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ABSTRACT

Increasing block tariffs (IBTs) are widely used in household electricity pricing to balance the dual policy goals of efficiency and affordability. This paper assesses the effectiveness of IBTs by examining how household electricity demand responds to prices and how this responsiveness varies with income. Using household panel data on monthly electricity consumption and appliance ownership matched with state-year IBT schedules, we account for the nonlinear structure of tariffs, appliance heterogeneity, and seasonal variation in electricity demand. We find that residential electricity demand is price inelastic in India, with a price elasticity of −0.12. Price responsiveness also varies nonlinearly with income, following an inverted-U pattern: it is highest among middle-income groups and lowest among the lower and higher-income groups. Our estimate of price elasticity is lower than those reported in previous studies using aggregate electricity consumption data. This suggests that aggregate demand estimates may mask differences in electricity demand associated with appliance ownership and use. Also, the results on price responsiveness across income groups indicate the limited potential of pricing policies in improving efficient electricity use.

Keywords: Household electricity demand, Increasing block tariffs, Conditional demand analysis, Price elasticity, India

JEL Code: D12, L94, Q41, Q48

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Nirmala* Manisha Jain† Disha Gupta‡

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Increasing block tariffs (IBTs) are widely used in household electricity pricing to balance the dual policy goals of efficiency and affordability. This paper assesses the effectiveness of IBTs by examining how household electricity demand responds to prices and how this responsiveness varies with income. Using household panel data on monthly electricity consumption and appliance ownership matched with state-year IBT schedules, we account for the nonlinear structure of tariffs, appliance heterogeneity, and seasonal variation in electricity demand. We find that residential electricity demand is price inelastic in India, with a price elasticity of -0.12*. Price responsiveness also varies nonlinearly with income, following an inverted-U pattern: it is highest among middle-income groups and lowest among the lower and higher-income groups. Our estimate of price elasticity is lower than those reported in previous studies using aggregate electricity consumption data. This suggests that aggregate demand estimates may mask differences in electricity demand associated with appliance ownership and use. Also, the results on price responsiveness across income groups indicate the limited potential of pricing policies in improving efficient electricity use.*

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1 Introduction

Residential electricity tariff design is a useful tool for meeting multiple energy policy goals, including promoting efficient energy use and providing affordable energy to all. Improving efficiency requires electricity prices to reflect supply costs, which in turn incentivizes efficient energy use. However, cost-reflective electricity prices could be unaffordable to low-income households. Increasing block tariffs (IBTs), a widely used electricity tariff design, aim to address the two competing goals of efficiency and affordability. Under an IBT, the marginal price of electricity rises with consumption. Hence, IBTs can serve the dual policy goal of promoting efficient electricity use and protecting low-income households through cross-subsidization.

The effectiveness of a tariff design can be assessed by examining how households' electricity demand changes with electricity prices, and how this responsiveness changes with income. To assess the effectiveness of IBTs, it is essential to account for their nonlinear structure in electricity demand modeling. Additionally, models should account for appliances in studying both long-run and short-run price responsiveness. In the long run, price responsiveness changes as appliance ownership and their use change. In the short run, price responsiveness also depends on appliances because of differences in the services they provide. For example, electricity for a refrigerator is not price responsive, but that of many other appliances is. Further, households that own basic appliances such as lights and fans would have lower price responsiveness compared to households that own appliances offering flexibility in electricity use.

In this paper, we assess the effectiveness of IBTs in India. We examine how household electricity demand responds to prices and how this price responsiveness varies with income. Standard demand theory assumes that electricity consumption should decrease when its price increases, but the magnitude of this response is an empirical question because electricity is a necessity good. Also, price responsiveness is expected to increase with income as appliance ownership and electricity consumption increase with income. Higher-income households may therefore have more flexibility to adjust their electricity consumption than lower-income households, which are more likely to own only basic appliances.

Most studies modelling electricity demand assume marginal or average prices in order to align with the assumption of linear budget constraint of the standard of demand theory. In these studies, the issue of endogeneity arising due to the dependence of marginal prices on consumption in an IBT tariff structure is addressed using an instrumental variable (IV) approach (Billings, 1982; Hung and Huang, 2015; Frondel and Kussel, 2019; Jia et al., 2021). Further, electricity demand is modeled as aggregate demand rather than demand for electricity services (Taylor, 1975; Filippini and Pachauri, 2004; Burke and Abayasekara, 2018; Chindarkar and Goyal, 2019). Electricity demand is often aggregated not only over appliances but also over time. Modeling electricity demand at an aggregate level may mask appliance heterogeneity and seasonal variation. Appliance ownership and use both depend on income, weather, electricity prices, and dwelling characteristics, which may differ across appliances.

Many countries have IBTs, but few studies have accounted for the nonlinear structure of tariffs, appliance heterogeneity, and seasonal variation (Nordin, 1976; Parti and Parti, 1980; Reiss and White, 2005; Ohler et al., 2022). In this study, we use a household panel dataset having monthly electricity expenditure and appliance ownership data, along with data on household characteristics. Using the state-year IBT tariff schedule and monthly electricity expenditure we calculate the electricity consumption and marginal prices for each household. To linearize the nonlinear budget constraint, we adjust the household income by accounting for the difference in the electricity expenditure calculated at the marginal prices and actual expenditure following Reiss and White (2005). We combine appliance ownership and consumption data to disaggregate total electricity consumption into appliance-specific demand, allowing household response to vary across appliances. The monthly frequency of the data helps address the challenge of temporal aggregation.

We find that the residential electricity demand is price inelastic in India, and the price responsiveness changes nonlinearly with income. Our short-run elasticity estimate is -0.12 and the price elasticity is lowest among low-income (-0.04) and high-income (-0.07) households and highest among middle-income (-0.13, -0.15) households. Our elasticity estimate is lower than those reported in most prior studies using aggregate electricity consumption data (Filippini and Pachauri, 2004; Harish et al., 2014; Chindarkar and Goyal, 2019), and close to the studies that account for appliance heterogeneity (Miller and Alberini, 2016). Existing studies examining price responsiveness with income show different patterns, including declining price responsiveness with income (Çetinkaya et al., 2015; Silva et al., 2017; Chindarkar and Goyal, 2019), increasing responsiveness (Schulte and Heindl, 2017), and a U-shaped relationship (Romero-Jordán et al., 2016; Tiwari, 2000). However, these studies do not account for appliance heterogeneity and the nonlinear structure of electricity tariffs.

We contribute to the existing literature on electricity demand by addressing the challenges in electricity demand modeling. Our study accounts for the nonlinear nature of IBT, aggregation over appliances and time. By accounting for these features, we show that price responsiveness can differ from estimates obtained from aggregate demand models. The lower price responsiveness among high-income households suggest that the effectiveness of IBTs in curtailing electricity demand through pricing policies is limited. Consequently, IBTs may not fully achieve broader energy policy goals.

The remainder of the paper is organized as follows. Section 2 discusses residential electricity demand modeling. Section 3 presents the theoretical framework. Section 4 describes the data and descriptive statistics. Section 5 presents empirical strategy. Section 6 presents results. Section 7 discusses the findings and their implications. Section 8 discusses policy implications. Section 9 concludes.

2 Electricity Demand Modeling

Electricity is not consumed directly like many other goods. Rather, it is used as an input to provide energy services such as lighting, cooling, heating, and refrigeration from which households derive utility. Therefore, electricity demand is a derived demand, arising from the demand for electricity services or appliance usage. Household electricity consumption arises from a joint, two-stage decision-making process. In the long run, households choose their appliance portfolio. In the short-run, conditional on the existing appliance stock, households decide how intensively to use these appliances (Dubin and McFadden, 1984). The difference between these two decisions corresponds to the different margins through which households can adjust their electricity consumption. In the short-run, when the appliance stock is fixed, households respond through the intensive margin, that is, changes in the usage intensity of existing appliances. In the long-run, the appliance stock can also vary, allowing households to respond through both the intensive and extensive margins (Taylor, 1975). Household electricity consumption is an aggregate of electricity use across different appliances.

An important characteristic of household electricity demand is that different appliances respond differently to income, electricity prices, and climatic conditions. Some appliances are largely insensitive to both electricity prices and climatic factors but depend on income. These include basic appliances such as lights, televisions, and refrigerators, which are essential for everyday life and tend to be used regardless of weather conditions or electricity prices (Ohler et al., 2022). A second group of appliances is mainly affected by climatic conditions but relatively insensitive to changes in electricity prices. Ceiling fans belong to this category. Their use increases with temperature, but because they consume relatively little electricity, their demand is less responsive to price changes (Roy and Wolak, 2021; Harish et al., 2020). A third group consists of appliances that depend on both income and climatic conditions, such as water heaters. Their use increases in colder climates and with higher income levels. In north India, however, there is also scope for fuel substitution, where households may switch from electric water heaters to traditional alternatives such as firewood, making income an important determinant along with climate (Chunekar et al., 2019; Gundimeda and Köhlin, 2008). Finally, the demand for some appliances may depend on income, electricity prices, and climatic conditions. Air conditioners and air coolers are examples of such appliances. These appliances are relatively expensive to purchase and operate, making their use sensitive to household income and electricity prices (Roy and Wolak, 2021), while their demand increases under extreme temperatures, particularly among higher-income households (Pavanello et al., 2021; Davis et al., 2021).

Understanding appliance-specific demand is important for several reasons. First, it helps identify the contribution of different appliances to total electricity consumption, which is crucial for designing targeted energy-efficiency policies. Second, it allows policymakers to assess how income, prices, and climate affect electricity demand across different appliances.[1] Third, it can improve demand forecasting by accounting for changes in appliance ownership and usage patterns.

Apart from appliance-level heterogeneity, another important feature of residential electricity demand is the pricing structure. Residential electricity is priced using nonlinear tariffs in many countries, including two-part tariffs, Increasing Block Tariffs (IBT), and Decreasing Block Tariffs (DBT).[2] Such pricing structures are feasible in part because electricity cannot be stored in significant quantities and is delivered to households through regulated distribution networks, which prevents consumers from reselling their purchases (Houthakker, 1951). Increasing block tariffs are widely used in residential electricity pricing (Foster and Witte, 2020), including across many Indian states, although tariff structures differ by state, distribution utility, consumer category, and tariff schedule (Chindarkar and Goyal, 2019). Under an IBT, marginal prices increase with the level of consumption. The tariff has a progressive structure, with defined thresholds separating successive consumption blocks. Each block has its own marginal price. When a household moves into a higher block, the additional units consumed are charged at the marginal price of that block. This creates a step like or staircase pattern in electricity prices, as shown in Figure 3.1.

Increasing block pricing has three main objectives: equity, efficiency, and cost recovery. First, it can protect lower consumption households by providing a subsidized initial block. The cost of this subsidy can be supported through cross-subsidies from higher consumption users, improving access to essential electricity services. Second, it can encourage conservation among higher consumption households by imposing higher marginal prices on consumption in higher blocks. Third, it can increase utility revenue and improve cost recovery by charging higher rates for higher levels of consumption (Borenstein, 2012).

However, the structure of IBT poses several challenges for demand estimation. In standard consumer theory, a household maximizes utility subject to a linear budget constraint. Prices are treated as constant and exogenous, allowing demand to be es-

[1]For example, changes in temperature may increase the use of cooling appliances. Price changes may also affect appliance use differently depending on appliance characteristics and usage patterns.

[2]Other forms of residential electricity tariffs include flat rate tariffs, multiple rate tariffs, two-part tariffs, and time of day tariffs (Houthakker, 1951).

timated using standard methods. This assumption does not hold under IBT, where the marginal price of electricity rises discontinuously as consumption crosses block thresholds, creating a kinked budget constraint (Henson, 1984; Hausman, 1985). This departure from the linear pricing assumption has two important implications for demand estimation. First, it raises the question of which price measure should be used: marginal prices, average prices, or the entire price schedule (Hausman, 1985). Second, it creates a simultaneity problem because consumption and tariff block assignment are determined together. The price faced by a household depends on its consumption level, and consumption also responds to that price (Taylor, 1975).

3 Theoretical Framework

This section presents the theoretical framework underlying the analysis. The framework begins with the conditional demand approach, which disaggregates total household electricity consumption into appliance-specific components using information on appliance ownership and household characteristics. It then incorporates India's nonlinear increasing block tariff structure and the virtual income correction used to linearize the kinked budget constraint.

3.1 Appliance Specific Demand

To estimate appliance-specific electricity demand without submetering, Parti and Parti (1980) developed an econometric method known as Conditional Demand Analysis (CDA).[3] The method is based on a covariance framework. Conditional on the household's appliance stock, it uses variation in appliance ownership across households to disaggregate total household electricity consumption into appliance-specific consumption.

Identification relies on cross-sectional variation in appliance ownership. Households that own a given appliance are compared with those that do not, holding other

[3] Two alternative approaches are direct submetering and engineering-based estimation. Direct submetering provides accurate measurements by installing meters on individual appliances. However, it is costly and difficult to implement at scale, particularly in a large developing country such as India. Engineering-based estimation requires detailed information on household characteristics and the technical features of appliances. It relies on technical assumptions rather than observed consumer behaviour and may not capture regional differences in income, prices, and household characteristics. As a result, its generalizability is limited.

appliance-ownership variables and household characteristics as constant. This conditional comparison isolates the average electricity consumption associated with that appliance. This identification requires sufficient variation in appliance ownership across households, referred to as a well-mixed sample. In such a sample, appliance ownership is neither nearly universal nor extremely rare.[4] When ownership of one appliance perfectly predicts ownership of another, the relevant comparison group disappears, so the two contributions can no longer be separately identified.

Let E_i denote the electricity consumption by appliance type i. The electricity demand for appliance type i depends on several variables, including electricity prices, household income, household size, and weather conditions measured by cooling degree days (CDD), heating degree days (HDD) and humidity. Let these variables be represented by the vector z. Therefore, the electricity demand for an appliance is given by a conditional demand function as follows,

$$E_i = f_i(z); \qquad i = 1, 2, ..., N, \tag{3.1}$$

Assuming a linear form of f_i we obtain:

$$E_i = b_{i1}z_1 + b_{i2}z_2 + ... + b_{im}z_M \tag{3.2}$$

Here, b_{ij} denotes the parameter associated with variable z_j in the demand function for appliance i. Alternatively, we can write it as:

$$E_i = \sum_{j=0}^{M} b_{ij}z_j \tag{3.3}$$

Now the total electricity demand is the sum of demand from each appliance. The electricity demand from appliances not explicitly modelled is treated as the baseline and is denoted by E_0. Therefore, total electricity demand is:

$$E = E_0 + E_1 + ... + E_N = E_0 + \sum_{i=1}^{N} E_i \tag{3.4}$$

[4]For example, basic appliances such as lights and fans are nearly universally owned, while luxury appliances such as air conditioners may have very low penetration in developing countries.

Since the electricity demand of appliance type i depends on ownership of that appliance, we can write:

$$E_i = \begin{cases} f_i(z), & \text{if household owns appliance type } i \\ 0, & \text{otherwise} \end{cases} \tag{3.5}$$

Let A_i denote a dummy variable for appliance ownership, which takes the value 1 if the household owns appliance type i and 0 otherwise. Then:

$$E_i = f_i(z).A_i \tag{3.6}$$

From equations (4) and (6), we obtain:

$$E = \sum_{j=0}^{M} b_{0j} z_j + \sum_{i=1}^{N} \sum_{j=0}^{M} b_{ij} z_j A_i \tag{3.7}$$

or

$$E = \sum_{i=0}^{N} \sum_{j=0}^{M} b_{ij} (z_j A_i) \tag{3.8}$$

where $j = 0, 1, \ldots, M$ indexes the variables in z, and $i = 1, 2, \ldots, N$ indexes the appliances, with $A_0 = z_0 = 1$ for all households. Here, A_0 represents the baseline category.

This specification leads to a large number of parameters and potential multicollinearity. Moreover, appliance-specific electricity consumption cannot be directly recovered from the parameters alone. Instead, it is computed by evaluating the parameters at the mean values of the explanatory variables. However, the overall mean is not appropriate for evaluating appliance-specific electricity consumption because it includes both households that own the appliance and those that do not. The characteristics of these two groups may differ. Therefore, the overall mean may not represent the characteristics of households that own the appliance. To address this, the model is rewritten in deviation form. Each variable is centered by subtracting the subgroup mean from its value. The subgroup mean is calculated only among households that own the relevant appliance.

$$\bar{E}_i = b_{0i} + \sum_{j=1}^{M} b_{ij}(\bar{z_{ij}}) \tag{3.9}$$

$$E = \sum_{i=0}^{N} \sum_{j=0}^{M} b_{ij}(z_j A_i) \tag{3.10}$$

Adding and subtracting equation (9) from equation (10) & rearranging the terms, we obtain:

$$E = \sum_{i=0}^{N} \tilde{E}_i A_i + \sum_{i=0}^{N} \sum_{j=1}^{M} b_{ij}[(z_j - \bar{z_{ij}})A_i] \tag{3.11}$$

Here, each appliance-specific parameter $\tilde{E}_i$ measures the electricity consumption associated with the appliance i. When $i = 0$, the parameter b_{00} on A_0 captures the average electricity consumption for baseline category. Thus, the deviation form allows the parameters on the appliance ownership variables to represent appliance - specific electricity consumption at the mean characteristics of households that own the appliance.

3.2 Demand under Nonlinear Pricing

The analysis of demand under nonlinear pricing was developed in labor supply by Hausman (1985) and later extended to electricity demand by Reiss and White (2005) for a two-block tariff structure. This study adopts the framework for India's six-block increasing block tariff (IBT) structure. As shown in 3.1, $\bar{x}_i$ represents the block thresholds for electricity consumption, and p_i denotes the corresponding block marginal prices.

Consider a representative household that derives utility in the long run from electricity services and other goods. The household allocates its income y between electricity consumption x and a composite numeraire good g. The composite good g is purchased at a constant price p_g, which can be normalized to one. Electricity, however, is priced according to the IBT schedule given below.

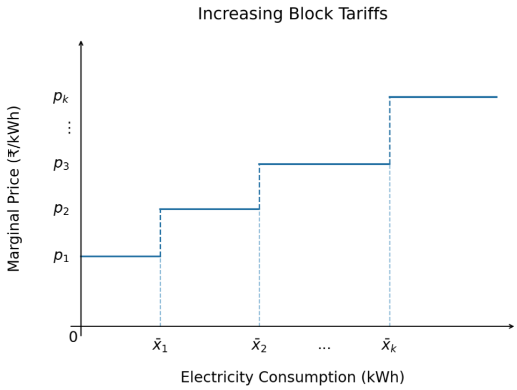

Figure 3.1. Increasing Block Tariff (IBT) structure. The x-axis represents electricity consumption (kWh) and the y-axis represents the marginal price (Rs./kWh). The tariff schedule is divided into k blocks, where $\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_k$ denote the block thresholds and $p_1, p_2, \ldots, p_k$ the corresponding marginal prices. The marginal price increases in a stepwise fashion at each threshold, with $p_1 < p_2 < \cdots < p_k$. *Source: Author's illustration.*

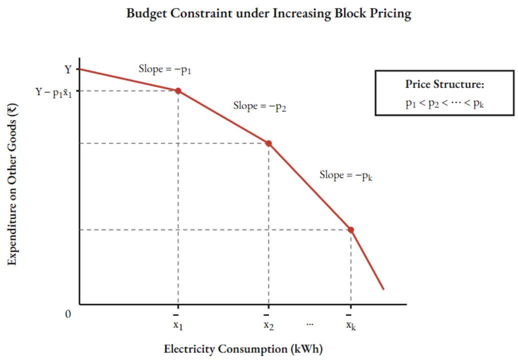

Figure 3.2. Budget constraint under Increasing Block Tariff (IBT) pricing. The x-axis represents electricity consumption (kWh) and the y-axis represents expenditure on all other goods (Rs.). Y denotes household income. The budget constraint is piecewise linear and concave, with kink points at the block thresholds $\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_k$. The slope of each segment equals the negative of the marginal price in that block $(-p_1, -p_2, \ldots, -p_k)$, becoming steeper as consumption crosses each threshold, reflecting the price structure $p_1 < p_2 < \cdots < p_k$. *Source: Author's illustration.*

$$f(x) = \begin{cases} p_1, & x \leq \bar{x}_1, \\ p_2, & \bar{x}_1 < x \leq \bar{x}_2, \\ \ldots \\ p_k, & x > \bar{x}_{k-1} \end{cases} \tag{3.12}$$

where

$$p_1 < p_2 < \ldots < p_k. \tag{3.13}$$

The household maximizes utility $u(x, g)$ subject to its income level y. Under standard consumer theory, each good is assumed to have a single constant price, so the budget constraint is linear. Under IBT, however, the price schedule is nonlinear and the budget constraint becomes kinked, as discussed above. For simplicity, consider a three-block structure first, and then extend it to the k- block case.

$$y = \begin{cases} p_1 x + g, & \text{if } x \leq x_1, \\ p_1\bar{x}_1 + p_2(x - \bar{x}_1) + g, & \text{if } \bar{x}_1 < x < \bar{x}_2 \\ p_1\bar{x}_1 + p_2(\bar{x}_2 - \bar{x}_1) + p_3(x - \bar{x}_2) + g, & \text{if } x > \bar{x}_2 \end{cases} \tag{3.14}$$

generalizing this to k- blocks, we get

$$y = g + p_k x + \sum_{j=1}^{k-1} (p_k - p_j)\left(\bar{x}_j - \bar{x}_{j-1}\right) \tag{3.15}$$

where $\bar{x}_{j-1} < x < \bar{x}_j, \quad j = 1, 2, \ldots, K$

Since the budget constraint is kinked, the standard econometric approach used in the literature is to linearize the budget constraint around the relevant marginal prices so that demand under nonlinear pricing can be expressed in a form similar to ordinary demand.

The insights behind the linearization lie in the concept of inframarginal discount and virtual income. Consider a household consuming in block k at marginal price p_k. Under the IBT structure, this household pays lower prices (p_1, p_2,...,p_{k-1}) for the units consumed in the lower blocks 1,2,..., $k-1$. If all units were instead charged at the marginal price p_k, the household would face a higher total expenditure for the same consumption bundle. The difference between this hypothetical expenditure and the actual expenditure is called the inframarginal discount.

To see this more clearly, suppose the household is in the third block. Instead of paying p_3 for all units, the household pays p_1 for the first block and p_2 for the second block. The discount obtained from the first two blocks is then given by

$$D_3 = \underbrace{(p_3 - p_1)\bar{x}_1}_{\text{discount in first block}} + \underbrace{(p_3 - p_2)(\bar{x}_2 - \bar{x}_1)}_{\text{discount in second block}} \tag{3.16}$$

Generalizing this to k- blocks, we have

$$D_k = \underbrace{(p_k - p_1)\bar{x}_1}_{\text{discount in first block}} + \underbrace{(p_k - p_2)(\bar{x}_2 - \bar{x}_1)}_{\text{discount in second block}} + \cdots + \underbrace{(p_k - p_{k-1})(\bar{x}_{k-1} - \bar{x}_{k-2})}_{\text{discount in } (k-1)\text{th block}} \tag{3.17}$$

or

$$D_k = \sum_{j=1}^{k-1} (p_k - p_j)(\bar{x}_j - \bar{x}_{j-1}) \tag{3.18}$$

Using this discount, the budget constraint can be written as

$$y = g + p_k x + D_k \tag{3.19}$$

or equivalently,

$$y + D_k = g + p_k x \tag{3.20}$$

The term D_k is added to income to obtain virtual income, so virtual income is defined as

$$y^v = y + D_k \tag{3.21}$$

Thus,

$$y^v = g + p_k x \tag{3.22}$$

By reformulating the problem in terms of virtual income y^v and marginal price p_k, the household's choice can be expressed as a standard demand function. If the ordinary demand function is $x = x(p, y)$, then when the household is in block k, optimal consumption is

$$x^* = x(p_k, y^v) = x(p_k, y + D_k) \tag{3.23}$$

subject to the consistency condition

$$\bar{x}_{k-1} < x^* \leq \bar{x}_k$$

which ensures that the optimal consumption level lies in block k.

Although the budget constraint can be linearized using the concepts of the infra-marginal discount and virtual income, an endogeneity problem remains because households' consumption and tariff-block positions are jointly determined. Consequently, the marginal price faced by a household is endogenous to its electricity consumption.

4 Data and Descriptive

In this paper, we combine data from the following three sources: (i) survey data on monthly household expenditure and income from the Consumer Pyramid Household Survey (CPHS), and (ii) slab-wise tariffs for Indian states documented in the annual reports of the Central Electricity Authority (CEA). (iii) Weather data from India Meteorological Department (IMD). The following sections describe each of these datasets in detail.

4.1 Electricity Prices Data

We utilize domestic slab-wise electricity tariff data sourced from the *Electricity Tariff & Duty and Average Rates of Electricity Supply in India*,[5] an annual report published by the Financial Studies and Analysis Division of the Central Electricity Authority (CEA), Government of India. The CEA compiles this data by analyzing tariff orders issued by the respective State Electricity Regulatory Commissions (SERCs). The report covers domestic, commercial, and industrial sectors across all Indian states and utilities, and is available from 2012 to 2025.

For this study, we restrict our sample to 28 Indian states over the period 2015–2019, to ensure consistency with the second dataset discussed in the next section.[6] The tariff structure in India is progressive, the electricity rate per unit increases as consumption moves to higher slabs, and varies across states and utilities. The report documents six consumption slabs for each state/utility: 0–100, 101–200, 201–400, 401–600, 601–800, and 801–1000 units. For each slab, the tariff is reported in three components: average rate (paisa/kWh), duty/tax (paisa/kWh), and total (paisa/kWh). We use the total (paisa/kWh) as it reflects the actual financial burden on the household. For states with multiple utilities, we take a simple average across all utilities in the state. The key variable from this dataset is the marginal price (paisa/kWh) for each consumption slab.

[5]Available at: https://cea.nic.in/financial-studies-assistance-division/?lang=en

[6]Several Union Territories and North-Eastern states are excluded as they are not covered in the second dataset of interest.

4.2 Electricity Expenditure Data

We use the monthly electricity expenditure of households to derive the monthly electricity consumption, provided by the Consumer Pyramid Household Survey(CPHS) conducted by the Center for Monitoring the Indian Economy (CMIE). The CPHS collects data on household consumption, income, demographics, employment status, assets, and amenities from a nationally representative sample of households. Starting in January 2014, households in 28 Indian states[7] are surveyed every four months and asked about their income and expenditure in the preceding four months as well as their assets and amenities at the time of the survey. Hence the survey collects household income and expenditure data at a monthly frequency. The dataset comprises four modules: (i) household consumption and expenditure ("Consumption Pyramids"), (ii) basic demographic and employment-related data ("People of India"), (iii) household incomes ("Income Pyramids"), and (iv) assets, investment, debt, and consumer sentiments ("Aspirational India")

We use data on the monthly electricity expenditure from the consumption pyramid to calculate the electricity consumption. Monthly data on household income comes from the income pyramid, which is the total household income from all sources, and a source-wise distribution of income is also provided. The household appliance ownership data comes from the Aspirational India. The appliances used in our analysis are air conditioners, coolers, washing machines, refrigerators, computers, and televisions. For each appliance, the data records the number of units owned by the household, rather than a simple yes/no indicator of ownership. The sample period is restricted to 2015-2019 to avoid oversampling before 2015 and due to a significant drop in response rates after 2019 caused by the COVID-19 pandemic. After restricting our sample period from 2015 to 2019, we obtain a panel of 9,894,699 household-month observations.

To obtain monthly electricity consumption (in units) from household electricity expenditure, we combine the survey data with the tariff data. In India, electricity is priced using an Increasing Block Tariff (IBT): the price per unit varies with the level

[7] The CPHS excludes certain smaller states and union territories, such as Andaman & Nicobar Islands, Arunachal Pradesh, Manipur, Mizoram, and Nagaland.

of consumption, and these block rates differ across states. Because of this structure, the total bill is not a linear function of units consumed; instead, it is the cumulative sum of charges across all slabs up to the household's consumption level.

To recover the units consumed from a household's reported bill, we iterate through the slabs sequentially. For each slab, we calculate the charge for consuming the full width of that slab. If the household's bill is large enough to cover the entire slab, we add those units and move to the next slab. Once the bill is no longer large enough to cover the next full slab, the household's consumption is identified as ending within that slab.The remaining units are then computed as the leftover bill divided by that slab's per-unit rate:

$$\text{Units consumed in final slab} = \frac{\text{Total bill} - \text{Cumulative charges up to previous slab}}{\text{Rate per unit in final slab}}$$

$$\text{Total units} = \text{Cumulative units up to previous slab} + \text{Units consumed in final slab}$$

This yields an estimated monthly electricity consumption for each household-month observation.[8]

4.3 Weather Data

Temperature and humidity are the primary weather variables that determine household cooling needs. Most appliances in our consumption dataset, such as air conditioners, coolers, and fans, respond directly to temperature and humidity conditions. Although temperature also derive heating needs, therefore the heating demand for electricity, our consumption dataset does not cover heating appliances, so we focus on cooling-related weather variables.

[8]Since electricity expenditure is self-reported in the CPHS, the derived consumption figures are estimates subject to reporting error. As a validation check, we compute the mean electricity consumption for Delhi using survey weights, which is 275 units. This is comparable to the mean reported by Harish et al. (2020) using billing data for Delhi, suggesting that our estimates of household electricity consumption derived from expenditure data using slab-wise rates are consistent with actual billing data.

To capture the effect of temperature on cooling demand, we construct the variable of Cooling Degree Days (CDD). We use the daily temperature data from the India Meteorological Department (IMD), which provides high-resolution gridded weather data with a spatial resolution of $1^\circ \times 1^\circ$. The IMD gridded dataset covers maximum temperature, minimum temperature, humidity, and sunshine hours, and is available from 1875 to the present date. The variables are available at hourly, daily, monthly, and annual frequencies. We use daily maximum and minimum temperature to compute the dialy mean temperature as thier simple average. The monthly CDD is then constructed by aggregating daily values using the formula:

$$\text{CDD} = \sum_{d=1}^{D} \max\left(T_{\text{mean},d} - 24,\ 0\right) \tag{4.1}$$

where $T_{\text{mean},d}$ is the daily mean temperature on day d, D is the number of days in the month, and 24°C is used as the base temperature, consistent with the existing literature on cooling needs of Indian households

Since the finest geographic resolution in our consumption dataset is the district level, we extract the IMD gridded temperature data at the district level using the shapefiles based on 2011 Census district boundaries. For districts whose boundaries were revised after the 2011 Census, we use the district definition in the consumption dataset and establish a one-to-one mapping between the districts in the weather and consumption datasets. The final sample covers 515 districts across 28 Indian states over the period 2015-2019, at monthly frequency.

To account for the effect of humidity on appliance usage, particularly air conditioners and fans we include relative humidity as a weather variable. Relative humidity data is sourced from the ERA5 reanalysis dataset, provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 provides global climate data from 1940 to the present date, with a spatial resolution of $0.25^\circ \times 0.25^\circ$. District- level relative humidity is extracted following the same shapefile - based procedure used for IMD temperature data, and the frequency is monthly to maintain consistency with other datasets.

4.4 Descriptive Statistics

Table 1 describes the data. Panel A reports household and climatic variables and Panel B reports appliance ownership, which is a binary variable. The reduction in observations from Panel A to Panel B reflects missing values in the appliance ownership. The final estimation sample comprises approximately 5.3 million household-month-year observations drawn from around 170,000 households surveyed each year, after dropping observations with missing values and zero reported electricity consumption.

Average monthly household electricity consumption across the 28 Indian states is 155 kWh. Appliance ownership rates shows a clear hierarchy of adoption: refrigerators are owned by approximately 62% of households and televisions by around 96%, compared to just 9.6% for air conditioners and 48% for evaporative coolers. This hierarchy suggests a sequential adoption pattern in which households acquire basic appliances first before moving to energy-intensive cooling equipment.

State-level variation in consumption and ownership is substantial (Tables B11 and B12).Chandigarh has the highest average monthly electricity consumption, at almost five times the national average. This is likely due to its higher income levels and widespread ownership of household appliances.[9] At the other end, Bihar and Karnataka report the lowest average monthly electricity consumption, while several northeastern states, including Meghalaya and Sikkim, show the lowest appliance ownership rates, likely reflecting lower incomes, limited electricity access, and different patterns of household electricity use.

Table B9 presents the appliance ownership by income quartiles and highlights the transition nature of middle -income groups. The increase in AC ownership from Q1 (2.2%) to Q4 (26%) is steep and concentrated in the upper quartiles, while cooler ownership rises more gradually from Q1 (34.7%) to Q4 (64.4%). Q2 and Q3 households sit at the threshold of major appliance adoption, particularly for refrigerators, washing machines, and air conditioners, meaning that modest income gains in these groups are likely to translate directly into new appliance purchases and consumption increases. This pattern motivates the income quartile elasticity analysis.

[9] Chandigarh's outlier status reflects its unique administrative character as a planned urban territory rather than a demographically representative state.

India follows an increasing block tariff structure for residential electricity pricing. Figure B1 shows the effective tariff structure for India, constructed by the CEA reports based on SERC tariff orders; the x-axis shows the consumption threshold and the y-axis the effective marginal price, illustrating how marginal prices rise as consumption crosses each threshold. The report provides data for all Indian states and union territories, but we restrict our sample to the 28 Indian states covered by our second dataset, with tariffs reported across six consumption slabs. The purpose of IBT is to protect low-income households while encouraging conservation among higher-consuming households, a distributional objective we investigate further through the income-quartile price and income elasticity analysis below.

Marginal prices vary substantially across states, ranging from approximately 0.85 to 12 rupees per kWh, and increase across consumption blocks within each state. The lowest block prices are found in Puducherry and the highest in Rajasthan and Maharashtra (Table B11; Figure B1). Two dimensions of this price variation are relevant for identification. First, as shown in Figure B1, there is substantial cross-state variation in electricity tariffs across all blocks. Second, as shown in Figure B2, tier 2 prices changed over the 2015-2019 study period in some states but not others. This state-specific and time-varying price variation, conditional on consumption tier, is what our instrument exploits and validates the adjacent block price instrument described in the methodology section.

5 Empirical Strategy

This section presents the empirical strategy used in the analysis. Following the theoretical framework, we first estimate the deviation-form demand specification to recover appliance-specific electricity consumption. We then address the endogeneity of marginal price under the increasing block tariff using an instrumental variable approach.

To disaggregate total electricity consumption into appliance-specific consumption, we follow the deviation-form specification of Parti and Parti (1980), as presented in the theory section, and estimate the following equation:

$$x_{hmt} = \sum_{i=0}^{N} \tilde{E}_i A_{iht} + \sum_{i=0}^{N} \sum_{j=1}^{M} b_{ij} \left[(z_{jhmt} - \bar{z}_{ijt}) A_{iht} \right] + \varepsilon_{hmt} \tag{5.1}$$

where x_{hmt} is the monthly electricity consumption (kWh) of household h in month m of year t. A_{iht} is an appliance dummy that takes the value 1 if household h owns appliance type i in year t and 0 otherwise. $\tilde{E}_i$ is the average monthly electricity consumption associated with appliance type i. z_{jhmt} denotes the j-th characteristic that determines electricity consumption for appliance type i, $\bar{z}_{ijt}$ is the mean of the j-th characteristic for households owning appliance type i. Since unspecified appliances are assumed to be owned by all households, the mean for the j-th characteristic is computed over the entire sample. The term ε_{hmt} is the error term. The characteristics included are marginal electricity price, monthly household income, household size, and monthly cooling degree days (CDD). In this specification, M indexes the variables determining household electricity consumption, while N indexes the appliances.

As shown in Eq. 5.1, we use the deviation-form model to recover appliance-specific consumption coefficients directly from the regression. The specification includes two types of deviation terms. First, the subgroup deviation terms center each continuous variable at the mean computed for households owning appliance type i in year t. Second, the baseline deviation terms center each continuous variable at the full-sample mean for the unspecified appliance group in year t. The subgroup means are computed separately for each year rather than pooled across years. This allows the means to vary over time and accounts for changes in appliance ownership, including purchases and replacements during the sample period.

The identification strategy relies on cross-household variation in appliance ownership, which we earlier referred to as a well-mixed sample. The coefficient $\tilde{E}_i$ on each appliance dummy captures the difference in average monthly electricity consumption between households that own appliance type i and those that do not, conditional on the other appliance ownership and household characteristics included in the regression.

As discussed in the theory section, households face a nonlinear tariff with multiple blocks rather than a single marginal price. The marginal price captures only the price of the last block, while ignoring the prices paid on inframarginal units consumed in the lower blocks. Since households receive discounts on these inframarginal units, observed income does not fully reflect the effective budget available to them. Following the theory, this issue is addressed by defining virtual income as observed income plus the inframarginal discount received by household h. We then re-estimate the above specification by replacing income with virtual income, while keeping the remaining specification unchanged. Subgroup means for the income variable are also recomputed using virtual income within each year and appliance ownership group.

The increasing block tariff creates a fundamental identification problem. Under IBT, the marginal price faced by a household is determined by its consumption block, while the block assignment itself depends on how much the household consumes. Households with higher electricity demand consume more, move into higher tariff blocks, and consequently face higher marginal prices. Therefore, the marginal price is not exogenous; it is jointly determined with consumption through the household's tariff-block assignment. As a result, marginal price is endogenous in the demand equation, and OLS estimation yields biased and inconsistent estimates.

To address this endogeneity, we use an instrumental variable (IV) approach (Billings, 1982; Hung and Huang, 2015; Frondel and Kussel, 2019; Jia et al., 2021). We instrument the household's endogenous marginal price with the state-year tariff price of the adjacent block in the SERC tariff schedule. Here, the adjacent block refers to the tariff block immediately above the household's current marginal-price block. Unlike the household's marginal price, which is determined by the household's consumption block, the adjacent block price is determined by the state-year tariff schedule. The adjacent block price is expected to be correlated with the household's marginal price because both are determined by the same state-year tariff schedule.

The validity of the instrument is supported by the institutional setting. Electricity tariffs are set by the State Electricity Regulatory Commissions (SERCs) at the state-year level before household electricity consumption is realized.[10] Thus, the

[10]One factor used in tariff design is household electricity consumption, but this is based on past-year consumption rather than current consumption. Even if current-year consumption changes slowly, tariff design is based on aggregate consumption rather than individual household consumption. Tariff setting also reflects several other factors, including power purchase and fuel costs, capital expenditure requirements, technical and commercial loss targets, revenue requirements, and cross-

tariff schedules are predetermined relative to household consumption, and current household consumption cannot influence the tariff schedule from which the adjacent block prices are obtained. Our IV strategy is based on the literature on nonlinear pricing (Nordin, 1976; Hausman, 1985; Dubin and McFadden, 1984; Reiss and White, 2005), in which the inframarginal effects of block tariffs are accounted for through virtual income. Thus, conditional on the exogenous demand determinants included in the model, the adjacent block price is assumed to have no direct effect on household electricity consumption.

To implement the IV strategy, we estimate the first-stage and second-stage equations as follows. Since only the marginal price is endogenous, we instrument the price term while keeping the remaining controls unchanged.

$$x_{hmt} = \sum_{i=0}^{N} \tilde{E}_i A_{iht} + \sum_{i=0}^{N} b_{ip} \left[(p^k_{hmt} - \bar{p}^k_{it}) A_{iht} \right] + \sum_{i=0}^{N} \sum_{j=1}^{M-1} b_{ij} \left[(\tilde{z}_{jhmt} - \bar{\tilde{z}}_{ijt}) A_{iht} \right] + \varepsilon_{hmt} \tag{5.2}$$

here k denotes the tariff block.

The first stage is given by:

$$p^k_{hmt} = \pi_0 + \pi_1 Z_{st} + \sum_{i=0}^{N} \pi_{i0} A_{iht} + \sum_{i=0}^{N} \pi_{iZ} (Z_{st} A_{iht}) + \sum_{i=0}^{N} \sum_{j=1}^{M-1} \pi_{ij} \left[(\tilde{z}_{jhmt} - \bar{\tilde{z}}_{ijt}) A_{iht} \right] + \nu_{hmt} \tag{5.3}$$

In the second stage, the endogenous marginal price is replaced by its fitted value from the first-stage estimation:

$$x_{hmt} = \sum_{i=0}^{N} \tilde{E}_i A_{iht} + \sum_{i=0}^{N} b_{ip} \left[(\hat{p}^k_{hmt} - \bar{p}_{it}) A_{iht} \right] + \sum_{i=0}^{N} \sum_{j=1}^{M-1} b_{ij} \left[(\tilde{z}_{jhmt} - \bar{\tilde{z}}_{ijt}) A_{iht} \right] + \varepsilon_{hmt} \tag{5.4}$$

The empirical specification does not include household, district, or state fixed effects because the conditional demand analysis framework requires variation across

subsidies across consumer categories. Therefore, the effect of one household's current consumption on the tariff schedule is negligible relative to the broader set of factors determining state-level tariffs.

households and tariff and environmental conditions to identify the appliance-specific demand parameters. Introducing fixed effects at these levels would absorb part of this variation and weaken the identifying variation available for estimating the appliance-specific price and demand coefficients. The absence of fixed effects leaves the possibility that district-level factors may influence electricity consumption and bias the estimates. These factors include power availability, local economic growth, infrastructure quality, and political factors. To account for differences in local economic activity and development, we use night-time lights at the district-month level. The night-time lights data are obtained from the Socioeconomic High-resolution Rural-Urban Geographic Platform (SHRUG).

5.1 Elasticity Estimation

Under an increasing block tariff (IBT), the calculation of price elasticity requires accounting for the nonlinear relationship between marginal prices and household electricity consumption. As discussed in the theoretical background section, this nonlinear pricing structure also affects household virtual income. Therefore, the calculation of price elasticity under the IBT needs to account for both the marginal price and the associated virtual-income effect. This section derives the price elasticity measure consistent with the IBT demand framework developed above.

Now, the demand function is given by Eq. 3.23. Differentiating the demand specification with respect to the household's marginal price p_k and applying the chain rule, we obtain:

$$\frac{\partial x^*}{\partial p_k} = \frac{\partial x}{\partial p_k} + \frac{\partial x}{\partial y^v} \cdot \frac{\partial y^v}{\partial p_k} \tag{5.5}$$

From Eqs. 3.18 and 3.21, virtual income can be written as

$$y^v = y + D_k = y + \sum_{j=1}^{k-1} (p_k - p_j)(\bar{x}_j - \bar{x}_{j-1}) \tag{5.6}$$

Differentiating with respect to the marginal price p_k, we obtain

$$\frac{\partial y^v}{\partial p_k} = \sum_{j=1}^{k-1} (\bar{x}_j - \bar{x}_{j-1}) = \bar{x}_{k-1}. \tag{5.7}$$

Here, $\bar{x}_{k-1}$ denotes the lower boundary of the household's current tariff tier. Substituting the value of $\frac{\partial y^v}{\partial p_k}$ into Eq. 5.5, we obtain:

$$\frac{\partial x^*}{\partial p_k} = \frac{\partial x}{\partial p_k} + \frac{\partial x}{\partial y^v} \cdot \bar{x}_{k-1} \tag{5.8}$$

For electricity demand x^* and marginal price p_k the price elasticity of electricity demand is given by:

$$\eta = \left(\frac{p_k}{x^*}\right) \left[\frac{\partial x}{\partial p_k} + \frac{\partial x}{\partial y^v} \cdot \bar{x}_{k-1}\right] \tag{5.9}$$

Moving from the general formula to the household-month level requires specifying $\frac{\partial x}{\partial p_k}$ and $\frac{\partial x}{\partial y^v}$ in terms of the empirical model. Under the conditional demand analysis framework, different appliances have different price and virtual income response coefficients. Therefore, the total price and virtual income responses depend on the specific appliances owned by each household. From the second-stage regression specification in Eq. 5.4, the partial derivative of electricity demand with respect to the marginal price is:

$$\frac{\partial x_{hmt}}{\partial p_{khmt}} = \mathcal{A}_h = b_p + \sum_a b_{ap} \cdot d_{ah} \tag{5.10}$$

where b_p is the baseline price coefficient, b_{ap} is the appliance-specific price interaction coefficient for appliance a, and d_{ah} is a binary variable that takes the value one if household h owns appliance type a and zero otherwise. Similarly, the partial derivative of electricity demand with respect to virtual income is:

$$\frac{\partial x_{hmt}}{\partial y^v_{hmt}} = \mathcal{B}_h = b_{\text{inc}} + \sum_a b_{a,\text{inc}} \cdot d_{ah} \tag{5.11}$$

where b_{inc} is the baseline virtual income coefficient, and $b_{a,\text{inc}}$ is the appliance-specific virtual income interaction coefficient for appliance a.

Substituting Eqs. 5.10 and 5.11 into Eq. 5.9, the household-month price elasticity is:

$$\eta_{hmt} = \left(\frac{p_{khmt}}{x^*_{hmt}}\right) (\mathcal{A}_h + \mathcal{B}_h \cdot \bar{x}_{k-1,ht}) \tag{5.12}$$

where p_{khmt} is the real marginal price faced by household h in month m and year t, x^*_{hmt} is household monthly electricity consumption, and $\bar{x}_{k-1,ht}$ is the lower boundary of the household's current tariff tier in year t.

Annual and Population Aggregation

The household-month elasticities are aggregated to the population level in two steps. First, we calculate a household-year elasticity by taking the weighted average of the household's monthly elasticities, where each household-month observation is weighted by the household's monthly electricity consumption relative to its total consumption in that year. In the second step, we take the average of these household-year elasticities across households to obtain the population mean elasticity.

The weight assigned to each household-month observation is defined as follows:

$$w_{hmt} = \frac{x_{hmt}}{x_{ht}^{annual}} \tag{5.13}$$

where x_{hmt} is the electricity consumption of household h in month m and year t, and x_{ht}^{annual} is the household's total electricity consumption in that year.

The annual price elasticity for household h in year t is:

$$\eta_{ht} = \sum_{m=1}^{12} w_{hmt}\eta_{hmt} \tag{5.14}$$

The population mean price elasticity is then:

$$\bar{\eta} = \frac{1}{N}\sum_{h=1}^{N} \eta_{ht} \tag{5.15}$$

The elasticities for the subsamples are calculated separately for each subgroup: rural and urban households, and income quartiles.

Income Elasticity

The income elasticity measures the responsiveness of household electricity consumption to changes in virtual income. Since real household income enters virtual income additively with a unit coefficient (Eq. 3.21), $\frac{\partial y^v_{hmt}}{\partial y_{hmt}} = 1$, the derivative of electricity consumption with respect to virtual income is:

$$\frac{\partial x^*_{hmt}}{\partial y^v_{hmt}} = B_h \tag{5.16}$$

The corresponding household-month income elasticity is:

$$\eta^y_{hmt} = \left(\frac{y^v_{hmt}}{x^*_{hmt}}\right) B_h \tag{5.17}$$

The household-month elasticities are aggregated to the population level using the same two-step aggregation procedure described above for price elasticity. Elasticities for each subsample are estimated separately.

6 Results

This section presents the results in two parts. The first part presents the conditional demand analysis estimates, which disaggregate the total household electricity consumption into appliance-specific consumption. We begin with the full sample and monthly IV-2SLS estimates. The monthly estimates show seasonal patterns in appliance consumption that cannot be seen in the full sample results. The second part presents the price and income elasticity estimates. We first report the full sample and monthly elasticities to examine how electricity demand responds to changes in price and income. We then estimate elasticities by income quartile to examine how demand responses differ across income groups.

6.1 Appliance-Specific Electricity Consumption

Under increasing block tariffs, household electricity consumption and the marginal price faced by the household are jointly determined. Households that consume more electricity move into higher tariff blocks and consequently face higher marginal prices. This creates simultaneity between electricity consumption and the marginal price. When the endogeneity of marginal prices is ignored, the OLS estimate of the marginal price coefficient is attenuated relative to the IV-2SLS estimate (Table C16). The IV-2SLS specification instruments the marginal price using the price of the next consumption block within the same state-year tariff schedule.[11] All results presented in this paper are therefore based on the IV-2SLS specification.

Table 2 presents the CDA estimates for the full sample and monthly cross-sections. The estimates are reported for six appliances and one baseline category. Each appliance dummy coefficient represents the estimated average monthly electricity consumption (kWh) associated with that appliance, evaluated at the mean characteristics of households owning that appliance. These appliance-specific estimates are obtained under a set of restrictions described in Appendix A.3. The average monthly electricity consumption associated with the baseline category is 105.4 kWh in the full sample. It varies only slightly across months, from 103.0 kWh in December to 106.4 kWh in August. This range spans about 3.2% of the full-sample baseline estimate.

The monthly results reveal seasonal patterns in electricity consumption associated with season-specific appliances. Appliances used throughout the year, such as refrigerators, show little monthly variation in electricity consumption. Refrigerator consumption ranges narrowly from 34.8 to 36.9 kWh, a variation of about 6% relative to its full-sample estimate of 36.2 kWh. Refrigerator consumption averages 36.2 kWh per month in the full sample, close to the 38.4 kWh monthly average (461 kWh/year) reported by Prayas (Energy Group)'s eMARC smart-meter study of Indian households. In contrast, weather-dependent appliances, particularly ACs, show seasonal patterns. AC-specific electricity consumption averages 74.9 kWh per month in the full sample, with the lowest monthly estimate in January at 49.3 kWh. From April to October, consumption averages about 76 kWh, roughly 54% higher than the January estimate. As a share of mean household electricity consumption, refrigerator consumption is similar across the year, at about 23% in January and 22% in August. In contrast, the AC-specific estimate increases from about 33% in January to about 49% in August, indicating that AC-specific consumption represents a larger share of household electricity use during the warmer months. Heating appliances are not observed in

[11] The marginal price coefficient increases in absolute magnitude from −11.7 under OLS to −14.5 under IV-2SLS, corresponding to an approximately 24% larger estimated price response. The appliance–price interaction coefficients are lower under IV-2SLS than under OLS. By contrast, the appliance ownership dummies, household size, and weather controls remain similar in magnitude across the two specifications. The difference between the OLS and IV-2SLS price coefficients is unlikely to reflect a weak-instrument problem. The joint endogeneity test rejects the null of exogeneity ($F = 4{,}358.1$, $p < 0.001$; Table C18).

our data and therefore cannot be included as separate appliance-specific components in the model. Consequently, electricity consumption from household heating cannot be separately identified. Heating degree days (HDD) are included in the winter specifications to control for temperature-related variation in electricity consumption.

Appliance-specific consumption may also vary across the income distribution, reflecting differences not only in ownership but also in usage intensity conditional on ownership. Table C13 presents the appliance-specific consumption estimates by income quartile.[12] Air conditioner and computer terms are not included in the Q1 and Q2 specifications due to near-zero ownership, which does not satisfy the well-mixed condition required for CDA identification (Table B9). The electricity consumption associated with the baseline category increases from 92.0 kWh in Q1 to 114.6 kWh in Q4, an increase of about 25% relative to Q1. However, the baseline category represents a smaller share of mean household consumption in Q4, accounting for about 84% in Q1 compared with 51% in Q4, as mean consumption more than doubles over the same range, from 110.1 to 225.2 kWh.

Differences in electricity consumption associated with each appliance reflect differences in both appliance ownership (Table B9) and usage intensity (Table C13), conditional on ownership. The former represents the extensive margin, while the latter represents the intensive margin. The largest difference is observed for air conditioners. AC-specific electricity consumption increases from 47.0 kWh in Q3 to 91.3 kWh in Q4, an increase of about 94%. Relative to mean household electricity consumption, the AC-specific estimate increases from about 30% in Q3 to 41% in Q4. This increase coincides with higher AC ownership in Q4, indicating differences in both the extensive and intensive margins. In contrast, the cooler shows the opposite pattern. Cooler ownership increases monotonically with income, while usage intensity declines from 9.3 kWh in Q3 to 5.6 kWh in Q4, a decrease of about 40%. This may reflect greater reliance on ACs among higher-income households, potentially limiting the use of evaporative coolers.

Beyond income, appliance-specific electricity consumption may also vary between

[12] A separate specification is estimated for each income quartile. Deviations of continuous covariates are computed from the corresponding appliance-owner subgroup means within each income quartile.

rural and urban households. Table C14 presents the appliance-specific consumption estimates for rural and urban households.[13] The baseline category is higher in absolute terms among urban households, rising from 96.3 kWh in rural households to 115.9 kWh in urban households, an increase of about 20%. However, as a share of total household consumption, the baseline category accounts for about 78% in rural households compared with 68% in urban households. This reflects the higher contribution of appliances explicitly specified in the model to electricity consumption among urban households. In rural households, a larger share of electricity use is captured within the baseline category, consistent with lower ownership of major appliances such as ACs and computers. Electricity consumption associated with appliances also differs between rural and urban households, with the pattern varying across appliances. Electricity consumption associated with the refrigerator is higher in rural households, at 40.8 kWh per month compared with 29.0 kWh in urban households. This represents about 33% of mean household electricity consumption in rural households and 17% in urban households. In contrast, electricity consumption associated with evaporative coolers is much higher in urban households, at 17.1 kWh compared with 2.8 kWh in rural households, representing about 10% and 2% of mean household consumption, respectively.

6.2 Demand Elasticities and Distributional Effects

Table 3 presents the price and income elasticities of Indian residential electricity demand. The full sample estimate indicates that electricity demand is price inelastic in India, with a price elasticity of -0.12. A 1% increase in the marginal price of electricity is associated with a 0.12% decrease in electricity consumption. The estimated income elasticity is 0.09, indicating that a 1% increase in household income is associated with a 0.09% increase in electricity consumption. Although residential electricity demand is price inelastic in India, the magnitude varies across months. Price responsiveness is highest in January, with an elasticity of -0.28, and lowest in November and December, at -0.17. In the remaining months, the estimates range from -0.19 to -0.22.

[13] Separate specifications are estimated for rural and urban households. Deviations of continuous covariates are computed from the means of the corresponding appliance-owner subgroups within each subsample. AC and computer are not included in the rural specification due to near-zero ownership, which does not satisfy the well-mixed condition required for CDA identification (Table B10).

The income-quartile results shown in Table 4 reveal an inverted-U-shaped pattern for both price and income elasticity. The magnitudes are lowest at both quartiles Q1 and Q4 and highest in the middle quartiles (Q2 and Q3), while mean electricity consumption increases monotonically across income quartiles. Price elasticity increases in magnitude from -0.04 in Q1 to -0.13 in Q2 and -0.15 in Q3, before declining to -0.07 in Q4. Income elasticity follows a similar pattern, increasing from 0.02 in Q1 to 0.30 in Q2 and 0.29 in Q3, before declining to 0.09 in Q4.

Three factors may help explain the inverted-U pattern in price elasticity across income quartiles.First, in Q1, the baseline category accounts for about 84% of mean household consumption, while ownership of major appliances is relatively low (Table C13) and (Table B9). Most consumption at this end of the distribution reflects essential, non-discretionary baseline use rather than major-appliance-driven use. As a result, households have limited scope to adjust their electricity consumption in response to price changes, which is consistent with the low elasticities observed in Q1. Second, in Q4, ownership of major appliances is highest across all quartiles, and consumption is concentrated in comfort-oriented appliances such as air conditioners, which alone account for about 41% of mean household consumption (Table C13) and (Table B9). Higher incomes may allow households to maintain higher electricity consumption despite price increases, particularly when consumption is associated with comfort-oriented appliances. This may limit the extent to which higher prices translate into reductions in electricity use, consistent with the relatively low price elasticity in Q4. Third, Q2 and Q3 households are in transition, with appliance ownership increasing across these income groups. For example, washing machine ownership increases from 14.9% in Q2 to 30.8% in Q3, while refrigerator ownership increases from 53.6% to 72.6%. This provides scope for adjustment through both new appliance adoption (the extensive margin) and changes in the use of existing appliances (the intensive margin), consistent with the higher price elasticities observed in Q2 and Q3.

Table 5 presents the price and income elasticities of residential electricity demand for rural and urban households. Both groups are price inelastic, but rural households are more responsive to price changes than urban households, with price elasticities of -0.18 and -0.09, respectively. Despite lower ownership of major appliances, rural households are more price responsive than urban households. This difference is not explained by appliance ownership alone. For several appliances that rural households do own, the electricity consumption associated with that appliance is higher than in urban households (Table C14). This suggests that the rural price response may operate more through the intensive margin, reflecting changes in the use of existing appliances rather than changes in appliance ownership.

Income elasticity is positive, with an estimate of 0.09 (Table 3). Across income quartiles, it follows an inverted-U pattern, increasing from 0.02 in Q1 to 0.30 in Q2 and 0.29 in Q3 before declining to 0.09 in Q4. The higher income responsiveness in Q2 and Q3 is consistent with the greater changes in appliance ownership observed across these income groups, particularly for major appliances (Table B9). Income elasticity is positive in both rural and urban households, with estimates of 0.08 and 0.11, respectively (Table 5). Urban households therefore show higher income responsiveness than rural households.

7 Discussion

This section discusses the findings in relation to the paper's three research questions. We first examine how appliance ownership influences residential electricity consumption, before analysing how households respond to prices under India's nonlinear tariff structure. We then explore differences in demand response across income groups and between rural and urban households, and conclude by discussing the implications of these findings for tariff design and demand forecasting.

7.1 Appliance Composition and Residential Electricity Demand

The CDA results are consistent with our expectations. Season-specific appliances, particularly cooling appliances, show variation in electricity consumption across months. Consumption associated with appliances that are not season-specific shows less variation across months. The appliance-specific estimates highlight substantial heterogeneity in household electricity demand. This suggests that changes in aggregate electricity consumption depend not only on how much electricity households consume, but also on the appliances they own and how intensively they use them.

By disaggregating total residential electricity demand into appliance-specific components, this study contributes to the Conditional Demand Analysis (CDA) literature. Previous studies using the CDA framework have focused on developed countries and, even within these countries, have analysed households served by a single electricity utility, with relatively limited variation in institutional and climatic conditions.(Parti and Parti, 1980; Aigner et al., 1984; Reiss and White, 2005). Building on this literature, the present study applies the CDA framework to residential electricity demand in India, where households differ substantially in appliance ownership, electricity consumption, climatic conditions, and electricity tariff structures. In addition, electricity is supplied through different utilities across states, with multiple utilities operating within some states. The empirical framework extends CDA to this more heterogeneous context by centering climate variables at the state rather than the national level. It also controls for unobserved district-level factors using night-time lights data.

7.2 Price Responsiveness under Nonlinear Tariffs

Our results show that residential electricity demand in India is price inelastic, despite the price incentives embedded in India's increasing block tariff structure. The CDA framework models electricity demand at the appliance level and conditions on the household's existing appliance stock. The resulting price elasticity can therefore be interpreted as a short-run price elasticity. It captures adjustments in usage intensity rather than changes in appliance ownership. For comparison, Table C15 reports short- and long-run elasticities from a log-log specification(Eq. A14) that does not condition on appliance stock. The short-run estimate from this specification is -0.18, larger in magnitude than our preferred estimate of -0.12. This difference may reflect appliance-level heterogeneity in price responses that the aggregate-level demand model does not capture. This is consistent with prior evidence that accounting for housing characteristics and capital stock yields lower price elasticity estimates (Miller and Alberini, 2016). The long-run estimate of -0.27 from equations A14 is consistent with the scope for adjustment when households can also adjust their appliance stock.

Under the CDA framework, our estimated price elasticity does not represent a single, uniform price response across households. It depends on household appliance ownership and the corresponding appliance-specific price responses. Economically, it reflects how much households are willing and able to adjust electricity use, given their existing appliance stock, when the marginal price rises. The elasticity also incorporates the indirect effect of the price change on households' effective purchasing power through the inframarginal discount.

Comparing our estimates with the international studies, our price elasticity of -0.12 is very close to the estimate of -0.116 reported by Sikl et al. (2025) in their meta-analysis after correcting for publication bias. Burke and Abayasekara (2018) report a short-run price elasticity of -0.10 for the United States, while Loi and Le Ng (2018) report estimates ranging from -0.05 to -0.37 for Singapore, depending on dwelling type. Branch (1993) report a short-run elasticity of -0.20 for the United States, while Alberini et al. (2019) find short-run elasticities ranging from -0.2 to -0.5 for households in Ukraine. Other studies report larger elasticities; for example, Frondel et al. (2019) estimate a short-run elasticity of -0.44 for Germany.More broadly, estimates for developed economies range widely, with Krishnamurthy and Kriström (2015) reporting estimates from -0.27 to -1.4 across 11 OECD countries. In the developing-country context, Cao et al. (2019) estimate an elasticity of about -0.7 for China, which is larger in magnitude than our estimate.

Our results are consistent with prior literature on the price elasticity of electricity demand in India, which similarly finds that demand is price inelastic. Our estimate of -0.12 is lower than most previous Indian studies, which primarily use aggregated electricity consumption: Bose and Shukla (1999) report an average price elasticity of -0.65, Filippini and Pachauri (2004) estimate elasticities ranging from -0.51 to -0.29 depending on the season, Harish et al. (2014) report an estimate of -0.32, and the most recent Indian study by Chindarkar and Goyal (2019) reports -0.39. Earlier Indian studies rely on aggregate consumption measures and average or marginal prices. Our estimate, by contrast, accounts for appliance-level heterogeneity and the full nonlinear tariff schedule. The difference may also reflect the data used in our analysis, which draws on a five-year monthly household panel rather than the cross-sectional survey data used in most earlier Indian studies.

Our study contributes to the literature on residential electricity demand under nonlinear pricing by accounting for India's six-block IBT structure together with appliance-level disaggregation. To our knowledge, no prior Indian study combines these two features. Earlier studies use different measures of electricity prices and household demand, including average or marginal prices and aggregate demand. Accounting for the full tariff schedule is important because simplifying the piecewise-linear tariff structure can affect estimates of price responsiveness. By jointly accounting for the nonlinear tariff structure and appliance-level heterogeneity, our study contributes to the CDA and nonlinear-pricing literature. We apply these approaches in a developing-country context with substantial climatic and institutional diversity.

7.3 Differences in Household Demand Response

In our study price responsiveness follows an inverted-U pattern across income quartiles, even though appliance ownership increases with income. Price responsiveness peaks among middle-income households, while both lower- and higher-income households respond less to changes in electricity prices. This relationship is not uniform across the broader literature. Several studies find price responsiveness declining monotonically with income, for example, Çetinkaya et al. (2015) for Turkey, Silva et al. (2017) for Portugal, and Maria de Fátima et al. (2012) for Mozambique. In India, Chindarkar and Goyal (2019) report elasticities for urban Maharashtra ranging from -0.58 for low-income households to -0.10 for high-income households. Contrary to this, Schulte and Heindl (2017) report higher price sensitivity among higher-income households in Germany. A U-shaped pattern, with the most price-responsive households at both ends of the distribution, is reported by Romero-Jordán et al. (2016) for Spain and, in the Indian context, by Tiwari (2000) for Bombay. Our finding of an inverted U pattern, which is the reverse of Tiwari (2000) U- shaped relationship, is distinct from the patterns reported in these studies. However, Tiwari (2000) estimates are drawn from city level data collected in 1987–88, more than three decades before our study period, and direct comparison should be treated with caution. The divergence may reflect the substantial expansion in appliance ownership across India since then.

The appliance ownership and appliance-specific consumption estimates reported earlier (Tables B9 and C13) may explain this pattern. In Q1, consumption is dominated by essential, non-discretionary baseline use, leaving limited scope for adjustment. In Q2 and Q3, greater ownership of energy-intensive appliances gives households more scope to adjust electricity use through changes in the use of their existing appliances, consistent with their higher price responsiveness. In Q4, appliance ownership is highest, and a greater share of consumption is associated with comfort-oriented appliances such as air conditioners. Higher incomes may allow these households to maintain such consumption despite price increases, limiting the reduction in electricity use.

Price responsiveness also differs between rural and urban households, with rural households more price-responsive than urban households. As shown in Table C14, this difference does not appear to be driven by higher ownership of major appliances in rural households, which is lower than in urban areas. This pattern is consistent with prior evidence, both internationally and within India. Silva et al. (2018) find rural households more price-responsive than urban households in Portugal (−0.88 versus −0.67), and Maria de Fátima et al. (2012) find the same pattern in Mozambique (−0.66 versus −0.49). Within India, Chindarkar and Goyal (2019) similarly report higher price elasticity in rural areas (−0.47) than in urban areas (−0.25).

Figure C1 shows that these differences are likely to become increasingly important as India's residential energy transition continues. Between 2015 and 2019, electricity use from air conditioners nearly doubled, while electricity use from evaporative coolers declined significantly, indicating a shift towards more energy-intensive cooling technologies.Since air conditioners consume almost six times more electricity than coolers during the cooling season, this shift is likely to raise household electricity demand. It may also increase differences in electricity consumption across households. The appliance-specific estimates in Table C14 further show that AC consumption is higher among urban households, while cooler use differs across rural and urban households. This highlights the need to account for household variation when designing future electricity tariffs and demand-side management policies.

8 Policy Implications

The findings have implications for tariff design and demand management in India. The effectiveness of increasing block tariffs depends not only on household income but also on appliance ownership and households' ability to adjust electricity use. The lower price responsiveness among higher-income groups suggests that the effectiveness of IBTs in curtailing electricity demand through pricing policies is limited. Tariff design and demand forecasting should therefore account for heterogeneity in household income, appliance ownership, and electricity use patterns rather than assume a uniform response to price changes.

This study suggests that accounting for the nonlinear structure of IBTs and appliance heterogeneity is important when estimating the price elasticity of residential electricity demand. Future research could apply this framework to other countries with increasing block tariffs. It could also examine how appliance-level price responses change as appliance ownership expands over time and combine appliance-level demand estimates with welfare and distributional analysis of IBT design.

9 Conclusion

In this study, we assess the effectiveness of increasing block tariffs (IBTs), in achieving the energy policy goals. We examine how household respond to price changes under IBTs and how this change differ across income groups and rural and urban areas. We account for the challenges in electricity demand modeling. Instead of using marginal or average prices as a measure of electricity prices, we account for the nonlinear structure of IBTs. Similarly, instead of treating electricity demand as aggregate across appliances, we allow the price response to vary across appliances by incorporating appliance heterogeneity into the model. We also provide estimates of the average electricity use associated with major appliances. We use monthly household panel data on electricity consumption, appliance ownership, and household characteristics for India from 2015 to 2019.

Our study finds that electricity demand is price inelastic in India, consistent with previous studies. Additionally, price responsiveness varies nonlinearly with income, following an inverted-U pattern: it is highest among middle-income households and lowest among the lower and higher-income groups. Also, rural households are more price responsive than urban households. Our estimated price elasticity is lower than those reported in previous studies using aggregate electricity consumption data. However, it is closer to estimates from studies that account for appliance heterogeneity. This suggests that modeling electricity demand at an aggregate level may mask differences across appliances and seasonal variations in electricity use. The appliance-specific estimates from the CDA results are consistent with our expectations and presents substantial heterogeneity in household electricity consumption. Season-specific appliances, particularly cooling appliances, show greater variation in electricity consumption across months. In contrast, appliances used throughout the year, such as refrigerators, show relatively less variation across months.

The analysis has some data and specification limitations. The data do not provide a comprehensive set of household appliances, particularly heating appliances, limiting the ability to identify their electricity consumption separately. Detailed dwelling characteristics that may influence electricity use are also not available. In addition, because the CDA specification conditions on existing appliance stock, the estimated price elasticity captures short-run adjustments in appliance use rather than changes in appliance ownership. Future research could use richer household data with detailed information on appliances and dwelling characteristics. Such data would allow for complete appliance-level demand estimates and a better understanding of heterogeneity in household price responses. Future studies could also examine appliance adoption alongside appliance use to capture responses beyond the short-run adjustment.

Tables

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max	Obs.
Panel A: Household and Climate Variables					
Monthly consumption (kWh)	155.67	111.25	0.24	5416.95	7,028,981
Monthly income (INR)	14,681	15,338	0.00	295,000	7,028,981
Household size	4.05	1.66	1.00	16.00	7,028,981
Marginal price (INR/kWh)	5.20	1.54	0.85	11.74	7,028,981
CDD (base 24°C)	101.03	90.32	0.00	375.88	7,028,650
HDD (base 24°C)	40.40	83.49	0.00	626.08	7,028,650
Relative humidity (%)	65.46	15.54	20.75	94.96	7,028,981
Panel B: Appliance Ownership (binary, 0/1)					
Refrigerator	0.62	0.48	0.00	1.00	5,302,721
Air conditioner	0.10	0.29	0.00	1.00	5,302,721
Evaporative cooler	0.48	0.50	0.00	1.00	5,302,721
Washing machine	0.29	0.45	0.00	1.00	5,302,721
Television	0.96	0.20	0.00	1.00	5,302,721
Computer	0.10	0.30	0.00	1.00	5,302,721

Notes: Data covers 28 Indian states, 2015–2019. Panel A reports household, price, and climate variables. Panel B reports appliance ownership rates. The difference in observations between panels reflects households with missing appliance ownership information. Consumption measured in kWh per month. Income in INR per month. CDD and HDD computed at base temperature of 24°C at district-month level. Marginal price is the block tariff price corresponding to the household's monthly consumption tier.

Table 2: Appliance-Specific Monthly and Whole Sample Electricity Consumption (kWh)

	Monthly Estimates (IV-2SLS)												
Appliance	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Full Sample
Refrigerator	34.8***	35.0***	35.2***	36.1***	36.7***	35.7***	35.5***	35.5***	35.8***	36.6***	36.2***	36.9***	36.2***
	(0.64)	(0.47)	(0.42)	(0.37)	(0.52)	(0.42)	(0.42)	(0.41)	(0.44)	(0.51)	(0.44)	(0.48)	(0.32)
AC	49.3***	68.2***	68.3***	75.1***	75.5***	77.1***	73.2***	77.2***	76.6***	75.3***	71.0***	77.7***	74.9***
	(2.26)	(1.72)	(1.49)	(1.37)	(1.30)	(1.30)	(1.30)	(1.29)	(1.44)	(1.52)	(1.29)	(3.06)	(1.20)
Evap. Cooler	−0.9	7.2***	6.4***	8.9***	10.2***	11.9***	11.8***	12.2***	10.9***	9.3***	11.3***	9.9***	9.4***
	(0.74)	(0.56)	(0.49)	(0.46)	(0.48)	(0.54)	(0.50)	(0.47)	(0.49)	(0.74)	(0.66)	(0.56)	(0.43)
Washing Machine	36.2***	42.5***	42.2***	44.7***	48.6***	46.6***	46.8***	44.1***	44.9***	41.7***	42.5***	46.0***	44.7***
	(1.44)	(1.12)	(1.04)	(0.76)	(1.10)	(0.74)	(0.76)	(0.70)	(0.97)	(1.17)	(0.78)	(1.04)	(0.55)
Computer	8.1***	11.6***	13.1***	18.8***	15.4***	15.6***	12.6***	11.7***	14.4***	15.8***	8.5***	3.1*	13.1***
	(2.09)	(1.61)	(1.28)	(1.15)	(1.14)	(1.19)	(1.18)	(1.19)	(1.50)	(1.58)	(1.14)	(1.84)	(0.93)
Baseline	104.4***	105.2***	104.9***	104.7***	105.3***	105.3***	106.3***	106.4***	106.1***	106.1***	105.3***	103.0***	105.4***
	(0.59)	(0.45)	(0.47)	(0.32)	(0.49)	(0.40)	(0.39)	(0.36)	(0.51)	(0.67)	(0.50)	(0.55)	(0.33)
Mean Consumption	149.7	151.1	152.8	155.4	157.6	158.4	158.6	159.2	158.4	157.5	155.5	154.1	155.7
Observations	114,371	248,806	373,638	510,068	504,721	503,500	506,810	517,800	506,745	503,110	496,697	496,738	5,283,004

Notes: Estimates are from the IV specification. Coefficients represent appliance-specific electricity consumption. The specification includes marginal price, household income, household size, CDD, HDD, and relative humidity, along with their interactions with the appliance dummy. All covariates are expressed as deviations from the subgroup means calculated among appliance owners only. Mean Consumption reports the average monthly electricity consumption (kWh) in the sample. Standard errors clustered at the household level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.
Source: estimated using CPHS (CMIE), CEA tariff data, and IMD gridded temperature data, 2015–2019.

Table 3: Price and Income Elasticity of Residential Electricity Demand

	Price Elasticity		Income Elasticity	
	Estimate	SE	Estimate	SE
Panel A: Full Sample Estimate				
Full Sample	−0.12	(0.003)	0.09	(0.002)
Panel B: Monthly Estimates				
January	−0.28	(0.011)	0.15	(0.008)
February	−0.21	(0.008)	0.17	(0.005)
March	−0.22	(0.006)	0.15	(0.006)
April	−0.22	(0.005)	0.13	(0.004)
May	−0.21	(0.006)	0.13	(0.006)
June	−0.22	(0.006)	0.15	(0.004)
July	−0.21	(0.005)	0.15	(0.004)
August	−0.21	(0.006)	0.16	(0.004)
September	−0.19	(0.006)	0.15	(0.006)
October	−0.18	(0.007)	0.15	(0.008)
November	−0.17	(0.006)	0.16	(0.006)
December	−0.17	(0.007)	0.14	(0.009)

Notes: Price and income elasticities are computed at the household-month level, following Eqs. (36) and (40), which incorporate both the direct price effect and the virtual-income effect induced by the IBT structure. Household-month elasticities are aggregated to the household-year level using each household's share of annual electricity consumption as weights, and the reported elasticity is the mean of the resulting household-year elasticities. Standard errors are computed using the delta method.
Source: estimated using CPHS (CMIE), CEA tariff data, and IMD gridded temperature data, 2015–2019.

Table 4: Price and Income Elasticity by Income Quartile

	Price Elasticity		Income Elasticity	
Income Group	Estimate	SE	Estimate	SE
Q1 (Lowest)	−0.04	(0.004)	0.02	(0.002)
Q2	−0.13	(0.004)	0.30	(0.005)
Q3	−0.15	(0.004)	0.29	(0.005)
Q4 (Highest)	−0.07	(0.005)	0.09	(0.005)
Full Sample	−0.12	(0.003)	0.09	(0.002)

Notes: Price and income elasticities are computed at the household-month level, following Eqs. (36) and (40), and estimated separately for income quartiles. Household-month elasticities are aggregated to the household-year level using each household's share of annual electricity consumption as weights. The reported estimates are the mean of the resulting household-year elasticities within each subsample.
Source: Estimated using CPHS (CMIE), CEA tariff data, and IMD gridded temperature data, 2015–2019.

Table 5: Price and Income Elasticity by Region Type

	Price Elasticity		Income Elasticity	
	Estimate	SE	Estimate	SE
Rural	−0.18	(0.005)	0.08	(0.002)
Urban	−0.09	(0.004)	0.11	(0.003)
Full Sample	−0.12	(0.003)	0.09	(0.002)

Notes: Price and income elasticities computed at the household-month level from the IV-2SLS conditional demand analysis, following Eqs. (36) and (40), estimated separately for rural and urban subsamples. Reported estimates are population means of household-month elasticities within each subsample. Virtual income follows Nordin (1976). Standard errors clustered at the household level. *Source:* estimated using CPHS (CMIE), CEA tariff data, and IMD gridded temperature data, 2015–2019.

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Appendix

A Variable Construction

The conditional demand analysis (CDA) framework requires that all covariates enter the regression in deviation form, centred at ownership-subgroup means. This ensures that the coefficient on each appliance dummy $\tilde{E}_i$ directly identifies the estimated average monthly electricity consumption associated with appliance i. This appendix describes the construction of all deviation variables used in estimation.

A.1 Deviation Variables

Annual Variables: The variables marginal price and household size vary annually; deviations for these variables are therefore computed relative to the national sample mean in each year t

$$\widetilde{p}_{ht} = p^k_{ht} - \bar{p}^k_t \tag{A1}$$

$$\widetilde{n}_{ht} = n_{ht} - \bar{n}_t \tag{A2}$$

where p^k_{ht} is the marginal price faced by household h in year t at tier k, $\bar{p}^k_t$ is the national mean marginal price in year t, n_{ht} is household size, and $\bar{n}_t$ is the national mean household size in year t.

Monthly Variables: The household income vary monthly therefore the deviation is computed relative to the national sample mean in each year-month ym:

$$\widetilde{y}^*_{hmt} = y^*_{hmt} - \bar{y}^*_{ym} \tag{A3}$$

where y^*_{hmt} is virtual income following Nordin (1976) and $\bar{y}^*_{ym}$ is the national mean virtual income in year-month ym.

For weather variables, cooling degree days, heating degree days, and relative humidity, deviations are computed relative to the *state-specific* year-month mean to account for regional climate heterogeneity across India's diverse agro-climatic zones:

$$\widetilde{\mathrm{CDD}}_{dsmt} = \mathrm{CDD}_{dsmt} - \overline{\mathrm{CDD}}_{s,ym} \tag{A4}$$

$$\widetilde{\mathrm{HDD}}_{dsmt} = \mathrm{HDD}_{dsmt} - \overline{\mathrm{HDD}}_{s,ym} \tag{A5}$$

$$\widetilde{\mathrm{RH}}_{dsmt} = \mathrm{RH}_{dsmt} - \overline{\mathrm{RH}}_{s,ym} \tag{A6}$$

where CDD_{dsmt} is monthly cooling degree days (base temperature is 24°C) at district d in state s, month m, year t, and $\overline{\mathrm{CDD}}_{s,ym}$ is the state-specific mean CDD in year-month ym. The same definitions hold for heating degree days HDD_{dsmt} and relative humidity RH_{dsmt}.

We calculate climate deviations at the state level rather than the national level because India's states have very different climates. For example, the weather conditions in Rajasthan are very different from those in Kerala. Using a national average would mix these different climatic conditions and provide a less meaningful measure of climate exposure. State-level deviations allow the CDD, HDD, and humidity interaction variables to capture changes in climate relative to the normal seasonal conditions of each state.

Appliance-Specific Subgroup Deviations. The main feature of the CDA deviation form is that interaction terms between appliance ownership dummies and continuous covariates are centred at the owners-subgroup mean rather than the population mean. For appliance ownership dummy $A_{iht} \in \{0, 1\}$ indicating whether household h owns appliance i in year t, the subgroup deviation interactions are constructed as follows.

Price interactions:

$$dp_{iht} = A_{iht} \left(p^k_{ht} - \bar{p}^k_{i,t} \right) \tag{A7}$$

where $\bar{p}^k_{i,t}$ is the mean marginal price among households owning appliance i in year t.

Virtual income interactions:

$$dvi_{ihmt} = A_{iht} \left(y^*_{hmt} - \bar{y}^*_{i,ym} \right) \tag{A8}$$

where $\bar{y}^*_{i,ym}$ is the mean virtual income among appliance i owners in year-month ym.

Household size interactions:

$$dh_{iht} = A_{iht} \left(n_{ht} - \bar{n}_{i,t} \right) \tag{A9}$$

where $\bar{n}_{i,t}$ is the mean household size among appliance i owners in year t.

Cooling degree day interactions:

$$dc_{ihdmt} = A_{iht} \left(\text{CDD}_{dmt} - \overline{\text{CDD}}_{i,s,ym} \right) \tag{A10}$$

Here, $\overline{\text{CDD}}_{i,s,ym}$ represents the average CDD for households that own appliance i in state s during a given year-month ym. These averages are calculated separately for each state, year, and month to account for differences in climate across regions. As a result, the CDD interaction terms capture how temperature exposure differs from the average climate conditions at that time within a particular state, rather than from a national average that may not reflect local weather conditions.

Relative humidity interactions:

$$drh_{ihdsmt} = A_{iht} \left(\text{RH}_{dsmt} - \overline{\text{RH}}_{i,s,ym} \right) \tag{A11}$$

where $\overline{\text{RH}}_{i,s,ym}$ is the mean relative humidity among appliance i owners in state s in year-month ym.

A.2 Variable Names and Notation

Tables A6 and A7 provide a brief description of the variables used in our empirical specifications A12.

Table A6: Variable Names and Notation: Core Variables

Notation	Variable name	Description
Outcome and household variables		
x_{hmt}	`estimated_units`	Monthly electricity consumption (kWh)
p_{ht}^k	`p_marginal`	Marginal price at assigned IBT tier (INR/kWh)
y_{ht}^*	`virtual_income`	Virtual income (INR/month), Nordin (1976)
n_{ht}	`hh_size`	household size
Climate variables		
CDD_{dmt}	`cdd_monthly_24`	Monthly CDD at district level (base 24°C)
RH_{dsmt}	`rh_`	Monthly relative humidity (%)
HDD_{dsmt}	`hdd_monthly_24`	Monthly HDD at district level (base 24°C)
Appliance ownership dummies		
A_{refrig}	`d_refrigerators_owned`	Refrigerator ownership (0/1)
A_{AC}	`d_acs_owned`	Air conditioner ownership (0/1)
A_{cooler}	`d_coolers_owned`	Evaporative cooler ownership (0/1)
A_{WM}	`d_washing_machines_owned`	Washing machine ownership (0/1)
A_{comp}	`d_computers_owned`	Computer ownership (0/1)

Table A7: Variable Names and Notation: Deviation Variables and Instrument

Notation	Variable name	Description
Baseline deviation variables (population means)		
$\widetilde{p}_{ht}$	dev_p_marginal	Annual price deviation from national mean
$\widetilde{y}^*_{hmt}$	dev_virtual_inc	Monthly virtual income deviation
$\widetilde{n}_{ht}$	dev_hh_size	Annual household size deviation
$\widetilde{\mathrm{CDD}}_{dmt}$	dev_cdd_monthly	Monthly CDD deviation from state mean
$\widetilde{\mathrm{RH}}_{dsmt}$	dev_rh_	Monthly RH deviation from state mean
$\widetilde{\mathrm{HDD}}_{dsmt}$	dev_hdd_monthly_24	Monthly HDD deviation from state mean
Appliance-specific subgroup deviation interactions		
dp_{AC}	dp_acs_owned	Price deviation × AC ownership
dp_{cooler}	dp_coolers_owned	Price deviation × cooler ownership
dp_{WM}	dp_washing_machines_owned	Price deviation × washing machine ownership
dp_{comp}	dp_computers_owned	Price deviation × computer ownership
dvi_{AC}	dvi_acs_owned	Income deviation × AC ownership
dvi_{cooler}	dvi_coolers_owned	Income deviation × cooler ownership
dvi_{WM}	dvi_washing_machines_owned	Income deviation × washing machine ownership
dvi_{comp}	dvi_computers_owned	Income deviation × computer ownership
dh_{refrig}	dh_refrigerators_owned	HH size deviation × refrigerator ownership
dh_{WM}	dh_washing_machines_owned	HH size deviation × washing machine ownership
dc_{refrig}	dc_refrigerators_owned	CDD deviation × refrigerator ownership
dc_{AC}	dc_acs_owned	CDD deviation × AC ownership
dc_{cooler}	dc_coolers_owned	CDD deviation × cooler ownership
drh_{AC}	drh_acs_owned	RH deviation × AC ownership
drh_{cooler}	drh_coolers_owned	RH deviation × cooler ownership
Instrument		
Z_{st}	dev_p_instrument	Deviation of state-year schedule price

A.3 Empirical Specification

The specifications are estimated subject to a common set of baseline restrictions. The refrigerator is assumed to have no price or income responsiveness, and television is excluded from the specification due to near-universal ownership with its consumption absorbed into the baseline category. Washing machines and computers are assumed to have no cooling- driven response.

The following equation shows the model used in the analysis, the variables are described in Table A6 & A7

$$\begin{aligned} x_{hmt} = \tilde{E}_0 + & \tilde{E}_{refrig}A_{refrig} + \tilde{E}_{AC}A_{AC} + \tilde{E}_{cooler}A_{cooler} + \tilde{E}_{WM}A_{WM} + \tilde{E}_{comp}A_{comp} + b_p\widetilde{p}_{ht} \\ & + b_{AC,p}\, dp_{AC} + b_{cooler,p}\, dp_{cooler} + b_{WM,p}\, dp_{WM} + b_{comp,p}\, dp_{comp} + b_{inc}\widetilde{y}^{*}_{hmt} \\ & + b_{AC,inc}\, dvi_{AC} + b_{cooler,inc}\, dvi_{cooler} + b_{WM,inc}\, dvi_{WM} + b_{comp,inc}\, dvi_{comp} + b_{hh}\widetilde{n}_{ht} \\ & + b_{refrig,hh}\, dh_{refrig} + b_{WM,hh}\, dh_{WM} + b_{cdd}\widetilde{\mathrm{CDD}}_{dmt} + b_{refrig,cdd}\, dc_{refrig} + b_{AC,cdd}\, dc_{AC} \\ & + b_{cooler,cdd}\, dc_{cooler} + b_{rh}\widetilde{\mathrm{RH}}_{dsmt} + b_{AC,rh}\, drh_{AC} + b_{cooler,rh}\, drh_{cooler} + b_{ntl}\,\mathrm{NTL}_{dmt} \\ & + \varepsilon_{hmt} \end{aligned} \tag{A12}$$

The instrument Z_{st} (`dev_p_instrument`) replaces $\widetilde{p}_{ht}$ in the first stage of the IV-2SLS estimation. The standard errors are clustered at the household level.

As an alternative specification, we estimate a dynamic log-log model using annual household-level data. The model specifies annual electricity consumption as a function of the annual marginal price, household income, lagged annual electricity consumption, household size, and annual climate and night-time lights measures. The annual marginal price is treated as endogenous and is instrumented using the annual adjacent block price. We also estimate a specification that additionally controls for appliance ownership.

The first-stage equation is given by:

$$\ln(p_{ht}) = \pi_0 + \pi_1 \ln(z_{ht}) + \pi_2 \ln(x_{h,t-1}) + \pi_3 \ln(y_{ht}) + \pi_4 HS_{ht} + \pi_5 CDD_{ht} + \pi_6 RH_{ht} + \pi_7 NTL_{ht} + \nu_{ht} \tag{A13}$$

The fitted marginal price from the first stage is then used in the second stage:

$$\ln(x_{ht}) = \alpha + \beta_p \ln(\widehat{p}_{ht}) + \beta_y \ln(y_{ht}) + \rho \ln(x_{h,t-1}) + \beta_s HS_{ht} + \beta_{cdd} CDD_{ht} + \beta_{rh} RH_{ht} + \beta_{ntl} NTL_{ht} + \varepsilon_{ht} \quad \text{(A14)}$$

Here, z_{ht} denotes the annual adjacent block price used as the instrument for the endogenous marginal price.

B Summary Statistics

Table B8 summarizes the panel structure in terms of new entry, exit and rejoin into the sample over the study period. In total,the dataset covers 204,259 households between 2015 and 2019. Each year, there are new entries and exits from the sample; however, there are no re-entries, implying that once a household exits the sample, it does not return. After studying the panel structure we move to our variables of interest. The first one is the monthly electricity expenditure, which we use to compute the household electricity consumption. Out of 9,894,699 household-month observations, data on monthly electricity expenditure are available for 8,275,187 household-month observations; for the remaining observations, the data is missing.

Table B8: Sample Structure by Year

Year	Observations (N)	Households	New Entry	Exit	Rejoin
2015	1,848,319	169,229	169,229	11,061	
2016	1,919,206	165,766	7,598	4,599	0
2017	1,963,316	182,959	21,792	13,792	0
2018	2,070,998	174,807	5,640	402	0
2019	2,092,860	174,405	0	–	0

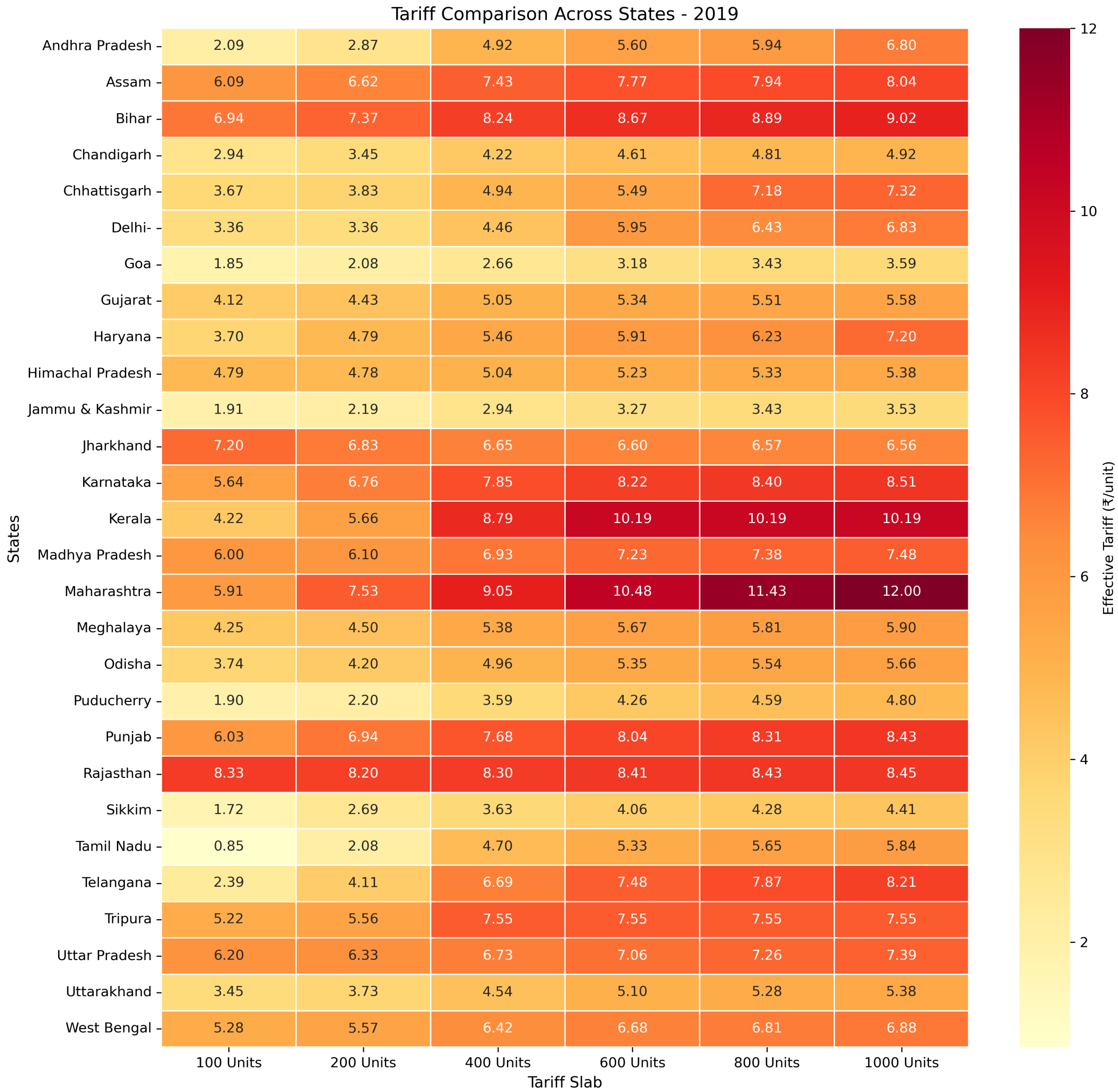

Figure B1. Slab-wise Electricity Tariffs Across States, 2019. The figure shows the marginal price (INR/kWh) for each of the six consumption slabs (100, 200, 400, 600, 800, and 1000 units) across the 28 Indian states. Tariffs are averaged across utilities within states with multiple utilities. Source: CEA tariff schedule data, 2019.

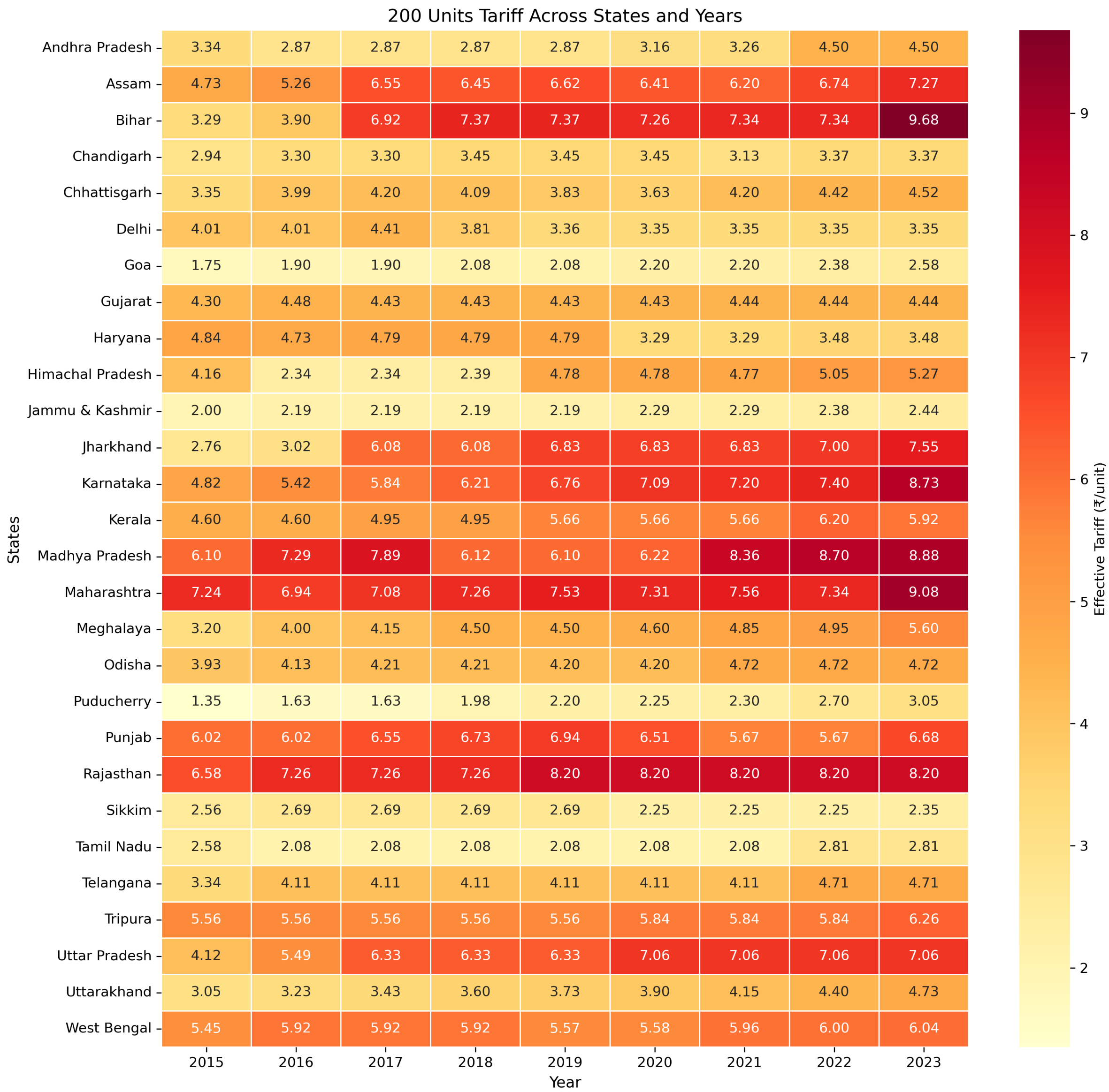

Figure B2. Electricity Tariffs for the 200-Unit Consumption Slab Across States and Years, 2015-2019. The figure shows the marginal price (INR/kWh) for the 200-unit consumption slab across the 28 Indian state, by year. Source: CEA tariff schedule data, 2015-2019.

Table B9: Appliance Ownership Rates and Rural/Urban Composition by Income Quartile (%)

Appliance	Q1 (Lowest)	Q2	Q3	Q4 (Highest)	Full Sample
Refrigerator	33.6	53.6	72.6	89.8	62.4
Air Conditioner	2.2	3.1	7.0	26.0	9.6
Evaporative Cooler	34.7	41.7	51.2	64.4	48.0
Washing Machine	7.5	14.9	30.8	62.8	29.0
Computer	1.3	2.8	7.8	29.1	10.2
Rural (%)	49.3	33.3	26.9	20.6	32.5
Urban (%)	50.7	66.7	73.1	79.4	67.5
Observations	1,322,223	1,327,026	1,328,344	1,325,128	5,302,721

Notes: Ownership rates expressed as percentage of household-month observations owning each appliance. Income quartiles defined on the basis of real household income over the full sample period 2015–2019. Q1 is the lowest income quartile and Q4 is the highest.
Source: Computed using CPHS (CMIE) data, 2015–2019.

Table B10: Appliance Ownership Rates by Rural/Urban (%)

Appliance	Rural	Urban	Pooled
Refrigerator	38.9	73.6	62.4
Air Conditioner	2.4	13.0	9.6
Evaporative Cooler	36.1	53.7	48.0
Washing Machine	12.7	36.8	29.0
Computer	2.4	14.0	10.2

Notes: Ownership rates expressed as percentage of household-month observations owning each appliance. Rural/urban classification based on `region_type`.
Source: Computed using CPHS (CMIE) data, 2015–2019.

Table B11: State-wise Summary Statistics: Core Variables

State	Estimated units	Price	Real income	HH size	CDD (24)	HDD (24)	RH
Andhra Pradesh	132.4	3.02	9827	3.0	129.9	3.7	67.1
Assam	104.7	5.68	13839	3.9	49.8	59.4	80.4
Bihar	81.4	5.60	10707	4.6	105.5	51.3	69.6
Chandigarh	780.1	4.58	28696	3.4	69.9	101.8	60.3
Chhattisgarh	118.5	3.97	11476	4.4	101.8	32.9	61.1
Delhi	274.8	4.80	32532	5.0	115.8	75.6	63.9
Goa	375.1	2.66	25552	3.8	87.8	0.8	77.5
Gujarat	281.5	4.62	12178	4.5	122.8	18.6	58.0
Haryana	311.2	5.47	26087	4.1	106.6	82.2	61.0
Himachal Pradesh	218.1	3.50	19761	4.1	28.5	136.5	65.5
Jammu & Kashmir	234.1	2.72	22434	4.4	15.3	215.0	64.6
Jharkhand	99.1	4.90	11080	4.2	101.6	43.7	67.9
Karnataka	85.9	5.11	12736	3.6	66.5	8.7	65.8
Kerala	173.3	5.78	15696	3.7	64.4	3.4	80.6
Madhya Pradesh	116.0	6.25	13104	4.2	100.9	44.9	57.8
Maharashtra	132.2	6.72	18052	4.2	94.4	13.4	61.3
Meghalaya	141.5	4.53	23898	5.4	43.9	64.5	84.1
Odisha	103.0	3.94	10563	3.7	108.1	21.4	72.4
Puducherry	202.9	2.27	15868	3.8	166.8	0.0	75.2
Punjab	337.6	7.06	22260	3.5	84.1	105.8	66.2
Rajasthan	203.6	7.41	15836	4.1	118.5	57.7	53.5
Sikkim	143.2	2.66	19087	4.3	39.7	75.0	81.5
Tamil Nadu	229.8	3.80	14273	3.6	133.1	0.9	67.9
Telangana	117.6	3.72	12631	3.1	123.4	6.7	60.7
Tripura	108.8	5.44	12628	3.6	46.1	60.9	80.3
Uttar Pradesh	161.2	4.96	14826	4.6	108.0	69.4	65.4
Uttarakhand	316.7	4.15	20351	3.5	39.4	117.2	69.6
West Bengal	111.9	5.87	11253	4.1	99.7	37.7	75.8

Table B12: State-wise Summary Statistics: Appliance Ownership

State	Ref. owned (%)	AC owned (%)	Cooler owned (%)	WM owned (%)	TV owned (%)	Computer owned (%)
Andhra Pradesh	61.0	5.1	36.4	11.6	99.6	1.7
Assam	44.7	2.4	2.0	12.2	86.1	16.8
Bihar	25.4	2.6	17.1	11.3	82.9	4.9
Chandigarh	99.7	65.0	98.0	94.2	100.0	51.1
Chhattisgarh	37.9	6.1	84.6	11.8	97.3	6.4
Delhi	95.8	38.3	93.1	85.0	99.7	29.1
Goa	94.7	18.8	4.0	71.7	99.6	37.7
Gujarat	70.0	4.1	4.4	5.6	96.6	3.5
Haryana	95.6	34.7	95.4	83.9	98.8	25.5
Himachal Pradesh	90.5	0.7	7.8	75.0	99.8	12.3
Jammu & Kashmir	88.0	18.1	54.5	76.7	97.9	14.3
Jharkhand	37.4	3.9	23.1	15.0	96.0	6.1
Karnataka	59.8	1.3	10.7	23.3	99.3	4.5
Kerala	88.5	4.6	4.7	45.3	99.6	19.0
Madhya Pradesh	52.3	6.2	83.3	19.9	96.6	8.0
Maharashtra	71.7	10.2	60.7	25.5	98.2	13.5
Meghalaya	21.5	0.1	0.1	5.7	76.7	15.2
Odisha	47.3	8.7	31.8	19.4	93.5	5.1
Puducherry	87.5	20.7	3.7	38.0	99.9	9.5
Punjab	99.5	39.7	89.8	87.2	99.9	23.9
Rajasthan	86.6	10.7	92.9	39.0	98.6	9.8
Sikkim	27.0	0.0	0.0	12.3	92.7	1.4
Tamil Nadu	69.8	14.6	3.5	38.3	99.8	15.7
Telangana	62.6	4.3	76.1	15.4	99.7	5.2
Tripura	41.8	1.0	0.6	1.2	93.1	5.7
Uttar Pradesh	66.8	10.4	72.3	38.0	95.0	9.9
Uttarakhand	87.3	24.0	85.3	74.4	99.6	24.2
West Bengal	37.0	5.6	1.1	7.5	87.0	11.0

C Results

This section presents additional results from the empirical analysis. It reports appliance-specific electricity consumption estimates across income quartiles and between rural and urban households, results from the annual log-log specification, and diagnostics for the validity of the instrumental variable.

Table C13: Appliance-Specific Electricity Consumption by Income Quartile (kWh/month)

Appliance	Q1 (Lowest)	Q2	Q3	Q4 (Highest)
Refrigerator	33.6***	30.2***	34.8***	47.9***
	(0.33)	(0.30)	(0.39)	(0.69)
Air Conditioner	—	—	47.0***	91.3***
			(1.03)	(1.34)
Evaporative Cooler	8.4***	10.8***	9.3***	5.6***
	(0.29)	(0.29)	(0.38)	(0.81)
Washing Machine	46.7***	29.2***	39.9***	52.1***
	(0.91)	(0.50)	(0.51)	(0.71)
Computer	—	—	−0.4	11.9***
			(0.86)	(1.07)
Constant	92.0***	102.0***	112.8***	114.6***
	(0.18)	(0.20)	(0.30)	(0.73)
Mean Consumption	110.1	128.2	159.2	225.2
Observations	1,320,715	1,323,614	1,322,716	1,316,085

Notes: (i) Appliance dummy coefficients are from IV-2SLS, estimated separately by income quartile. Coefficients represent estimated average monthly electricity consumption (kWh) associated with each appliance, evaluated at subgroup-specific owner means. (ii) Mean Consumption average monthly electricity consumption (kWh) within each income quartile. (iii) Air conditioner and computer are omitted from Q1 and Q2 specification due to insufficient ownership variation to satisfy the well-mixed sample condition required for CDA identification (see Table B9). (iv) Standard errors clustered at the household level are reported in parentheses. (v) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.
Source: Estimated using CPHS (CMIE), CEA tariff data, and IMD gridded temperature data, 2015–2019.

Table C14: Appliance-Specific Electricity Consumption: Rural versus Urban (kWh/month)

	Rural		Urban	
Appliance	Estimate	SE	Estimate	SE
Refrigerator	40.8***	(0.46)	29.0***	(0.42)
Air Conditioner	—		75.6***	(1.45)
Evaporative Cooler	2.835***	(0.49)	17.08***	(0.54)
Washing Machine	63.7***	(1.04)	40.1***	(0.85)
Computer	—		7.3***	(1.09)
Constant	96.3***	(0.26)	115.9***	(0.53)
Mean Consumption	124.3		170.8	
Observations	1,702,378		3,580,787	

Notes: (i) Appliance dummy coefficients are from IV-2SLS, estimated separately for rural and urban subsamples. Coefficients represent estimated average monthly electricity consumption (kWh) associated with each appliance, evaluated at subgroup-specific means of all covariates. (ii) Mean Consumption reports the average monthly electricity consumption (kWh) within each region type. (iii)Air conditioner and computer are omitted from rural specification due to insufficient ownership variation to satisfy the well-mixed sample condition required for CDA identification (see Table B10). (iii) Rural and urban subgroup deviations for price, virtual income, and household size are computed separately within each region type. (iv) We use the same climate deviation variables as in the full-sample analysis because CDD and relative humidity do not vary between rural and urban households within a district. (v) The instrument is constructed separately for rural and urban subsamples. (vi) Standard errors clustered at the household level are reported in parentheses. (vii) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.
Source: Estimated using CPHS (CMIE), CEA tariff data, and IMD gridded temperature data, 2015–2019.

Table C15: Short-Run and Long-Run Elasticities from Dynamic IV-2SLS Estimates

	Short Run		Long Run	
Elasticity	Estimate	SE	Estimate	SE
Price Elasticity	−0.18***	(0.003)	−0.27***	(0.004)
Income Elasticity	0.43***	(0.001)	0.65***	(0.002)

Notes: Price and income elasticities are estimated from a dynamic IV-2SLS specification of residential electricity demand in log-log form. Short-run elasticities are obtained from the estimated coefficients, while long-run elasticities are derived from the short-run coefficients using the estimated partial-adjustment coefficient. Standard errors clustered at the household level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.
Source: Estimated using CPHS (CMIE), CEA tariff data, and IMD gridded temperature data, 2015–2019.

Table C16: OLS versus IV-2SLS Estimates: Appliance-Interacted Specification

	OLS		IV-2SLS	
Variable	Coefficient	SE	Coefficient	SE
Panel A: Price and Income				
Marginal price deviation	-11.7^{***}	(0.18)	-14.5^{***}	(0.23)
AC × price deviation	21.5^{***}	(0.73)	8.6^{***}	(0.77)
Cooler × price deviation	25.5^{***}	(0.30)	22.2^{***}	(0.34)
Washing machine × price deviation	8.4^{***}	(0.33)	2.1^{***}	(0.36)
Computer × price deviation	-17.5^{***}	(0.66)	-21.8^{***}	(0.67)
Virtual income	0.0014^{***}	(0.00006)	0.0014^{***}	(0.00007)
Household size	2.1^{***}	(0.08)	2.5^{***}	(0.08)
CDD (base 24°C)	0.2^{***}	(0.01)	0.2^{***}	(0.01)
Relative humidity	0.8^{***}	(0.02)	0.9^{***}	(0.02)
Panel B: Appliance Ownership Effects (kWh/month)				
Refrigerator	36.1^{***}	(0.31)	36.2^{***}	(0.32)
Air conditioner	74.0^{***}	(1.17)	74.9^{***}	(1.20)
Evaporative cooler	8.1^{***}	(0.44)	9.4^{***}	(0.43)
Washing machine	45.3^{***}	(0.55)	44.6^{***}	(0.55)
Computer	9.5^{***}	(0.92)	13.1^{***}	(0.93)
Constant	106.1^{***}	(0.32)	105.4^{***}	(0.33)
Observations	5,283,004		5,283,004	
R^2	0.328		0.317	

Notes: The dependent variable is monthly household electricity consumption (kWh). Marginal price and appliance × price deviation terms enter as deviations from owner-subgroup means. Standard errors clustered at the household level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C17: Instrument Relevance: Shea Partial R^2 for Endogenous Regressors

Endogenous variable	Shea Partial R^2
Marginal price deviation	0.760
AC × price deviation	0.851
Cooler × price deviation	0.777
Washing machine × price deviation	0.823
Computer × price deviation	0.846
Observations	5,283,004
Household clusters	184,051

Notes: Shea partial R^2 statistics for each endogenous regressor in the appliance-interacted IV-2SLS specification, computed to account for collinearity among the instrumented regressors. See Table C16 for the corresponding second-stage estimates and Table C18 for the joint test of endogeneity.

Table C18: Endogeneity Test: OLS versus IV-2SLS

Diagnostic	Result
Joint endogeneity test, $F(5, 184{,}050)$	4,358.1
p-value	< 0.001
Observations	5,283,004
Household clusters	184,051

Notes: Joint test of the null hypothesis that OLS and IV-2SLS estimates are statistically indistinguishable for the five potentially endogenous regressors (marginal price deviation and its four appliance interactions). Rejection of the null indicates that IV estimation is required. See Table C16 for coefficient estimates and Table C17 for instrument relevance diagnostics.

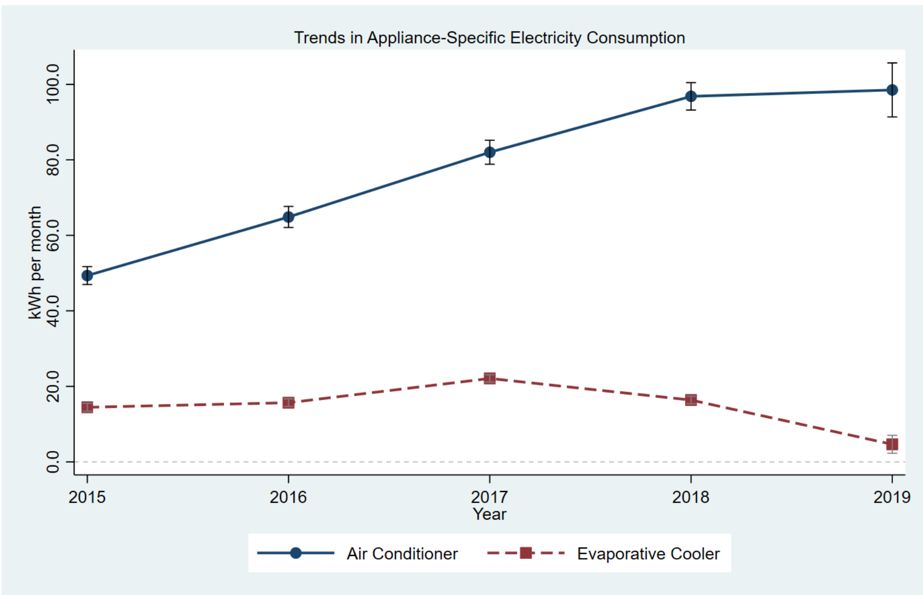

Figure C1. Coefficient plot for trend in electricity consumption associated with the AC and cooler from 2015 to 2019, from the conditional demand analysis