	88.48
7th	>500	12.49	100.00	11.52	100.00
Observations		3,769,678		8,009	

Table 3. Descriptive statistics

Variables	Mean	St. dev.	Median
Monthly bill at electric meter level	137.93	124.74	110.01
Monthly electricity consumption in kWh at electric meter level	266.02	289.14	211.34
Service charge at electric meter level	10.03	3.92	10.24
Index for stock of appliances at electric meter in kW	7.65	4.64	6.80
Total monthly income at electric meter level	8824.69	9080.30	5800
Dummy for monthly income per capita: (0 to 3 based on the quartiles)	1.51	1.12	2
Total monthly expenses on food, mobile, internet, asset and house rent at electric meter level	4853.76	4990. 55	3346
Total monthly fuel expenses for firewood, charcoal, LPG and kerosene at electric meter level	537.53	1704.06	290
monthly expense for firewood	46.40	137.11	0
monthly expense for charcoal	377.26	1477.02	190
Average monthly price per liter for LPG	10.62	63.87	0
Average monthly price per liter for kerosene	3.80	8.01	0
Total number of people that use electricity at an electric meter	6.36	5.04	5
Dummy for shared connection: =1 if shared 0 otherwise	.288	.45	0

Table 4. Comparison of average monthly electricity consumption across covariates

Variables	(1)	(2)	(3)
	Dummy=0	Dummy=1	Diff.
Monthly income at electric meter level	211.28	320.10	-108.82***
	(3.68)	(4.91)	(6.15)***
Stock of electric appliances in kW	191.28	340.63	-149.34***
	(3.22)	(5.12)	(6.05)
Cooking stoves, injera baking stoves	124.08	276.42	-152.33***
	(11.06)	(3.23)	(12.31)
Baking injera at home	191.29	271.48	-80.19***
	(10.82)	(3.26)	(12.41)
Shared connection	249.65	306.91	-57.25***
	(3.28)	(7.18)	(6.90)
Number of individuals at electric meter	208.02	297.07	-89.05***
	(4.12)	(4.21)	(6.50)
Monthly hours of power outages	261.27	270.63	-9.36
	(4.30)	(4.54)	(6.26)

Table 4 compares average monthly electricity consumption across different covariates. Column 1 shows mean monthly electricity consumption if the value of the dummy variable is zero and Column 2 shows consumption if the value of the dummy variable equals one. Column 3 is the difference in monthly electricity consumption between the two dummies. The dummy for continuous variables such as income, stock of electric appliances, monthly hours of power outages and number of individuals is equal to zero if it is below the median value; otherwise it is one. The standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ for t-test.

Table 5. Estimates of price elasticity of demand using bunching evidence

Kinks	Bandwidth = 8 kWh	Bandwidth = 12 kWh
25 kWh	-.0002	-.0047***
	(0. 0005)	(0. 0006)
	[104,901]	[159,373]
50 kWh	0.0000	0.0002
	(0.0001)	(0.0002)
	[135,890]	[203,976]
105 kWh	0.0012***	0.0019***
	(0.0001)	(0.0001)
	[216,847]	[318,267]
200 kWh	0. 0293***	0.0614***
	(0.0034)	(0.0043)
	[225,983]	[335,435]
300 kWh	0.0002***	0.1296***
	(0.0000)	(0.0005)
	[147,077]	[219,159]
400 kWh	0.0366***	0.0343***
	(0. 0072)	(0. 0087)
	[86,628]	[129,746]
500 kWh	0.0024	0.0051***
	(0. 0016)	(0. 0019)
	[50,122]	[74,819]

Table 5 presents estimates of the price elasticity of demand for residential electricity based on the bunching evidence around the kink points of the monthly electricity consumption using two different bandwidths (8 kWh and 12 kWh). Standard errors obtained by the delta method are in parentheses. *** denotes significance at 1%, ** at 5% and * at 10%. Numbers of observations in the bands surrounding the kink that are used in the estimation are reported in squared brackets.

Table 6. AR (1) specifications for the key variables

Variables	OLS	Fixed Effects	Diff GMM	System GMM
Monthly consumption:				
$\ln(kWh_t)$				
$\ln(kWh_{t-1})$	0.734***	0.023	0.068**	0.042
	(0.020)	(0.027)	(0.033)	(0.037)
Lagged marginal price:				
$\ln(MP_{t-1})$				
$\ln(MP_{t-2})$	0.747***	0.036	0.024	0.091***
	(0.017)	(0.026)	(0.028)	(0.031)
Lagged difference: $diff_{t-1}$				
$diff_{t-2}$	0.591***	-0.081***	-0.099***	-0.019
	(0.026)	(0.024)	(0.027)	(0.028)

Table 6 presents simple AR (1) specifications for three series: monthly electricity consumption, lagged marginal price and lag of the Nordin's difference using various estimators. We control for month by year fixed effects. All the series are found not persistent even using OLS estimates (which are upward biased); therefore, we strongly reject that the coefficients are equal to one under the null hypothesis (P-value=0.00). Robust standard errors clustered at electric meter level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7. Regression results of dynamic panel data model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lagged ln(kWh)	0.542***	0.054	0.244**	0.065	0.479	0.210*	0.171	0.295***	0.019
	(0.053)	(0.050)	(0.121)	(0.111)	(0.402)	(0.117)	(0.155)	(0.109)	(0.075)
lagged ln(MP)	0.867***	-0.080	-0.826			-0.412	-0.210	-1.293*	-0.340
	(0.171)	(0.167)	(0.625)			(0.607)	(0.616)	(0.659)	(0.479)
lagged diff	0.000	0.001	0.002			0.003	0.003	-0.002	-0.003
	(0.001)	(0.001)	(0.002)			(0.002)	(0.002)	(0.003)	(0.002)
lagged ln(AP)				-0.065					
				(0.647)					
lagged ln(Bill)					-0.420				
					(0.393)				
Months fixed effects	yes	Yes	Yes	yes	Yes	yes	yes	yes	yes
Constant	3.072***	5.020***							
	(0.379)	(0.354)							
Observations	7,075	7,075	6,189	6,189	6,191	4,430	4,745	3,124	1,293
No. of electric meters	714	714	709	709	709	505	478	360	145
R-squared	0.56	0.008							
Arellano Bond test for AR(2)			0.83	0.74	0.95	0.97	0.85	0.81	0.59
Hansen test for overid.			0.62	0.26	0.40	0.87	0.15	0.53	0.67
Difference-in-Hansen test			0.75	0.72	0.99	0.52	0.81	0.12	1.00

Table 7 reports regression results of the dynamic panel data. The dependent variable is $\ln(kWh_{it})$. Column (1) presents OLS estimates while Column (2) is fixed effects estimates. Columns (3)–(5) are the diff GMM estimates when the variables in the price specification are marginal prices (including Nordin difference), average prices and monthly bills, respectively. Columns (6)–(9) are diff GMM estimates for different sub-samples. Column (6) displays results for private connection and Column (7) for sample electric meters excluding with at least one month non-positive kWh record. Column (8) shows estimated results for samples of households that experience more monthly hours of power outages (i.e. above the median of the sample) and Column (9) for samples of households that do have knowledge of the existing tariff structure. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The figures reported for Arellano Bond test for AR (2), Hansen test for over-identification, and difference in Hansen test are the P-values for the null hypothesis–the valid specification.

AR (2) tests the null hypothesis that the difference errors in period ‘t’ and‘t-2’are uncorrelated.

The Hansen’s tests test for validity of the instruments.

Table 8. Estimates of linear panel data model

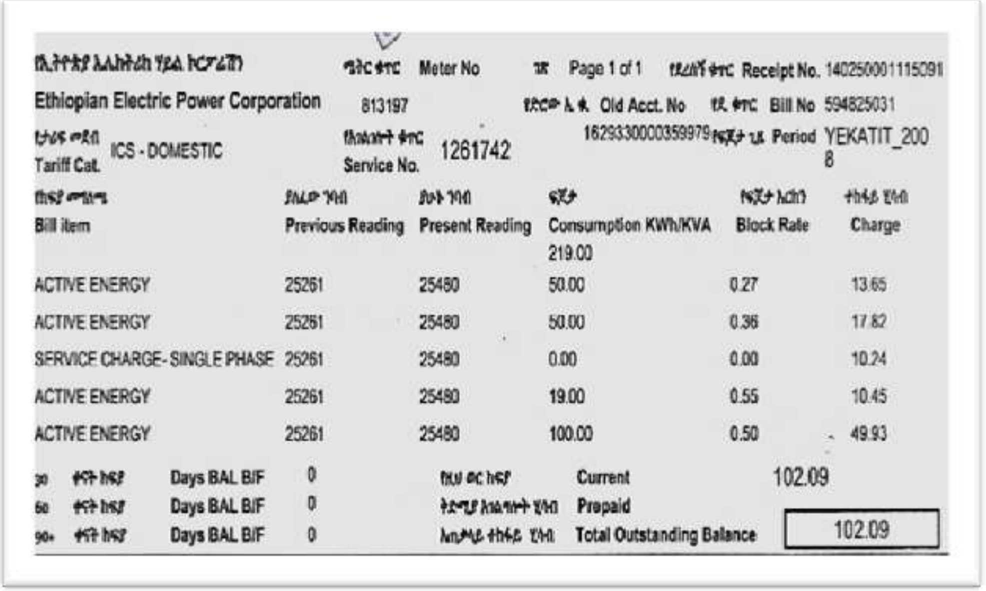
Variables	(1)	(2)	(3)	(4)	(5)	(6)
log of marginal price	3.156***					
	(0.091)					
Nordin difference	-0.004***					
	(0.001)					
log of instrumented marginal price		-0.518	-0.341	-0.073	-0.476	
		(0.647)	(0.425)	(0.522)	(0.337)	
instrumented Nordin difference		-0.002	-0.007	-0.005	-0.004	
		(0.007)	(0.005)	(0.005)	(0.005)	
log of index for stock of electric appliances	0.062***	0.480***	0.435***		0.461***	0.406***
	(0.013)	(0.052)	(0.049)		(0.045)	(0.020)
=1 if income per capita is between the 25th and 50th Percentile	0.028	0.045	0.033		0.032	0.061*
	(0.022)	(0.066)	(0.068)		(0.036)	(0.035)
=1 if income per capita is between the 50th and 75th Percentile	0.040**	0.160**	0.145**		0.151***	0.194***
	(0.019)	(0.066)	(0.067)		(0.032)	(0.032)
= 1 if income per capita is above the 75th percentile	0.026	0.152**	0.116*		0.130***	0.167***
	(0.022)	(0.069)	(0.070)		(0.040)	(0.037)
log of monthly firewood expenses	0.002	-0.024*	-0.017		-0.024**	-0.025***
	(0.004)	(0.013)	(0.014)		(0.010)	(0.009)
log of monthly charcoal expenses	0.005	0.001	-0.000		-0.001	-0.007
	(0.006)	(0.016)	(0.016)		(0.009)	(0.009)
log of average LPG price	0.005	0.050***	0.049***		0.054***	0.057***
	(0.004)	(0.017)	(0.017)		(0.010)	(0.010)
log of average kerosene price	-0.008	-0.015	-0.012		-0.013	-0.015
	(0.007)	(0.019)	(0.020)		(0.020)	(0.020)
=1 if shared connection	0.036	0.454**	0.458**		0.550***	0.416***
	(0.066)	(0.203)	(0.205)		(0.152)	(0.156)
log of total no. of individuals at electric meter	0.008	0.500***	0.445***		0.499***	0.460***
	(0.023)	(0.078)	(0.078)		(0.058)	(0.052)
Shared connection log of total no. of individuals at electric meter*	-0.010	-0.269**	-0.269**		-0.309***	-0.231***
	(0.035)	(0.107)	(0.107)		(0.075)	(0.073)

month effects	yes	yes	yes	yes	yes	yes
Constant	7.110***	3.095***	3.264***	4.881***	3.140***	3.733***
	(0.092)	(0.609)	(0.423)	(0.448)	(0.343)	(0.095)
Observations	8,053	7,761	7,761	7,761	7,761	8,054
R-squared (overall)	0.859	0.256	0.255	0.02	0.591	0.590
No. of electric meters	715	687	687	687	687	715

Table 8 presents regression results of the linear panel data model. The dependent variable is log of monthly electricity consumption. Column (1) is for OLS estimates, whereas Columns (2)–(5) are IV estimates for pooled, random effects, fixed effects and panel corrected standard error models, respectively. Finally, Column (6) displays estimated results without the price variables for the panel corrected standard error model. Robust standard errors clustered at electric meter level are in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix B: List of Figures

Figure 1. Sample monthly electricity bill for residential electricity service in Ethiopia



Ethiopian Electric Power Corporation

Meter No 813197 | Page 1 of 1 | Receipt No. 140250001115091

Old Acct. No 1629330000359979 | Bill No 594825031

Tariff Cat. ICS - DOMESTIC | Service No. 1261742 | Period YEKATIT_2008

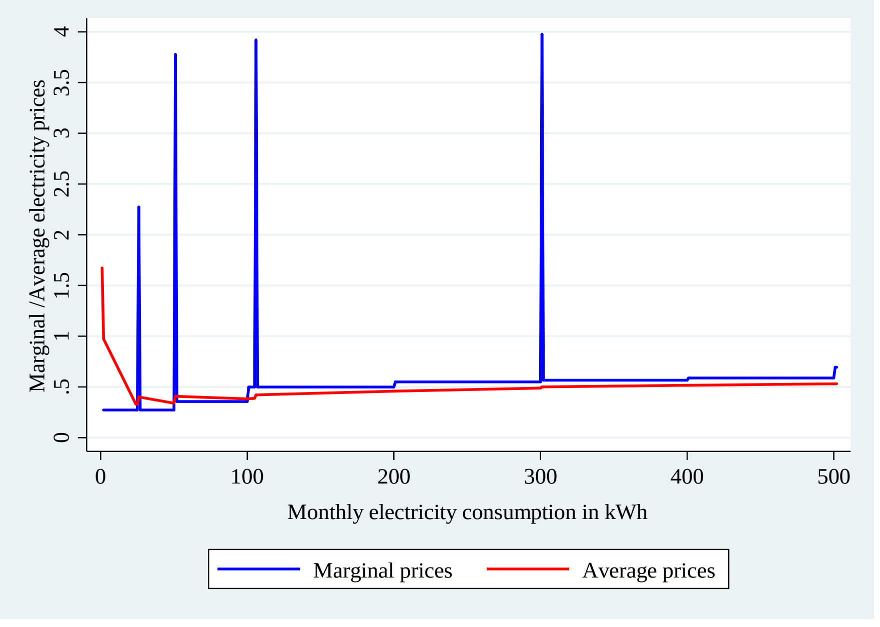
Bill item	Previous Reading	Present Reading	Consumption KWh/KVA 219.00	Block Rate	Charge
ACTIVE ENERGY	25261	25480	50.00	0.27	13.65
ACTIVE ENERGY	25261	25480	50.00	0.36	17.82
SERVICE CHARGE- SINGLE PHASE	25261	25480	0.00	0.00	10.24
ACTIVE ENERGY	25261	25480	19.00	0.55	10.45
ACTIVE ENERGY	25261	25480	100.00	0.50	49.93

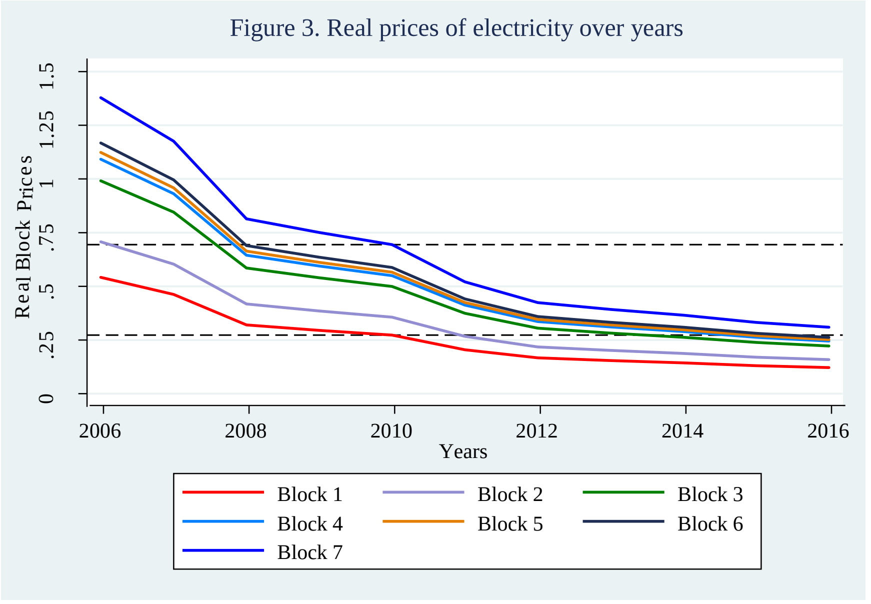
30 Days BAL B/F 0 | Current 102.09

60 Days BAL B/F 0 | Prepaid

90+ Days BAL B/F 0 | Total Outstanding Balance 102.09

Figure 2. Marginal and average prices of the increasing block tariff





Source: Author's own computation using consumer price index (annual average) data from the World Bank. The base year used is 2010.

Figure 4. Density of average monthly electricity consumption over 12 months across customers

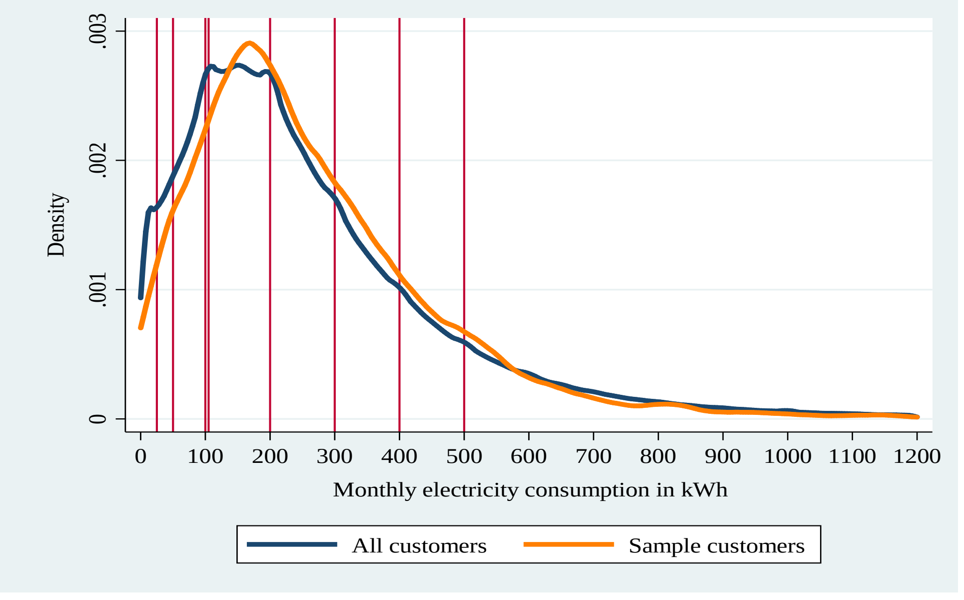


Figure 5. Density of average monthly electricity consumption over 12 months across connections

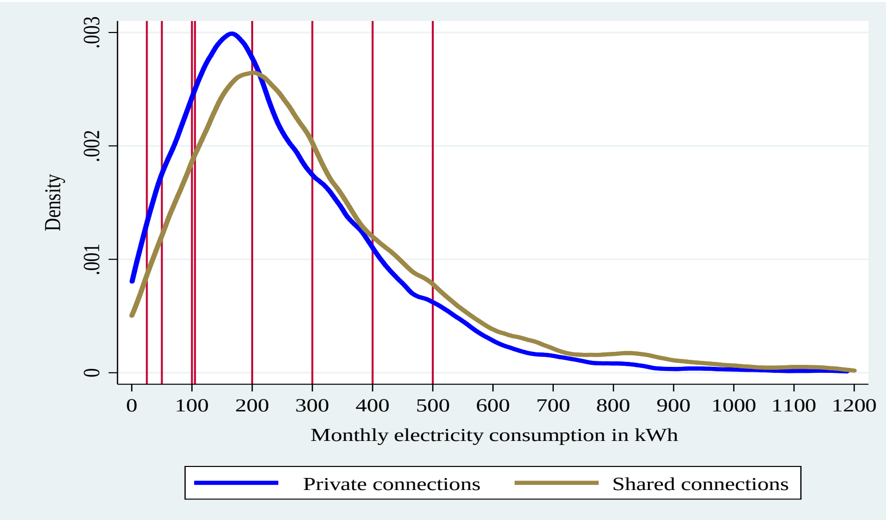


Figure 6. Histogram of average monthly electricity consumption over 12 months (bandwidth=8)

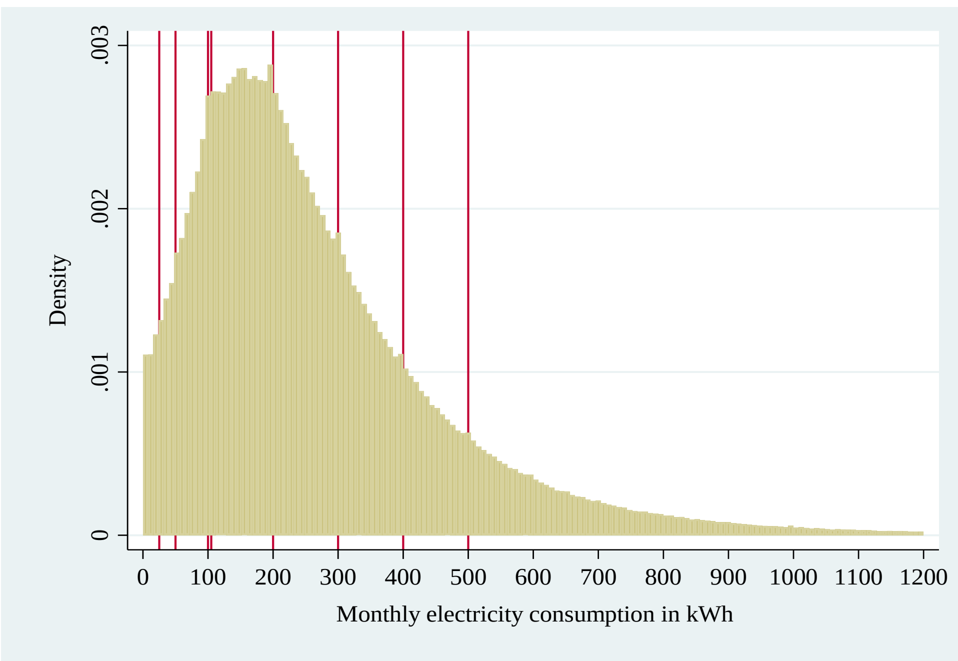


Figure 7. Density of average monthly electricity consumption over 12 months (bandwidth=8)

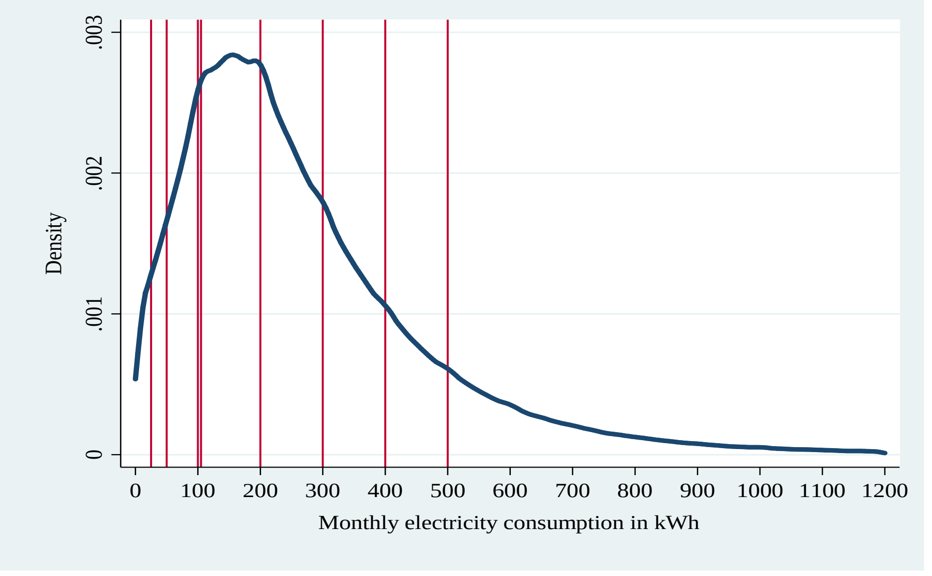
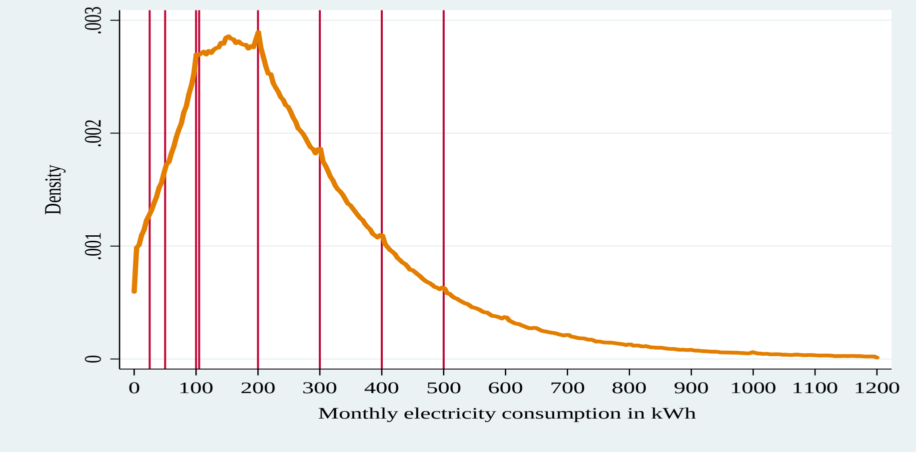
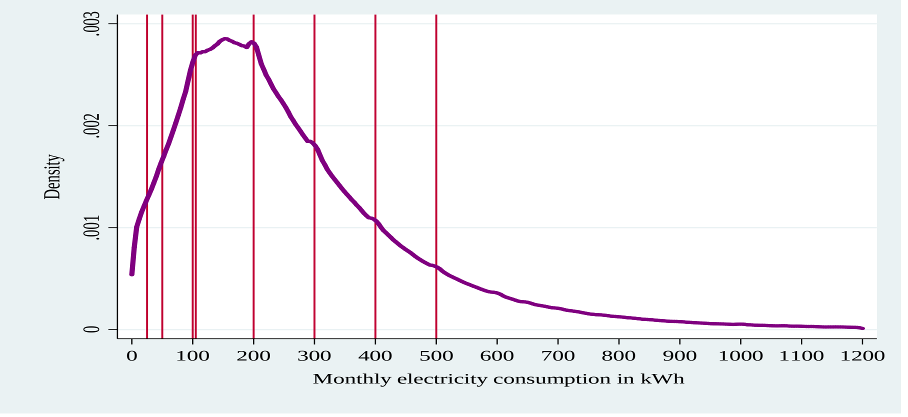


Figure 8. Density of average monthly electricity consumption over 12 months with different bandwidths

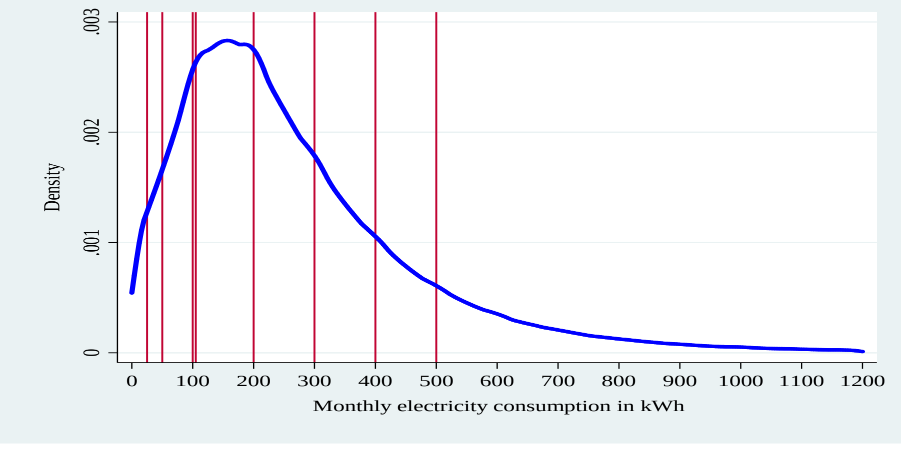
A. Bandwidth =2.5 kWh



B. Bandwidth =5 kWh



C. Bandwidth =10 kWh



D. Bandwidth =15 kWh

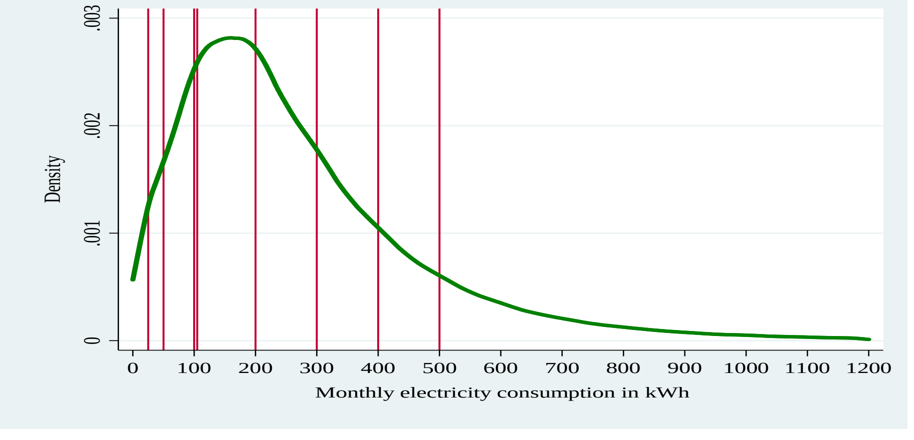


Figure 9: Density of monthly electricity consumption from May 2015 to April 2016 (Bandwidth=8)

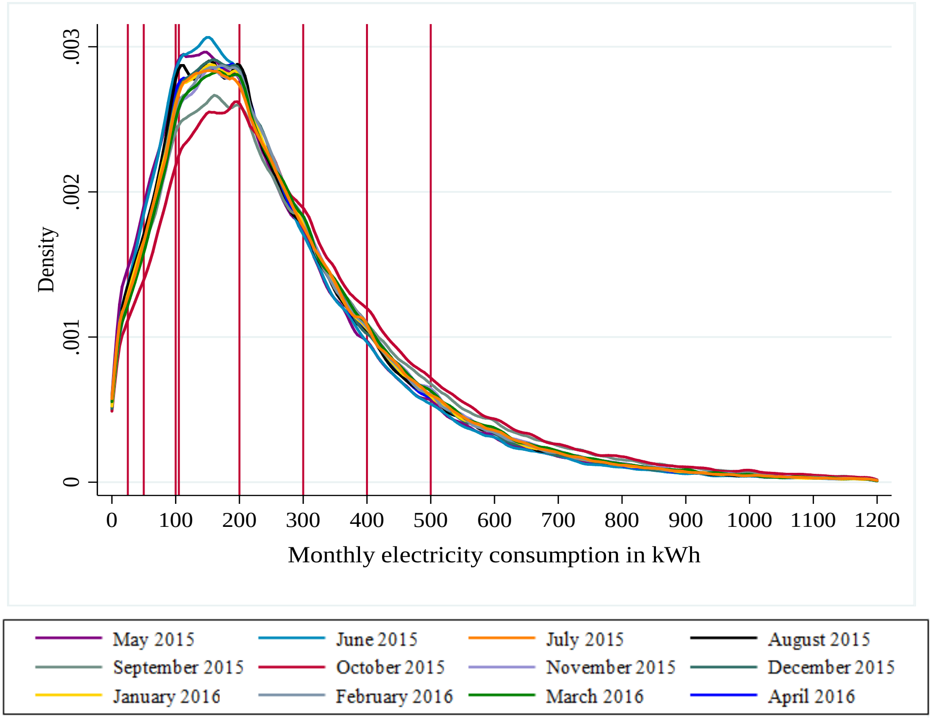
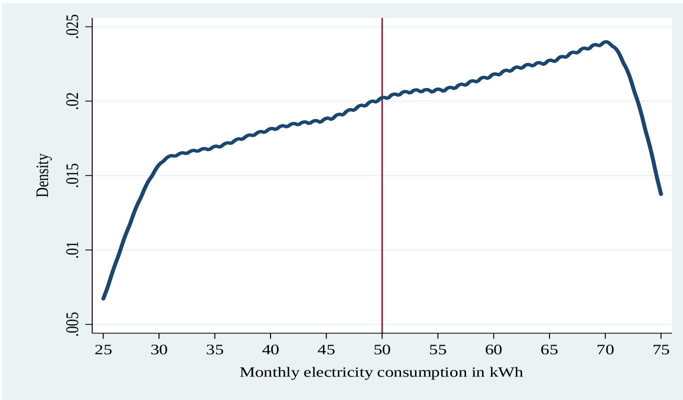
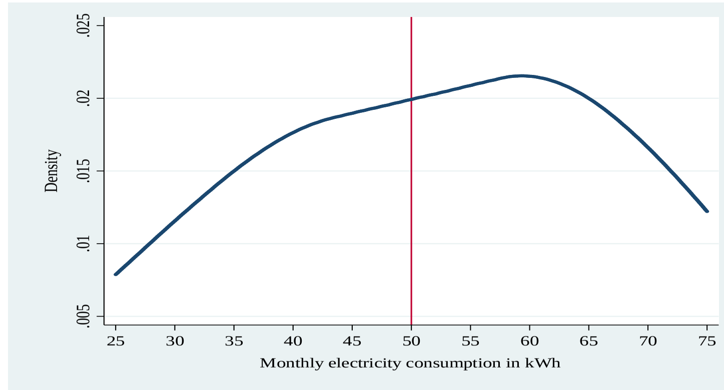


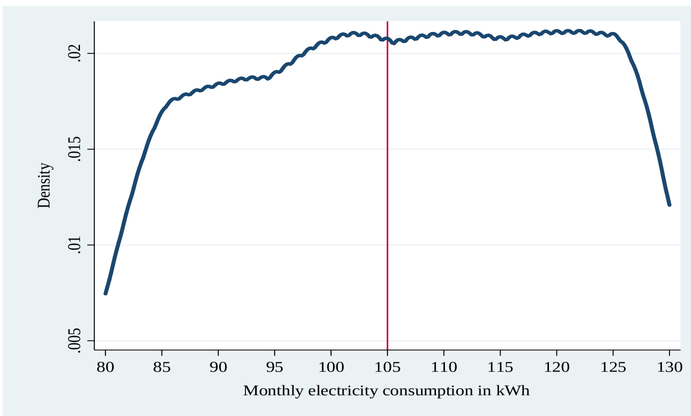
Figure 10. Density of average monthly electricity consumption locally around the kink points

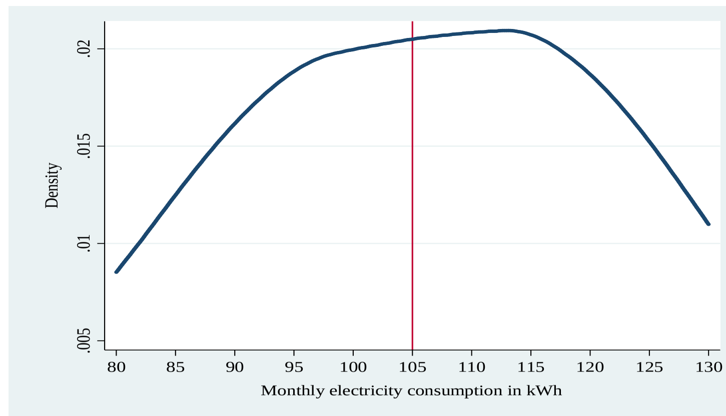
A. Bandwidth =2.5 kWh



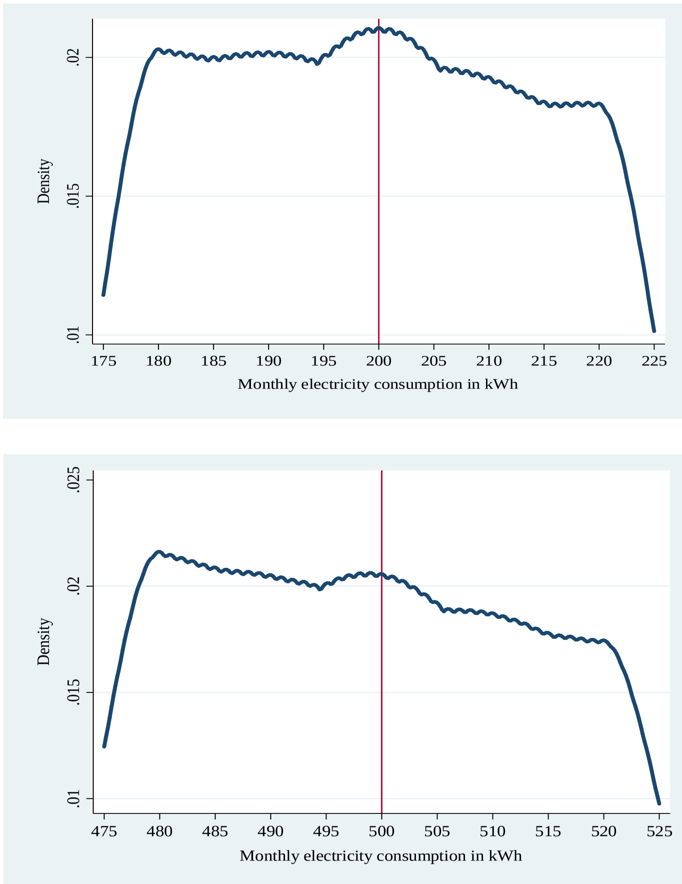
B. Bandwidth =8 kWh



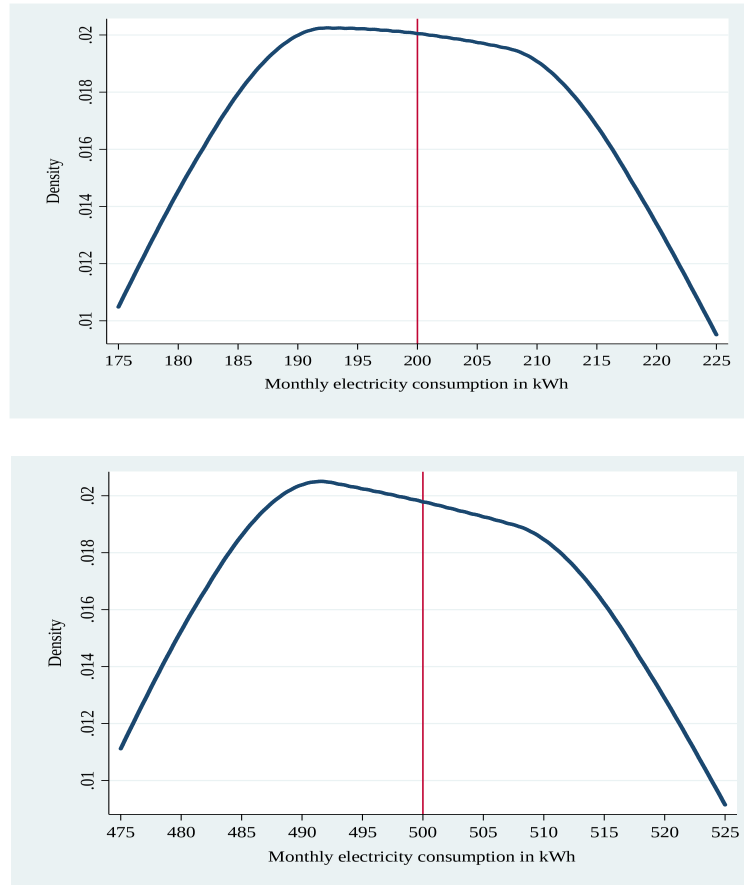




A. Bandwidth =2.5 kWh



B. Bandwidth =8 kWh



Chapter III

Billing Knowledge and Consumption Behavior: Experimental Evidence from Nonlinear Electricity Tariffs

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Abstract

Increasing block tariff for electricity services is a popular tariff structure in developing countries with the ambition to promote resource conservation among users with high consumption and to provide subsidy for low-income consumers. However, in a complex pricing structure, such as increasing block tariff (IBT), consumers may not know the marginal price they face and might not fully understand how their bill is computed. Thus, in this study, we investigate whether educating consumers about how their monthly electricity bill is calculated in an IBT structure affects electricity consumption. To evaluate the effect of the treatment, we conduct a field experiment with residential electricity consumers in Ethiopia where electricity price is heavily subsidized and shared connections are common. Using monthly consumption data from the electric meters, we find no statistically significant effect after six months in response to the treatment. Our finding suggests that it is not the lack of billing information that makes residential electricity consumers insensitive to the IBT. Alternative reasons, such as the low electricity price are provided.

JEL Classification: C93, D12, D83, H42, L94

Key-words: Billing knowledge, consumer behavior, non-linear electricity price, field experiment

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1. Introduction

On the assumption that consumers would respond to marginal prices, many electric utilities in developing countries commonly use an increasing block price (IBP) structure as a means to subsidize low-income consumers, and to recover costs of providing the service and to promote resource conservation among high-users (Komives et al., 2005, 2006; Whittington et al., 2015; Nauges and Whittington, 2017). In an increasing block price, a different price per unit is charged for different blocks of consumption and the marginal price charged rises with each successive consumption block. Consumer's responses to the marginal prices, however, depend on their knowledge of the price scheme and their attentiveness to their consumption. In a complex price structures like IBP, lack of knowledge about the marginal price they face and how the bill is computed (Wichman, 2014), could prevent consumers from responding to their marginal prices[1] and then they possibly use some rule of thumb. In developing countries, the presence of a heavily subsidized electricity price (Foster and Morella, 2011), shared connections (Nauges and Whittington, 2017), and billing irregularities (Smith, 2004; Rao, 2012) could be additional constraints for responding to the marginal electricity prices.

Empirical literature reports that people tend to be inattentive to non-salient taxes (Chetty, Looney and Kroft, 2009) and to opaque add-on costs such as shipping and handling charges (Hossain and Morgan, 2006), out-of-pocket insurance costs (Abaluck and Gruber, 2011), and fees for road use (Finkelstein, 2009). Similarly, studies on energy use in block pricing schedules in the USA document that consumers are unaware of the marginal price they face and do not understand how their energy bill is computed (see, e.g., Shin, 1985; Liebman and Zeckhauser, 2004; Borenstein, 2009; Ito, 2014). As a result, they respond to average price or other perceived price, instead of marginal price – in contrast to the way that standard economic theory might predict (Borenstein, 2009; Ito, 2014). This could lead to failure of pricing policies to achieve their objectives of electricity conservation.[2] Another related study by Sexton (2015) shows that consumers tend to misperceive –either underestimate or overestimate – prices that are not salient. Attari et al. (2010) also show that people tend to overestimate electricity savings from reducing low electricity-consuming activities, e.g., turning off lights. Allcott (2011) documents consumers' cognitive inattention in calculating fuel costs. Wichman (2017) indicates that it is not clear whether consumers respond to the

[1] We use block pricing schedules, block tariff, and non-linear pricing structure interchangeably in this paper.

[2] For instance, response to average price instead of marginal price has a negative policy implication for electricity conservation because the average price is lower than the marginal price in an increasing block tariff.

price information, the quantity information, or both in monthly bills that contain price and quantity information.

For consumers to respond to the correct price incentives, supporting technology like advanced meters that allow tracking electric usage and prices in real time is very useful. In view of the advantage, developed countries have started deployment of smart meters some years ago (see, e.g. European Commission, 2016). However, many developing countries do not have the resources and are still using the traditional post-paid electricity meters for billing the electricity consumed (Rao, 2012). In the post-paid metering technology, it is difficult for consumers to know how much electricity is consumed by a given electricity-consuming activity and what it costs until the bill arrives. Monthly bills might help consumers to remind about their past usage and price paid but still lack of knowledge about the electricity prices and how the bill is calculated could undermine the response to changes in the marginal prices of electricity. Could educating consumers about how their bill is calculated in an IBP affect their electricity consumption behavior?

The objective of the present paper is to analyze whether educating consumers about their monthly electricity bill in an IBP structure affects monthly electricity consumption in the short term. The study is designed to investigate whether billing education makes consumers aware of the non-linear price incentives and, if so, whether consumers then change their consumption behavior accordingly. To evaluate the effect of the intervention, we conduct a field experiment with a random sample of 715 households in Ethiopia, where shared connection is common, electricity price is heavily subsidized, and tariff reform is often difficult for political reasons.

To analyze the effect, about half of the sample households were randomly selected to the treatment and respondents from these households receive an educational package and oral explanations of the package by well-trained fieldworkers. The educational package includes information, beyond what is already provided in billing statements, about the marginal prices in the IBP scheme and about how the monthly bill is determined in such a tariff structure. It also includes control questions to test respondent’s understanding of the marginal prices in the IBP structure. Following the treatment, we tracked both the control and treatment group’s monthly billing data from the Ethiopian Electric Utility for six months in 2016 and compared it with the same months in 2015 to control for seasonal variation in electricity consumption.

The educational campaign is predicted to influence electricity usage by reminding consumers about the information on their bill, raising attention, making consumption more salience, and changing the perception of the price incentives (see, e.g. Wichman, 2017; Szabó and Ujhelyi, 2015; Gilbert and Graff Zivin, 2014; Jessoe and Rapson, 2014; Chetty and Saez, 2013; Grubb and Osborne, 2013; Allcott, 2011). Based on the literature, the educational campaign is expected to have mixed effect. Consumers with poor understanding of the billing system and those that presume electricity is expensive are expected to increase their monthly electricity consumption in response to the treatment. The opposite is predicted for those who presume electricity is cheap prior to the intervention. However, if consumers thought that the prices are still low, they might not change their monthly consumption in response to the treatment.

A growing body of literature in a wide range of settings explores whether information provision changes consumer's behavior. Nevertheless, results remain mixed. For instance, providing information about the benefits of retirement plans (Duflo and Saez, 2003), a higher price tier of cellphone use (Grubb and Osborne, 2013), and the take-up rate of government transfer programs (Bhargava and Manoli, 2013) dramatically changes people's decision making. Similarly, previous studies in the case of electricity and water consumption show that resource conservation can be encouraged by more detailed information on household energy (Abrahamse et al., 2005; Delmas et al., 2013), peer comparisons (see, e.g., Schultz et al., 2007; Allcott, 2011; Ayres et al., 2013; Costa and Kahn, 2013; Dolan and Metcalfe, 2013; Ferraro and Price, 2013; Allcott and Rogers, 2014), educational material about complicated rate structures (Kahn and Wolak, 2013), real-time feedback (Jessoe and Rapson, 2014; Wolak, 2014), and a change in metering technology – switching from postpaid to prepaid (Jack and Smith, 2016). A related strand of literature finds positive and significant results for the effect of teaching about the tax code on labor supply and earning decisions (Chetty and Saez, 2013), of providing information about social security on the labor force participation of old individuals (Liebman and Lutter, 2015), of informational campaigns in reducing non-payment for public utilities (Szabó and Ujhelyi, 2015), and of financial literacy training on financial knowledge and behavior (Sayinzoga et al., 2016). In contrast, other studies (e.g., Wichman, 2017; Strong and Goemans, 2014) find an increase in consumption when consumers are provided more information, as it reduces the wedge between perceived and actual prices and quantity consumed.

Our study is related to recent field experiments that use information intervention, peer comparisons, and real-time feedback through smart meters to change consumers' behavior (see, e.g., Delmas et al., 2013; Allcott, 2011; Allcott and Rodgers, 2014; Jessoe and Rapson, 2014; Pellerano et al., 2017). However, our work is conducted in a developing country setting, where electricity consumption is expected to be low, and with consumers who receive detailed billing information in their monthly electricity bills from a utility. It is also carried out in a context where shared connection is common and electricity price is heavily subsidized. Unlike previous highly impersonal interventions, such as sending letters and emails and delivering a narrow message, we analyze an educational campaign that involves visits to consumers by well-trained and experienced fieldworkers that possibly provide a better opportunity to communicate detailed information to respondents.

The present study exploits a particular institutional feature in an electric utility. Monthly bills for residential electricity consumers in Ethiopia contain detailed billing information. For example, they show the amount of monthly electricity consumption in kWh and the period of consumption; price for each consumption block, including the block where the monthly consumption ends up and the corresponding monetary value of the consumption in each block; and service charges and current charges as well as any previous balances. However, consumers might not be aware of the marginal price they face in each of the blocks or they might not fully understand how their bill is calculated within the block-based pricing structure (Nataraj and Hanemann, 2011; Wichman, 2014). This provides us with an opportunity to test whether an educational campaign that involves information about the block prices, service charges and how monthly consumption is translated into the monthly bill in the IBP structure, could make consumers aware of and understand the electricity billing system and then change their consumption behavior accordingly.

Our results from the difference-in-difference estimation show that the monthly electricity consumption is 5.69–14.34 kWh higher for the treated group than for the control group, but this difference is statistically insignificant at all the conventional levels. This implies that, on average, educating consumers about their bill does not have a significant effect on monthly electricity consumption. The 2.1%–5.3% increase in consumption relative to pre-intervention monthly consumption is comparable in magnitude to the 4–6% increase in residential electricity use due to automatic bill payment programs (Saxton, 2015), the 3.5–5% increase in water consumption in response to more frequent billing information (Wichman, 2017), and the 1.4–3.3% reduction in energy consumption due to peer comparisons (Allcott, 2011). When we further examine heterogeneity in the treatment effects across different sub-groups of the sample, we find statistically significant results for household head respondents, a larger number of individuals per electric meter, and a shared connection.

The overall lack of significant differences between the comparison groups is most likely related to the existing low electricity prices. The nominal prices have not been updated for a decade despite inflation. Given that the prices are low, the benefit may simply be too small compared with the cost of acquiring and utilizing the additional information provided.

The rest of the paper proceeds as follow. Section 2 describes the experimental design and explains the data. Section 3 provides the empirical strategy and presents the results. Finally, Section 4 concludes the paper.

2. Experimental Design and Data

2.1 Institutional Background

A single state-owned utility – Ethiopian Electric Utility – provides electricity services for all customers in Ethiopia, including residential electricity customers.[3] Residential electricity customers pay their electricity bill monthly at the end of a consumption period. This follows a process of bill preparation that involves several steps: manual meter reading at the premise of the customer, recording the reading into a database, and preparing and sending out the monthly bill to local offices where customers collect and pay their bills at predefined dates.[4] This post-paid billing system is prone to billing irregularities and unpaid bills (Smith, 2004). In view of this, the amount reported in a customer's monthly bill might not always be the actual power used.

As in many other electric utilities, the utility in Ethiopia uses an increasing block price for residential customers as a tool to subsidize low-income consumers, while promoting electricity conservation and cost recovery among high-users (Ethiopian Electric Power Corporation, 2012). The increasing block tariff consists of consumption block based tariff and service charges. The consumption block based price consists of seven blocks (see Figure 1). As shown in Figure 1, the price of electricity varies from 0.27 birr/kWh for the lowest consumption block (0 to 50 kWh) to 0.69 birr/kWh for the upper consumption block (above 500 kWh).[5] The service charge for a single-phase electric meter depends on the amount of the monthly electricity consumption in kWh. It ranges from 1.40 birr to 13.65 birr. However, the service charges for three-phase and active-reactive meters are fixed amount. More than 99% of the residential electric meters in Addis Ababa are single-phase meters.

The existing tariffs have been stable in nominal terms since 2006 despite the high inflation in 2008. For instance, the real consumption block prices in 2016 have declined by about 20

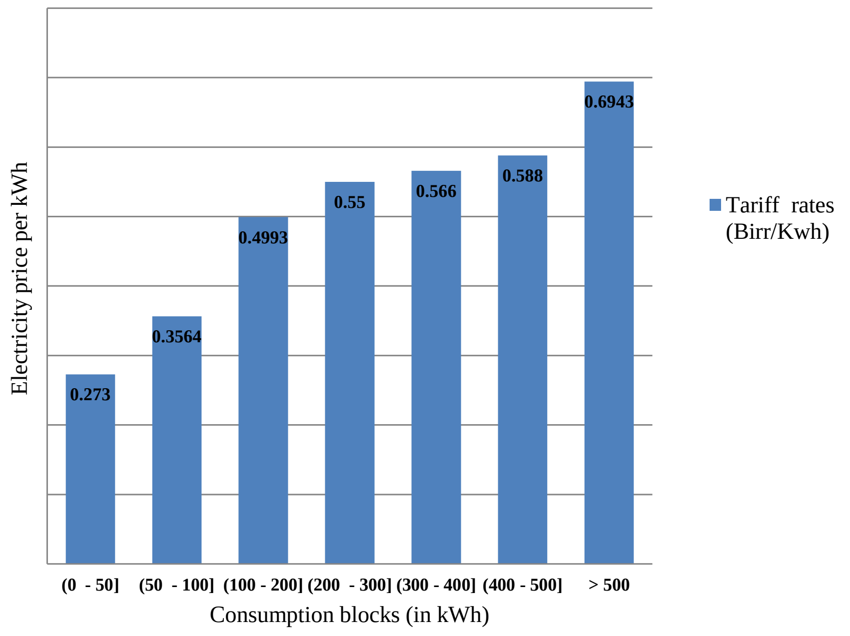
[3] A customer is equivalent to a unit receiving electricity services from an electric meter.

[4] The dates for meter reading for all customers, including residential customers, consist of four distinct groups within a month. In this paper, groups for electric meter reading imply these dates for meter reading.

[5] Birr is the Ethiopian currency. 1 USD ≈ 21 birr in May 2016.

times from what they were in 2006.[6] Also, the real consumption block price for the highest block in 2016 (0.31 birr) is much lower than the real consumption block price for the lowest block in 2006 (0.54 birr). Overall, the existing average consumer tariff of 0.49 birr/kWh (0.025 USD/kWh) is much more lower than the average tariff of 2.93 birr/kWh (0.15 USD/kWh) that would be required to fully cover the costs of supply (Addis Ababa Distribution Master plan, 2015).

Figure 1. Increasing block pricing structure for residential electricity services in Ethiopia



As discussed above, residential electricity customers in Ethiopia receive detailed billing information in their monthly bills when they collected the bill from local office at the time of payment. This billing information includes the block price of electricity along with the quantity consumed for each consumption block, monetary value of the consumption in each block, current charges, and previous balances (e.g., see Figure 2 in the appendix).

[6] Author's own computation using consumer price index (annual average) data from the World Bank. http://data.worldbank.org/indicator/FP.CPI.TOTL?locations=ET). The base year is 2010.

2.2 Sampling

The field experiment was conducted in conjunction with a household survey on electricity and water use in Addis Ababa, Ethiopia, carried out April 28–May 26, 2016. For the entire survey, we obtained a list of all residential electric meters in Addis Ababa from the Ethiopian Electric Utility. Then we randomly selected 715 electric meters using a stratified random sampling technique with a proportional allocation of the sample size between strata. Due to the presence of shared connections, our sampling units were electric meters instead of households.

In Addis Ababa city, the administration for electricity distribution is divided into four districts (North, East, South, and West), which comprise a total of 35 centers. Customers in a given center are grouped into a smaller administrative unit called a book. A book is a list of customers (electric meters) for meter reading. A standard book comprises a list of 400 customers in a neighborhood. In reality, the numbers of customers could be higher or lower. In the first step of the sampling procedure, we allocate the 715 electric meters to each of the four districts in proportion to the numbers of residential electric meters. Then, half of the centers from each of the four districts were selected randomly. After that, in proportion to size and on the assumption that five or six electric meters per book would be representative, 3 to 13 books per center were randomly chosen. In the final step, five or six electric meters were randomly selected from each book. A book is a list of customers (electric meters) for meter reading. A standard book comprises a list of 400 customers in a neighborhood. In the case of a shared connection, the other households that share a connection were also included in the household survey.

For the experiment, households that use electricity from the 715 electric meters were randomly assigned into a treatment group (355 households) and a control group (360 households) at book level. If a household shares a connection with other households, the household responsible for the monthly electricity bill was considered for the intervention.

2.3 Experimental Design

The intervention was implemented in conjunction with the household survey. In addition to the intervention part, the household survey questionnaire covered a wide range of topics, including household-level information on basic socio-demographic characteristics, consumers’ knowledge about the tariff structure and the monthly bill information, stock of electric appliances at electric meter level, alternative sources of energy, power outages, and household water use information. During the household survey, the treatment was presented before the questions on household water use information and after the questions related to energy uses. The educational material was provided and explained to the households in the treatment group only, and detail of the intervention is discussed below.

The whole survey was conducted by a group of 24 professional fieldworkers, i.e., 21 enumerators under direct supervision of three supervisors. The fieldworkers introduced themselves as part of the field research that was being conducted by a semi-autonomous government research think-thank – the Ethiopian Development Research Institute.[7] The enumerators were instructed to conduct the survey with household heads, if not available, with spouses or other adult members of the household who had better knowledge about the household otherwise make appointment. In case of difficulty, they were directed to involve other household members to assist the main respondent.

For the treatment, we prepared an intervention material – a two page paper (see Figures 2 and 3 in the appendix). The material contained the following information:

(i) A table of electricity prices for each consumption block (birr/kWh) and the corresponding monetary value (in birr) of the consumed amount in each block.

(ii) A table that shows the total service charges for monthly electricity consumption.

(iii) Two sample monthly bills from the utility in which the important pieces of information are highlighted and the information on the bills is briefly explained.

The information provided with the sample electricity bills explained how a consumer can identify a given month's consumption by differencing the current and previous meter readings; in which block the monthly consumption ended up; the consumption in each block translated into monetary value; and how the total monthly bill, including the service charge, is computed. One of the sample monthly bills is with consumption of 219 kWh and the other is with monthly consumption of 843 kWh. The reason for providing two sample bills instead of one was to help households in the treated group to better understand the information by offering more explanations and examples. The content of the material was identical for all households in the treatment group and it was written in Amharic – a local language.[8]

In addition, respondents from the treatment group were asked two control questions to check whether they understood the block prices they face in the existing increasing block tariff. The first question was a comparison of own household monthly electricity consumption with a neighbor at a different level but within the same consumption block (i.e. 50 kWh

[7] The household survey was conducted by the University of Gothenburg (Sweden) in collaboration with the Ethiopian Development Research Institute (EDRI), the World Bank, and the University of North Carolina at Chapel Hill (USA).

[8] Though many languages are spoken in Ethiopia, Amharic is the language spoken and understood by people who live in Addis Ababa – the capital city of Ethiopia.

versus 40 kWh). The second question compared own household monthly consumption for different periods at different levels and blocks (i.e. 50 Kwh versus 70 kWh). Following each question, respondents were presented with multiple choices on whether the price of the additional unit is lower (declines), the same, and higher (increases).

Fieldworkers were provided training on the intervention material and were instructed to provide and explain the material to sample households in the treatment group only. Before the main survey, we carried out a pilot test for 64 randomly selected households. The intervention material was provided and explained to all households included in the pilot, to enable the fieldworkers to practice it thoroughly. During the main field survey, only respondents from the treatment group were provided explanations verbally by the field workers about the intervention material. After the explanations were completed, the intervention material was given to the respondents so that any member of the household could have an opportunity to learn. Also, enumerators were asked to rate the respondent's level of understanding of the intervention material for the treatment group on a scale from 1 (very poor) to 10 (excellent). For households in the control group, the visit was exactly the same except they were not exposed to the educational treatment as described above. They were asked the other parts of the survey questionnaire including whether respondents knew that the existing pricing structure is increasing block price and whether any household members checks details of their monthly bill.

3. Empirical Analysis and Results

3.1 Empirical Strategy

We are primarily interested in how residential electricity consumers change their monthly electricity consumption in response to the treatment. We estimate the average treatment effects of the following specification using a difference-in-difference estimator.

$$kwh_{it} = \beta Treat_i * Post_{it} + \gamma Post_{it} + \lambda_{ty} + \eta_i + \varepsilon_{it}, \qquad (1)$$

where the dependent variable kwh_{it} denotes monthly electricity consumption in kWh at an electric meter i in month t; $Treat_i$ is a dummy variable equal to 1 if it is in the treatment group and zero otherwise; and $Post_{it}$ is a post-intervention indicator that takes a value of 1 for months after May 2016 (post-intervention periods) and zero for months before May 2016. η_i and λ_{ty} are electric-meter fixed effects and month by year fixed effects, respectively, and ε_{it} is the error term, which is uncorrelated with the regressors due to randomization. β is the coefficient of interest that captures the effect of the intervention. The coefficient γ controls for difference in monthly electricity consumption between pre- and post-intervention periods in the absence of the intervention. η_i captures unobserved differences between the treatment and control groups prior to the intervention. This equation is estimated by OLS using the standard fixed effects estimator, and standard errors are clustered at electric meter level.

Because there could be variation across households in both learning the information and paying attention to consumption, we further estimate heterogeneity in the treatment effects. We consider baseline differences in average monthly electricity consumption, consumption around the kink points, monthly income per capita, types of connections, respondent's level of education, prior knowledge of the tariff structure, and whether household members check the details of their monthly electricity bills.

To estimate the heterogeneous treatment effects, we introduce an interaction term of the variables of interest with the treatment effect for the specification in Equation (1). In cases where the variables of interest are continuous, we construct an indicator variable based on the mean values of the variables. The indicator variable equals one for values above the average sample value of the variable of interest; otherwise, it is zero.

Our empirical analysis is based on the monthly billing data, an in-depth survey of socio-economic and demographic characteristics of the sample households, and respondents' knowledge about the existing block pricing structure. Following the treatment, we tracked the monthly electricity bill data from the utility for both the treatment and the control group for six months (June–November 2016). In total, we obtained access to monthly electricity billing data from the utility for 20 months from April 2015 to November 2016. However, the monthly bills for six customers (three from the treatment and three from the control group) in the post-intervention periods were missing, so these customers are excluded from our analysis.[9] Thus, the analysis is based on 709 households. The intervention month, May 2016, is also excluded from our analysis.

3.2 Results

We begin our analysis by presenting the descriptive statistics of the sample for the field experiment. About 51% of the respondents were household heads and the rest were either spouses or other adult members of the household who had better knowledge about the household. The mean age of the respondents is 45 years. As for education, 43.86% had completed primary school or below, 45.98% had completed high school, and 10.16% held a

[9] The monthly bill data for the six customers also were missing for some of the months prior to the intervention. We checked the status of the customers from the billing information; most of them became inactive.

bachelor's degree or above. Around 28.63% of the sample electric meters are shared connections. The average number of individuals at an electric meter is 6. See Table 1, Column 1, for details of the descriptive statistics.

Table 1. Mean differences of the baseline survey data across comparison groups

		Full sample			Restricted sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Whole	Control	Treatment	Diff.	Control	Treatment	Diff.
Three months average electricity consumption in kWh (February 2016 –April 2016)	278.651	281.012	276.284	4.728	264.33	288.44	-24.11
	(261.5)	(250.9)	(271.9)	(0.24)	(177.1)	(220.8)	(-1.29)
12 months average electricity consumption in kWh (May 2015 – April 2016)	266.715	266.715	265.027	1.688	261.43	282.97	-21.53
	(182.1)	(182.1)	(217.9)	(0.11)	(162.0)	(209.6)	(-1.24)
Index for stock of electric appliances (in kW)	7.681	7.593	7.748	-0.155	7.530	8.064	-0.534
	(4.639)	(4.851)	(4.430)	(-0.44)	(4.452)	(4.269)	(-1.32)
Monthly income per capita (in birr)	1636.6	1583.0	1690.7	-107.7	1473.1	1544.4	-71.34
	(3055.1)	(1718.5)	(3974.9)	(-0.47)	(1419.8)	(1758.2)	(-0.48)
No. of individuals at electric meter	6.360	6.325	6.392	-0.067	6.062	6.592	-0.531
	(5.053)	(5.067)	(5.039)	(-0.18)	(4.305)	(5.623)	(-1.14)
No. of other HHs that share connection	0.696	0.689	0.713	-0.024	0.639	0.794	-0.155
	(1.713)	(1.695)	(1.741)	(-0.19)	(1.491)	(1.921)	(-0.97)
Duration of monthly power outages in hours	58.58	56.71	60.47	-3.766	57.02	60.41	-3.390
	(52.72)	(51.93)	(53.45)	(-0.95)	(53.95)	(54.55)	(-0.67)
=1 if live in own home	0.545	0.543	0.545	-0.002	0.533	0.559	-0.026
	(0.498)	(0.499)	(0.499)	(-0.05)	(0.500)	(0.498)	(-0.56)
Districts for electricity distribution (4 districts)	2.580	2.571	2.591	-0.019	2.366	2.429	-0.063
	(1.120)	(1.111)	(1.124)	(-0.23)	(1.110)	(1.099)	(-0.61)
= 1 if respondent is HH head	0.507	0.499	0.517	-0.018	0.502	0.563	-0.061
	(0.500)	(0.501)	(0.500)	(-0.49)	(0.501)	(0.497)	(-1.31)
Age of respondent in years	44.89	43.73	46.04	-2.31*	44.95	47.40	-2.452
	(16.41)	(16.55)	(16.20)	(-1.88)	(16.72)	(16.69)	(-1.58)
= 1 if respondent is male	0.315	0.300	0.332	-0.032	0.313	0.366	-0.053

	(0.465)	(0.459)	(0.472)	(-0.93)	(0.465)	(0.483)	(-1.20)
Dummies for respondent's education (0=primary or below, 1=high school, 2=bachelor or above)	0.664	0.678	0.648	0.030	0.687	0.672	0.015
	(0.654)	(0.653)	(0.654)	(0.61)	(0.654)	(0.651)	(0.25)
Dummies for highest education in the main HH	1.181	1.182	1.176	0.006	1.198	1.189	0.009
	(0.607)	(0.607)	(0.611)	(0.13)	(0.610)	(0.611)	(0.16)
= 1 if respondent has job	0.444	0.448	0.440	0.008	0.423	0.454	-0.031
	(0.497)	(0.498)	(0.497)	(0.21)	(0.495)	(0.499)	(-0.67)
Interviewers (21 enumerators)	10.64	10.76	10.49	0.270	10.12	10.47	-0.347
	(6.098)	(6.150)	(6.052)	(0.59)	(5.971)	(6.192)	(-0.62)
Groups for electric meter reading (4 distinct date groups)	2.462	2.517	2.409	-0.108	2.419	2.433	-0.014
	(1.131)	(1.130)	(1.132)	(-1.27)	(1.123)	(1.118)	(-0.14)
=1 if respondent knows the pricing structure	0.208	0.208	0.207	0.001	0.217	0.218	-0.002
	(0.406)	(0.406)	(0.406)	(0.02)	(0.413)	(0.414)	(-0.04)
=1 if respondent's HH members check details of the monthly bill	0.138	0.146	0.131	0.015	0.142	0.134	0.007
	(0.346)	(0.354)	(0.338)	(0.59)	(0.349)	(0.342)	(0.22)
Dummies for self-reported relative status of monthly electricity usage (0=do not know, 1=lower, 2= the same, 3=higher)	1.631	1.657	1.605	0.052	1.673	1.639	0.034
	(1.109)	(1.106)	(1.112)	(0.63)	(1.107)	(1.127)	(0.33)
=1 if at least one month non-positive kWh records	0.345	0.364	0.324	0.040			
	(0.476)	(0.469)	(0.482)	(1.13)			
No. of electric meters	709	357	352	709	227	238	465

Table 1 reports average values of variables across sample groups, and mean differences between control and treatment groups for the baseline survey data. Standard deviations are in parentheses for the mean values in the whole sample, control and treatment groups, whereas, for the Diff., *t* statistics are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Note that the statistical significance of the variables across the comparison groups for the full sample and the restricted sample remains the same with non-parametric, Mann-Whitney test.

The average monthly electricity bill recorded by the utility over 12 months prior to the intervention was 138 birr. This accounts for about 2% of the average reported monthly income of households responsible for the bill payment. When we split the average monthly bill across connection types, it is 128 birr at a private connection and 162.50 birr at a shared connection.

In the monthly electricity consumption records (in kWh) from the utility, we observe a negative or zero records for about 35% of the sample electric meters for at least one month in either the pre-intervention or post-intervention periods. Clearly, these records do not reflect the actual monthly electricity use. The records are possibly a balance for previous month's higher recorded figures than the accurate one, and error could occur at several stages from meter reading to recording to the database. They could also be inaccurate power use records due to technical defects at the electric meter itself. This does not mean that records in electric meters with positive records throughout are accurate. There could be unintentionally recorded lower or higher figures than the actual and records could be lower than the actual power use due to non-legitimate consumer's behavior such as meter tampering and bribing meter readers and office staffs (Smith, 2004; Rao, 2012). In our analysis, we conduct a number of robustness checks of the main results using the entire sample of electric meters by excluding meters with non-positive monthly records and meters with positive records that shows a large monthly deviation from the median monthly consumption records in pre and post intervention periods.[1]

During the survey, all the respondents who participated in the study were asked whether they knew that the existing pricing structure is increasing block price and whether any household member regularly checks the details of the monthly electricity bill. Only 20.70% of them said they knew the pricing structure and 13.85% said somebody checks the details of the monthly bills. The majority (79.30%) said they did not know the pricing structure and 86.15% said they only check the amount due for the month and no other details. Similarly, in another study on whether marginal prices in the increasing block price affect monthly electricity consumption, using the same sample, the author does not find statistically significant results.[2]

Regarding the two control questions to test the understanding of respondents in the treatment group about the consumption block prices in the IBP, a majority of the respondents

[1] To find the deviation from the median monthly kWh records, we first compute the median kWh by sample electric meter and period of intervention (pre and post) and then calculate the absolute difference between the recorded kWh of a month and the median kWh of an electric meter by period of intervention.

[2] Hadush, T. (2017). "Do Consumers Respond to Marginal Prices of Electricity under Increasing Block Tariff?" Unpublished paper.

(68.73%) answered both questions correctly; 22.54% answered one of the two questions correctly, and the remaining 8.73% answered both questions incorrectly. See Table 2 below for the detailed distribution of the answers to the control questions across respondents, knowledge of the existing tariff structure and households that check details of their monthly electricity bill.

Table 2. Distribution of answers to the control questions

	All treatment	Head of household	Not household head	Knew the tariff structure	Checks details of the monthly bill
Answered both questions correctly	68.73%	65.93%	71.68%	72.60%	80.43%
Answered one of the two questions correctly	22.54%	21.43%	23.%	27.40%	19.57%
Answered both questions incorrectly	8.73%	12.64%	4.62%	0%	0%
Number of observations	355	182	173	73	46

Using a chi-squared test, we check the distribution of the correct and incorrect answers across the two control questions. The distribution is significantly different at the 1% level of significance. When we look at the proportions of incorrect answers, it declines from 29.86% for the first question to 10.14 % for the second control question.

In addition, enumerators rated 87.04% of the respondents in the treatment group 5 or higher (i.e., good and above) on the scale from 1 (very poor) to 10 (excellent) about their understanding of the intervention material. 80.43% of the respondents who were rated below 5 have primary school education or below and have a median age of 60 years, whereas the corresponding figures for those who were rated good and above are 39.87% and 42 years. Enumerator's subjectivity in rating the respondents on the scale from 1 to 10 is possible. We check whether those respondents who were rated good and above answered the two control questions correctly. 76.38% of them answered both questions correctly; 20.39% answered one of the two questions correctly, and 3.24% answered both questions incorrectly

Table 1, Columns (2)–(7), provides pair-wise mean comparisons between the control and the treatment group. We compare the two groups in terms of baseline monthly electricity consumption, socioeconomic and demographic characteristics of the households and respondents, and prior knowledge of the pricing structure and details of the monthly electricity bill. Apart from monthly electricity consumption, all variables of interest were collected only once during the survey period and were assumed to remain similar over the period of analysis. Column (1) presents mean values of the variables at baseline for the whole sample. Columns (2)–(4) are average values of the variables across control and treatment groups and their differences for the full sample. Columns (5)–(7) show mean values of variables across the comparison groups and their differences for a restricted sample in which sample electric meters with at least one month negative or zero records are excluded.

When comparing the historical monthly electricity consumption levels (average of 12 months and three months before the intervention), we fail to reject the null hypothesis that the two groups had the same level of average monthly electricity consumption prior to the intervention. Given our detailed data on household and respondent characteristics and on the respondent's assessment of the electricity pricing and own monthly consumption, we were also able to test differences in these respects between the two groups. We do find a significant difference in only one variable: age. The respondents in the treatment group are two years older on average (significant at the 10% level). To further check our randomization, we alternatively run a probit model by assigning a value of one for the treatment group and zero for the control group, and found similar results (not reported here but available upon request). All explanatory variables except age are statistically insignificant at all the conventional levels of significance. This confirms that our sample is randomly allocated into the treatment and the control group.

In the presence of billing problems, which possibly happen due to meter reading errors, recording errors and technical problems at the electric meter, it is difficult to identify a behavioral response in monthly electricity consumption resulting from the treatment. Thus, we further analyze our results by excluding electric-meters with non-positive monthly records and meters with positive records that show a large monthly deviation from the median monthly consumption records in pre and post intervention periods. In Table 1, Columns (5)–(7) provide mean differences between the treated and control groups for the restricted sample (N=465) where electric meters with at least one month non-positive kWh records are excluded. As in the full sample, we do not find statistical significant difference between the control and treated groups, except that the mean differences for some variables are larger in absolute value in the restricted sample compared to the full sample. This is partly attributed to the smaller sample size.[3]

[3] We also check whether electric-meters with non-positive monthly kWh records are associated with observable variables in the baseline and the treatment, using a probit model. We find significant coefficients only for age of respondents and two dummies for districts. The estimated coefficient on treatment variable is negative and insignificant.

Table 3. Mean differences in average monthly electricity consumption across comparison groups

	Full sample			Restricted sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Period	Control	Treatment	Diff.	Control	Treatment	Diff.
Pre-intervention	270.10	265.03	5.07	266.96	286.43	-19.47
(June – November 2015)	(201.00)	(220.61)	(0.32)	(168.32)	(219.55)	(-1.07)
Post-intervention	282.29	289.80	-7.51	285.31	313.42	-28.11
(June – November 2016)	(202.84)	(217.429)	(-0.48)	(172.53)	(227.23)	(-1.50)
No. of electric-meters	357	352	709	227	238	465

Table 3 reports average monthly electricity consumption across control and treatment groups and their differences. Columns (1)–(3) are for the full sample (N=709 households) and Columns (4)–(6) are for the restricted sample (N=465 households), where electric meters with at least one month non-positive kWh records are excluded. Standard deviations are in parentheses for the mean in the control and treatment groups, whereas, for the Diff., *t*-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Note that using non-parametric, Mann-Whitney test, we do not also find statistically significant difference in the average monthly electricity consumption in the pre- and post-intervention periods for both the full sample and the restricted sample.

Table 3 displays raw results that compare the average monthly electricity consumption between the treatment and the control groups in both the pre- and post-intervention periods. Columns (1)–(3) are for the full sample (N=709 households). In the pre-intervention period, the average monthly electricity consumption is 5.07 kWh higher for the control group than for the treatment group, but the difference is not statistically significant (p-value=0.75). This shows that, prior to the intervention, there were no systematic differences in average monthly electricity consumption between the control and the treatment groups. In contrast, the monthly consumption was 7.51 kWh lower for the control group than for the treatment group in the post-intervention period, but this difference is not significant either (p-value=0.63). We observe an increase in monthly electricity consumption for both groups after the intervention. We check whether the average increase in consumption is driven by outliers by looking at the proportion of households that increased their monthly consumption. Our data reveals that 57.26% of all households increased their monthly electricity consumption. The share is 60.51% for the treatment group and 54.06% for the control group. A chi-squared test shows that the distribution of the share is significantly different (p-value=0.083) across the two comparison groups.

Columns (4)–(6) in Table 3 show differences in average monthly electricity consumption for the restricted sample (N=465 households), where electric meters with zero or negative monthly electricity consumption records (in kWh) are excluded. After excluding the electric meters with non-positive monthly kWh records, the average monthly electricity consumption in the control group becomes lower than the corresponding average values in the treatment group but the differences are not statistically significant.[1] Dropping the electric meters with zero or negative monthly kWh records substantially reduces the sample size.

In our regression estimates, we control for the non-positive monthly kWh records by introducing a dummy variable equals to one if the recorded monthly electricity consumption is zero or a negative value; otherwise it is zero. Furthermore, we exclude sample electric meters with a negative or zero kWh records for at least one month, and electric meters with positive records that have a monthly record of higher or lower than 30% of the median monthly records in pre and post intervention periods. Since the selection of 30% of the median monthly record is an ad hoc, we check sensitivity of the results using a lower and a higher percentage (i.e., 20%, 40%, and 50%).

Next, we analyze the effect of the intervention on monthly electricity consumption using regression models. Our regression estimation begins with the average treatment effect of the intervention. Table 4 presents regression estimates that correspond to the specification in Equation (1). Columns (1) and (2) provide treatment effects for the whole sample that participated in the field experiment, respectively without and with an indicator variable for months with non-positive kWh records.[2] Column (3) presents estimated results for the restricted sample, in which sample electric meters with at least one month's non-positive billing records are excluded.[3] Column (4) provides estimation results for a more restricted sample by excluding sample electric meters with at least one month non-positive monthly kWh records and with positive monthly kWh records higher or lower than 30% of the median monthly kWh records in pre and post intervention periods. The estimated results remain statistically insignificant with a lower and higher percentages deviation from the median

[1] In the pre-intervention period, the average monthly electricity consumption for electric meters in the control groups with at least one month's negative recorded readings and with at least one month zero recorded readings are 193.56 kWh and 312.05 kWh, respectively. The corresponding average values in the treatment groups are 178.99 kWh and 237.19 kWh, respectively. Similarly, the average monthly values in the post-intervention period for electric meters in the control groups with at least one month's negative recorded readings and with at least one month's zero recorded readings are 212.68 kWh and 314.68 kWh , respectively. The corresponding average values in the treatment groups are 185.67 kWh and 267.25 kWh.

[2] We also check the average treatment effects over months by introducing an interaction term between months in post-intervention periods with the treatment variable for the same specification as in Table 4 Column (1). The estimated coefficients are 3.61, -0.21, 16.60, 22.02, 0.23, and 28.49 for June, July, August, September, October and November 2016, respectively. All the estimated results remain statistically insignificant.

[3] For the restricted sample that excludes meters with at least one month non-positive monthly kWh record, we further check the treatment effects using a propensity score matching approach. However, in the probit regression results for estimating the propensity score, we do not find any variable statistically significant.

monthly kWh records as well[4]. The regression results in Column (5) are for the full sample but respondents with poor understanding of the intervention material and those who answered both control questions incorrectly are excluded.

Our findings from the difference-in-difference estimation show that monthly electricity consumption is 5.69–14.34 kWh higher for the treatment group than for the control group, but the results are insignificant at all the conventional levels of significance.[5] The differences in monthly electricity consumption across comparison groups are about 2.1% to 5.3% relative to the pre-intervention monthly consumption.[6]

A possible explanation for the increasing trend in monthly electricity consumption following the intervention is that consumers in the treatment group became more aware that the existing electricity price is low and therefore responded by increasing their consumption.[7] This suggests that providing information that aims at improving consumers' billing knowledge can have the perverse effect of increasing consumption. This increment is comparable to the 4–6% increase in residential electricity use due to automatic bill payment programs (Saxton, 2015), to the 3.5–5% increases in water consumption in response to more frequent billing information (Wichman, 2017), and to the 1.4–3.3% reduction in energy consumption due to peer comparisons (Allcott, 2011).[8] However, on average, our intervention does not have a significant effect on monthly electricity consumption.[9]

The overall lack of significant differences between the comparison groups is mostly likely related to the existing low electricity prices. As noted above, the real consumption block prices in 2016 are 20 times lower than they were in 2006. The real price for the highest block in 2016 (0.31 birr) is much smaller than the real price for the lowest block in 2006 (0.54 birr). Given that prices are low, households may not be interested in investing any significant resources in obtaining price and quantity information. Another reason could be the absence of

[4] The estimated results are 52.231, 33.926 and12.106 when the sample electric meters with non-positive monthly kWh records and those with higher than 20%, 40% and 50% of the median monthly kWh records are excluded. The corresponding numbers of electric meters are 15, 135 and 216 respectively.

[5] The p-values for the average treatment effects in Table 4, Columns (1)–(5), are 0.289, 0.195, 0.453, 0.766 and 0.242, respectively.

[6] The average monthly electricity consumption before the intervention for the whole sample is 266.72 kWh (see also Table 1).

[7] In Ethiopia, electricity is customarily considered as more expensive than alternative fuels such as firewood, charcoal, kerosene and LPG for cooking and baking.

[8] Also, over-consumption has been documented in toll road use (Finkelstein, 2011), alcohol purchases (Chetty et al., 2009) and bank overdrafts (Stango and Zinman, 2011).

[9] The insignificant result could be partly due a smaller sample size compared to other studies. For instance, the percentage change in the studies by Allcott (2011) and Wichman (2017) use sample sizes of 600,000 and 59,000, respectively.

real-time feedback, so that the time lapse between the consumption and expenditure causes salience problems (Gilbert and Graff Zivin, 2014). It could be also that the intervention in this study is weak. Since the intervention was implemented in conjunction with a household survey and one member of the household - the respondent - received the material and an explanation of it. Thus, the respondents might be missed the relevance of the intervention and failed to share the necessary information with members of the household and the other households in the case of a shared connection.

Table 4. Average treatment effects

Variables	(1)	(2)	(3)	(4)	(5)
=1 if Post–intervention	10.976	10.986	10.827	-3.658	6.715
	(11.092)	(10.445)	(9.449)	(12.830)	(11.426)
Treatment* Post–intervention	11.745	14.340	8.638	5.685	13.855
	(11.079)	(11.045)	(11.491)	(19.030)	(11.819)
Electric meter fixed effects	Yes	Yes	Yes	Yes	Yes
Month by year fixed effects	Yes	Yes	Yes	Yes	Yes
=1if monthly kWh is non-positive		-369.930***			
		(25.982)			
Constant	275.296***	292.647***	280.674***	323.603***	278.637***
	(5.830)	(5.710)	(5.029)	(7.403)	(6.237)
Observations	8,477	8,477	5,579	816	7,805
No. of electric meters	709	709	465	68	653
Adjusted R-squared	0.426	0.500	0.630	0.902	0.429

Table 4 shows the average treatment effects of the intervention. The dependent variable is monthly electricity consumption in kWh. Estimation results shown in Column (1) are for the full sample without controlling for the non-positive monthly kWh records, whereas, in Column (2) the results shown are after including a dummy for non-positive monthly kWh records. Column (3) presents results for a restricted sample in which sample electric meters with at least one month non-positive monthly kWh records are excluded. Column (4) provides estimation results excluding sample electric meters with at least one month non-positive monthly kWh records and with positive monthly kWh records higher than 30% of the median monthly kWh records in pre and post intervention periods. Column (5) reports estimated results excluding respondents who were rated by the enumerators as poor regarding to their understanding of the intervention material, and those who answered both control questions incorrectly. Robust standard errors clustered at electric meter level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We further investigate whether there is a heterogeneous treatment effect. We allow the treatment effect to vary across different sub-groups of the sample. We base the heterogeneity in treatment effects on the specification in Equation (1) for the full sample that corresponds to Table 4, Column (1). Results are provided in Table 5, Panels A–C. We find statistically significant results for household represented by head respondents, for a larger number of individuals per electric meter, and for a shared connection.[1]

Panel A reports the effect of the intervention by considering differences in pre-intervention monthly electricity consumption and for electric meters with at least one month non-positive kWh record. Based on three months' electricity consumption prior to the intervention, we construct dummy variables equal to one for monthly consumption above the average, and for average monthly consumption of 20 kWh within the kink points.[2] Out of the total, 14.47 % of the average monthly electricity consumption is within 20 kWh above the kink points and 14.18% are within 20 Kwh below the kink points. Households who historically consume above the average and within 20 kWh below the kink points increase their consumption by 27.91 kWh and 12.65 kWh compared to their counterparts in the treatment group. On the contrary, households who historically consume within 20 kWh above the kink points reduce their consumption by 7.13 kWh relative to their counterparts in the treatment group. Average monthly electricity consumption in electric meters with at least one month a negative or zero kWh record is 5.75 kWh less than its counterpart in the treatment group. In all cases, the results are statistically insignificant at the conventional levels of significance.

Panel B shows the effect of the intervention for various households related characteristics, such as monthly income per capita, shared connections, numbers of individuals at the electric meter, districts for electricity distribution, and monthly hours of power outages. Households with higher monthly income per capita reduce their consumption in response to the intervention. Compared with the control group, the monthly consumption for households with above-average monthly income per capita is 4.98 Kwh lower in the treatment group. However, this is not statistically significant at the conventional levels of significance. At the baseline, the economic status of households is significantly and positively correlated with

[1] The sample size might not be sufficient to draw conclusions based on those findings. It is, rather, useful to probe what might explain the lack of significance in the overall treatment effects. This could be related to the studies by Allcott (2011) and Costa and Kahn (2013), who document evidence of differences in energy consumption between high and low users, and based on political ideology (liberals versus conservatives), respectively.

[2] To avoid overlapping, between the kink points at 25 kWh and 50 kWh, and the kink points at 100 kWh and 105 kWh, we do not consider the 20 kWh average monthly consumption within the kink points at 25 kWh and 105 kWh.

monthly electricity consumption. The correlation coefficient was 0.32 and the associated p-value equals 0.00. We do not also find statistically significant results in the dummies for the districts and for hours of monthly power outages though the estimated coefficients are positive (see Panel B, Columns 4–5).

On the other hand, the monthly electricity consumption in a shared connection significantly increased in response to the treatment. Compared to the monthly consumption in a private connection, the consumption in a shared connection is 30.17 kWh higher. This is statistically significant at the 10% level. In Panel B, Column (3), households with more individuals per electric meter (more than six) significantly increase their monthly electricity consumption in response to the intervention. The monthly electricity consumption for these households is 40.45 kWh (around 15% relative to the pre-intervention average consumption) higher than their counterparts in the treatment group. This difference is significant at the 5% level.

In panel C, Column (1), households represented by head respondents significantly reduces their monthly electricity consumption in response to the treatment. This hold statistically significant even after excluding sample electric meters with at least one month non-positive kWh record (see Panel C, Column 2). Compared to the other respondents, the monthly consumption for households represented by head respondents is 29.81 kWh lower (around 11% lower relative to pre-intervention average consumption). This is statistically significant at the 10% level. Following the treatment, we also find an increase in monthly electricity consumption among households represented by more educated respondents, that know the existing tariff structure and those who check details of their bill prior to the intervention (see Table 4, Panel C). However, results are not statistically significant.[3]

[3] We also check whether the treatment effects vary across enumerators. But, we do not find systematic differences.

Table 5. Heterogeneity in treatment effects

Panel A: Baseline monthly electricity consumption (Average of three months prior to the intervention)

Variables	(1)	(2)	(3)	(4)
= 1 if Post–intervention	12.049	12.070	12.079	10.963
	(11.161)	(11.162)	(11.163)	(11.089)
Treatment* Post–intervention	0.266	11.842	9.250	13.591
	(9.962)	(12.034)	(11.677)	(11.552)
Treatment* Post–intervention*Above average monthly electricity usage	27.910			
	(20.006)			
Treatment* Post–intervention* At most 20 kWh above the kink points		-7.134		
		(15.886)		
Treatment* Post–intervention* At most 20 kWh below the kink points			12.648	
			(21.234)	
Treatment* Post–intervention* At least one month non-positive monthly kWh records				-5.748
				(19.646)
Electric meter fixed effects	Yes	Yes	Yes	Yes
Month by year fixed effects	Yes	Yes	Yes	Yes
Constant	275.733***	275.735***	275.735***	275.295***
	(5.867)	(5.863)	(5.864)	(5.829)
Observations	8,429	8,429	8,429	8,477
Adjusted R-squared	0.426	0.426	0.426	0.426

Panel B: Households characteristics

Variables	(1)	(2)	(3)	(4)	(5)
= 1 if Post–intervention	10.972	10.964	10.954	10.975	10.977
	(11.092)	(11.092)	(11.092)	(11.093)	(11.092)
Treatment* Post–intervention	18.381	2.900	-1.961		9.482
	(12.533)	(12.821)	(12.799)		(12.381)
Treatment* Post–intervention*Above average monthly income per capita	-23.361				
	(17.051)				
Treatment* Post–intervention*Shared connection		30.168*			
		(16.019)			
Treatment* Post–intervention*Above average number of electricity users			40.450**		
			(16.613)		
North district				5.214	
				(14.362)	
East district				0.627	
				(19.090)	
South district				18.180	
				(15.140)	
West district				20.532	
				(21.289)	
Treatment* Post–intervention*Above average monthly hours of power outages					5.923
					(17.500)
Electric meter fixed effects	Yes	Yes	Yes	Yes	Yes
Month by year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	275.295***	275.295***	275.294***	275.296***	275.297***
	(5.821)	(5.822)	(5.819)	(5.831)	(5.829)
Observations	8,477	8,477	8,477	8,477	8,477
Adjusted R-squared	0.426	0.426	0.427	0.426	0.426

Panel C: Respondents characteristics, and prior tariff and billing knowledge

Variables	(1)	(2)	(3)	(4)	(5)
= 1 if Post–intervention	10.982	10.827	10.951	11.610	11.591
	(11.092)	(9.450)	(11.092)	(11.096)	(11.095)
Treatment* Post–intervention	27.146**	28.715**	4.212	8.044	8.677
	(12.358)	(13.402)	(12.880)	(12.153)	(11.587)
Treatment* Post–intervention *head of household	-29.815*	-35.660**			
	(16.259)	(17.157)			
Treatment* Post–intervention*Respondent is high school or above			13.685		
			(16.155)		
Treatment* Post–intervention *Know the tariff structure				17.425	
				(17.808)	
Treatment* Post–intervention *Check details of the monthly bill					22.714
					(23.393)
Electric meter fixed effects	Yes	Yes	Yes	Yes	Yes
Month by year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	275.297***	280.674***	275.293***	275.085***	275.083***
	(5.833)	(5.031)	(5.832)	(5.837)	(5.833)
Observations	8,477	5,579	8,477	8,465	8,465
Adjusted R-squared	0.426	0.631	0.426	0.426	0.426

Panels A–C in Table 5 present heterogeneous treatment effects across various groups of covariates. In Panel C, Columns (1) and (2) reports estimated results for the full sample and for a restricted sample where sample electric meters with at least one month non-positive kWh records are excluded. Robust standard errors clustered at electric meter level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4. Conclusion

Households typically receive utility bills at the end of their consumption periods. However, simply sending billing information to consumers might not be sufficient to help them make well-informed decisions. For instance, lack of knowledge about the marginal price they face and difficulty in understanding how their bill is calculated could prevent households from responding to their marginal prices in a block-based pricing scheme. Consumers' understanding of the tariff system is necessary for its success. Thus, in the present paper, we investigate whether educating consumers about how their monthly electricity bill is determined in an increasing block pricing structure affects monthly electricity consumption in the short term. To evaluate the effect of the intervention, we conduct a field experiment with a sample of 715 households in Ethiopia, where shared connection is common, electricity price is highly subsidized, and tariff reform is often difficult for political reasons.

Our findings show that, on average, the treatment increases monthly electricity consumption by 5.69–14.34 kWh, which is equivalent to a 2.1%–5.3% increase in consumption relative to the pre-intervention monthly consumption. This is comparable to the 4–6% increase in residential electricity use due to automatic bill payment programs (Saxton, 2015), the 3.5–5% increases in water consumption in response to more frequent billing information (Wichman, 2017), and the 1.4–3.3% reduction in energy consumption due to peer comparisons (Allcott, 2011). However, on average, our intervention does not have a significant effect on monthly electricity consumption.

Our intervention highlights that, if electricity price is low, consumers do not worry about their electricity consumption, and providing additional information and education does not affect their behavior. The insignificant effect on monthly electricity consumption could also be that the intervention focuses on one member of a household and thus, the respondent possibly does not share the information to other members of the household. This research adds to the literature on information-based intervention to change consumers' behavior in the context of developing countries. It is also worth mentioning that, in the presence of shared connections and billing irregularities, it could be difficult to monitor monthly electricity consumption. Thus, we call for policy interventions that encourage private connections, such as subsidizing connection fees, and that reduce billing problems, such as switching to pre-paid metering technology, which will at least avoid reading and recording errors.

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Appendix

Figure 2. Sample intervention material (in Amharic)

የኢትዮጵያ ኤሌክትሪክ ሃይል ኮርፖሬሽን (ETHIOPIAN ELECTRIC POWER CORPORATION)

1. የመኖርያ ቤት የኤሌክትሪክ ሃይል ፍጆታ ታሪፍ (Tariff for Domestic Electricity Consumption)

ብሎክ	የፍጆታ እርከን	የፍጆታው መጠን Consumption in KWh/KVA	የእርከኑ ታሪፍ (ለእያንዳንዱ ፍጆታ: KWh/KVA)	የእርከኑ ጠቅላላ ታርፍ
1	ከ 0 እስከ 50	50	0.273 ብር ወይም ≈ 27 ሳንቲም	50x 0.273ብር = **13.65ብር**
2	ከ 51 እስከ 100	50	0.3564 ብር ወይም ≈ 36 ሳንቲም	50x 0.3564ብር = **17.82ብር**
3	ከ 101 እስከ 200	100	0.4993 ብር ወይም ≈ 50 ሳንቲም	100x 0.4993ብር = **49.93ብር**
4	ከ 201 እስከ 300	100	0.55 ብር ወይም ≈55 ሳንቲም	100x 0.55ብር = **55.00ብር**
5	ከ 301 እስከ 400	100	0.5666 ብር ወይም ≈57 ሳንቲም	100x 0.5666ብር = **56.66ብር**
6	ከ 401 እስከ 500	100	0.588 ብር ወይም ≈ 59 ሳንቲም	100x 0.588ብር = **58.80ብር**
7	ከ 500 በላይ	**ጠቅላላ ፍጆታ - 500**	0.6943 ብር ወይም ≈69 ሳንቲም	**(ጠቅላላ ፍጆታ - 500)**x 0.6943ብር=______ ብር

2. ለመኖርያ ቤት ደንበኞች የኤሌክትሪክ ሃይል አገልግሎት ክፍያ (Service Charge for Domestic Electricity Consumption)

የኤሌክትሪክ ቆጣሪ አይነት (Meter type)	የወር ፍጆታ (Monthly Consumption, KWh/KVA)	ጠቅላላ የአገልግሎት ክፍያ
ሲንግል ፌዝ (Single Phase)	ከ 0 እስከ 25	1.40 ብር
	ከ 26 እስከ 50	3.40 ብር
	ከ 51 እስከ 105	6.82 ብር
	ከ 106 እስከ 300	10.24 ብር
	ከ 300 በላይ	13.65 ብር
ስሪ ፌዝ (Three Phase)	-	17.06 ብር
አክቲቭ ሪአክቲቭ (Active Reactive)	-	37.56 ብር

3. የአንድ ወር የኤሌክትሪክ ቢል ናሙና (Sample Monthly Electric Bill)

A. ደንበኛ አንድ

Kifiya Financial Technology PLC — Cash Receipt — Page 1 of 1 — Customer No. 71AABS678

Customer Name [redacted]

Total Paid in words: One Hundred Two Birr and Nine Cents — Total Paid in figures: 102.09

Payment Method — Cheque — No. — Cash — Signature

የኢትዮጵያ ኤሌክትሪክ ሃይል ኮርፖሬሽን — Ethiopian Electric Power Corporation

ሜትር ቁጥር Meter No 813197 — ገጽ Page 1 of 1 — የደረሰኝ ቁጥር Receipt No. 14025000111 5091

የድሮው ሒ.ቁ. Old Acct. No 1629330000359979 — ቢ.ቁጥር Bill No 594825031

የታሪፍ መደብ Tariff Cat. ICS - DOMESTIC — የአገልግሎት ቁጥር Service No. 1261742 — የፍጆታ ጊዜ Period YEKATIT_2008 — ወር

የክፍያ መግለጫ Bill Item	ያለፈው ንባብ Previous Reading	ያሁኑ ንባብ Present Reading	ፍጆታ Consumption KWh/KVA 219.00	የፍጆታ እርከን Block Rate	ተከፋይ ሂሳብ Charge
ACTIVE ENERGY	25261	25480	50.00 1ኛ ብሎክ	0.27	13.65
ACTIVE ENERGY	25261	25480	50.00 2ኛ ''	0.36	17.82
SERVICE CHARGE-SINGLE PHASE	25261	25480	0.00	0.00	10.24
ACTIVE ENERGY	25261	25480	19.00 4ኛ ብሎክ	0.55	10.45
ACTIVE ENERGY	25261	25480	100.00 3ኛ ''	0.50	49.93

30 ቀናት ክፍያ Days BAL B/F	0	የዚህ ወር ክፍያ Current	102.09
60 ቀናት ክፍያ Days BAL B/F	0	ቅድሚያ አገልግሎት ሂሳብ Prepaid	
90+ ቀናት ክፍያ Days BAL B/F	0	አጠቃላይ ተከፋይ ሂሳብ Total Outstanding Balance	102.09

የዚህ ወር ክፍያ

1. የዚህ ደንበኛ የወር የኤሌክትሪክ ሃይል ፍጆታ = የሁኑ ንባብ - ያለፈው ንባብ
   = 25480 – 25261 = <u>219</u>
2. ይህ ፍጆታ ከ 201 እስከ 300 ስለሆነ መጨረሻው 4ኛ ብሎክ ነው::
3. የመጨረሻው ብሎክ ማለትም የ4ኛው እርከን ጠቅላላ ታርፍ = (ጠቅላላ ፍጆታ - የ3ኛ ብሎክ የፍጆታ እርከን መጨረሻው)x 0.55ብር
   = (219 -200) x0.55ብር = 19x0.55ብር - <u>10.45 ብር</u>
4. በተጨማሪ ከ 4ኛው ብሎክ በታች ላሉት የፍጆታ እርከኖች የሚከፈለው የያንዳንዱ እርከን ክፍያ ከቢሉ ማየት ይቻላል።

5. ይህ የሲንግል ፌዝ ቆጣሪ ፍጆታ ከ 106 እስከ 300 ስለሆነ የኤሌክትሪክ ሃይል አገልግሎት ክፍያው (Service Charge) <u>10.24 ብር</u> ነው::

6. አጠቃላይ የወሩ ተከፋይ ሂሳብ = ጠቅላላ የፍጆታ ክፍያ + የኤሌክትሪክ ሃይል አገልግሎት ክፍያ

= 91.85 ብር + 10.24 ብር = <u>102.09 ብር</u>

B. ደንበኛ ሁለት

የኢትዮጵያ ኤሌክትሪክ ሃይል ኮርፖሬሽን
Ethiopian Electric Power Corporation

ሜትር ቁጥር Meter No 62717 | ገጽ Page 1 of 1 | የደረሰኝ ቁጥር Receipt No. 14025000111410

የድሮው ሂ.ቁ. Old Acct. No 1370113000313765 | የሂ. ቁጥር Bill No 595002795

የታሪፍ መደብ Tariff Cat. ICS - DOMESTIC | የአገልግሎት ቁጥር Service No. 1296246 | የፍጆታ ጊዜ Period YEKATIT_2008 ወር

የክፍያ መግለጫ Bill Item	ያለፈው ንባብ Previous Reading	የአሁኑ ንባብ Present Reading	ፍጆታ Consumption KWh/KVA 843.00	የፍጆታ እርከን Block Rate	የክፍያ ሂሳብ Charge
ACTIVE ENERGY	75774	76617	50.00 --- 1ኛ ብሎክ	0.27	13.65
ACTIVE ENERGY	75774	76617	50.00 --- 2ኛ "	0.36	17.82
ACTIVE ENERGY	75774	76617	100.00 -- 3ኛ "	0.50	49.93
SERVICE CHARGE SINGLE PHASE	75774	76617	0.00	0.00	13.65
ACTIVE ENERGY	75774	76617	100.00 -- 4ኛ ብሎክ	0.57	56.06
ACTIVE ENERGY	75774	76617	100.00 -- 5ኛ ብሎክ	0.59	58.80
ACTIVE ENERGY	75774	76617	343.00 -- 7ኛ "	0.69	238.14
ACTIVE ENERGY	75774	76617	100.00 -- 6ኛ "	0.55	55.00

የቆጣሪው ዐይነት

30 ቀናት ክፍያ	Days BAL B/F	0	የዚህ ወር ክፍያ	Current	503.65
60 ቀናት ክፍያ	Days BAL B/F	0	ቅድሚያ አገልግሎት ሂሳብ	Prepaid	
90+ ቀናት ክፍያ	Days BAL B/F	0	አጠቃላይ ተከፋይ ሂሳብ	Total Outstanding Balance	503.65

የዚህ ወር ክፍያ

7. የዚህ ደንበኛ የወር የኤሌክትሪክ ሃይል ፍጆታ = የሁኑ ንባብ - ያለፈው ንባብ

= 76617 – 75774= <u>843</u>

8. ይህ ፍጆታ ከ 500 በላይ ስለሆነ መጨረሻው 7ኛ ብሎክ ነው::

9. የመጨረሻው ብሎክ ማለትም የ7ኛው እርከን ጠቅላላ ታርፍ = (ጠቅላላ ፍጆታ - የ6ኛ ብሎክ የፍጆታ እርከን መጨረሻው)x 0.6943ብር

= (843 -500) x0.6943ብር = 343x0.6943ብር = <u>238.14 ብር</u>

10. በተጨማሪ ከ7ኛው ብሎክ በታች ላሉት የፍጆታ እርከኖች የሚከፈለው የታንጂ እርከን ክፍያ ከቢሉ ማየት ይቻላል ::

11. ይህ የሲንግል ፌዝ ቆጣሪ ፍጆታ ከ 300 በላይ ስለሆነ የኤሌክትሪክ ሃይል አገልግሎት ክፍያው (Service Charge) <u>13.65ብር</u> ነው::

12. አጠቃላይ የወሩ ተከፋይ ሂሳብ = ጠቅላላ የፍጆታ ክፍያ + የኤሌክትሪክ ሃይል አገልግሎት ክፍያ

= 490.00 ብር + 13.65 ብር = <u>503.65 ብር</u>

Figure 3. Sample intervention material translated into English

ETHIOPIAN ELECTRIC POWER CORPORATION

1. Tariff for Domestic(Residential) Monthly Electricity Consumption

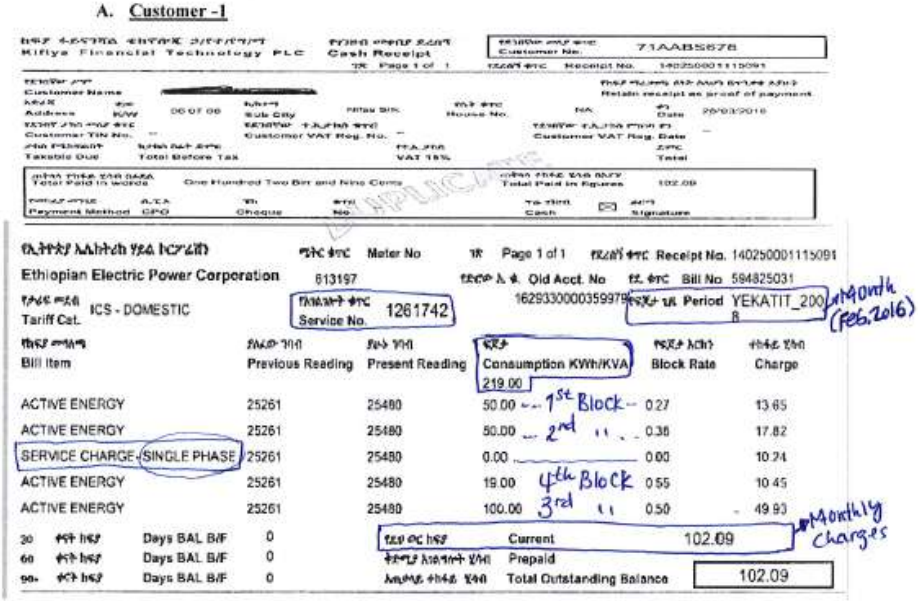
Block	Consumption blocks	Consumption amount in KWh (KVA)	Block tariff: price per KWh(KVA)	Monetary value of the consumption amonut in each block
1st	0 to 50	50	0.273 Birr or ≈ 27 cents	50x 0.273 = **13.65** Birr
2nd	51 to 100	50	0.3564 Birr or≈ 36 cents	50x 0.3564 = **17.82** Birr
3rd	101 to 200	100	0.4993 Birr or ≈ 50 cents	100x 0.4993 = **49.93** Birr
4th	201 to 300	100	0.55 Birr or ≈55 cents	100x 0.55 = **55.00** Birr
5th	301 to 400	100	0.5666 Birr or ≈57 cents	100x 0.5666 = **56.66** Birr
6th	401 to 500	100	0.588 Birr or ≈ 59 cents	100x 0.588 = **58.80** Birr
7th	above 500	Total consumption – 500	0.6943 Birr or ≈69 cents	(Total consumption - **500**)x 0.6943 = ___ Birr

2. Service Charge for Domestic (Residential) Monthly Electricity Consumption

Electric Meter type	Monthly Consumption in KWh(KVA)	Total service charges
Single Phase	0 to 25	1.40 Birr
	26 to 50	3.40 Birr
	51 to 105	6.82 Birr
	106 to 300	10.24 Birr
	Above 300	13.65 Birr
Three Phase	-	17.06 Birr
Active Reactive	-	37.56 Birr

3. Sample Monthly Electricity Bill

A. Customer -1



1. For this customer, the monthly electricity consumption = current reading – previous reading = 25480 – 25261 = **219**
2. Given the monthly electricity consumption is between **201** and **300**; it ends up in the 4th **block**.
3. The charge for the last block (4th block) = (Total consumption – Upper limit of the 3rd block) x 0.55Birr = (219 – 200) x 0.55ብር = 19x0.55ብር = 10.45 ብር
4. Look at the charges for each consumption blocks below the 4th block from the sample bill.

5. Since the monthly electricity consumption of this **single phase electric meter** is from **106 – 300**, the service charge is **10.24 Birr**.

6. Total monthly bill = total charges for consumption + service charge
   = 91.85 Birr + 10.24 Birr = **102.09 Birr**

B. Customer -2

Ethiopian Electric Power Corporation | Meter No 62717 | Page 1 of 1 | Receipt No. 1402500011149

Tariff Cat. ICS - DOMESTIC | Service No. 1296246 | Old Acct. No 1370113000313765 | Bill No 595002795 | Period YEKATIT_2008 | Month (Feb.2016)

Bill Item	Previous Reading	Present Reading	Consumption KWh/KVA 843.00	Block Rate	Charge
ACTIVE ENERGY	75774	76617	50.00 … 1st Block	0.27	13.65
ACTIVE ENERGY	75774	76617	50.00 … 2nd "	0.36	17.82
ACTIVE ENERGY	75774	76617	100.00 … 3rd "	0.50	49.93
SERVICE CHARGE-SINGLE PHASE	75774	76617	0.00	0.00	13.65
ACTIVE ENERGY	75774	76617	100.00 , 4th Block	0.57	56.66
ACTIVE ENERGY	75774	76617	100.00 … 5th "	0.59	58.80
ACTIVE ENERGY	75774	76617	343.00 – 7th "	0.69	238.14
ACTIVE ENERGY	75774	76617	100.00 … 6th "	0.55	55.00

Monthly charges

30	Days BAL B/F	0	Current	503.65
60	Days BAL B/F	0	Prepaid	
90+	Days BAL B/F	0	Total Outstanding Balance	503.65

7. For this customer, the monthly electricity consumption = current reading – previous reading
   = 76617 – 75774= **843**

8. Given the monthly electricity consumption is **above 500**; it ends up in the **7th block**.

9. The charge for the last block (7th block) = (Total consumption – Upper limit of the 6th block) x 0.6943Birr
   = (843 – 500) x 0.6943Birr = 343x0.6943Birr = **238.14 Birr**

10. Look at the charges for each consumption blocks below the 7th block from the sample bill.

11. Since the monthly electricity consumption of this **single phase electric meter** is **above 300**, the service charge is **13.65 Birr**.

12. Total monthly bill = total charges for consumption + service charge
    = 490.00 Birr + 13.65 Birr = **503.65 Birr**

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