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A Household-Level Model of Demand for Electricity Services and Welfare Analysis of Electricity Prices in Rajasthan

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Abstract

This paper estimates a model of household-level demand for electricity services and electricity demand in the Indian state of Rajasthan using a combination of household-level survey and administrative data. The model incorporates customer-level demographic characteristics, billing cycle-level weather variables, and the fact that households face increasing block prices of electricity. The model allows estimating consumer response to price changes by four categories of energy services demand, namely, heating and cooling, lighting, and for domestic and business end-uses. The knowledge of demand response across different end-use helps in differentiating the impact of price changes along the income distribution. The model finds that the demand for heating and cooling energy is the most price inelastic and income elastic service, whereas the demand for domestic end-use is the most price elastic and income inelastic service of all four categories. The structural demand model also helps in comparing the welfare implications of current energy tariffs to those based on normative principles of efficient retail electricity pricing. For this analysis, first, the social marginal cost of electricity is calculated using publicly available data on generation, transmission, and distribution losses and emissions. The social marginal cost estimate, in combination with observable household characteristics, is then used to examine alternative tariff structures that are more affordable, equitable, and revenue sufficient for the utility than current price structure. An alternative tariff design, comprising of an energy price set to the social marginal cost of electricity and a fixed cost component determined by proxy indicators of household willingness to pay, performs better on the above parameters than the current schedule. Other sources of technical losses, related to transmission or distribution, are not studied in this paper.

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SECTION I: Introduction

This paper specifies a model of household demand for electricity services and demand in the Indian state of Rajasthan using a combination of survey data, conducted in two districts of Rajasthan, and administrative data, comprising of billing cycle level consumption and charges. This model incorporates customer-level demographic characteristics and weather variables. The model also accounts for the fact that households face increasing block price schedules to recover the parameters of the household's indirect utility function, which is subsequently used to evaluate the welfare impacts of alternative retail pricing structures.

Our model of the household-level electricity demand embodies the fact that electricity consumption is the result of a household's demand for hours of service from all electricity-consuming capital goods that it owns. For example, a household does not directly consume electricity, but instead consumes lighting services, which combines electricity use with an electricity-consuming lighting device. The amount of electricity that an hour of lighting service consumption depends on the number of lighting devices a household owns. Combining household-level survey data on electricity appliance holdings and the monthly hours of use of each appliance with the household's billing cycle electricity consumption and total bill, allows us to recover an estimate of the household's demand for the following electricity services: (1) lighting, (2) general appliances for domestic end-uses, (3) heating and cooling and (4) business end-uses of electricity.

A two-step estimation procedure is employed that first recovers a household-level "electricity production function" which characterizes the relationship between the household's billing cycle electricity consumption in kilowatt-hours (kWh) and hours of use of each of four electricity services during that billing cycle. The partial derivative of this "electricity production function" with respect to an electricity service times the marginal price of electricity faced by the household is the effective rupees per hour of use price that the household pays for the last hour consumed of that electricity service. These effective prices and the hours of electricity services consumed along with information on the customer's monthly electricity bill are used to estimate the household's billing cycle-level demand for each electricity service. The demand for each electricity service is derived from an underlying model of utility-maximizing behavior subject to a nonlinear budget constraint that arises because the household faces an increasing block price schedule for their electricity consumption. Moreover, there is a nonlinear relationship between a household's demand for each electricity service and its total electricity consumption for the billing cycle. This structural demand system also offers an estimate of a range of own-price elasticities that can be used to assess the household-level welfare implications of facing different tariff schedules for their monthly electricity consumption.

Our electricity service demand model recovers separate price and income responsiveness for different uses of electricity by the household, as well as cross-price elasticities between the different electricity services. These measures can provide valuable input to the tariff design process. If certain energy services are more inelastically demanded, there are greater opportunities to recover revenues for the distribution utility through price increases to households that consume significant amounts of these services. Alternatively, if certain electricity services are elastically demanded, then providing subsidies to purchase the capital goods necessary to consume these electricity services will increase the willingness to pay of households for electricity. Understanding which of the four energy services has the highest income elasticity will allow the rate designer to tailor tariffs to recover more revenues from customers that consume these services. It also allows us to unpack the heterogenous effects of price changes on household consumption across the income distribution.

Our estimate of the electricity production function implies significant price heterogeneity across customers for the same energy service. There are two main reasons for this result. First, there is heterogeneity in the rate at which appliances consume electricity across customers. For example, depending on what kind of television, washing machine, or microwave oven a household owns, the electricity consumption per hour of use of each appliance can vary across customers. How intensively the various appliances within each energy service category are used can vary depending on weather conditions. For example, when it is extremely hot outside a household might stay inside and watch more television and wash clothes, rather than use other appliances in that energy service category. Second, a given appliance can consume more electricity depending on weather conditions. For example, one hour of use of an air conditioner when it is extremely hot outside consumes more electricity than it does during milder days.

Results from our energy services demand system finds significant differences in the own-price elasticity of demand across the four energy services. The own-price elasticity of demand for these energy services vary from -2.7 for domestic end-use appliances to -0.3 for heating and cooling services. There is also considerable heterogeneity in the income elasticity of demand across these four services with the highest and lowest income elasticity for heating and cooling end-uses and for domestic appliance end-uses, respectively observed in the data.

These estimates from the structural model are then used to analyze the performance of a tariff schedule recently proposed by India's central power ministry. The results show that the proposed tariff structure will increase consumption for all households in Rajasthan by reducing the retail cost of energy. However, consumption gains will be regressive: the average gains for households in the top income quintiles will be significantly more than the poorest ones. Moreover, the proposed tariff structure will reduce revenues for the utility by 32 percent relative to current levels.

Moving away from ad-hoc determination of tariffs, we then examine if normative principles of electricity pricing can be used to set revenue-sufficient prices that are progressive and efficient. These principles recommend a two-part tariff comprising of variable and fixed costs. The variable cost of energy should be set to the social marginal cost of electricity (the cost of producing an extra unit of energy) for all households. The fixed cost should however vary across households and should be based on their willingness to pay for power.

The social marginal cost of electricity in Rajasthan is calculated using publicly available data on energy generated by power stations at 15-minute block intervals. The marginal cost of generating power is estimated using bidding data from a segment of the wholesale electricity market. The marginal cost of transmission and distribution losses and the external cost of carbon dioxide emissions as a result of thermal power generation is also calculated to estimate the overall social marginal cost of power in Rajasthan. In calculating these costs, the paper shows that including the marginal cost of carbon emissions in the retail price of energy can increase electricity prices by approximately 50%. This result indicates that given India's current electricity generation mix, passing the full cost of carbon externalities to the retail price of electricity may lead to an impractical rise in the price of power.

Finally, the paper demonstrates how a utility can leverage its administrative billing database to recover estimates of household willingness to pay for power and use this information to set fixed prices. Based on the social marginal cost estimate and the historical consumption data from the administrative data set, the paper propose a two-part tariff which allows the utility to fully break-even on its costs. As variable costs are set to the social marginal cost for all households, the recommended tariff does not distort consumption by charging some households more than others, achieving the goal of economic efficiency. The recommended tariff design leads to progressive prices: it generates an average gain of Rs. 4.5 to Rs. 10 for households at the lowest quintile of the income distribution and an average loss of Rs. 20 per month for households in the top quintile.

The proposed schedule aims to stem losses from the residential sector and is likely to benefit both consumers and utilities. Other sources of technical losses, either related to transmission or distribution, are not studied in this paper.

The remainder of the paper proceeds as follows. Section II sets the context by describing the current challenges facing the Indian power sector and summarizes previous topically or methodologically related research. Section III describes the data sets used in our analysis and presents descriptive statistics to provide background for our analysis. Section IV describes the two-step econometric model of energy services demand. Section V describes the estimation procedure and results. Section VI estimates the social marginal cost for electricity in Rajasthan and describes counterfactual tariff experiments using own-price elasticity estimates from the demand model. Section VII concludes the paper.

SECTION II: Residential Electricity Prices and Policies in India and Rajasthan

Electricity for household consumption accounts for approximately a quarter of all electricity sales in India. As shown in Figure 1, the share of residential end-use of electricity was approximately 27 percent of all sales in 2014-15 and varied between 50 to 17 percent in the larger states. A sizable portion of these sales made by publicly-owned electricity distribution companies ("discoms"), were at prices significantly lower than the average revenue required to recover discoms' costs. The resulting losses on discoms' balance sheets, account for 83 to 90 percent of all financial losses in the power sector.[1]

In Figure 2, discoms' losses are decomposed into losses due to collections, distribution and underpricing of electricity. In 2003, the average price charged by discoms was well over the average cost of supply, but by 2011 this trend had reversed: underpricing accounted for 16 percent of the annual losses in the sector. Instead of addressing mispricing directly, discoms have attempted to cover their revenue shortfall by (i) raising external debt to finance operational expenditures (ii) charging a higher price of electricity for industrial and commercial end-uses to cross-subsidize agricultural and domestic consumers as shown in Figure 3[2] (iii) rationing the supply of power to only a few hours of the day to

[1] Khurana, Mani, and Sudeshna G. Banerjee. 2013. "Beyond Crisis: Financial and Operational Performance of India's Power Sector."

[2] Pargal, Sheoli; Banerjee, Sudeshna Ghosh. 2014. More Power to India: The Challenge of Electricity Distribution. Directions in Development--Energy and Mining. http://openknowledge.worldbank.org/handle/10986/18726

bring down their total power purchase cost; and (iv) developing a complex tariff structure made up of several increasing block-tariff (IBTs) rates, fixed costs, surcharges and duties.

Recent developments indicate that policy attention is now turning towards addressing issues of pricing electricity. The central Ministry of Finance through its annual Economic Survey 2015-16 has recently proposed a strategy to make residential price schedules equitable and easier for consumers to comprehend and respond to. The Power Ministry has proposed a draft amendment to simplify tariff categories and rationalize retail prices.[3] At the state level, other regulators, such as Andhra Pradesh's State Electricity Regulatory Commission (APERC), have undertaken studies to design better residential electricity pricing.[4] Like APERC, Rajasthan's Electricity Regulatory Commission is also evaluating efficient strategies to better price their residential electricity consumers.

A better understanding of the relationship between socioeconomic and demographic characteristics of households and their willingness to pay for electricity is an important input into the process of designing tariff schedules that can achieve revenue sufficiency for the discoms. Understanding the economic determinants of a household's monthly electricity consumption, especially for low-income consumers, is also essential for meeting the affordability and equity objectives of the government, regulator and the utility.

This paper uses a structural demand model to propose an alternative tariff structure that can achieve these three objectives. Even though the demand model and welfare analysis outlined in this paper can be used to set prices for any discom in India, the paper uses data from the state of Rajasthan to illustrate the methodology to set tariff levels. The average revenue generated by domestic consumers of a utility in Rajasthan in FY2016-17 was Rs. 6.31 per kWh as against an average revenue requirement of Rs. 7.74 per kWh of energy for the utility. This suggests that domestic consumers of the utility were undercharged by Rs. 1.43 per kWh on average, a shortfall that is cross-subsidized by commercial and industrial consumers of the discom. By achieving cost-neutrality, the proposed alternative tariff design aims to remove the need to cross-subsidize residential users and reduce the higher cost of power currently borne by other consumer categories. However, addressing challenges known to be endemic to India's power sector, such as low-collection efficiency, high transmission and distribution losses, ineffective dispatch mechanisms, etc., will require policy interventions that are outside the scope of this paper.

Electricity prices in Rajasthan, like much of rest of India, follow an increasing block tariff (IBT) structure, consisting of a marginal price component called an energy charge, and a fixed charge.[5] As shown in Figure 4, the marginal price is the same for all consumption on a block or range of monthly consumption but increases for higher amounts of consumption. Rajasthan's tariff schedule also has a lower first-block energy charge for households possessing a below poverty line (BPL) card. The utility provides an energy price subsidy of rupees 1.9/kWh and rupees 1.3/kWh for households below and above the poverty line (APL) consuming less than 50 kWhs per month, respectively. An additional fixed charge subsidy of rupees 30 per connection is also provided to households below the poverty

[3] https://powermin.nic.in/sites/default/files/webform/notices/Seeking_comments_on_revised_provision_at_Para.pdf

[4] APERC, Public Notice, October 4th , 2016. http://www.aperc.gov.in/aperc1/assets/uploads/files/6581e-pn_tariffcategories_goi_mop_04102016.pdf

[5] There are several other charges, subsidies, incentives and taxes in the tariff schedule. We describe these charges in further sections of the paper.

line. BPL households are APL energy and fixed charges if their consumption exceeds 50 kWh of consumption during a billing cycle.

The IBT schedule seeks to provide a minimum amount of electricity at an affordable cost to low-income/low-consumption households. IBTs also enable a utility to achieve its revenue goals, by deriving a larger share of its revenue from high-income and high-consumption households. From the perspective of balancing affordability and revenue sufficiency goals, designing an efficient IBT schedule amounts to separating households into distinct groups based on their willingness and ability to pay for electricity and using observable household characteristics to optimally setting consumption blocks at an appropriate marginal price.

IBTs are not unique to India and the estimation of residential electricity demand under IBT schedules has been studied extensively in developed country settings. Reiss and White (2001) use a representative sample of California households, and summarize how the structure of electricity demand varies across customers.[6] The model is then used to analyze the effect of tariff changes on changes in consumption and the share total monthly expenditure a household spends on electricity.

McRae (2015) is one of the few papers that conducts a similar exercise in a developing country setting,[7] by building an asset ownership model using Colombian census data and pairing it with a utility's administrative billing data, to show that government subsidies for electricity programs disincentivizes greater investments in electricity infrastructure and ensnares poorer households in a low-level subsidy trap. McRae (2015) uses the demand estimation under non-linear pricing econometric modeling framework developed by Hanemann (1984)[8] to recover the parameters of household-level preference functions.

More recently, Wolak (2016) applies an enriched version of this modeling framework to water utility customers in California and uses it to find price schedules that "optimally" balance the revenue and conservation goals of water utilities.[9] Households choose their consumption level to maximize a utility function which depends on their demographic characteristics. Despite the household's best intentions to use only utility a maximizing level of water, each water service demand has technological uncertainty in the exact amount of water consumed. For example, running water for a hot shower on a cold day takes longer than on a warm day and therefore uses more water. Therefore, it is practically impossible for a household to precisely adjust their consumption to arrive at the utility-maximizing consumption, i.e., the kink points on their piecewise linear budget set. For this reason, in addition to the usual error term capturing the unobservable household characteristics in econometric models, a second stochastic unobservable called the optimization error is introduced into the demand model in Wolak (2016). This term accounts for uncertainty in the actual amount of water consumed by the household relative to their intended water service consumption level.

In the Indian context, two data sources that have been previously used to study electricity demand are the National Sample Survey Office's (NSSO) consumption expenditure rounds and panels

[6] Household Electricity Demand, Revisited. Reiss and White. 2001. http://www.nber.org/papers/w8687.pdf

[7] Infrastructure quality and Subsidy Trap. Shawn McRae. 2015. https://www.aeaweb.org/articles?id=10.1257/aer.20110572

[8] Hanemann, W. Michael. "Discrete/continuous models of consumer demand." Econometrica: Journal of the Econometric Society (1984): 541-561.

[9] Wolak, Frank. 2016. Designing Non-linear Price Schedules for Urban Water Utilities to Balance Revenue and Conservation Goals. http://web.stanford.edu/group/fwolak/cgi-bin/sites/default/files/water_paper_wolak_draft-9.pdf

of the India Human Development Survey. Both sources are known to miss the top of the income distributions and report electricity consumption based on self-reported figures. These surveys are not designed to accurately measure residential electricity consumption and therefore do not capture the full distribution of electricity consumed in a region. Figure 5 compares the consumption distribution from the administrative billing data from one of Rajasthan's power utilities from 2015-16 to NSSO's consumption expenditure survey of 2011-12 for districts served by this utility. The figure highlights the fact that, assuming distribution neutrality between these sets of years, NSSO consumption data is particularly imprecise in capturing the top ends of the consumption distribution and therefore unsuitable to conduct counterfactual pricing analysis.

This paper uses appliance level ownership from a household survey and household's billing cycle-level electricity consumption from administrative billing data to estimate a demand model for energy services. Consumption-specific charges under the IBT schedule and variation in weather conditions within a household's billing cycle are accounted for in the estimation of this model. The model also incorporates heterogeneity in residential demand due to observable socio-economic characteristics—such as, income, family sizes and other observable factors that differ across customers. This allows us to recover the price-responsiveness of demand into four categories of energy services demand as well as the overall responsiveness of electricity demand to the price of electricity.

SECTION III: Data and Descriptive Background

The data used in this paper are from three different sources:

(i) administrative data on billing cycle-level electricity consumption and bills issued for every household in two districts of Rajasthan – Jaipur and Alwar and served by a local electricity utility called JVVNL[10] for four years.

(ii) detailed household demographic characteristics and appliance ownership and use from a survey designed and implemented in 2017; and,

(iii) spatially disaggregated daily temperature and precipitation data from Indian Meteorological Department.

Each of these data sources is described below with additional details offered in Appendix 2.

2.1 Electricity consumption and prices data

Administrative cycle-level billing data for residential consumers were collected directly from JVVNL. The data set contains a unique billing code identifier which is used to match households across survey and administrative data sets. The administrative data provides information on the total energy consumed during the billing cycle, the calendar dates on which the meter was read, the total energy charges and fixed charges, electricity duties, subsidies, and other charges included in the bill. However, it does not record the tier of the IBT schedule corresponding to the monthly consumption and the corresponding marginal price of electricity. These are backed out by calculating the energy price implicit

[10] JVVNL is one of the three electricity distribution companies in Rajasthan. JVVNL serves approximately 40 percent of total demand for power in Rajasthan. The entire state of Rajasthan is divided into three distinct service areas which are served by each utility. As geographic areas are demarcated across utilities, there is no retail competition across utilities.

in the billing data and comparing it to the IBT structure publicly issued by the utility. Appendix 2 contains an example of how this exercise is carried out.

In general, JVVNL generates a new bill once every two months. In some cases, however, bills are delivered before or after the two-month interval based on the route taken by the utility's roving meter readers to visit respective households. Observations for which the billing interval is more than 180 days are excluded from the analysis. If the meter reader is unable to establish contact with the household or if the meter appears to be malfunctioning at the time of reading, the consumption figures for the household are not captured in the billing data set. In such cases, JVVNL makes an imputation based on the average consumption of the household over the past six months. Such observations are dropped from the sample resulting in exclusion of an additional 1,250 observations (13% of the data).

To provide an overview of prices and consumption variables in the data set, Table 1 shows the summary statistics for all households over 2014-2017 period. The average monthly per capita consumption of electricity in the sample is 39.7 kWhs – more than double the per capita residential usage of 15 kWh in Rajasthan in 2012.[11] The increase in the per capita electricity consumption reflects robust economic growth and rapid rates of electrification in the region.

Policy induced changes in prices are key to recovering model estimates. Marginal prices on the increasing block tariff for residential consumption were revised twice within the sample period. Figure 6 shows the distribution of average daily household consumption by the month of bill issuances,[12] with red labels in the horizontal axis indicating the periods in which these price changes occurred. There is considerable heterogeneity in consumption across households within a month which provides the household-level variation required to estimate the parameters of the model. Expectedly, there is seasonality in the consumption levels – with peak and lows during the summer and winter months respectively. Appendix 2 contains additional validation checks.

2.2 *Household characteristics*

Household characteristics were collected through a survey carried out in two districts of Rajasthan. The survey, conducted as part of World Bank electricity lending program in the state, was administered by a local team of fieldworkers with extensive experience working and residing in these areas. The goal of the survey was to collect household demographics, socio-economic data, appliance ownership and use, and unique household level billing codes to match survey data to the billing database. The survey enumerated approximately 2,000 households.[13]

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[11] Prayas (Energy Group), Residential Electricity Consumption in India: What do we know? December 2016. http://www.prayaspune.org/peg/publications/item/download/709_95c95aa4a9ad64d4f944fc8dcd78000c.html

[12] Average daily household consumption by month of issuance $= \frac{Total\ number\ of\ units\ consumed\ in\ the\ bill}{total\ number\ of\ days\ covered\ in\ the\ bill\ period}$

[13] The sampling for the survey was done in two stages. The first stage picked a representative population of villages for rural areas, and enumeration blocks (EBs) for urban areas, stratified by district. In the second stage, all structures within a village or EB were enumerated, and then a representative sample was drawn from this listing. In rural areas, a single household was randomly drawn from each structure, stratifying on three strata: (i) Households with no electricity bills, (ii) Households receiving electricity bills and below the poverty line, (iii) Households receiving electricity bills and above the poverty line. In urban areas, households were sampled randomly without stratification. In all 67 enumeration blocks and 60 villages were listed and 4,755 structures were selected for sampling of households at the second stage. The total population in our sample was approximately 11% more than the total census-2011 population. The population growth reflects an annualized growth rate of 1.8% in this region.

The survey reveals a near complete electrification rate in urban areas and 92 and 94 percent electrification rates in rural areas of Alwar and Jaipur respectively. The National Family Health Survey (NFHS) of 2015-16 closely reflects these findings, reporting 99 and 96 percent electrification in urban and rural areas of Jaipur, and 97 percent electrification in rural areas of Alwar. Of 2,027 households surveyed in the sample, 1,637 households had a metered electricity connection; 904 of these households had complete socioeconomic information and matched to the administrative billing data. Table 2 shows that the consumption distribution of the sampled households is able replicate the consumption distribution from the billing cycle-level data set over the selected period.[14] These matching patterns allay concerns related to sample selection in the overall distribution, except from the 95th percentile onwards of the consumption distribution - where our sample appears to represent a lower fraction of households than in utility's customer database.

To capture household-level income, the survey contained modules pertaining to farming, livestock, self-employment, casual labor activities, salaries jobs and remittance earnings for each adult member of the household. Total household income was calculated as the sum of incomes across each of these modules and household members. The survey had a non-response rate of approximately 9% on income questions -- these non-responsive households were also excluded from the sample. To keep the survey tractable and short, data on household consumption expenditure or assets and liabilities information was not collected. As a result, household disposable income cannot be calculated separately from total household income. Finally, household-bills for which the annualized electricity bill amount was greater than 75% of annual reported household income were excluded. This restriction is imposed to account for the fact that households also need to pay for food and other essentials besides electricity throughout the year.

After excluding observations based on the income criteria and after matching household survey data to the administrative data, the final sample contained 7,615 billing-cycle level observations comprising of 805 unique customers with an average of 13.4 billing cycles per customer in the data set. Ninety-six percent of these observations are from consecutive cycles, implying that a majority of households do not sort in and out of the panel. Tables 3 summarizes socioeconomic characteristics of the sampled households and shows the share of households by various employment categories.

The survey also collected information on ownership and intensity of use of electrical appliances, to estimate the demand for residential energy services. Detailed usage information in the survey combined with official wattage statistics of common household appliances, are used to calculate the demand for household energy services.[15] The demand for energy at the appliance level is computed by summing the total hours for which an appliance is used over all days in the billing cycle multiplied by its standard wattage information and divided by the number days in the billing cycle. Each of the 24

[14] We selected the consumption distribution from January and February 2017 to produce this graph as these are the last two months in the administrative data that is closest to the period that we began survey data collection (April 2017). This allows us to best compare the consumption distribution across the two data sets.

[15] We obtain wattage information of common household appliances from Bureau of Energy Efficiency standards for 2012-13 and online load calculators provided by Tamil Nadu Generation and Distribution Corporation (https://www.tangedco.gov.in/load_calculato.html) and Paschim Gujarat Vij Company Limited (http://www.pgvcl.com/consumer/CONSUMER/calculate_n.php)

appliances covered in the survey is categorized into one of four energy services: heating and cooling, lighting, domestic end-use appliances, and business-end use appliances (the assignment is provided in Appendix 1, table 1). The energy demand for the four energy services is calculated by totaling the energy services demand for all appliances categorized under each group. Similarly, the total household level energy services demand is the sum of energy services for all appliances owned by the household.[16]

The household demand for energy services based on survey data is expected to be close to the electricity consumed by the household as observed in the billing data.[17] To check this relationship, the (log of) household demand for energy services per day from the survey is regressed on the (log of) per-day electricity consumption observed in the billing data.[18] Results in Table 5 show that the household demand for energy services demand calculations based on appliance ownership and usage is a better predictor of households observed daily demand at levels more than 0.67 kWhs per day (~20 kWhs per month). Therefore, we expect our demand estimation models to fit better for customers above that threshold.

The data on household income and appliance ownership is based on self-reported household surveys. To the extent that the errors in these self-reported measures are independent of the latent true variable (i.e., classical measurement error), the instrumentation approach in GMM estimation allows us to obtain consistent point estimates of parameters of interest.

2.3 *Temperature and precipitation data*

The daily temperature and rainfall data are at a 1x1 degree and 0.25x0.25-degree gridded resolution from Srivastava, et. al (2009) and Pai, et al. (2014), respectively. The locations of the villages and census enumeration blocks are matched to these grids to obtain household-level measures of temperature and rainfall. Figure 9 shows deviations of daily temperature and rainfall in an area from its three-year period average (2014-2017). The precipitation curve shows that there is little variation in rainfall across time and regions. The low average precipitation levels in the region also explains the high ownership rates of air coolers (a device for precipitative cooling) as observed in the survey data. The temperature curve meanwhile highlights the wide heterogeneity in climatic conditions across villages and enumeration blocks even within the same month. This heterogeneity in temperatures across

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16 The minimum amount of household energy services demand based on appliance ownership and usage that we incorporate in our sample is 11.1 kWhs per month. This corresponds to ownership of 1 CFL light (of 20 W) and 1 mobile phone (of 6 W), used daily for 1.5 and 1 hour respectively over 30 days. Households reporting less than this subsistence level of energy services, through ownership or hours of usage, are excluded from the sample.

17 In section IV, we describe the actual model of energy consumed over a billing cycle (E) as a function of demand for energy services based on ownership and intensity of appliance use (s), weather and household characteristics. In this section, we are interested in checking for the average unconditional correlation between E and s, to establish some basic stylized facts about the data used in our sample.

18 Let, $e = \alpha * d$, where e is household energy services demanded per day based on the survey data $(e = \sum_i (wattage_i * number\ of\ appliance\ i\ owned * number\ of\ hours\ and\ minutes\ of\ daily\ usage_i)$ where i denotes the type of appliance and d is the total annual energy demand based on the billing data set $\left(d = \frac{(sum\ of\ electricity\ consumed\ over\ all\ bills\ in\ one\ year\ period)}{(number\ of\ days\ between\ first\ and\ last\ bill\ received\ by\ the\ household\ over\ the\ year)}\right)$. Taking logs, $\ln(e) = \ln(\alpha) + \ln(d)$, implying that if we were to linearly regress the energy demand based on survey data to that of the billing data in per-day terms, and if appliance ownership were to capture energy demand well, we would expect the constant term of the regression to be zero ($\ln(\alpha) \sim 0$, implying $\alpha \sim 1$) and beta coefficient of $\ln(d)$ to be positive and close to 1.

regions is exploited in later sections to estimate household-level demand. We refer the reader to Appendix 2 for additional validations conducted on the temperature and rainfall data.

SECTION IV: Modeling Demand for Energy Services

The model makes use of the data from the household survey of electricity-consuming appliance ownership and use in order to estimate a model of the demand for energy services. It captures the well-known fact that electricity is a derived demand. Specifically, a household's overall demand for electricity is derived from the demand for an energy service provided by an electricity-consuming capital good such as a light bulb, fan, air conditioner, etc. Moreover, the amount of electricity consumed to provide a fixed quantity of electricity services, say an hour computer use, is uncertain because of back- ground factors such as the background temperature and intensity of use of the appliance. Let s_i equal the households demand for energy service i in hours of use per day within the billing cycle, and $\boldsymbol{s} = (s_1, s_2, \dots, s_N)'$equal the vector of energy services demand for the N services that the household consumes. Let E equal the household's electricity consumption in kilowatt-hours (kWh) per day during the billing cycle.

A household's demand for a vector of energy services is related to its use of electricity during the bill cycle through the electricity production function, $E = f(\boldsymbol{s}, A, \epsilon)$. This function characterizes the technological relationship between the vector of energy services a household consumes and the electricity use they require. This function also depends on A, a vector of weather and household characteristics that impacts how the vector of energy services demand translates into electricity consumption, and ϵ, a random variable that is unobserved by the household and the researcher that captures the uncertain amount of electricity, E, used by a household that consumes the vector of energy services, $\boldsymbol{s}$.

Let $p(e)$ equal the potentially nonlinear price schedule that the household faces, where $p(e)$ is the marginal price paid at electricity consumption level e. Let $T(E) = \int_0^E p(e)\, de$ equal household's total bill for the billing cycle under the nonlinear price schedule $p(e)$ for consumption level, E. Note the $p(e)$ includes the fixed charge, if one exists, that must be paid regardless of the household's billing cycle-level consumption of electricity.

Assume the household consumes a composite "outside" good beside electricity, x, and that the household has a preference function, $U(\boldsymbol{s}, x, A, \upsilon)$ which depends on the vector of energy services demanded by the household, its daily demand for x during the billing cycle and observable characteristics of the household and the weather conditions the household faces, A, and υ is a vector of unobservable household characteristics. Note that different elements of A are likely to enter $U(\boldsymbol{s}, x, A, \upsilon)$ and $f(\boldsymbol{s}, A, \epsilon)$. The household's budget constraint is equal to $\mathrm{T}(E) + p_x x \leq M$, where p_x is the price of x and M is the household's daily income during the billing cycle. We normalize all magnitudes to daily values in within the billing cycle because billing cycles have different lengths.

The household's budget constraint is nonlinear for two reasons. The first is because of the increasing block price schedule $p(e)$. The second is because the household consumes a vector of electricity-consuming services, $\boldsymbol{s}$, which translates into the household's billing cycle-level electricity use, E, through a potentially nonlinear function, $E = f(\boldsymbol{s}, A, \epsilon)$.

The household is assumed to maximize expected utility (where the expectation with respect to the technological uncertainty ϵ). The problem takes the form:

$$\max_{s,x} E_\epsilon[U\ (\boldsymbol{s}, x, A, \upsilon)]\ subject\ to\ T(f\ (\boldsymbol{s}, A, \epsilon))\ +\ p_x x\ \leq\ M \tag{1}$$

where $E_\epsilon[.]$ implies taking the expectation with respect to the distribution of ϵ. Using the budget constraint to solve for the demand for x given the demand for $\boldsymbol{s}$ yields:

$$x = \frac{(M - T(f\ (\boldsymbol{s},A,\epsilon))}{p_x} \tag{2}$$

Substituting into the household's utility function yields the equivalent problem to (1):

$$\max_{s} E_\epsilon[U\ \left(\boldsymbol{s}, \frac{(M - T(f\ (\boldsymbol{s},A,\epsilon))}{p_x}, A, \upsilon\right)] \tag{3}$$

which has the first-order conditions:

$$\frac{\partial E_\epsilon[U\left(\boldsymbol{s}, \frac{(M - T(f\ (\boldsymbol{s},A,\epsilon))}{p_x}, A, \upsilon\right)]}{\partial s_k} = 0\ \ k = 1,2, \dots, N \tag{4}$$

Switching the order of differential and integral yields

$$\frac{\partial E_\epsilon[U\left(\boldsymbol{s}, \frac{(M - T(f\ (\boldsymbol{s},A,\epsilon))}{p_x}, A, \upsilon\right)]}{\partial s_k} = E_\epsilon[\frac{\partial U}{\partial s_k} + \frac{\partial U}{\partial x}\frac{\partial T}{\partial E}\frac{\partial f}{\partial s_k}\frac{1}{p_x}] = 0 \tag{5}$$

Note that ${\partial T}/{\partial E}$ is equal to $p(E)$, the marginal price at electricity consumption level E. The other terms in (5) can computed once functional forms are chosen for $U(\boldsymbol{s}, x, A, \upsilon)$ and $f(\boldsymbol{s}, A, \epsilon)$.

The system of equations in (5) gives rise to a demand system for the vector (s, x) that depends the price p_x, marginal prices for electricity services, $p_i = \frac{\partial T}{\partial E}\frac{\partial f}{\partial s_k}$ and net income $M_N = M + D$. $D = p(E)E - T(E)$ is the difference between the household's billing cycle level consumption, E, valued at the billing cycle level marginal price paid by the household, $p(E)$, and the household's electricity bill $T(E)$. D is the additional income or reduction in income the household receives because it pays for its billing cycle-level electricity consumption according to nonlinear prices. If $p(E)$ is an increasing block price schedule, D can be either positive or negative depending on the magnitude of the monthly fixed charge paid by the household.

SECTION V: Estimation Procedure and Results

Let $s_i(p_x, p, MN, A, \eta)$, $\ i = 1,2,3,4$ and $x(p_x, p, MN, A, \eta)$ where $p = (p1, p2\ p3, p4)'$ and η is function of the unobserved variables, υ, in the household-level utility function, equal the energy service and composite good demand functions that result from solving (5). Substituting these demand functions into the direct utility function, $U(\boldsymbol{s}, x, A, \upsilon)$, yields the indirect utility function

$$V(p_x, p, MN, A, \eta) =$$
$$U(s_1(p_x, p, MN, A, \eta), \dots, s_4(p_x, p, MN, A, \eta), x(p_x, p, MN, A, \eta), A, \upsilon). \quad (6)$$

We assume a translog indirect utility functional form for (6). Let $w_{it} = p_{it}s_{it}/M_N(t)$ equal the expenditure share for good $i = 1,2, \dots, 5,$ where good 5 is the composite good, so that $p_x = p_5$ and $s_5 = x$. Apply Roy's Identity to this indirect utility function to derive the expenditure share equations:

$$w_{it} = \frac{1}{D(p, M_N, A)}\left(\alpha_i + \sum_{j=1}^{5}\beta_{ij}\ln\left(\frac{p_{it}}{M_N(t)}\right) + \sum_{k=1}^{K}\gamma_{ik}A_{kt}\right) + \upsilon_{it} \quad (7)$$

where $D\left(p_x, p, M_{N,}A\right) = -1 + \sum_{i=1}^{5}\sum_{j=1}^{5}\beta_{ij}\ln\left(\frac{p_{it}}{M_N(i,t)}\right) + \sum_{i=1}^{5}\sum_{k=1}^{K}\gamma_{ik}A_{kt}$ for i=1,2,…,5.

The υ_{it} are assumed to be zero mean random variables that are orthogonal to, Z_{it}, a vector of instruments composed of household characteristics, weather variables within the billing cycle, and interactions of these two sets of variables. The weather variables include average temperature and rainfall in the first stage unit that the household belongs to. The household characteristics included in the instrument are age and years of schooling of the head of the household, household size, urban or rural classification, number of rooms in the house and average daily income.

Operationalizing the estimation of the parameters of the indirect utility function requires an estimate of the electricity production function $f(\boldsymbol{s}, A, \epsilon)$ to compute estimates of $p_i = \frac{\partial f}{\partial s_i}(\boldsymbol{s}, A, \epsilon)p(E)$ for $i = 1,2,3,4$ for each household and billing cycle. We assume the following functional form $f(\boldsymbol{s}, A, \epsilon)$

$$E_t = \delta + \sum_{j=1}^{4}\exp\left(\sum_{m=1}^{M}\lambda_{im}W_t\right)s_{jt} + \epsilon_{it} \quad (8)$$

where ϵ_{it} are zero mean regression errors and the W_t are a vector of weather characteristics for the household during billing cycle t. This specification imposes the restriction that all marginal prices are positive, because $p_j = exp(\sum_{m=1}^{M}\lambda_{jm}W_t)\ for\ j = 1,2,3,4$. The elements of W_t are a constant, average daily temperature in the billing cycle, and average daily rainfall in the billing cycle. These weather variables are included to account for the fact that different combinations of appliances within each of the four energy service categories are likely to be used in different combinations, depending on temperature and rainfall conditions within the billing cycle. For example, warmer weather with less rainfall, may cause the household to use different lights in the household with different intensities and each of these lights consume electricity at a different rate. Cooler and rainy weather may cause the household different combinations of general appliances that hotter and drier weather. For instance, the household may be less likely to use an iron and run their refrigerator more intensively during hot weather than during cooler and more rainy weather.

Table 8 contains the nonlinear least equations estimates of equation (8) with the standard errors clustered at the household level. Figures 10-13 contains the distribution of billing cycle-level marginal prices for each of the four classes of energy services computing using the estimated parameters of equation (8), so that $p_j = exp(\sum_{m=1}^{M}\hat{\lambda}_{jm}W_t)\ for\ j = 1,2,3,4$ where the $\hat{\lambda}_{jm}$ are the nonlinear least squares estimates of the λ_{im}.

Given these prices, the expenditure shares for each energy service and the composite good can be computed, which completes the data necessary to estimate the translog model. Table 9 contains Generalized Methods Moments (GMM) estimates of the translog demand system with standard errors clustered at the household level.

Table 10 presents the sample mean own-price elasticity of demand and expenditure elasticity for each energy service and the composite good. Heating and cooling are the most inelastically demanded energy service and general appliance use is the most elastically demanded energy service. All energy services have positive net income elasticities.

The translog parameter estimates can also be used to compute a household's elasticity of the demand for electricity. Let $p(E)$ equal the marginal price at the customer's actual level of consumption. The own-price elasticity of the demand for electricity with respect to this marginal price is equal to

$$\varepsilon_E = \frac{dE}{dp(E)}\frac{p(E)}{E} = \sum_{i=1}^{4}\theta_i \sum_{j=1}^{4}\epsilon_{ij}, \text{ where } \theta_i = \frac{\partial f}{\partial s_i}\frac{s_i}{f} \text{ and } \epsilon_{ij} = \frac{\partial s_i}{\partial p_j}\frac{p_j}{s_i}$$

The θ_i is elasticity of electricity use with respect to the i^{th} electricity service and ϵ_{ij} is the cross-price elasticity of the demand for the i^{th} energy service with respect to the price of the j^{th} energy service.

SECTION VI: Counterfactual Price Simulations and Welfare Analysis

Under the assumption that the estimated parameters of translog demand system are consistent with theory of utility maximizing behavior, the indirect utility function $V(p_x, p, M_N, A, \eta)$ can be used to evaluate the household-level welfare implications of alternative nonlinear pricing plans. Define $V^0 = V(p_x, p, M_N, A, \eta)$, indirect utility at the observed nonlinear pricing plan.

Consider an alternative pricing plan $p^*(e)$ with $N > 0$ price steps, $p_n^*, n = 1,2, \dots N$. Define $D_n = (p_n^*)E^* - T^*(E^*)$, where E^* is the household's electricity use under pricing plan $p^*(e)$. Solving the following equation in CV,

$$V^0 = max_{\{n \le N\}} V(p_x, p_n, M + D_n - CV, A, \eta)$$

yields the compensating variation associated with moving from the initial price schedule $p(E)$ to the new price schedule $p^*(E)$ for a household with income M, observable attributes, A, and unobservable attributes, η. This compensating variation can be computed for each household in the data set. If the sum of compensating variations across all customers is positive, then it is theoretically possible to improve the welfare of households moving from $p(E)$ to $p^*(E)$ with the appropriate lump-sum transfers among households.

A strength of the energy services demand approach is that it considerably expands the set of counterfactual tariffs that we can consider. For example, a tariff that subsidizes the purchases of any single or group of electricity consuming appliances can be assessed using demand for these energy services. However, the utility and the regulator does not have access to demand parameter estimates for all households in its administrative data set. Therefore, in order to practically use our estimates to study the welfare consequences of alternative tariff structures, own-price elasticity estimates in the range of -0.1 to -0.4 from the structural demand model are used to calculate household level counterfactual consumption under the assumption of a linear price elasticity of electricity demand. The range of these elasticities serve as bounds for the welfare estimates under counterfactual schedule, as the structural demand model suggests that household level own-price elasticities will be within this range.

Finally, the short-run welfare consequences of tariff reforms can be studied using changes in consumer surplus as a proxy for household level compensating variation. In the short-run, household level demand is assumed to be constant and changes in prices cause the consumer to move up or down its demand curve. With changes in incomes in the long-run, the household may adjust its bundle of consumer durable appliances. Ownership of these new appliances can considerably expand the household's energy choices and lead to a shift in the household's short-run demand curve. Therefore, in the short-run, changes in consumer surplus serves as a sufficient indicator for studying household-level welfare changes (Wilig (1976)[19]).

- **COUNTERFACTUAL 1: Tariff schedule proposed by the Ministry of Power**

In 2018, India's Central Ministry of Power (MOP) issued a notification to simplify tariff categories and rationalize tariff rates across states. The notification proposed an IBT structure consisting of fixed and energy charges. The energy charges in the plan varied over five consumption tiers: 0 to 200, 201 to 400, 401 to 800, 801 to 1200 and greater than 1201 units. The fixed charges varied by the sanctioned load of the household under the following categories: 0 to 2 kW, 2 to 5 kW, 5 to 10 kW, 10 to 25 kW and greater than 25 kW. The proposal however did not specify the level of the energy and fixed charges and left the determination of these prices to state level regulators.

The paper uses the consumption categories proposed in MOP's notification to construct the first counterfactual tariff schedule. To illustrate the welfare impacts of this tariff schedule, we assign energy charges from JVVNL's 2016-17 tariff order to the consumption tiers in the notification. This illustration also uses the consumption tiers of the notification to assign fixed charges instead load categories varying by the sanctioned load. This is because the sanctioned load variable in JVVNL's data set is either missing or noisily estimated, rendering it unusable for fixed cost imputations at the household level. Since the range of consumption in each tier of MOP's notification is larger than the range in JVVNL's tariff order (for instance, the first tier of consumption in JVVNL's tariff order ends at 50 units, whereas the first tier in MOP's proposal ends 200 units) for the same energy and fixed charge, one can expect this tariff design to result in higher consumer surpluses across all households but also lead to a revenue shortfall compared to the current tariff.

To study the welfare impacts of this tariff schedule and all other counterfactual schedules thereafter, the following methodology is used. A short-run linear demand curve is calibrated for each household using estimates of electricity demand own-price elasticities in the range of -0.1 to -0.4, which are consistent with the magnitudes estimated from our structural demand model. The calibrated household demand curve passes through the household consumption observed in household level billing data set and the corresponding marginal prices observed in JVVNL's 2016-17 tariff order. Using this demand curve, consumer surplus at current tariff rates and under counterfactual tariffs can be calculated as the area under the short-run demand curve and above the step-wise marginal price curve, less the applicable fixed charges. The marginal price faced by a household includes the energy charges,

[19] Willig, R. (1976). Consumer's Surplus Without Apology. The American Economic Review, 66(4), 589-597.

electricity duty and urban cess. Fixed and energy charges are adjusted for subsidies provided to the household.

The difference between current and alternative tariff measures the welfare impact of counterfactual tariffs. If consumer surplus under the counterfactual tariff is greater than JVVNL's current tariff order, the counterfactual price design to be welfare enhancing over the current tariff order. Conversely, a lower consumer surplus indicates loss of welfare relative to the current tariff order.

Next, JVVNL's FY16-17 financial disclosure statements are used to calculate the average revenue requirement per unit of energy sales. This metric is used to test for the revenue sufficiency implications of the alternative tariff schedule for the utility. JVVNL sold 19.48 billion kilowatt-hours (kWh) with an annual revenue requirement of rupees 150.76 billion across all consumers in FY16-17. This translates to an average revenue requirement of Rs. 7.74 per kWh of energy sold (inclusive of taxes, subsidies and cess). A counterfactual design that achieves this price for each unit sold to the residential sector will be revenue neutral and will eliminate cross-subsidization of power from commercial or industrial consumers.

Figure 14 shows the difference in average monthly consumer surplus over the income distribution using MOP's proposed prices and JVVNL's current tariff schedule. As expected, MOP's recommended price schedule increases welfare for all households across the income distribution. Table 11 shows the gain in consumer surplus in rupees per month for a median household in each quintile. Expectedly, welfare gains are higher when demand is more price-elastic. Even though all households are better off under MOP's proposed tariff design, welfare gains are regressive over the income distribution. This is because the per-unit price reduction under the MOP's tariff is higher for top quintiles than the bottom ones.

In addition to being regressive, the schedule also results in significant revenue losses. The reduction in marginal prices under MOP's design reduces the gross revenue generated from the residential sector to Rs. 3.017 billion (at an own-price elasticity of -0.1). This represents a 31.2% loss in revenue under the current tariff (which is currently at 4.465 billion rupees). Adapting MOP's pricing proposal would therefore require cross-subsidy transfers from commercial and industrial consumers. At more elastic demand levels, the amount of revenue shortfall and cross-subsidy requirements will be even larger.

- **COUNTERFACTUAL 2: An efficient retail price of electricity**

Under an efficient price schedule, the amount a consumer pays for an additional unit of consumption (her marginal price) is equal to the cost of supplying the additional unit of energy incurred (the utility's marginal cost). The cost of supplying the additional unit of energy includes the cost of power purchase, the technical losses incurred in transmitting electricity through power lines and the social cost of carbon embedded in the generation of power. In Rajasthan, this cost also includes the state level taxes and cess incurred by the utility that are passed through to the final consumer. In situations where the marginal price of residential energy exceeds its social marginal cost (SMC), households consume too little energy and vice-versa. The determination of an efficient retail pricing structure in Rajasthan therefore requires an estimate of SMC in the state. This section with the estimation of Rajasthan's SMC, followed by a dead-weight loss analysis to quantify the distortionary effects of current energy prices. It concludes by analyzing alternative schedules that set marginal prices to SMC across all households and distributes fixed costs disproportionately across households to meet the three goals of economically efficient consumption, revenue neutrality and equity.

(i) Calculating the SMC for Rajasthan

The marginal cost of electricity is the price at which a utility buys an additional unit of electricity from power generating companies to meet an additional unit of demand. Because electricity cannot be stored over the grid, the demand for electricity is instantaneously matched with supply. The marginal price of electricity at time t ($P_t^{marginal}$) is calculated using the following formula:

$$P_t^{marginal} = \left(P_t^{generation} + P_t^{carbon}\right)\left(1 + \frac{1}{(1 - loss_t^T - loss_t^D)}\right) + \tau_t$$

where, $P_t^{generation}$ is the marginal cost of producing an additional unit of electricity, P_t^{carbon} is the marginal cost of emissions due to the additional unit of electricity generated, $loss_t^T$ and $loss_t^D$ are technical losses over the transmission and distribution network and τ_t are the duties and cess per hWh levied by the utility.

The four components of the marginal price of power are calculated as follows:

- **Marginal price of generation**

The market to match the instantaneous demand to supply is managed by a system operator. In an ideal setting, the operator meets total demand by cumulatively discharging energy from generating companies in an increasing order of their cost of generation, until supply matches demand. The variable cost of the infra-marginal plant is therefore the marginal cost of the system. However, in practice, the order of dispatching generators (also called the merit order) that is followed by the system operator in Rajasthan is a function not only of the variable cost of the infra-general generator but also of the transmission capacity of the grid, the stability of the grid at any time and the structure and regulations governing different electricity markets. Like Rajasthan, most states in India dispatch generators based on a combination of these factors.

The total instantaneous demand for electricity in India is classified under two categories: scheduled and unscheduled demand. Scheduled demand is a utility's forecast for a day's worth of demand. There are two trading mechanisms available to the utility to meet its estimate of scheduled power: bilateral contracts and the day-ahead market. Bilateral contracts – set more than one year before dispatch are called long-term contracts and supply 90% of overall demand (Ryan (2018)[20]). Bilateral contracts – set less than one year from the moment of dispatch are called the short-term markets and supply 5% of the total demand. The last avenue to trade in scheduled power is the day ahead market which serves approximately 2% of the market. The prices and quantum of electricity in the day-ahead market at each 15-minute block in a day are determined through a double-sided closed bidding process.

Utilities and generators hold positions in all three segments of the wholesale market to meet their demand and supply requirements. The system operator plays a key role in reconciling these positions across markets. Demand projections from a utility at each 15-minute block for each generator

[20] Ryan, Nick. "The Competitive Effects of Transmission Infrastructure in the Indian Electricity Market". 2018.

is intimated to the system operator (also called the state load dispatch center (SLDC)), one-day prior to dispatch.[21] The SLDC verifies this demand against supply-side information provided by generators, such as, capacity at 15-minute intervals, machine maintenance schedule and overall expected congestion in the system. Based on these factors, the SLDC notifies the final drawl schedule for the next day to the generating company and the utility.

Finally, unscheduled power is the difference between forecasted (i.e., scheduled) and real-time demand. The market for unscheduled demand, also called the unscheduled interexchange (UI), is a real-time balancing mechanism that allows utilities and generators to adjust the scheduled demand to the instantaneous demand and supply of power.

Given that utilities and generators can take arbitrage positions across all the different segments of the short-term market, the prices in these sequential markets are expected to be closely correlated. As price determination in the day-ahead market occurs through an auctioning process, we consider the market clearing price of this market segment to be the best economic measure of marginal cost of generation at each 15-minute interval that best encapsulates the marginal cost of generation and transmission constraints.

To test if the market clearing price (MCP) from the India Energy Exchange (IEX) wholesale market[22] reflects the instantaneous price of power in the UI market, the generator-wise dispatch information from Rajasthan's SLDC is compared to the MCP information of the N2 region of IEX (comprising the state of Rajasthan) for January to December 2018. Aggregating all prices to daily frequency, the correlation between average prices in the two markets to be 0.76. Ryan (2018) using data for 2009-2010, finds a correlation of prices in these two markets to be 0.808 – supporting the view that even though the wholesale electricity market in India comprises of different segments with separate rules and regulatory limits on market participation, the prices discovered in the short-term segments of the wholesale market appear to move closely together. Moreover, the strong correlation of prices also suggests that the cost of transmission constraints as measured through MCP in the IEX market reflects the cost of constraints in other segments of the market.

Given these features of India's short-term wholesale markets, this paper uses IEX's N2 regional price at every 15-minute interval to be marginal cost of power generation for Rajasthan. The average market clearing price in the N2 region for FY2016-17 is Rs. 3.93 with a standard deviation of 1.55.

- **Transmission losses**

The marginal price of energy delivered to a household will be higher due to transmission losses. Transmission losses imply that for each unit of energy delivered to the consumer, the utility must buy an extra amount of energy from the generator that is lost over wires. This energy is lost in the form of heat dissipated as a natural consequence of electrical resistance. Electrical resistance increases with the square of electricity flowing through the wire, meaning that loss per unit of additional energy is highest during hours of peak-demand. Moreover, transmission losses are lower when electricity is transmitted

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[21] The utility does not have to inform the operator about the variable cost of each generator. As a result, the system operator does not have to necessarily follow a merit order dispatch schedule.

[22] India also has another wholesale market named Power Exchange India. Given that bidders can freely move between the two exchanges, prices discovered in IEX and PEI are highly correlated: 0.92 and 0.98 at hourly and weekly frequency (Ryan (2018)).

through a high-voltage line. A greater share of losses therefore occurs over the distribution network, maintained at a lower-voltage (at 11kV), compared to transmission lines (for example, at 142kV).

To calculate transmission losses, a data set from Rajasthan's state transmission company containing the total energy generated and total transmission losses for each day between May 2016 to March 2018 is used. Following McRae and Wolak (2019), this information is used to first fit a quadratic relationship between input energy and energy losses, as follows:

$$loss_t = \beta_0 + \beta_1 Q_t^d + \beta_2 (Q_t^d)^2 + \varepsilon_t$$

where, Q_t^d is the energy inserted into the transmission network and $loss_t$ are technical losses at time t. We differentiate the above equation to calculate marginal transmission loss, ${loss_t}^T = \beta_1 + 2\,\beta_2 * \sum_{i=1}^{n} Q_{R,t}^i$, where $\sum_{i=1}^{n} Q_{R,t}^i$ is the electricity dispatched by all generators at 15-minute intervals (t). Data on generator-wise energy dispatched at 15-minute time intervals ($Q_{R,t}^i$) comes from Rajasthan's SLDC. Although this high-frequency data set captures the impact of peak load on technical losses, the data set suffers from three limitations, for which we make certain assumptions and adjustments.

First, the data is available only for the calendar year 2018. We use this data under the assumption that the distribution of marginal transmission losses at 15-minute intervals in financial year 2016-17 is not different from calendar year 2018. Second, the SLDC data set provides electricity dispatch information for the entire state of Rajasthan. The state of Rajasthan is serviced by three utility companies, only one of which is JVVNL. The latter serves approximately 40 percent[23] of the total state-level demand. We rescale the state-wide dispatch figures by 40% to estimate JVVNL's share of dispatch at 15-minute intervals. Finally, this data set contains dispatch information from state owned generator units only. State-owned generators serve 57.1 percent of JVVNL's annual demand. The residual portion of the demand is met through a portfolio of centrally-owned generators, renewable sources and captive power plants. Real-time dispatch information from these other generation sources are unavailable. As a result, the total dispatch in the SLDC data are scaled by a factor of 1.7513 (=100/57.1) to estimate energy dispatched across all generation units at 15-minute intervals. Based on these adjustments, the marginal transmission level losses are estimated to be 5.2% with a standard deviation of 1%.

- **Distribution losses**

The total energy entering the distribution network (Q_t^D) is calculated as the difference between energy dispatched by all generators ($\sum_{i=1}^{n} Q_{R,t}^i$) and the marginal transmission losses at 15-minute intervals (${loss_t}^T$): $Q_t^D = \sum_{i=1}^{n} Q_{R,t}^i - {loss_t}^T$. Marginal losses in the distribution network can be calculated by first estimating the quadratic relationship between losses and input energy, and then calculating the marginal distribution losses as ${loss_t}^D = \beta_1 + 2\,\beta_2 * Q_t^D$.

A cross-sectional data set on feeder level losses is used to estimate the quadratic relationship between energy entering the distribution network and network level losses. This data was collected under an audit conducted by the World Bank's Energy Practice as part of a lending program in Rajasthan. The data set contains information on total losses for the period April to December 2017

[23] Source: http://www.pfcindia.com/DocumentRepository/ckfinder/files/Operations/Performance_Reports_of_State_Power_Utilities/1_Report%20on%20the%20Performance%20of%20State%20Power%20Utilities%202013-14%20to%202015-16.pdf (page 126).

from 3,954 randomly sampled feeders within JVVNL's network. The data set separates technical losses from losses due to commercial and billing inefficiencies. The former component leads to an overall reductional in society's welfare, while the latter represents a welfare transfer from households that are billed for their consumption, to household that consume electricity without a bill. We use technical losses at the feeder level to estimate the quadratic relation. Using Q_t^D calculations for each 15-minute period and the parameter estimates of fitted quadratic equation, we estimate marginal distribution losses. The average marginal distribution losses in our sample is 18.4% with a standard deviation of 3%. Figure 15 shows the frequency distribution of marginal transmission and distribution losses based on these calculations.[24]

- **Marginal cost of emissions**

The final component of SMC is the external cost associated with emissions from generating plants that increase their output in response to an increase in demand. Ideally, the cost of emissions should be calculated separately for all pollutants such as carbon dioxide, nitrogen oxide, sulfur dioxide and particulate matter. However, this paper calculates only the cost carbon dioxide emissions, as generator-wise emissions data for other pollutants is unavailable in India. Moreover, to precisely estimate the marginal cost of carbon, emissions data at 15-minute or hourly intervals for each generator are required. Such detailed data sets are unavailable in the Indian context.

Facing these limitations, the marginal cost of emissions is proxied by the average carbon dioxide emissions per unit of energy produced by each generator. A data set[25] that contains information on annual carbon dioxide emissions for FY2016-17 for each power generating company in India is used for this purpose. The data set uses plant-level information on the type of fuel used, the calorific value of the fuel mix and its emission and oxidation factors to calculate the total carbon dioxide emitted by the plant in a year. The annual tons of carbon dioxide divided by the total units of energy produced by a plant in a year gives a plant-level estimate of average tons of carbon dioxide per unit of energy generated. The social cost of carbon per unit of energy generated by a plant is estimated by multiplying the average tons of carbon dioxide per kWh by Rs. 2184 (Nordhaus (2018) cost estimate for a ton of carbon emission is \$33.60; at approximately Rs. 65/USD this amounts to Rs. 2184 per ton of carbon dioxide). Finally, using the SLDC high-frequency data set on generator-wise energy dispatch at 15-minute time intervals from Rajasthan's system operator, the price of emission at each period[26] (P_t^{carbon}) is calculated as:

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[24] The average marginal transmission loss estimate is comparable to the average annual transmission 3.95% reported by JVVNL in its FY2016-17 financial petition to the regulator: http://energy.rajasthan.gov.in/content/dam/raj/energy/jaipurdiscom/pdf/tariff/2018/true/additional_submission.pdf . In reporting, the average annual distribution loss, JVVNL pools commercial losses (that occur due to billing inefficiencies) with physical losses over the wire. For the estimation of social marginal costs, we are interested in measuring the physical losses that occur over the distribution network. This estimate can be found in a report by the Forum of Regulators (2012) that shows the average distribution losses over a three-month period at a representative feeder within JVVNL's network to be 9.2%. This is lower than the 13.4% average marginal losses calculated using our methodology.

[25] CO2 baseline database for the Indian power sector produced by the Central Electricity Authority (Version 14), available at: http://www.cea.nic.in/tpeandce.html.

[26] Because we are using high-frequency plant-wise data, the carbon cost of emission in our calculation for each 15-minute interval is based only on state-owned generators.

$$P_t^{carbon} = \frac{\sum_{i=1}^{n} P_{t,i}^{carbon} * Q_{R,t}^{i}}{\sum_{i=1}^{n} Q_{R,t}^{i}}$$

where, $P_{t,i}^{carbon}$ the average cost of emission for generator i, $Q_{R,t}^{i}$ are the unit dispatched by a generator i generator at a 15-minute interval and $\sum_{i=1}^{n} Q_{R,t}^{i}$ are total units generated by all units. The mean cost of carbon using these calculations is Rs. 2.08 with a standard deviation of 0.08.

Combining the four components of the marginal cost of electricity consumption: the area clearing price from the wholesale market, the emission costs, and the transmission and distribution losses at 15-minute intervals estimates the SMC for Rajasthan. Electricity duty and urban cess charges are also added to this value. Figure 16 shows the distribution of social marginal cost (SMC) across all periods in the sample. The mean value of marginal cost of electricity inclusive of the social cost of carbon is Rs. 8.2/kWh. Excluding the social cost of carbon reduces the mean marginal price to Rs. 5.5/kWh. The latter price (i.e, Rs. 5.5/kWh) is used for counterfactual tariff calculations, as the high share of thermal generation in Rajasthan's energy mix[27] makes the carbon-inclusive SMC to be practically infeasible. In the following sections, we analyze the welfare implications of setting the energy price at this price.

(i) Distortionary effects of current retail prices

The deadweight loss of pricing above or below the SMC can be calculated using the range of elasticities from the structural demand model. The deadweight loss represents the difference between the marginal benefit and the marginal cost of consuming an extra unit of electricity. Figure 17 illustrates the procedure for calculating the deadweight losses based on the demand curve, the current energy prices, the SMC and the own-price elasticity. The deadweight loss is the area of the shaded triangle indicated in the figure. Since the SMC is below the current marginal prices (and therefore $Q^d < Q^{\text{opt}}$) in this illustration, the deadweight loss for this household is indicative of loss of consumption even though the marginal benefit of consuming an additional unit for the household would have been more than its marginal cost. Conversely, for households that have their current energy prices below the SMC (households in the first consumption tier for example), the deadweight loss will indicate excess consumption.

Table 12 summarizes the deadweight losses across income quintiles for FY16-17. The columns show the results over the range of own-price elasticities. A more elastic demand response implies greater sensitivity of consumption to price distortions from SMC. As a result, the deadweight loss estimates are greater for more elastic demand. Estimates of average deadweight loss for households in the first quintile are in the range of Rs. 3.1 to Rs. 12.4 per month and highest across all other categories.

[27] Existing literature suggests that there are significant differences between domestic and global values of the social cost of carbon (SCC) exists, but these papers provide limited agreement on the distribution of the global SCC by countries. Moreover, the existing literature appears to suggest a range of carbon costs: from Nordhaus (2018) estimate of \$33.60 / tCo2 to EPA's estimate of \$12, \$42 and \$62 per tCO2 at 5, 3 and 2.5% discount rates. Reconciling the calculations undertaken in the past literature (using a combination of IAM models and growth assumptions) to calculate a robust SCC estimate for India is outside the scope of this paper. However, in a recent paper Ricke, Drought, Caldeira and Tavoni (2018), estimate that India's share of global SCC is 21%. Our best approximation would be to use Nordhaus' estimate of \$33.60 / tCo2 to calculate India's share of global SCC = .21*33.60 = Rs. 458.64/ tCo2. Back-of-the envelope calculations suggest that this will increase the SMC to approximately Rs. 6.13/kWh (a 11.4% increase from the current estimate of Rs. 5.5/kWh). We do not consider this as a separate counterfactual exercise but show the welfare impact of including the domestic cost of SCC into SMC in footnote 31.

This is because the difference between the current marginal price and SMC is the largest for households in the first quintile, given their low energy prices under the current schedule.

Table 13 shows the same estimates but scaled as a proportion of the household's expenditure on electricity purchases. At the own-price elasticity of -0.3 and under a linear demand curve, deadweight losses are approximately 4.3 to 5 percent of total household expenditure on electricity. These results are close to the other estimates in the literature in other country contexts. For example, McRae and Wolak (2018)[28] estimate deadweight losses in Colombia as a share of household's total expenditure to be around 4.3 to 7.1 percent across socioeconomic stratum using similar own-price elasticity assumption of -0.3 and under a linear demand curve.

Deadweight loss estimates would be zero and a socially optimal level of consumption would be achieved if energy charges were set to the SMC. However, revenues collected from just a SMC energy price would be insufficient to cover the fixed costs incurred by the utility. These costs are incurred due to activities such as transmission of power, distribution, retailing, returns on invested capital, debt servicing, etc. As these costs do not vary by per-unit of energy supplied, they are not incorporated in the SMC calculation.

Using a combination of energy charges (set to SMC) and fixed charges (to recover utility's fixed costs) under a two-part tariff can achieve the twin-goals of optimal consumption and revenue neutrality. Fixed charges distributed across all residential consumers would enable the utility to cover its fixed costs. The way these fixed charges are apportioned across households however introduces equity considerations in the design of the two-part tariff, as households that benefit the most from consuming electricity (i.e., have the highest willingness to pay for it) should be expected to pay a greater share of the fixed cost requirements. The fixed cost per connection should also be designed in away so that it does not serve as a barrier for poor and vulnerable households to enter the grid.

(ii) Designing an efficient, revenue neutral and equitable two-part tariff schedule for residential consumers

To calculate the total fixed cost requirements for JVVNL in FY16-17, recall that the average revenue requirement of Rs. 7.74 covers both the variable and fixed costs of the utility. The variable cost of electricity each month is the per unit cost of power purchase, transmission losses and duties levied. As noted in the earlier section, these costs are embedded in the SMC calculations. Thus, the total variable cost to be recovered by the utility can be calculated by multiplying the SMC with the aggregate annual residential demand (i.e, $\sum Q^{opt}$). The aggregate annual revenue requirement is the average revenue requirement (Rs. 7.74) multiplied by aggregate residential demand. Finally, the total fixed cost to be recovered by the utility is the difference between the total annual revenue requirement and the total variable cost recovered through energy prices set to SMC.

The simplest counterfactual tariff schedules consists of a two-part tariff design: energy prices set to SMC and fixed costs requirements distributed equally across all households. The distributional effects observed under this tariff design will provide a useful benchmark for comparing other alternative tariff designs. The welfare implication of switching from current energy prices to an alternative tariff design can be studied through changes in consumer surplus. If counterfactual

[28] Shaun D. McRae and Frank A. Wolak (2018). "Retail Price Regulation in Colombia to Support the Efficient Deployment of Distributed Generation and Storage and Electric Vehicles". available at http://www.stanford/edu/~wolak.

consumer surplus is greater than the surplus under current tariff schedule, the counterfactual schedule is considered to be welfare enhancing. Other variants of counterfactual tariff design will consider variants where the fixed charge requirements can be distributed unequally across households (while keeping the energy price pegged to the SMC), so that the consumer surplus under the alternative options is greater than the current surplus.

The first counterfactual tariff design is where all subsidies are eliminated, and the fixed costs are distributed equally across all households in the sample. This benchmark scenario raises energy and fixed prices for all households relative to current levels and will result in loss in consumer surplus across the distribution. Figure 18 quantifies this result. The median household in the bottom quintile will face an average loss between Rs. 248 to 254 rupees per month, while median household at the top quintile will loose on average Rs. 70 to 76 per month. Households in the top income quintile currently pay a price higher than the SMC. As a result, under this benchmark scenario, their consumer losses are smaller than other households in the distribution.

Given the regressive nature of this design and the practical infeasibility of the benchmark scenario, the next counterfactual explores if household level subsidies paid directly to the utility as a lump-sum transfer can produce welfare gains. In this scenario, the total household-wise energy and fixed cost subsidies for FY16-17 are transferred by the state government to the utility directly. While marginal prices are still set to SMC, the lump-sum transfer of subsidies to the utility (instead of transferring it to the household) helps in defraying the fixed cost burden on the households. The subsidy adjusted fixed cost requirement is then distributed equally among all residential consumers.

Figure 19 shows that even with a lump-sum subsidy transfer to the utility, there are distribution-wide welfare losses. Expectedly, these losses are lower than the benchmark case, as transfers help in reducing the fixed cost burden. A median household at the lowest and top income quintile will respectively lose on average Rs. 205 to 210 and Rs. 27 and 32 per month. Even though this scenario results in welfare losses, lump-sum subsidy transfers to the utility, prevents distortions away from optimal consumption levels and circumvents the issue of targeting transfers to intended beneficiaries.

Other counterfactual tariff designs build further on the lump-sum subsidy transfer to the utility and relax the assumption of equal allocation of fixed cost across households. Ideally, households with greater willingness to pay of electricity should be allocated a larger share of the overall fixed cost requirement. However, calculating fixed costs based on current levels of consumption is practically infeasible because these charges do not vary per-unit of consumption by definition. Therefore, a household's willingness to pay requires identifying certain proxy indicators that are not related to cotemporaneous consumption.

The first approach is to spatially aggregate households into groups that have similar characteristics. The group level characteristics can then serve as a proxy for household level willingness to pay for electricity. In other developing country contexts such as Colombia, distribution areas of a utility are divided into different socio-economic strata. This geographic classification of neighborhoods is then used as a proxy to set tariff rates. In the Rajasthan context, the coarsest form of a spatial distinction available is the urban or rural classification of the household's location. Average rural household incomes are about a quarter of the mean urban income and the total electricity consumed in rural areas as a fraction of all residential sales is about 27.2 percent. Given these differential characteristics, the urban and rural shares of consumption can be used as weights to proportionately allocate fixed costs across households.

More specifically, 27.8% and 72.2% of the utility's total annual fixed cost requirements (after adjusting for lump-sum transfer of subsidies) are divided equally across all rural and urban households respectively. Figure 20 shows the results of this exercise. In contrast to Figure 19, the consumer welfare goes up in all quartiles but change in surplus relative to the current schedule persists to be negative.

To further improve the targeting of fixed costs, and especially to defray the fixed costs borne by households in the lowest quintile, the next counterfactual explores the use of historical household-level consumption data as a proxy for household's willingness to pay for electricity. Historical consumption data is indicative of the level of investment made by households in buying electrical appliances. Households with greater ownership of these appliances (and therefore greater consumption in the past periods) will have a higher demand for energy and may potentially be willing to pay more for electricity. Following this rationale, fixed costs across households are allocated using the following formula:

$$FC_i = (FC - 1) * \left(1 + \frac{{Q_i}^2 - \left(\sum_n {Q_i}^2/N\right)}{\left(\sum_n {Q_i}^2/N\right)}\right) + 1$$

where, FC_i denotes the fixed cost allocated to household i for each day in the billing cycle, FC is the per household per day fixed cost requirement of the utility,[29] ${Q_i}^2$ is the square of historical consumption across all billing cycles in a year and N is the total number of residential consumers served by the utility. The term $\sum_n {Q_i}^2/N$ is the mean of the square of annualized consumption across all residential consumers. The deviation of household's annual consumption from the mean is used as a weighting factor to allocate fixed costs. Households with low levels of yearly consumption have a larger negative deviation from the mean and therefore pay a smaller share of the total fixed cost requirement. In contrast, large consumers pay a larger share due to a larger positive deviation from the mean. The square of consumption term allocates larger weights on observations that further from the mean – implying lower fixed cost charges for households with historically low levels of consumption and vice-versa. Finally, the constant 1 is included in the equation to ensure that irrespective of the weighting factor, all households pay at least 1 rupee per day as their contribution to fixed cost requirements.

Figure 21 shows that median households in the first to the third income quintile are expected to achieve positive gains in consumer surplus under this scenario. The welfare loss for the median household in the fourth and fifth quintile is approximately Rs. 9 and Rs. 21 per month respectively.[30] Welfare gains in the first three quintile are achieved by transferring a greater share of fixed cost requirements to historically high consuming households in the richest quintiles. To illustrate the fixed cost burden on households implicit under this scenario, Figure 22 compares the allocation of fixed costs under JVVNL's current tariff schedule to the counterfactual scenario. The figure shows that the

[29] $FC = \frac{(ARR - SMC * Q)}{(365 * N)}$, where ARR is the annual revenue requirement in rupees per unit, SMC is the social marginal cost in rupees per unit, Q is the cotemporaneous total residential energy demand in kWh across all households under a given marginal price and N is the total number of residential consumers.

[30] Based on footnote 28, if we included the domestic SCC into SMC, the energy cost of power would rise to Rs. 6.13/kWh. The welfare gains for each quintile using this methodology and updated SMC would be Rs. –4.2, Rs.7, Rs. –9.3, Rs. –30 and Rs. –44 per month, at an elasticity of -0.3 (negative sign indicates welfare losses).

median monthly fixed cost for households consuming less than 200 units per month under the counterfactual schedule is lower than JVVNL's current tariff schedule. The fixed charge for households consuming more than 500 units per month are however significantly greater than the current schedule, and ranges between Rs. 1,600 to 2,800 per month.

If fixed cost allocations for households are too high, there is a risk of consumer surplus turning negative. Theoretically, at negative consumer surplus, the household would be better-off disconnecting from the grid rather than continuing to pay fixed charges at any level of consumption. In Figure 23, we check if annual consumer surplus under counterfactual tariff is negative at any quintile. The figure shows that the consumer surpluses are positive for almost all households in the sample, except for households in the fifth quintile with the most elastic response to price. These households are at the greatest risk of disconnecting from the grid under the recommended tariff schedule. In a less extreme scenario, these households can be expected to adopt energy efficient appliances or energy conservation practices so that their annual consumption moves in the direction of the mean and the fixed cost allocations can be reduced. Another possibility is that high consumption households may substitute away from grid-based electricity to captive generation. To assess the chances of substituting away from grid-based energy, more information on the private marginal cost of running a small generating unit to meet household's base load requirements is required. As this information is not readily available, we are unable to test for this potential substitution away from the grid and propose this as an interesting future topic of research.

Given the overall welfare gains, economic efficiency of consumption and revenue neutral properties, this design is our preferred schedule for residential consumers of JVVNL.

SECTION VII: CONCLUSION

This paper calibrates the extent to which residential consumption responds to changes in power prices. The findings suggest that a 10 percent increase in power prices reduces household consumption by about 1 to 4 percent. Changes in prices however heterogeneously affect demand response across end-uses. Consumption for heating and cooling purposes is least affected by price changes, while consumption for domestic end-uses of power (such as for lighting) is most affected by these changes. These results suggest that holding current income levels constant, rationalizing residential tariff rates will lead households to adjust their domestic end-use of electricity more than others.

Using these model estimates, the paper tests if normative principles of electricity pricing can be used to produce a progressive and efficient tariff design. These principles recommend a two-part tariff with the variable cost of energy set to the social marginal cost of electricity, with fixed costs varying across households based on their willingness to pay.

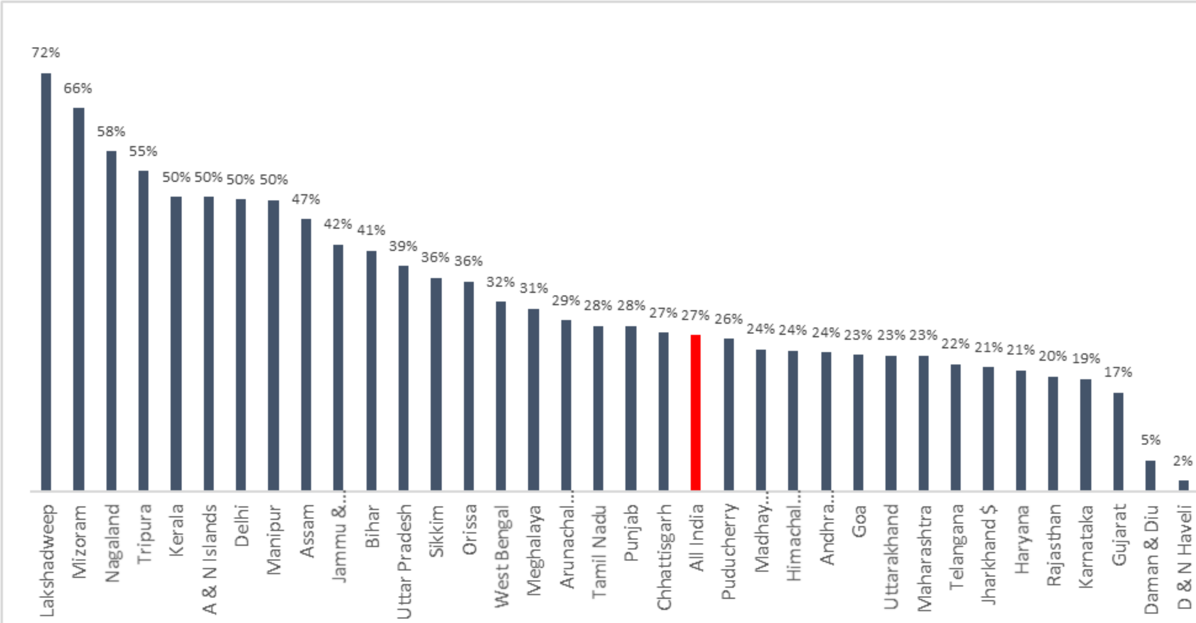
The social marginal cost of power is estimated as the sum of marginal cost of generating power, the marginal cost of distribution and transmission losses, and the external cost of carbon emissions. Calculations suggest that including the marginal cost of carbon emissions in the retail price of energy can increase electricity prices by approximately 50%. The means that given India's current electricity generation mix, passing the full cost of carbon externalities to the retail price of electricity may lead to an impractical rise in the price of power.

Next, the welfare enhancing consequences of adopting a two-part tariff which allows the utility to fully break-even on its costs is studied. As per-unit costs are set to the social marginal cost for all households under this design, prices do not distort consumption by charging some households more than others, achieving the goal of economic efficiency. The recommended tariff design also leads to progressive prices: it generates an average gain of Rs. 4.5 to Rs. 10 for households at the lowest quintile of the income distribution and an average loss of Rs. 20 per month for households in the top quintile.

Due to the poor quality of outages information maintained by the utility, the relationship between household demand and supply quality is not considered in this paper. Although a future line of research can explore this relationship in greater detail, the proposed tariff design addresses a key feature of how supply is rationed across consumers during periods of load-shedding. Under current prices, a utility has a greater incentive to supply power to larger consumers during periods of rationing. As the per-unit price of electricity is higher for these users, during periods of scarcity, the utility earns more per unit of dispatch by supplying to these consumers rather than smaller consumers situated at lower consumption brackets. In contrast, a uniform energy price across consumers under the recommended design, takes away the incentive of dispatching power to larger consumers and rebalances the existing disparities in dispatch across users. To the extent that the utility does offer greater dispatch to high consumption households during periods of scarcity, under the recommended tariff plan, the share of power supply to rural areas will likely increase as rural consumption share is lower than urban areas. Thus, rebalancing of supply dispatches across households is an additional virtue of our proposed plan in addition to its efficiency, equity and cost-neutral properties.

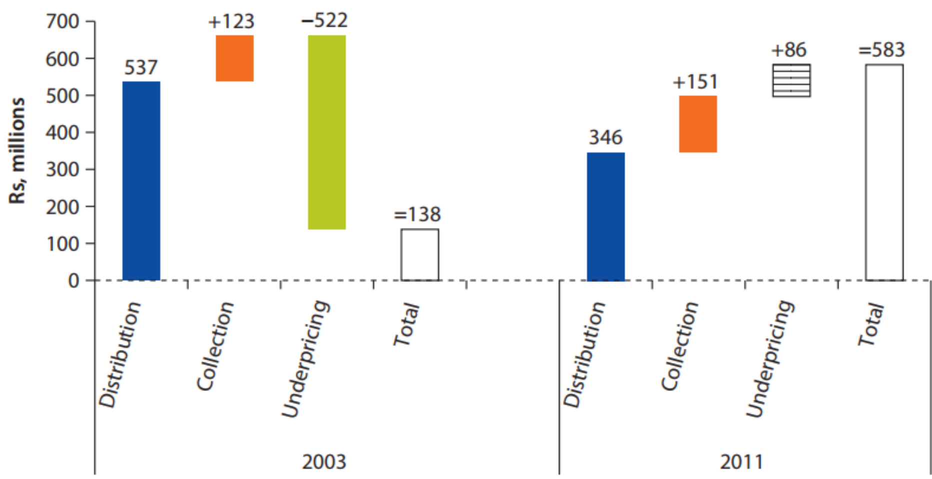
Finally, the simulated results in this paper are only as good as the utility's ability to send bills and collect revenues from households based on their actual monthly consumption. The analysis of the utility's billing data set suggests recurring cases of "average billing", in which the household's bill amount was imputed based on its average half-yearly consumption rather than the cotemporaneous consumption. There could be several reasons for why these bills had to be generated, including the possibility of faulty meters or meters being inaccessible to the meter reader or, in the worst case, a potential collusion between the meter reader and the consumer to deflate the cost of electricity consumption. Designing incentives to prevent the issuance of such imputed bills and modeling the impact of their strategic position on household level demand is outside the scope of this paper. However, an increase in the incidence of average billing cases will result in greater fixed cost burden per household. As a result, households that pay their bills based on their actual contemporaneous consumption face significant welfare losses.

Figure 1: Residential power consumed as a share of all power sold in the state



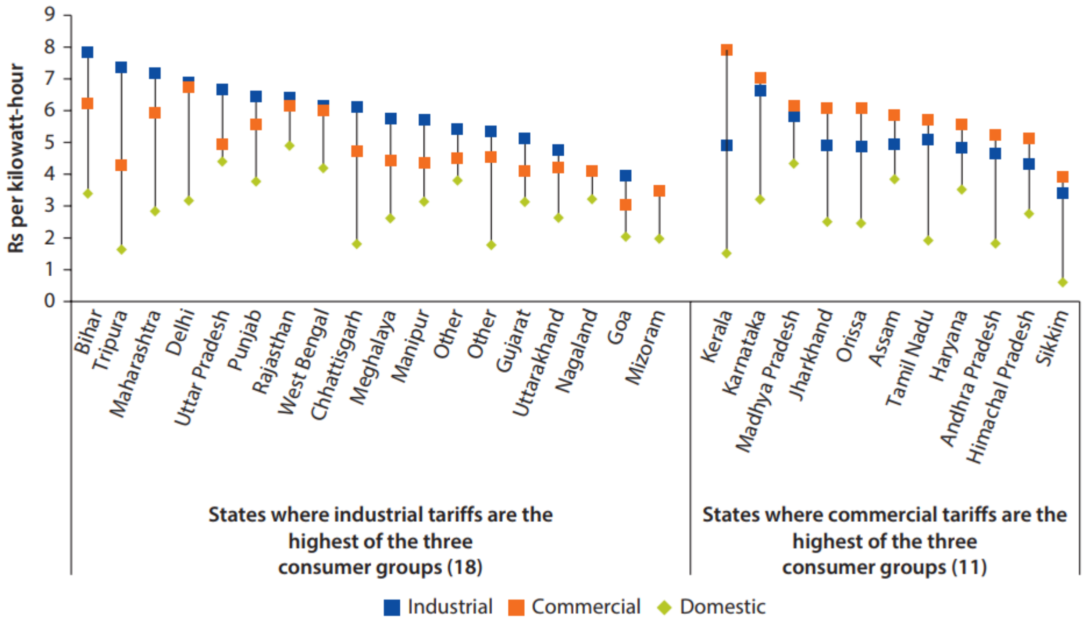
Notes: Compiled by the authors using data end-use consumption data from Central Electricity Authority for FY14-15

Figure 2: Decomposition of losses in the power sector



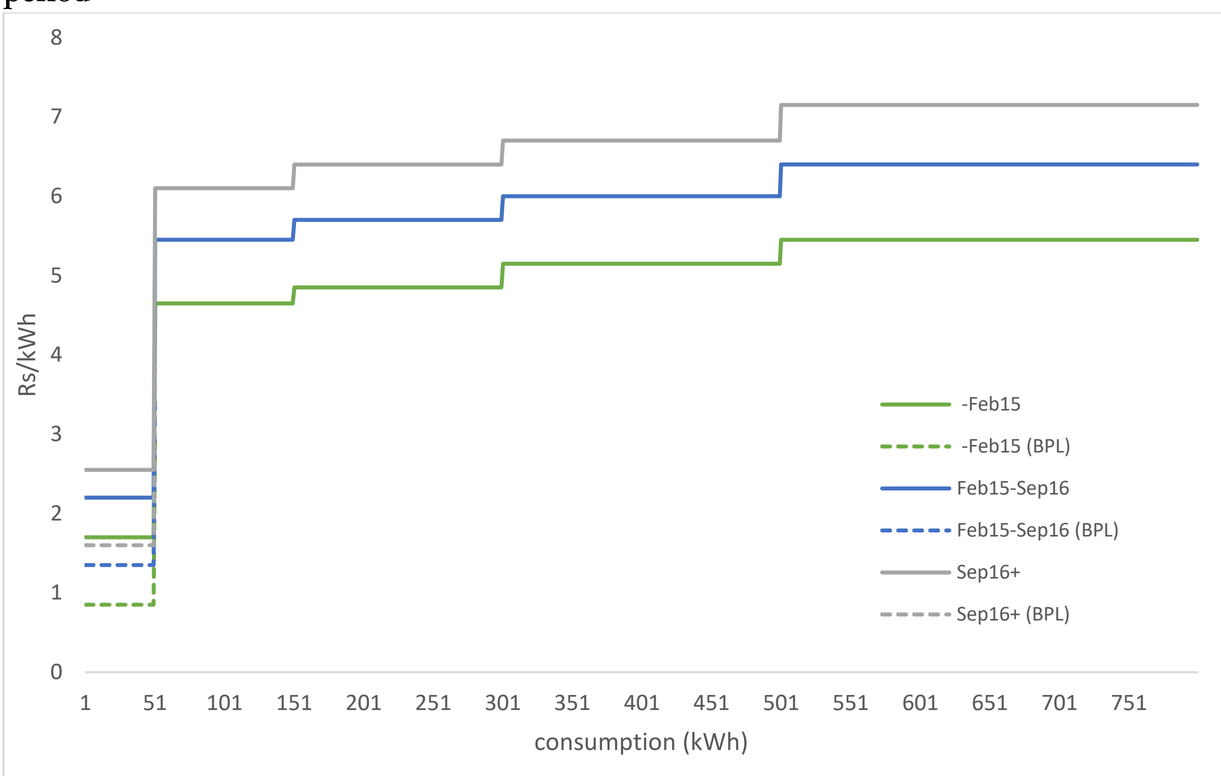
Notes: Source: Khurana and Banerjee (2013)

Figure 3: Effective Tariffs by Consumer Groups



Notes: Reference year is 2012. Source is Pargal and Banerjee (2014)

Figure 4: Energy Charges applicable on residential consumers of Rajasthan over the same period



Notes: Energy and fixed prices obtained from various tariff orders issued by JVVNL

Figure 5: Consumption distributions from NSS survey and administrative billing data

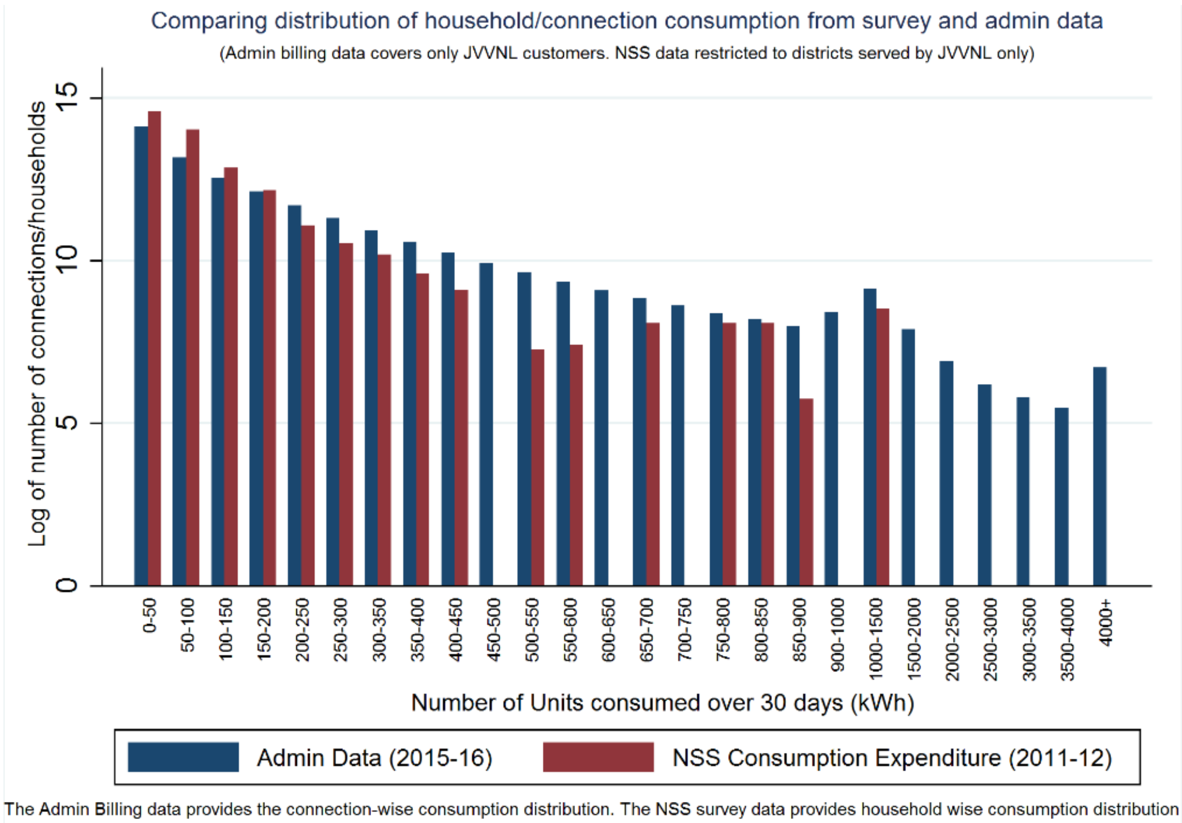
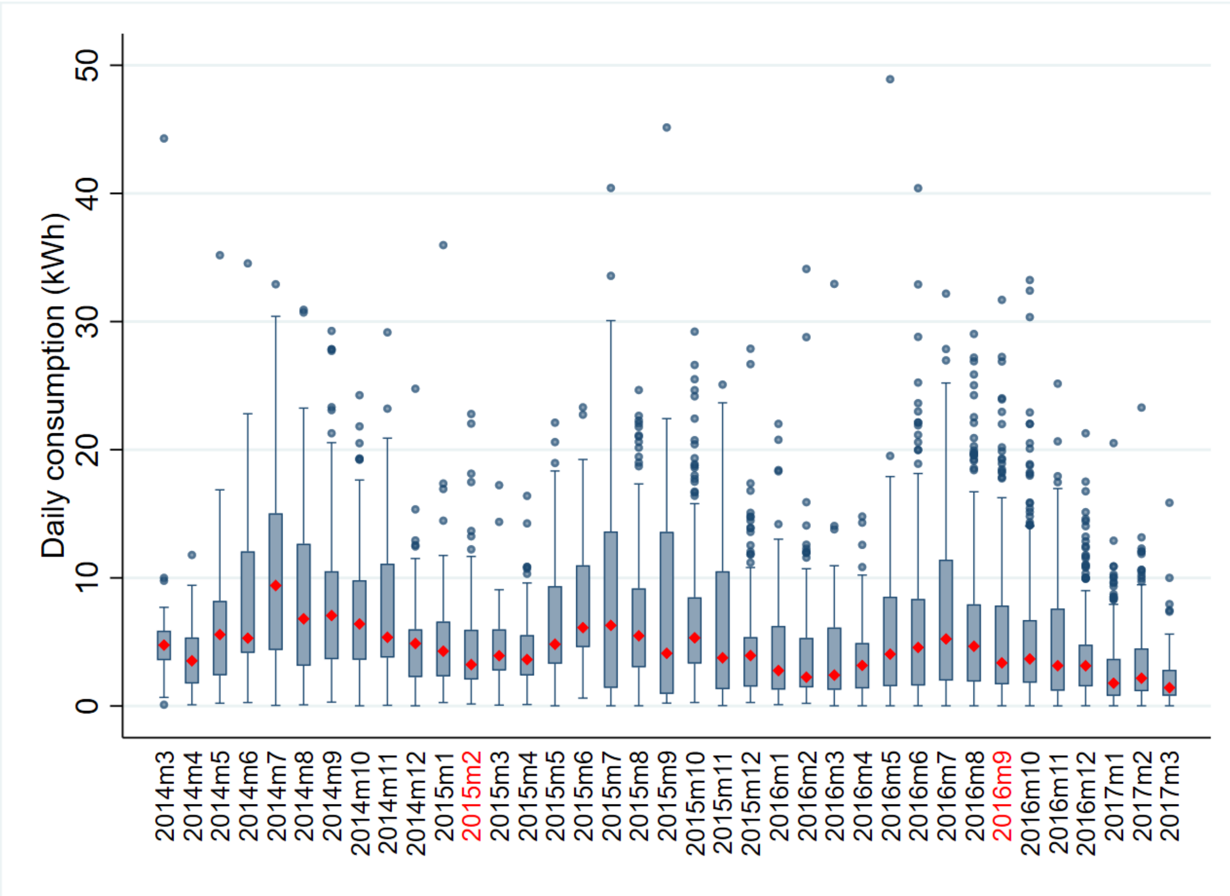
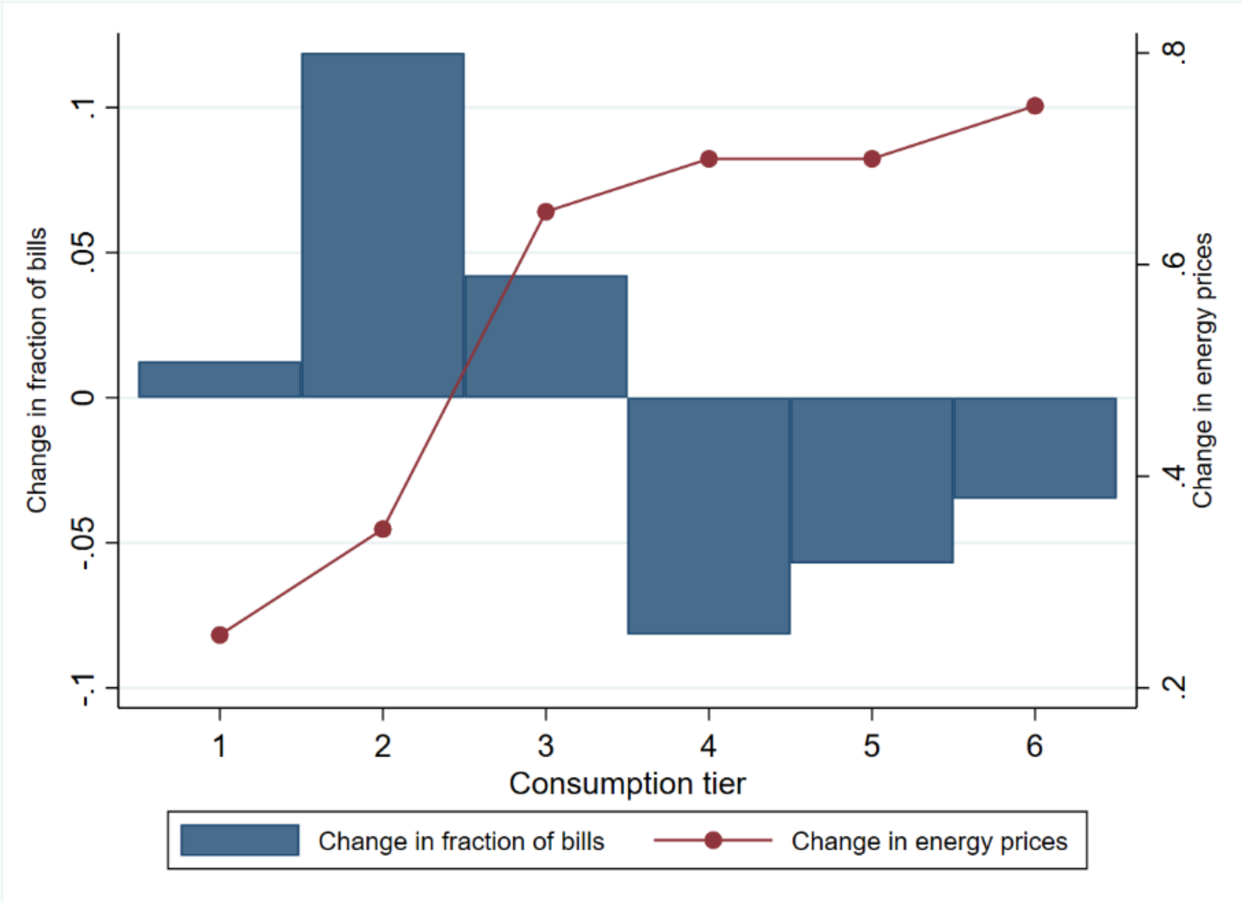


Figure 6: Daily consumption distribution by month – red labels indicate months in which price revisions occurred



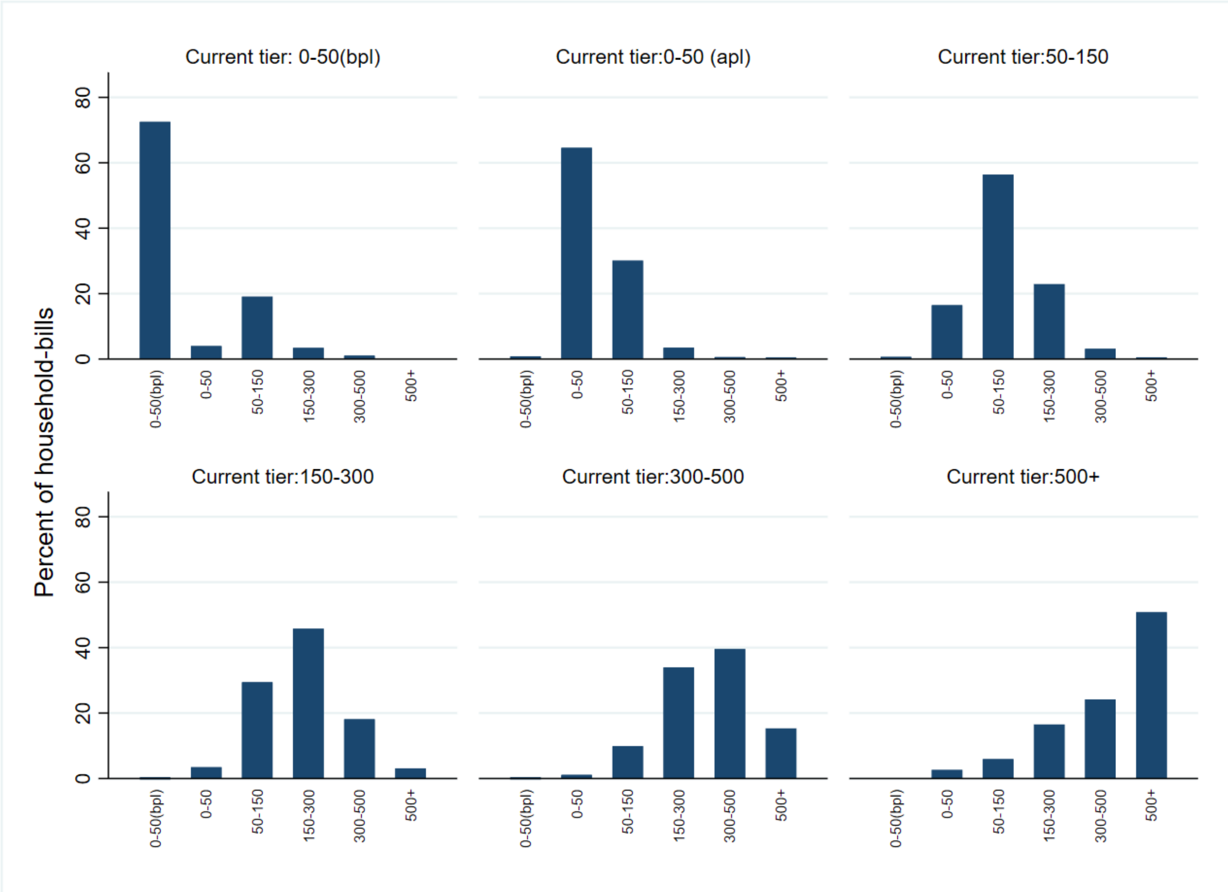
Notes: Daily consumption is calculated as the total consumption over the billing cycle divided by the number of days in the billing cycle. The monthly distribution of daily consumption is weighted by the sampling probabilities. The labels on the horizontal axis denote the month of bill issuance. Red diamonds indicate the median daily consumption over the month and red monthly labels indicate the period at which a revision in tariff schedule occurred.

Figure 7: Changes in the fraction of household bills and energy prices by consumption tiers



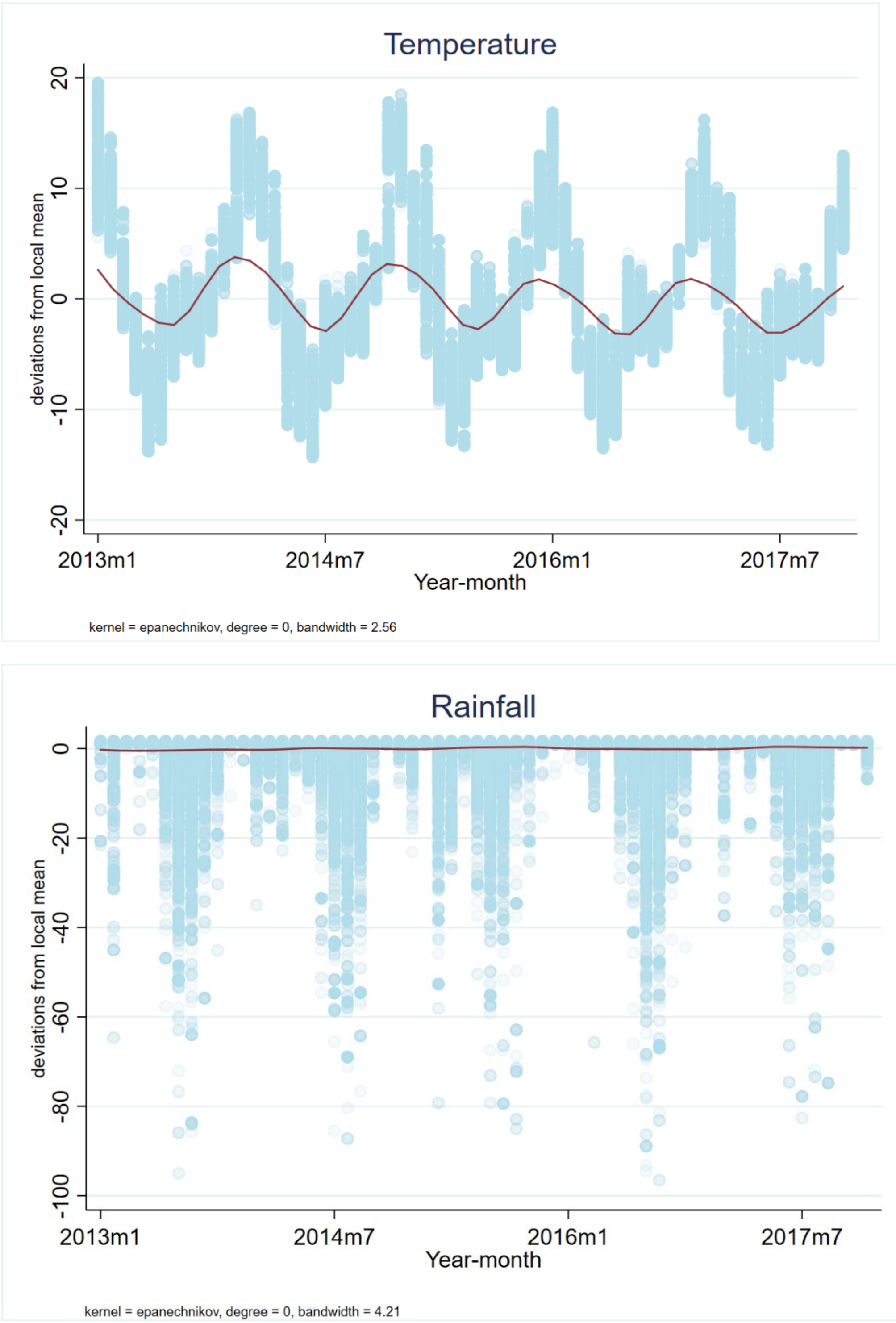
Notes: The graph indicates the correlation between changes in the fraction of bills by consumption tiers and the changes in energy prices. These changes are calculated over two periods: September-2016 to March-2017 and February-2015 to September 2016. The fraction of bills in a period is calculated as the number of bills in a consumption tier divided by the total number of bills across all tiers in that period. The price changes are calculated using the energy prices as prescribed in tariff schedules. The six consumption tiers indicated in the graph respectively correspond to 0-50 kWhs (BPL), 0-50 kWhs (APL), 51-150 kWhs, 151-300 kWhs, 301-500 kWhs, and greater than 500 kWhs.

Figure 8: Consumption transitions across tiers over consecutive billing cycle



Notes: The graph compares the probability of transitioning across consumption tiers over consecutive billing cycles. The consumption tiers from the previous period (t_0) are indicated in the horizontal axis. The percentage of household-bills is calculated as the total number of bills that were in consumption tier i in the previous period t_0 divided by all household-bills that are in consumption tier j in current period (t_1) (consumption tier j in period t_1 is denoted as "Current tier: X-Y" in the figure). The percentages are weighted by sampling weights.

Figure 9: Changes in temperature and precipitation from three year (2014-2017) average levels



Notes: The vertical axis shows the deviation of daily temperature and rainfall in a region from the local four-year period (2013-2017) means of temperature and rainfall

Figure 10: Histogram of Marginal Prices for Heating and Cooling Services

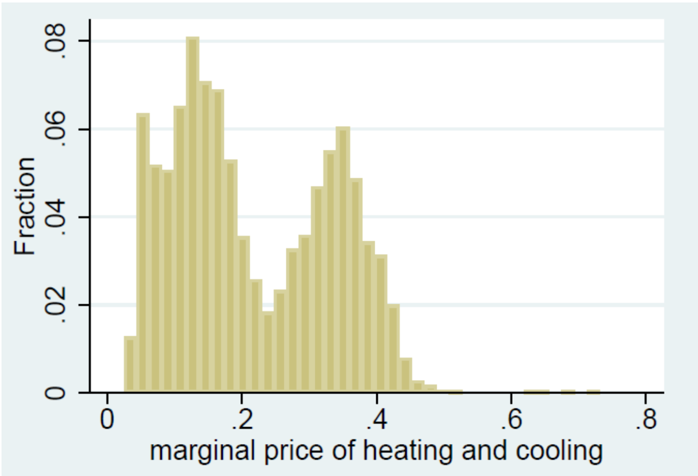


Figure 11: Histogram of Marginal Prices for Lighting

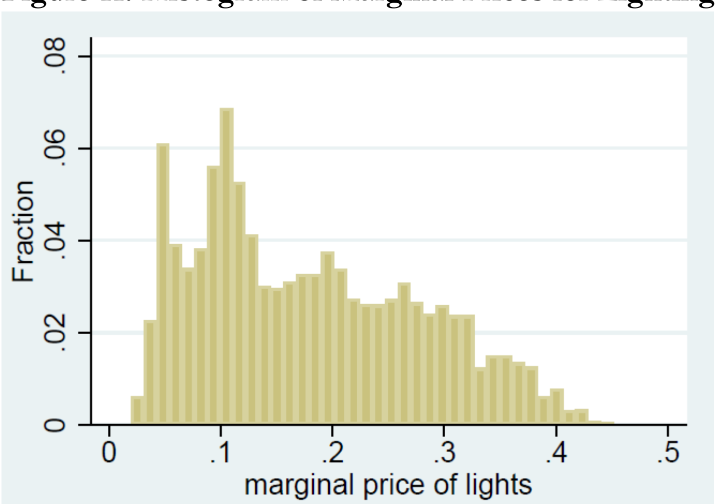


Figure 12: Histogram of Marginal Prices for Appliances

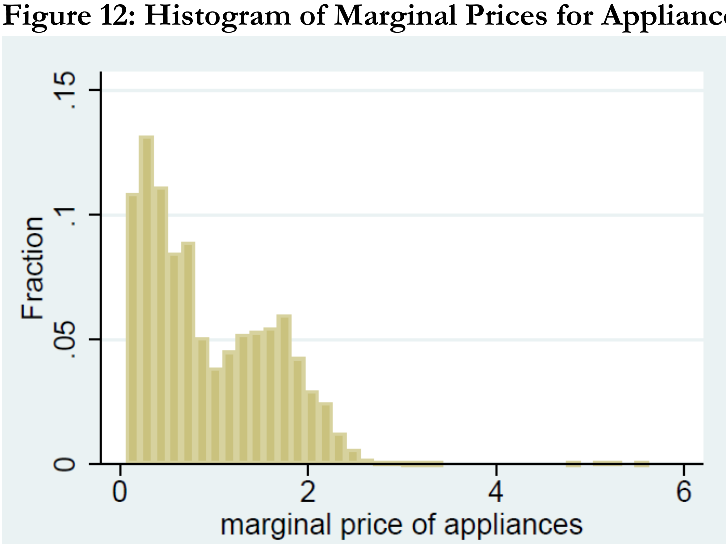


Figure 13: Histogram of Marginal Prices for Business Equipment

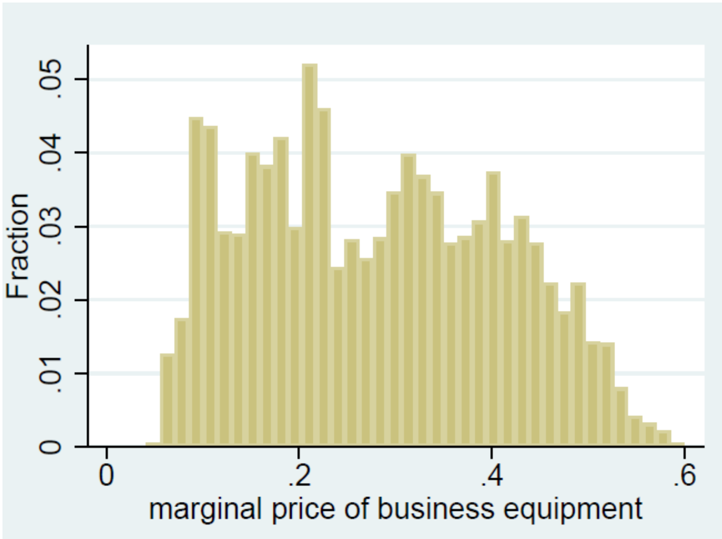
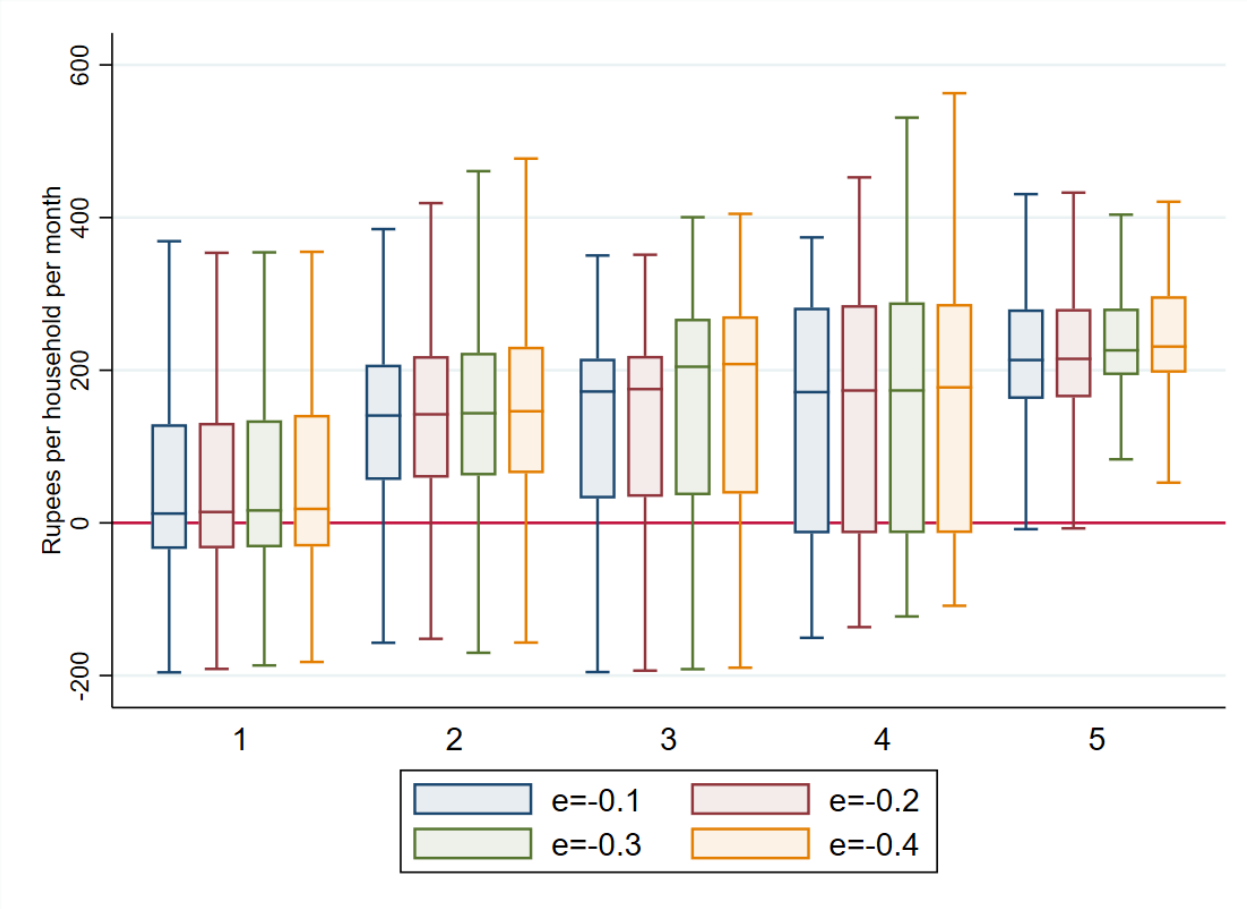
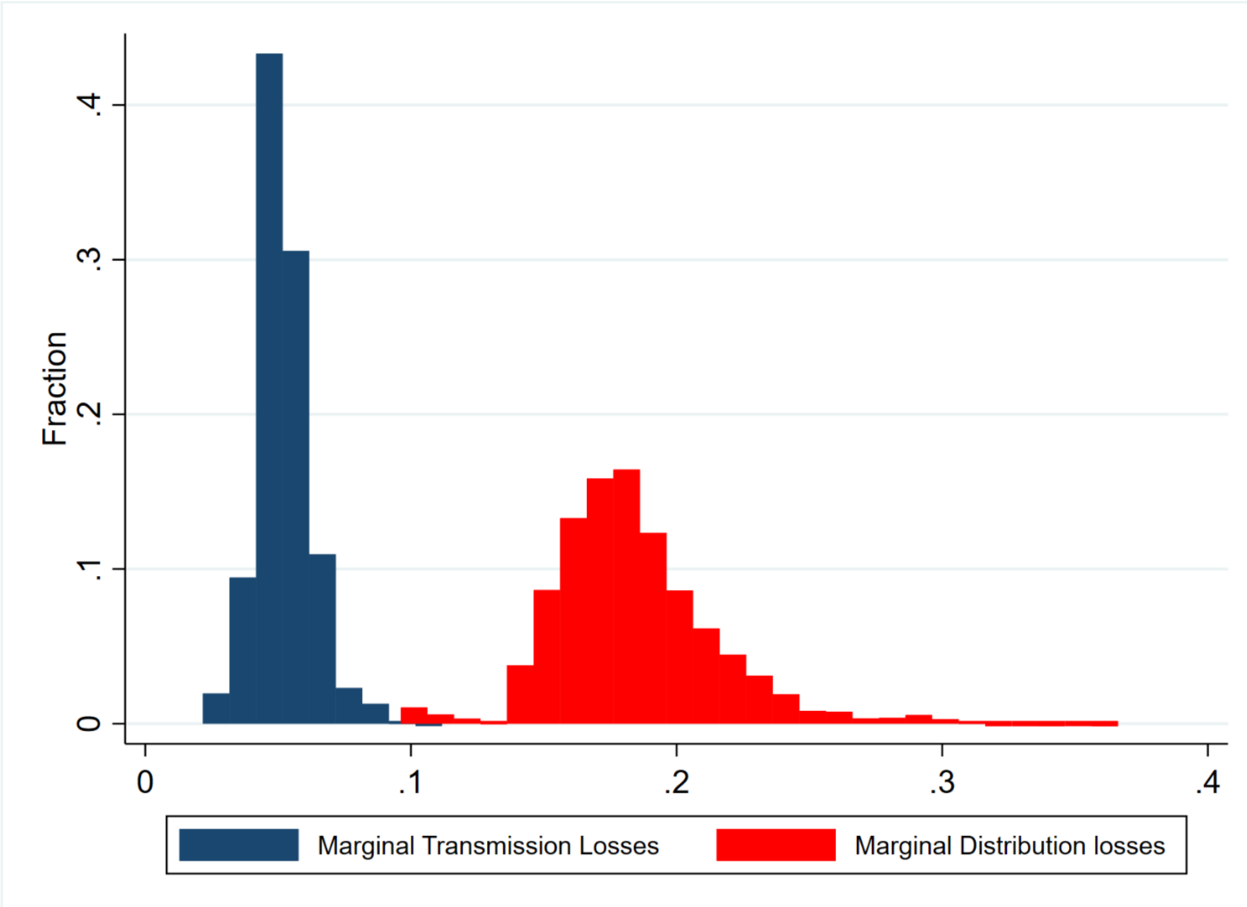


Figure 14: Changes in consumer surplus due to MOP's recommended tariff schedule



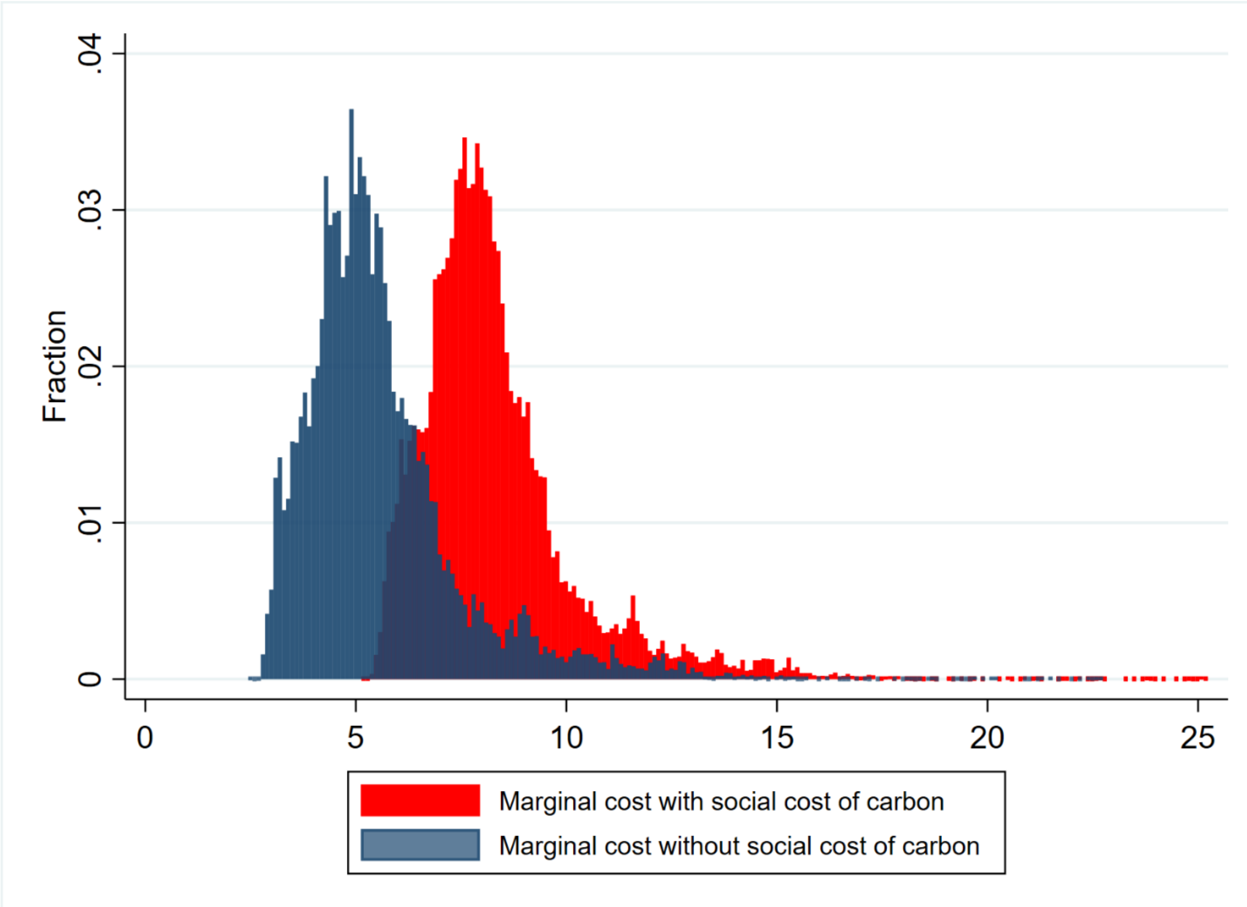
Notes: Income quintiles denoted in the horizontal axis. The vertical axis is the difference between the consumer surplus calculated at the counterfactual price and the JVVNL 2016-17 tariff order. The counterfactual price in this scenario is MOP's recommended tariff. e denotes the own-price elasticity of demand. The graph excludes outside values, i.e., observations that outside a range of 1.5 times the interquartile range of the distribution.

Figure 15: Distribution of marginal transmission and distribution losses



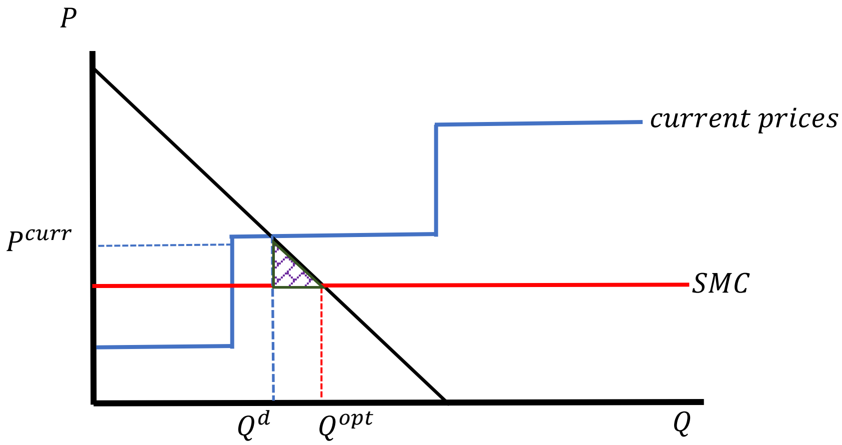
Notes: Marginal transmission network are calculated as a share of total energy generated over 15-minute blocks. Marginal distribution losses are calculated as a share of total energy in the distribution network over 15-minute blocks. The total energy in the distribution network in a 15-minute block is the total energy generated net of marginal transmission losses.

Figure 16: Distribution of Social Marginal Cost



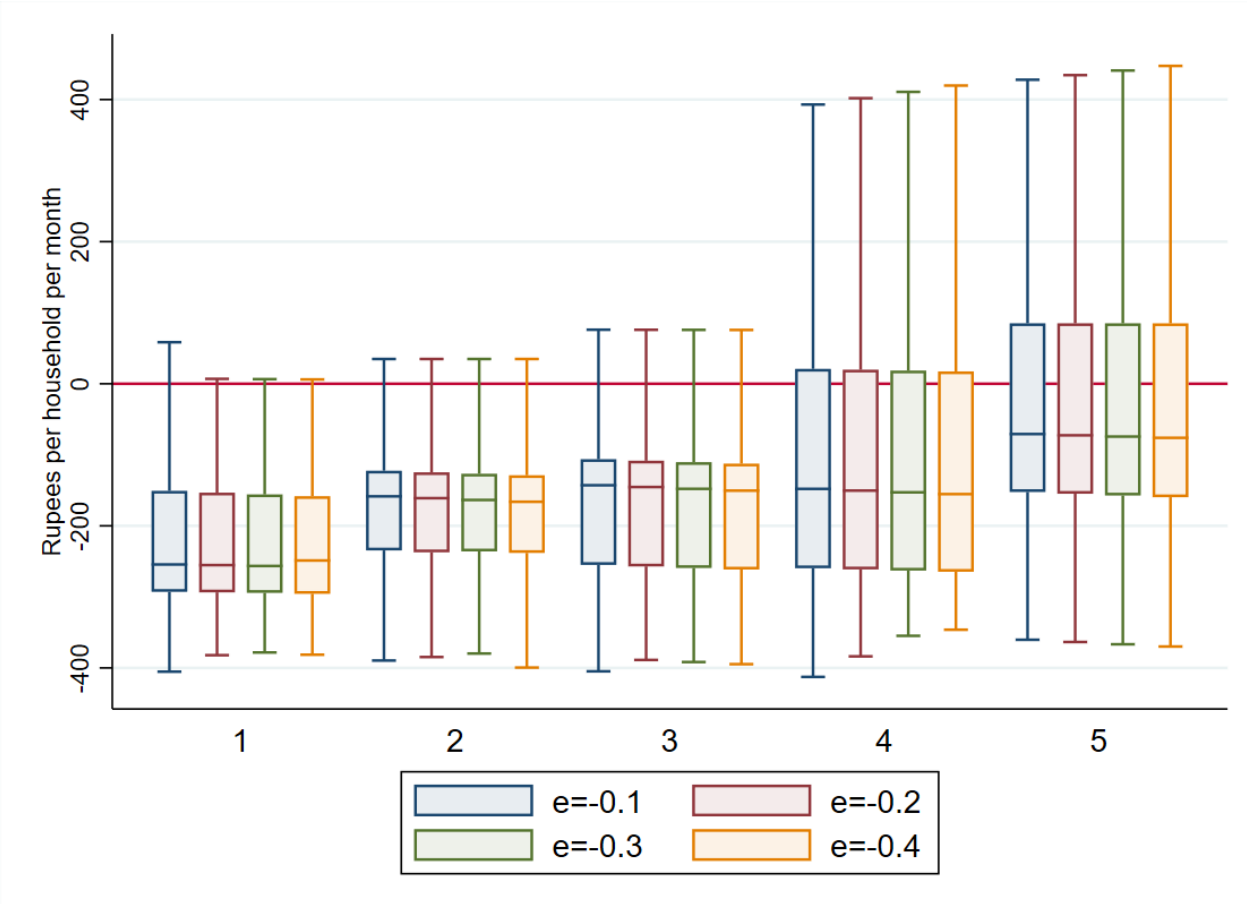
Notes: The figure shows the distribution of social marginal cost of electricity for all 15-minute in the sample. The social marginal cost includes the market clearing price of the wholesale electricity market, transmission and distribution losses and duties and cess levied by the utility. The distribution of total marginal cost is shown separately for calculating including and excluding the social cost of carbon dioxide emissions.

Figure 17: Distortions in current pricing schedule: deadweight loss analysis



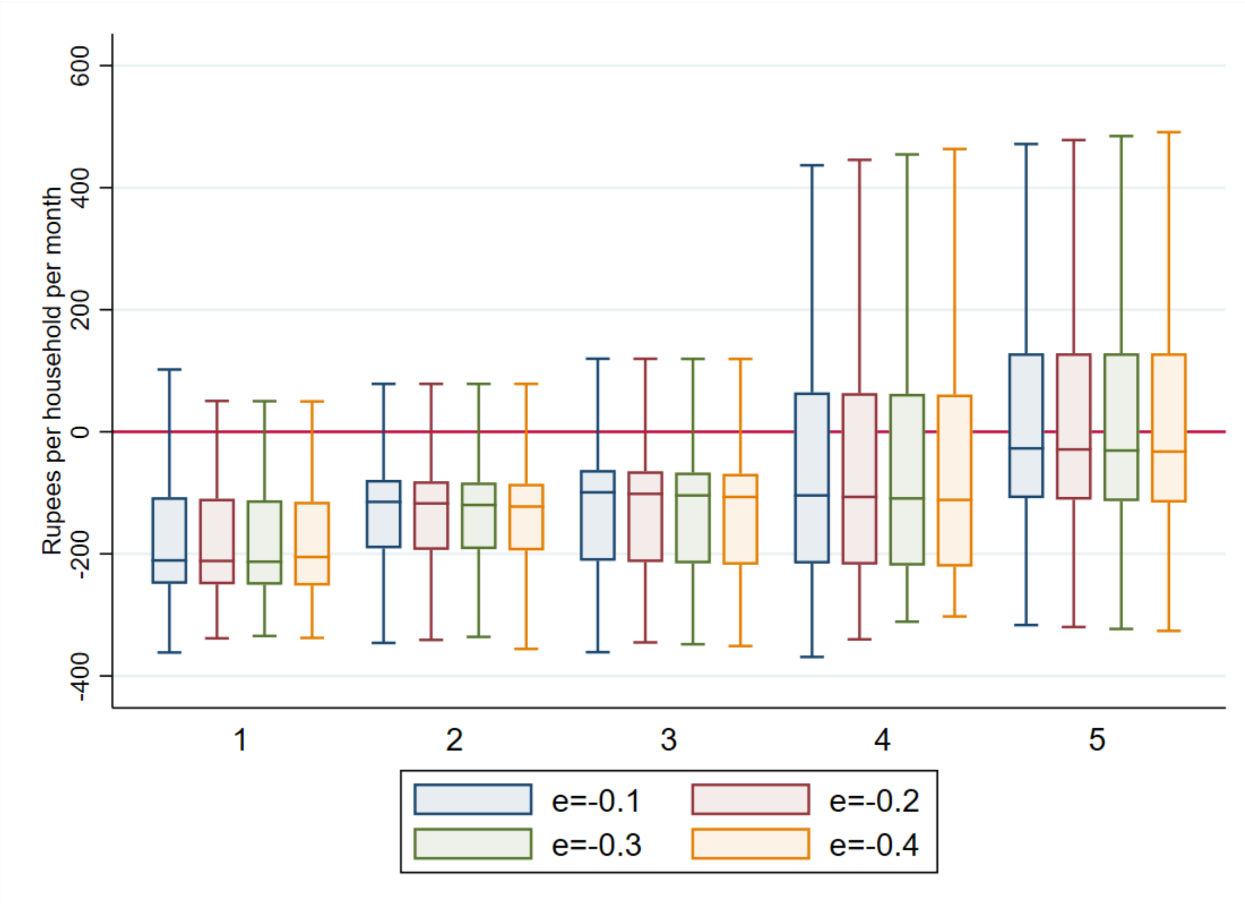
Notes: Q^d indicates the consumption under the current prices (P^{curr}) using the calibrated linear demand for electricity. Q^{opt} indicates the consumption of the household under a uniform energy price set to SMC. The deadweight loss is the area of the triangle as shaded in the figure. The area of the triangle can be calculated as $DWL = \frac{1}{2}(P^{curr} - SMC) * \frac{(P^{curr}-SMC)}{b} = \frac{1}{2b}(P^{curr} - SMC)^2$ where $b = \frac{P^{curr}}{Q^{d} * \varepsilon}$ the slope of the inverse demand curve and ε if the own-price elasticity of consumption

Figure 18: Distributional consequences of equal energy and fixed charges (without subsidy transfers)



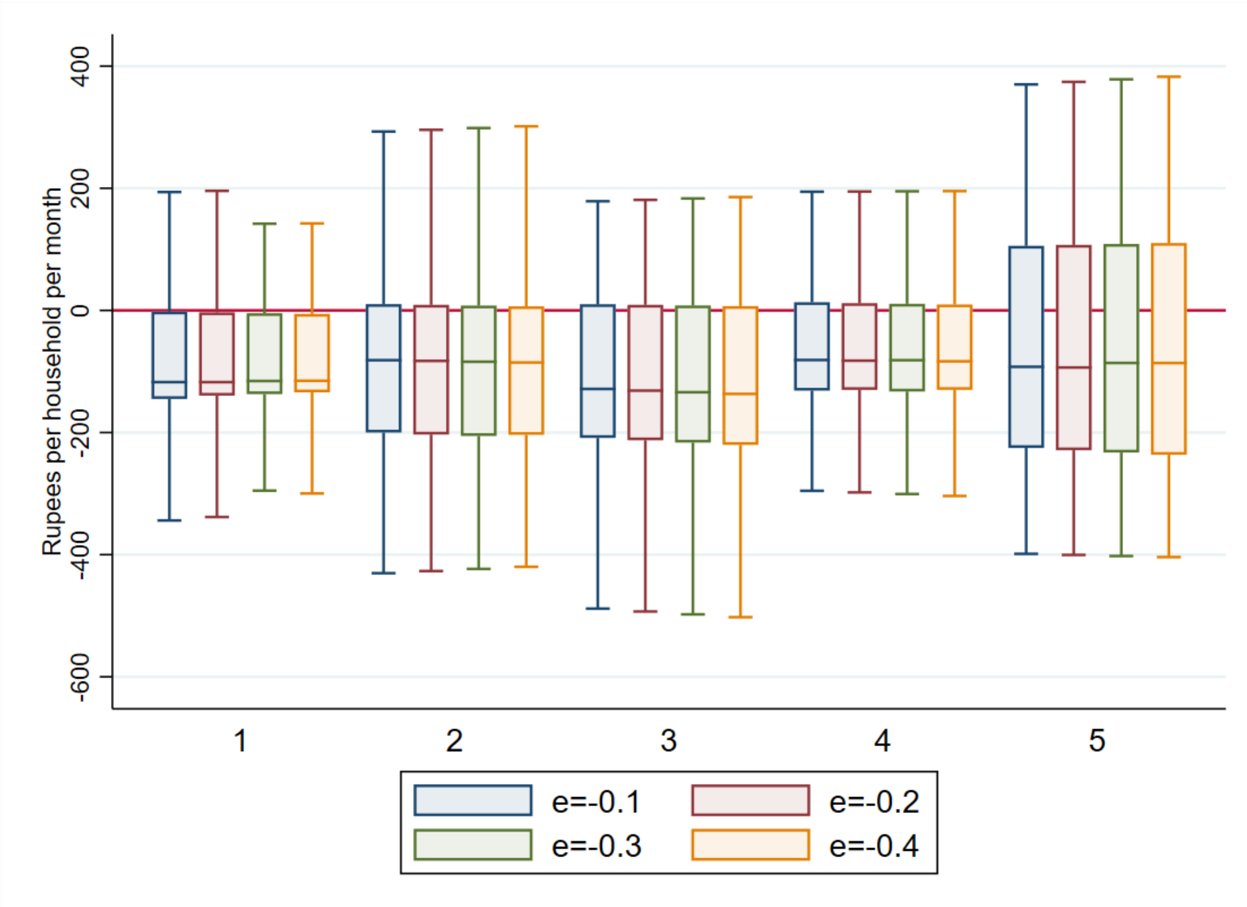
Notes: Income quintiles denoted in the horizontal axis. The vertical axis is the difference between the consumer surplus calculated at the counterfactual price and current prices. Fixed costs are divided equally amongst households with no transfer. e denotes the own-price elasticity of demand. The graph excludes outside values, i.e., observations that outside a range of 1.5 times the interquartile range of the distribution.

Figure 19: Distributional consequences of equal energy and fixed charges (with subsidy transfers)



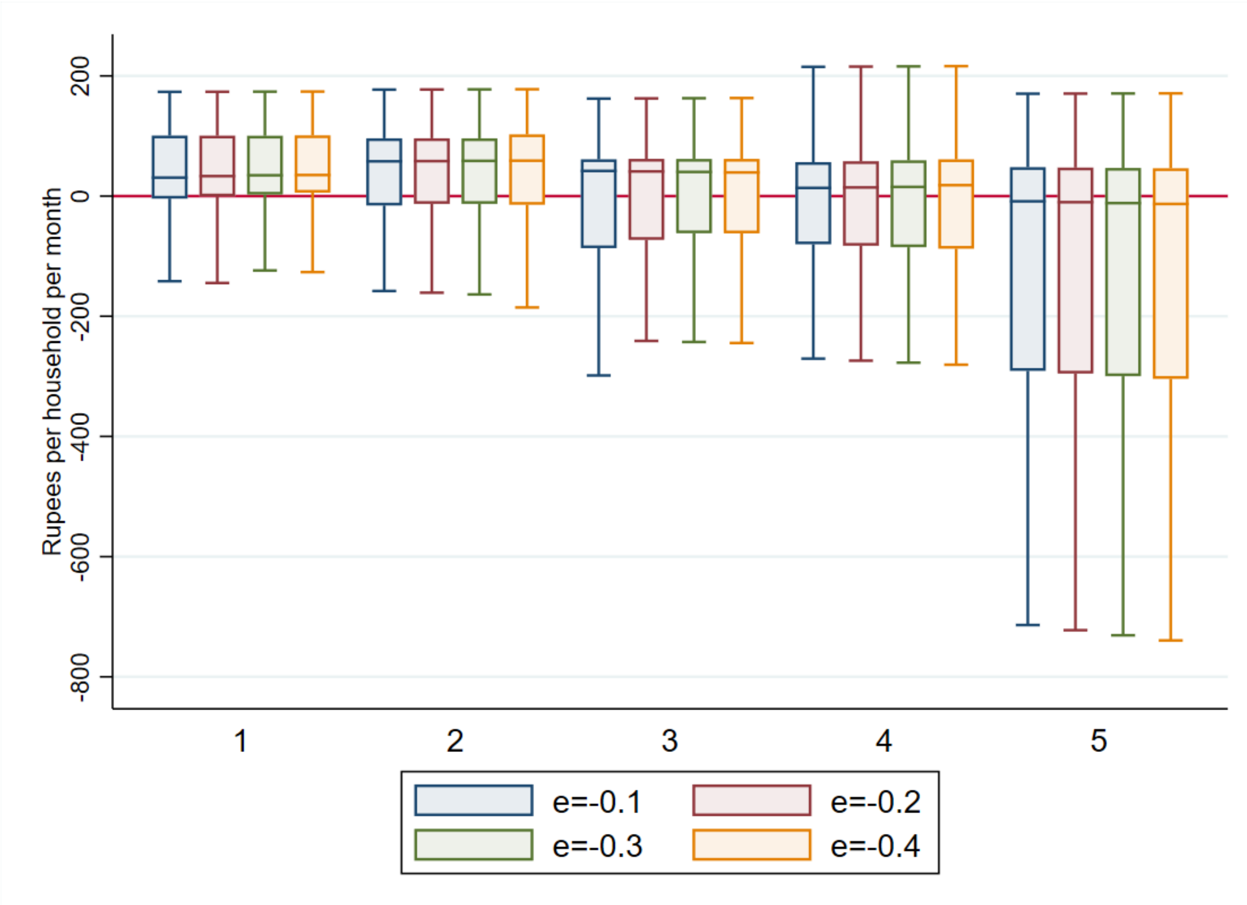
Notes: Income quintiles denoted in the horizontal axis. The vertical axis is the difference between the consumer surplus calculated at the counterfactual price and current prices. The total fixed cost requirement is net of total energy and fixed cost subsidies paid by the state in FY16-17. The fixed cost has been divided equally amongst all households. e denotes the own-price elasticity of demand. The graph excludes outside values, i.e., observations that are outside a range of 1.5 times the interquartile range of the distribution.

Figure 20: Distributional consequences of equal energy charges and proportional fixed charges based on shares of rural and urban consumption



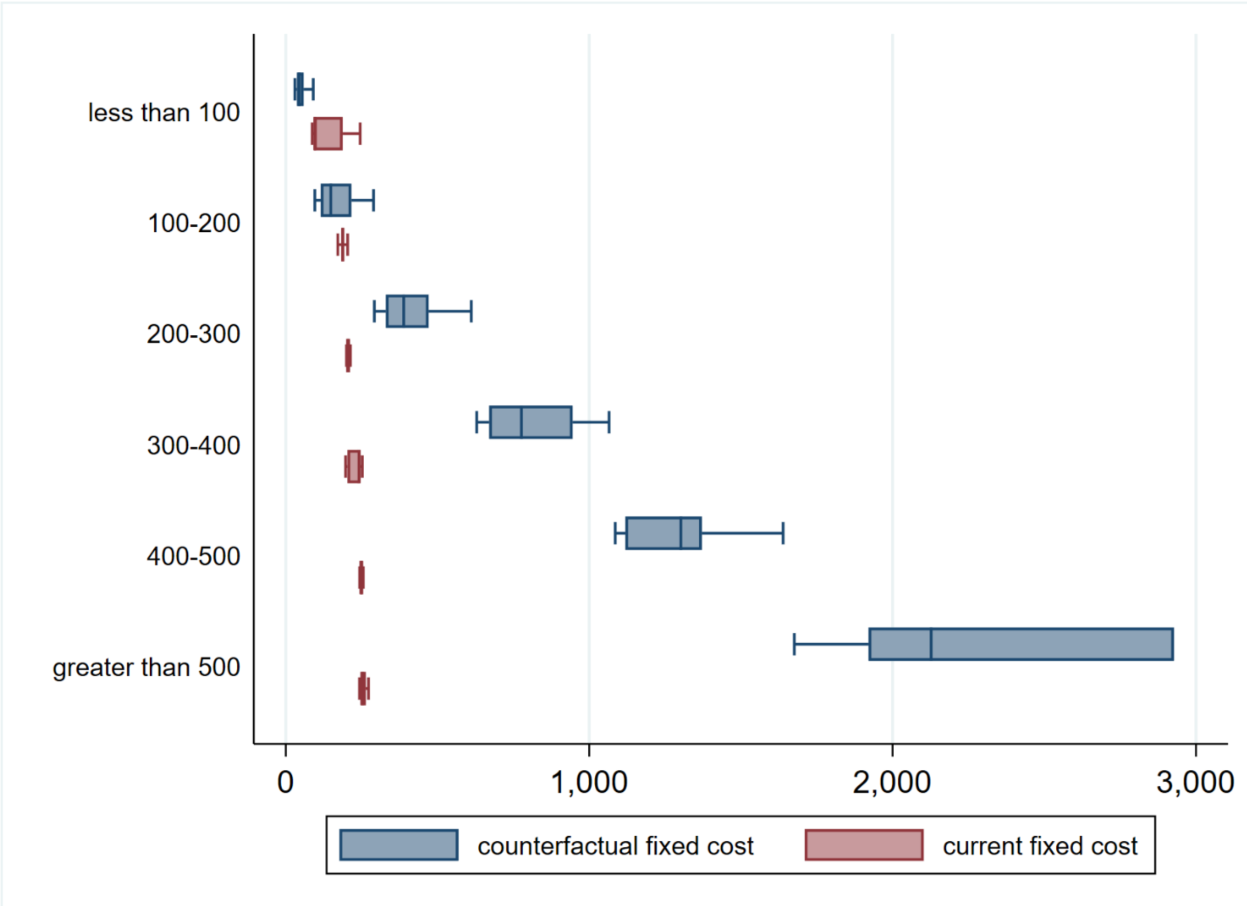
Notes: Income quintiles denoted in the horizontal axis. The vertical axis is the difference between the consumer surplus calculated at the counterfactual price and current prices. The total fixed cost requirement is net of total energy and fixed cost subsidy paid by the state in FY16-17. 37 percent of this fixed cost is divided equally among all rural households; 63 percent of the remaining cost is distributed equally among urban households. e denotes the own-price elasticity of demand. The graph excludes outside values, i.e., observations that outside a range of 1.5 times the interquartile range of the distribution.

Figure 21: Distributional consequences of equal energy charges and proportional fixed charges based on deviation of historical consumption from them mean



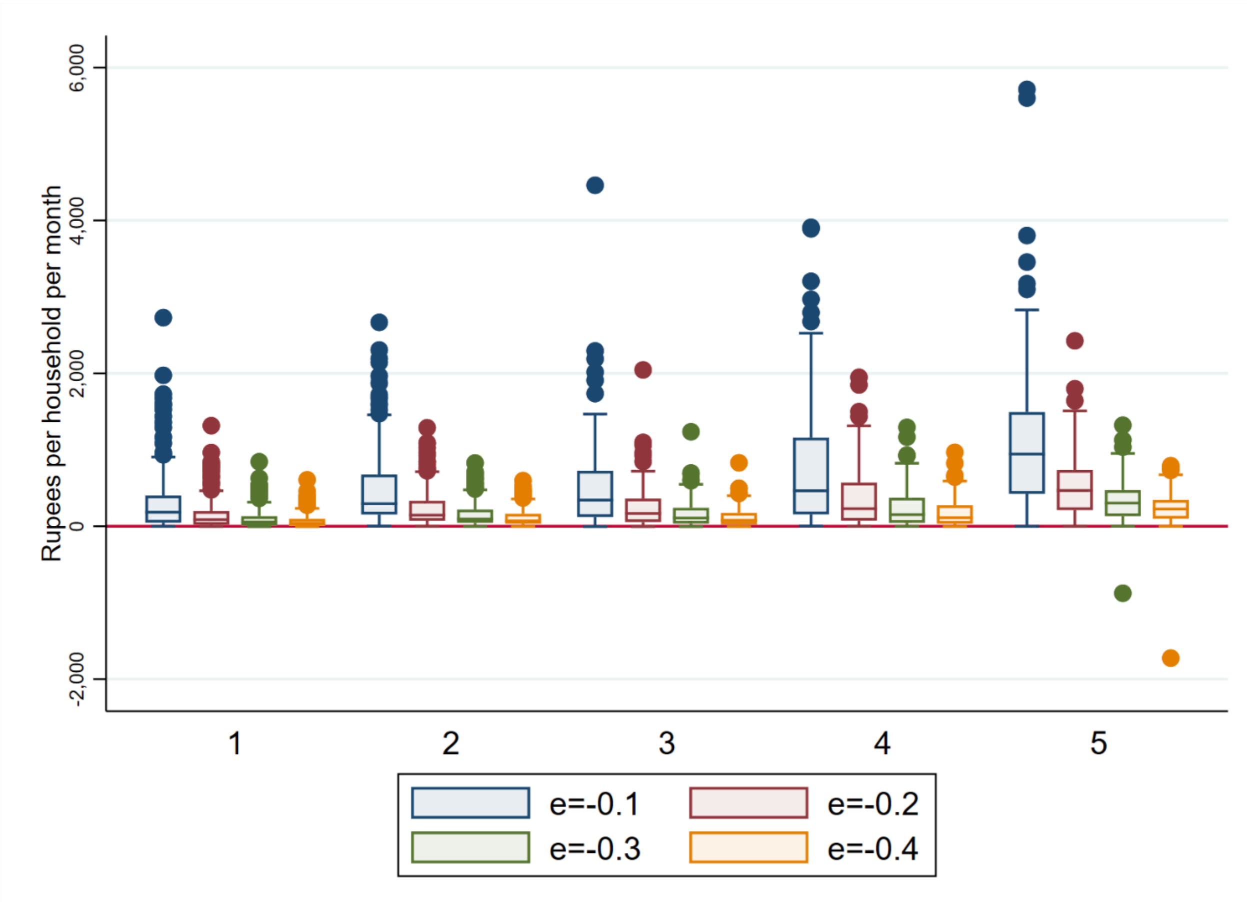
Notes: Income quintiles denoted in the horizontal axis. The vertical axis is the difference between the consumer surplus calculated at the counterfactual price and current prices. The total fixed cost requirement is calculated as net of total energy and fixed cost subsidy paid by the state in FY16-17. The net fixed cost charges are distributed unequally across households using the difference between a household's squared annual consumption and mean squared consumption across all households. e denotes the own-price elasticity of demand. The graph excludes outside values, i.e., observations that outside a range of 1.5 times the interquartile range of the distribution.

Figure 22: Comparison of fixed cost allocation across consumption groups based on current JVVNL tariff schedule and counterfactual scenario



Notes: Fixed cost in rupees per month per connection denoted in the horizontal axis. The vertical axis is the average monthly consumption of a household. The counterfactual fixed costs are calculated using the deviation of squared annual consumption from the mean of squared consumption. These are calculated after assuming a lump-sum transfer of current subsidies to the utility. The current fixed costs are based on JVVNL's current tariff schedule. The graph excludes outside values, i.e., observations that outside a range of 1.5 times the interquartile range of the distribution.

Figure 23: Consumer surplus under counterfactual tariffs



Notes: Income quintiles denoted in the horizontal axis. The vertical axis is total between the consumer surplus calculated at energy price set to SMC and fixed cost allocated in proportion to the deviation from the mean of squared consumption. e denotes the own-price elasticity of demand. The graph does not exclude outside values, i.e., observations that outside a range of 1.5 times the interquartile range of the distribution.

Table 1: The distribution of various charges in the data set

	Mean	10th percentile	90th percentile
monthly consumption	166.3 kWh	24.7 kWh	374.5 kWh
monthly consumption per capita	39.7 kWh	4.4 kWh	87.6 kWh
energy charges	₹ 1729	₹ 181	₹ 4086
fixed charges	₹ 348	₹ 180	₹ 480
electricity duty	₹ 138	₹ 20	₹ 310
tariff subsidy	₹ -15.1	₹ -66.3	₹ 0

Notes: Total number of observations in the sample are 7,615. The distribution was weighted by sampling probabilities.

Table 2: Comparing the consumption distribution of sampled households to billing data set

Percentiles	Admin billing data (all HH)	Admin billing data (surveyed HH)
1%	1	1
5%	15	14
10%	30	28
25%	62	58
50%	115	119
75%	240	263
90%	452	436
95%	645	562
99%	1283	762
Mean Value	208	189

Notes: This table compares the distribution of consumption for all households in the two district of Rajasthan in the administrative data to the consumption distribution obtained from the survey using sampling probabilities. The sample period for both data sets is restricted to January and February 2017.

Table 3: Socioeconomic profile of the households

Variable	Proportion of households
Proportion of general caste	29%
Pukka Wall	97.1%
Pukka Roof	99%
Pukka Floor	44.4%
Tap water connection	63.4%
Top Income Source: Farming	15.8%
Top Income Source: Livestock	3.4%
Top Income Source: Own Business	19.5%
Top Income Source: Casual Labour	23.2%
Top Income Source: Salaried Work	36.2%
Top Income Source: Remittances	2.8%
Living in a tented house	5.5%
Ownership of Below Poverty Line Card	18.2%

Table 4: Proportion of households owning at least one appliance

Appliance	Ownership share	Appliance	Ownership share
Air cooler	68.9%	Television	73.5%
Air conditioner	7.4%	Refrigerator	60.1%
Room heater	1.2%	Water purifier	7.6%
Warm air blower	0.3%	Microwave oven	2.9%
Ceiling fan	92.8%	Mobile charger	97.2%
Table fan	16.3%	Desktop computer	4.7%
Immersion rod	4%	Laptop computer	10.7%
Water heater (geyser)	10.5%	Electric iron	33.2%
CFL	78.1%	Sewing machine	1.5%
Bulbs	39.6%	Water pump	37.4%
Tube lights	34%	Washing machine	19.2%

Notes: Proportions are calculated using sampling probabilities

Table 5: Proportion of households owning at least one appliance

Dependent Variable: log(daily energy services demand based on survey data)	(1)	(2)	(3)	(4)	(5)
log(observed daily consumption)	0.546*** (0.0557)	0.6*** (0.0624)	0.603*** (0.0636)	0.602*** (0.0656)	0.606*** (0.0678)
Constant	0.225*** (0.0723)	0.148* (0.0797)	0.144* (0.0819)	0.145* (0.0854)	0.138 (0.0901)
Observations R-squared	805 0.294	780 0.293	769 0.291	760 0.282	749 0.277

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observed daily consumption is calculated as $\frac{(sum\ of\ electricity\ consumed\ by\ a\ household\ over\ all\ bills\ in\ one\ year\ period)}{(number\ of\ days\ between\ first\ and\ last\ bill\ received\ by\ the\ household\ over\ the\ year)}$ based on the billing data set. The daily energy services demand based on survey data is calculated as $\frac{annual\ energy\ services\ demanded\ by\ the\ household\ based\ on\ survey\ data}{365}$. Model (1) comprises of the entire sample of 805 households, whereas models (2), (3), (4) and (5) correspond to trimmed samples, comprising of households with monthly consumption above 14.9, 16.5, 18.2 and 20.1 units in the billing data respectively.

Table 6: Relationship between temperature, humidity and observed demand

Dependent var: Log (consumption per day over billing cycle)	
Log (average temperature over billing cycle)	1.219*** (0.134)
Log (average rainfall over billing cycle)	-0.0268** (0.0119)
Constant	-3.002*** (0.462)
Observations R-squared	7,613 0.041

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Averages of temperature and rainfall are calculated at the household level for each billing cycle in the data set. The regression is weighted by sampling probabilities and clustered at the town and village level.

Table 7: Relationship between temperature, humidity and demand for energy services based on appliance ownership and usage data

Dependent var: log(predicted daily consumption)	
Log (average temperature over billing cycle)	0.262*** (0.0624)
Log (average rainfall over billing cycle)	-0.0554*** (0.0134)
Constant	-0.0154 (0.233)
Observations R-squared	3,828 0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Averages of temperature and rainfall are calculated at the household level for each billing cycle in the data set. The regression is weighted by sampling probabilities and clustered at the town and village level. The sample is trimmed to include approximately 365 days of temperature and rainfall data for each household.

Table 8: Nonlinear Least Squares Estimates Electricity Production Function

δ	2.971 (0.23)		
Lamba: Heating and Cooling energy services		**Lamba: Lighting energy services**	
Constant	-3.287 (0.30)	Constant	-3.481 (0.34)
Temperature	0.0642 (0.04)	Temperature	0.081 (0.02)
Rain	0.0376 (0.04)	Rain	-0.061 (0.05)
Lambdas: Domestic end-use energy services		**Lambdas: Business end-use energy services**	
Constant	-1.938 (0.27)	Constant	-2.977 (0.63)

Temperature	0.0945 (0.03)	Temperature	0.0566 (0.02)
Rain	0.0647 (0.03)	Rain	-0.046 (0.09)

Notes: Standard errors clustered on households in parentheses. Total number of observations in the sample is 7451. Refer to equation (8) for the functional form used to estimate $E = f(s, A, \epsilon)$

Table 9: Instrumental Variables Estimates of Parameters of Translog Demand System

α	
Heating and cooling	-0.0412 (0.022)
Lighting	0.0164 (0.018)
Domestic end-use	-0.0734 (0.010)
Business end-use	0.0167 (0.010)
β	
Heating and cooling * Heating and cooling	-0.0343 (0.0051)
Heating and cooling * Lighting	0.0083 (0.0021)
Heating and cooling * Domestic end-use	-0.00369 (0.0041)
Heating and cooling * Business end-use	0.00194 (0.0065)
Heating and cooling * Composite goods	0.0257 (0.0047)
Lighting * Lighting	0.00367 (0.0028)
Lighting * Domestic end-use	-0.0138 0.00012
Lighting * Business end-use	0.00357 (0.0037)
Lighting * Composite goods	-0.00318 (0.0044)
Domestic end-use * Domestic end-use	0.0244 (0.0015)
Domestic end-use * Business end-use	-0.00602 (0.0034)

Domestic end-use * Composite goods	-0.00781 (0.0061)
Business end-use * Business end-use	0.00124 (0.00020)
Business end-use * Composite goods	-0.00142 (0.00251)
Composite goods * Composite goods	-0.11 (0.0227)
γ	
Heating and cooling * Household fixed effects	-0.000020 (0.00039)
Heating and cooling * Temperature	-0.00081 (0.00004)
Heating and cooling * Urban	0.00915 (0.00505)
Lighting * Household fixed effects	0.00003 (0.00011)
Lighting * Temperature	-0.000386 (0.00028)
Lighting * Urban	0.00243 (0.00152)
Domestic end-use * Household fixed effects	0.000678 (0.00052)
Domestic end-use * Temperature	-0.00058 (0.00021)
Domestic end-use * Urban	0.00624 (0.00323)
Business end-use * Household fixed effects	-0.00002 (0.00007)
Business end-use * Temperature	-0.00039 (0.0002)
Business end-use * Urban	-0.00252 (0.00089)
Composite goods * Household fixed effects	-0.011 (0.00379)
Composite goods * Temperature	0.00328 (0.00029)
Composite goods * Urban	0.0518 (0.02609)

Notes: Standard errors clustered on households in parentheses. Total number of observations in the sample is 7451. Refer to equation (7) in the text for the demand equation under translog indirect utility functional form.

Table 10: Mean Customer and Billing Cycle Level Own-Price and Net Income Elasticities

Service	**Own-Price Elasticity**	**Net Income Elasticity**
Heating and Cooling	-0.344	1.336
Lighting	-1.378	1.167
Domestic end-use	-2.719	0.794
Business end-use	-1.194	1.341
Composite good	-0.947	1.012

Table 11: Average marginal prices in FY2016-17 under current price schedule and MOP's recommended tariff

Income quintile	e=-0.1	e=-0.2	e=-0.3	e=-0.4
1	12.21	14.24	16.27	18.30
2	140.59	142.19	143.65	146.26
3	172.06	175.24	204.59	208.00
4	171.31	173.38	173.45	177.52
5	213.35	214.88	226.03	230.99

Table 12: Deadweight loss estimates (in rupees per month) by income quintile

Income quintile	e=-0.1	e=-0.2	e=-0.3	e=-0.4
1	3.10	6.19	9.29	12.39
2	2.57	5.14	7.71	10.28
3	3.22	6.43	9.65	12.86
4	1.97	3.94	5.91	7.88
5	3.03	6.06	9.09	12.12

Table 13: Deadweight loss estimates (as a share of total expenditure) by income quintile

Income quintile	e=-0.1	e=-0.2	e=-0.3	e=-0.4
1	1.4%	2.8%	4.3%	5.7%
2	1.0%	2.1%	3.1%	4.2%
3	1.6%	3.3%	4.9%	6.6%
4	1.0%	2.1%	3.1%	4.2%
5	1.7%	3.3%	5.0%	6.6%

Appendix 1

Category of energy services	Appliances	Standard Appliance Wattage
Heating or Cooling	Air cooler	200 W
	Air conditioner	2000 W
	Room heater	2000 W
	Warm air blower	2000 W
	Ceiling fan	80 W
	Table fan	80 W
	Immersion rod	1000 W
	Geyser	2000 W
Lighting	Cfl/leds	20 W
	Bulbs	100 W
	Tube lights	40 W
Domestic end-use appliances	Television	200 W
	Refrigerator	60 W
	Water purifier	60 W
	Microwave	800 W
	Electric iron	1000 W
	Sewing machine	100 W
	Water pump	740 W
	Washing machine	700 W
	Others: Flour grinder, juicer, milk churner, mixer	200 W
Business end-use appliances	Cell phone charging	6 W
	Desktop computer	200 W
	Laptop computer	65 W

Notes: Standard wattage information of common household appliances from Bureau of Energy Efficiency standards for 2012-13 and online load calculators provided by Tamil Nadu Generation and Distribution Corporation (https://www.tangedco.gov.in/load_calculato.html) and Paschim Gujarat Vij Company Limited (http://www.pgvcl.com/consumer/CONSUMER/calculate_n.php)

Appendix 2: Data Appendix

(1) An example illustrating backing out the applicable energy price of electricity based on observed consumption

Consider for example, a billing cycle for a customer starting on 1st June to 1st August 2015, with a total bi-monthly consumption of 310 kWhs and total energy cost of Rs. 1,497. Given 310 kWhs consumed over two months, we expect this consumer to fall in the fourth consumption tier (corresponding to 150 to 300 kWhs of monthly consumption tier in the tariff schedule). Based on the prevailing electricity prices at the time, the total energy cost for the customer for this cycle is calculated as: Rs. 3.50 per kWh for first the 100 kWhs of consumption (i.e., the first tier of the tariff schedule) + Rs. 5.45 per kWh for the next 200 kWhs of consumption (i.e., the second tier) + Rs. 5.7 for the remaining 10 kWhs of consumption (i.e., the third tier). The total energy cost based on this calculation is the same as that appears in the data set (i.e., Rs. 1,497). For such bills, we attribute the Rs. 5.7 per unit figure (i.e., the energy charge of the consumption tier on which the household lies) as the marginal price for this customer-billing cycle. Additional duties, surcharges and cess, levied on per-unit of consumption are then added to this marginal price to arrive at the gross final marginal price faced by the customer in this cycle.

Comparing the per-kWh energy cost derived from the billing data set to per-unit prices prescribed in tariff schedule is straightforward, except for the months during which tariff revisions occur. If new tariff schedules are issued mid-cycle, JVVNL prorates the total consumption by the number of days of the billing cycle that falls under each of the tariff schedules. For instance, tariff revisions occurred on 1st September 2016. Consider a billing cycle, starting 1st August to 1st October 2016. To calculate the energy charges, first, the total consumption over the billing cycle is divided into two, weighted by the fraction of days in the cycle that falls under each tariff schedule (1st Aug – 1st Sept = 31 days and 1st Sept – 1st October = 30 days). The total energy charge is then calculated by applying the energy charges prescribed under each tariff schedule and on basis of the prorated consumption. The marginal price of consumption for each half of consumption is then calculated using the same formulas as noted in the text above. In such cases of mid-cycle tariff revisions, we have split the cycle into two, starting 1st Aug to 1st Sept and 1st Sept to 1st October, prorating consumption, fixed costs, total electricity prices, etc. for each of the two cycles.

(2) Additional validation checks conducted on the administrative billing data

We validate if the household consumption, in general, reacts inversely to changes in prices. Figure 7 illustrates the changes in the density of consumption and energy prices for periods between the first and second price revisions (September-2016 to March-2017 and February-2015 to September-2016 respectively). The figure indicates a sharper increase in prices for consumers at top-most tiers. This higher increase in prices also appears to be correlated with a leftward movement along the consumption distribution. Between September 2016 and March 2017, the fraction of bills[31] in the 0-50 kWhs above poverty line (APL) category increased by more than 10

[31] Share of household-bills in tier i in price period t is $= \frac{\sum_t^i number\ of\ household-bills\ in\ tier\ i}{total\ number\ of\ household-bills\ across\ tiers\ in\ period\ t}$

percentage points while price increased by Rs. 0.4. Price increase for greater than 500 kWhs of consumption category was about double that amount and was associated with fall of about 3 percentage points in the fraction of bills. More generally, the share of household-bills in the top three consumption tiers (for which prices have risen the most) has fallen, while it has increased in the bottom two tiers (for which prices rose moderately).

The shift in the density of consumption could also be due to selection, wherein, large numbers of newly connected households with low initial levels of consumption could have added mass to the left of the distribution during September 2016 to March 2017. However, we do not find evidence of selection in the data--only 1 percent of sample comprises of consumers-bills that were newly added to the data set during this period, insignificant enough to have moved the distribution so sharply to the left. To be sure, we exclude these households from the data set to find the leftward shift in consumption to persist. We interpret this result to be the first indication that consumers in our sample show a negative response to rising prices.

The consumption data for a given household in our sample also appears to be stable over consecutive billing periods. Figure 8 compares the consumption tier of a household in the previous cycle (in the horizontal axes) to the consumption tier in the current cycle (in boxes). Households below the poverty line have low demand for energy services and therefore may not transition to higher consumption tiers. The opposite is true for some consumers in the higher tiers. A large proportion of both groups therefore are observed to reside within their own tier over consecutive billing cycles. For others, transitions to one-tier above or below their current consumption tier is more likely. Transitions to more than two tiers away over consecutive cycles, reassuringly, appears to be rare in the data.

(3) Additional validation checks conducted on the temperature and rainfall data

We check to see if increasing temperatures and low rainfall is associated positively with higher electricity demand. To describe this relationship, we regress the log of average temperatures and rainfall to the log of average daily household consumption over a billing cycle. Table 6 shows the positive and negative relationship between daily household consumption and temperature and rainfall, respectively. A 10 percent increase in average temperature and rainfall is associated with 12 percent increase and 0.3 percent decrease in daily consumption, on average.

Finally, we check if households in locations with higher average temperatures and rainfall over billing cycles are associated with a higher demand for energy services based on their ownership and use of electrical appliances. We regress the log of daily energy services demanded by the household based on the survey data to the average temperature and rainfall across all billing cycles. Table 7 shows a 10 increase in average temperatures across billing cycles increases the predicted energy demand of a household by 2.6 percent. In contrast, a 10 percent increase in rainfall in the area reduces the demand for energy services by 0.5 percent.