DOI: 10.71317/jgst.2.9(s).2026.657

Journal of Global Social Transformation

Journal homepage: https://rjsaonline.org/index.php/JGST

Do Electricity Tariffs Change Household Consumption? Evidence from Block and Peak-Hour Pricing in a Developing Country

Muhammad Jaffar[1], Farhatullah[2], Khalid Khan[3]

[1] Balochistan University of Information Technology, Engineering and Management Sciences, Pakistan.
Email: **mohammad.jaffar@buitms.edu.pk**

[2] Balochistan University of Information Technology, Engineering and Management Sciences, Pakistan.
Email: **farhat.ullah@buitms.edu.pk**

[3] Applied Economics Research Centre, University of Karachi.

ARTICLE INFO

Submission:
August 02, 2026
Revised:
August 18, 2026
Accepted:
September 06, 2026
Available Online:
September 22, 2026

Keywords:
Household Electricity Consumption; Electricity Tariffs; Block Pricing; Peak Hour Pricing; Time-of-Use Tariffs; Peak Hour Duration; Demand Side Management; Ordered Logit

Corresponding author:
Muhammad Jaffar
Email:
mohammad.jaffar@buitms.edu.pk

ABSTRACT

Electricity tariff reform is increasingly used as a demand-side management instrument in developing economies facing rising electricity demand, supply constraints, fiscal pressures, and dependence on imported fuels. However, the effectiveness of price-based interventions remains debated, as residential electricity is a necessity and household demand is likely relatively inelastic to price increases. This study investigates the impact of electricity tariffs on household electricity consumption in Quetta, Pakistan. It identifies three components of the residential tariff structure: electricity block tariffs, peak-hour price tariffs, and peak-hour duration tariffs. This research collected primary data through systematic random sampling of households, obtaining 497 usable responses from 515 target households for analysis. Monthly electricity consumption data were categorized into eight ordered classes from 1-100 units to >700 units, consistent with the consumption blocks in the local electricity-pricing system. An ordered-logit model, marginal effects, and predicted-probability analyses were used for results analysis. Results show that all three tariff dimensions are strongly related to the shift to lower electricity-consumption categories. Block tariffs drive the largest change: a one-unit increase in the block tariff variable raises the probability of being in the 1-100 and 101-200 block categories by 5.70 and 6.84 percentage points, respectively. It lowers the probability of consumption above 700 units by 3.53 percentage points. This research finds similar patterns for peak-hour price and peak-hour duration, but peak-hour duration changes probabilities more than peak-hour price for several categories. The findings show that the electricity price level is not the only factor that determines electricity demand management, but also the tariff structure, such as progressive blocks, time-of-use price differentials, and duration of peak periods. The evidence is relevant for regulators trying to balance demand reduction and household affordability in energy-constrained developing economies.

Introduction

Electricity consumption and savings remain a core concern for developing economies dependent on imported fuels. According to the latest research by Ahmad et al. (2025) and Manoharan et al. (2026), Electricity tariff reform, as a demand-side management tool, helps these economies address rising electricity demand, supply constraints, fiscal pressures, and dependence on imported fuels. Electricity pricing is among the main economic tools that can influence household demand. Tariff reform, unlike many behavioral interventions, can be implemented directly through the regulatory system and can provide a financial incentive for consumers to reconsider both the volume and timing of electricity consumption (Fraija et al., 2022; Lanot & Vesterberg, 2021;

Weidenbörner et al., 2025). Therefore, electricity tariffs are considered an important instrument for encouraging conservation and controlling residential demand (Albatayneh et al., 2022; Lin & Lan, 2023; Lin & Wang, 2020; Sun & Lin, 2013).

However, the efficacy of tariff interventions remains debatable. According to the latest literature, electricity is not a purely discretionary consumer good but a necessity; as such, households cannot simply reduce consumption in response to price increases. Avoiding certain electricity services such as refrigeration, lighting, cooling, and heating is difficult. Hence, demand for residential electricity may be relatively inelastic to price. Thus, existing studies provide mixed evidence on how much tariff hikes reduce household consumption. Evidence on the effectiveness of tariff mechanisms with inelastic responses is mixed, with important heterogeneity across household groups (Balarama et al., 2020; Klug et al., 2022; Lanot & Vesterberg, 2021; Lin & Wang, 2020).

Using household panel data from Bangladesh, Balarama et al. (2020) identify substantial heterogeneity in residential electricity-demand elasticities. Their results show that households do not respond uniformly to changes in electricity prices. Similarly, Lanot and Vesterberg (2021) estimate electricity-demand elasticity and find smaller responses to marginal price incentives than expected. Their findings support the proposition that pricing policy effectiveness cannot be taken for granted.

The problem is more complicated when electricity pricing is nonlinear. The price per unit consumed can differ across households. Instead, electricity can be priced based on total consumption, time of use, or periods of especially high system demand. Block tariffs, time-of-use pricing, and critical peak pricing thus provide different types of financial incentives to consumers (Freier & von Loessl, 2022; Kiguchi et al., 2021; Lin & Lan, 2023). Block tariffs split monthly consumption into successive blocks and apply different rates to each block. In such a framework, the marginal financial burden of consumption may increase as households move to higher electricity consumption categories. Time-of-use tariffs differ because they charge different prices depending on when you use electricity. Peak-hour tariffs therefore incentivize households to reduce or shift consumption during periods of high system demand. A third, less frequently isolated dimension is the length of the peak-price period. Even if the price remains the same, extending the period during which the peak-hour price applies can increase the household's exposure to the tariff signal.

These distinctions are essential to the electricity-pricing system under study. In Pakistan, the residential tariff structure includes three types of tariffs: block pricing, peak-hour price differentiation, and peak-hour duration. Block pricing uses different rates for different levels of electricity consumption, peak-hour tariffs identify the cost at different times of use, and peak-hour duration defines the period during which the higher tariff applies (Ali & Shafiq, 2021; NEPRA, 2023). Pakistan-specific literature also identifies key institutional and consumer barriers to demand-side management, such as inadequate policy and financial infrastructure, weak institutional commitment, and limited consumer motivation (Ali & Shafiq, 2021).

This is an increasingly important problem with tariff reform. The residential tariff structure was completely revamped in 2023. The block tariff for 1- 100 units for households increased to PKR 20.85 from PKR 13.48, while the tariff for 101- 200 units increased to PKR 27.32 from PKR 18.95. The 201–300 unit rate rose from PKR 22.14 to PKR 31.51, and the 301–400 unit rate rose from PKR 25.53 to PKR 38.41. Similar increases were seen in 401–500, 501–600, 601–700, and above-700 unit categories (NEPRA, 2023). At the same time, peak-hour pricing emerged. The peak-period rate has been increased from PKR 34.39 to PKR 48.27, a reported increase of 40.36%. The off-peak tariff rose from PKR 28.07 to PKR 41.95. The peak-hour tariff duration was also extended. In 2022, peak charges ran from 6:00 PM to 10:00 PM, a four-hour window. In 2023, the window was extended to 5:00 PM-11:00 PM, which increased the peak-hour duration to six hours, a reported increase of 50% (NEPRA, 2023). These changes provide a useful empirical setting because households face three types of price pressures simultaneously. Higher block tariffs make consuming larger quantities of electricity more expensive. Electricity costs increase in peak hours. Longer peak hours increase the number of hours when consumers face that higher cost.

International research to date indicates that such mechanisms may influence electricity consumption, but the effects are far from uniform. Increasing-block pricing has been discussed as a conservation instrument in residential markets (Jaffar et al., 2024; Jaffar & Latiff, 2024; Jia et al., 2018; Lin & Lan, 2023; Sun & Lin, 2013). Researchers have investigated mechanisms to shift or reduce peak demand, such as time-of-use and dynamic tariffs (Freier & von Loessl, 2022; Kiguchi et al., 2021; Wesseh & Dogah, 2022). In contrast, research on tariff reform and elasticity suggests that household responses may be small or heterogeneous, and that distributional consequences should be taken seriously (Balarama et al., 2020; Klug et al., 2022; Lanot & Vesterberg, 2021).

Because opinions diverge in the literature, researchers should measure household responses to tariff changes rather than assume them. This is especially relevant in developing economies, where constraints on income, appliance ownership, building quality, electricity reliability, and consumer understanding of tariff structures may differ from conditions in developed electricity markets.

Another gap is the need to disaggregate tariff components. The consumption effects of electricity tariffs can vary by pricing structure (block pricing, peak-hour pricing, and peak-duration arrangements), which a single aggregate variable might mask. A household may be very responsive to movements between blocks of consumption but quite unable to move electricity use at peak hours. In contrast, a longer peak window may be a better incentive than a higher peak price (Fischer, 2008).

This paper tackles this issue by disentangling the relationship between these three tariff dimensions and monthly household electricity consumption. It therefore focuses on block tariffs, peak-hour price tariffs, peak-hour duration tariffs, and electricity-consumption categories.

This study addresses the following research question: What is the impact of electricity block tariffs, peak-hour price tariffs, and peak-hour duration tariffs on household electricity consumption patterns in Quetta, Pakistan? Hence, the main research objective is to investigate the impacts of electricity block tariffs, peak-hour price tariffs, and peak-hour duration tariffs on household electricity consumption categories in Quetta, Pakistan. The study has three main contributions. First, it distinguishes among several features of electricity-tariff architecture, rather than treating residential electricity prices as a single homogeneous factor. Second, it analyses electricity consumption in eight ordered categories, or consumption blocks, used in the local tariff system. Third, it uses marginal effects and predicted probabilities to show how tariff variables redistribute the probability of households belonging to low-, moderate-, and high-consumption categories.

These contributions are both academically and practically relevant. Academically, the study extends tariff response research to an urban developing country context with nonlinear pricing and energy constraints (Lanot & Vesterberg, 2021; Wang et al., 2022). In practice, it provides evidence to inform regulatory decisions on how tariff structures can be designed to reduce excessive electricity consumption while acknowledging affordability challenges for households.

Review of literature

Studies of residential electricity pricing have consistently found that household responses are not homogeneous. Andruszkiewicz et al. (2020) find seasonal variation in electricity-price elasticity for households with zonal tariffs in Poland. Their findings show that responsiveness varies over time and emphasize the need to use contemporaneous, context-relevant information when assessing tariff effects. Similarly, Balarama et al. (2020) find heterogeneous price elasticities among households in Bangladesh. These results suggest that differences in household resources, appliance ownership, lifestyle, and essential electricity needs can affect how much prices affect consumption. Lanot and Vesterberg (2021) find relatively low price elasticities, meaning households respond little to marginal incentives. This contrasts with research showing stronger demand-management effects from tariffs and points to the need for more context-specific evidence. Klug et al. (2022) review electricity tariff reform in Africa and show that tariff changes have economic and social consequences beyond simple consumption effects. The study is particularly relevant to developing countries, where regulators must balance efficiency, financial sustainability, and affordability. Govaerts et al. (2023) also examine the welfare effects of electricity tariff structures, while Maestri and Andrade (2022) examine tariff compensation in distributed electricity generation. In sum, these studies underscore that tariff design is a multidimensional policy problem.

The literature relevant to specific forms of electricity tariffs covers a range of research. Block tariffs may be used for various policy purposes. Lower blocks provide relatively cheap electricity for basic household needs, while higher blocks add cost for excessive use. Such a structure would, in principle, encourage greater conservation by households in higher usage ranges. Sun and Lin (2013) study residential electricity-tariff reform using a block-pricing approach and contribute meaningfully to the literature on progressive electricity prices. Then Lin and Lan (2023) analyze the implementation of increasing-block pricing and policy perceptions of residents, reinforcing the continuing relevance of this tariff instrument. This research considers a tariff system with eight electricity-consumption blocks. As a result, monthly consumption and electricity prices are strongly correlated. As a household uses more units and moves up the categories, it becomes increasingly exposed to the price structure. The 2023 revisions substantially increased prices in these blocks. The country is an ideal place to examine the degree to which stronger tariff signals are associated with movement toward lower consumption categories. In theory, we would expect that the greater the sensitivity to block pricing, the higher the probability that households remain in the lower consumption ranges and the lower the probability that they are in very high consumption groups.

Secondly, Time-of-use pricing provides another mechanism. Instead of linking price only to the amount consumed, it differentiates prices by the time of consumption. Electricity demand varies significantly over the course of a day. Operational and infrastructure pressures can increase on electricity systems during periods of high demand. Peak-hour pricing aims to reduce this pressure by charging consumers more during high-demand periods. Kiguchi et al. (2021) study household outcomes under time-of-use tariffs using smart-meter data. Their work shows that tariff reforms can have heterogeneous effects on consumers, and calls for the analysis of heterogeneous responses. Freier and von Loessl (2022) focus on designing dynamic electricity tariffs for private households. They emphasize that tariff architecture must be carefully designed to generate useful demand responses without creating unreasonable consequences for consumers. Wesseh and Dogah (2022) also analyze dynamic tariffs and their economic welfare implications in the retail electricity markets. Their analysis shows that tariff design interacts with broader policy goals and should not be evaluated solely on revenue generation. The main behavioral principle behind peak-hour pricing is that consumers can either reduce their electricity consumption or shift flexible consumption to off-peak times. For example, some appliances can be run later in the evening or at a different time of day (Chung et al., 2022; Gorman et al., 2025; Weidenbörner et al., 2025). Other uses of electricity, however, are harder to shift, especially when they involve cooling or heating in extreme weather conditions. This is especially relevant for Quetta, where climatic conditions may drive time-sensitive electricity demand. Thus, consumers may have economic reasons to change consumption but limited capacity to avoid some peak-period electricity use.

Third, the latest research considers peak-hour duration separately. While peak prices are more explicitly addressed, peak-hour duration is also an important part of time-of-use tariff design. A peak-time tariff is defined by at least two related parameters: the price differential and the period of time to which the differential applies. Applying the tariff for four hours and six hours, respectively, could therefore generate the same peak price for two electricity systems but very different household incentives. The longer the peak persists, the longer households face higher prices. It also limits how many off-peak hours are available nearby when consumers can conveniently shift electricity use. This is further underscored by the reported tariff changes for Pakistan. The peak window was extended from four hours to six hours, from 6:00 PM–10:00 PM to 5:00 PM–11:00 PM (NEPRA, 2023). This is a 50% increase in the length of time that the price is higher. Thus, this study considers peak-hour duration separately from the assumption that peak-hour price captures the full effect of time-differentiated tariffs.

The literature under review establishes two important facts. First, electricity prices can influence household demand, but the size of the response varies considerably across contexts and consumer groups. Second, electricity tariff design involves various mechanisms that do not need to be aggregated into a single price variable (Albatayneh et al., 2022; Nelson et al., 2018; Sun & Lin, 2013). Despite considerable international research, relatively little household-level evidence exists on the simultaneous operation of block tariffs, peak-hour prices, and peak-hour duration in energy-constrained urban settings in developing countries. The country context is also particularly policy relevant, as recent tariff reforms altered all three components. This leaves us with one key question unanswered given the evidence we have: Are these tariff mechanisms associated with meaningful changes in the likelihood that households move into lower or higher electricity consumption categories? This paper fills that gap by using an ordered-response approach that directly models households over the eight consumption categories used in the electricity-pricing system.

Theoretical Background

The theoretical background is based on two economic theories: the law of demand and price discrimination theory. The analysis is grounded in the economic principle of an inverse relationship between price and quantity demanded. Ceteris paribus, an increase in a commodity's price generally motivates consumers to decrease the quantity demanded (Evans, 1967). In particular, for residential electricity, the theory implies that households facing higher electricity costs should reduce consumption whenever possible. However, the strength of the relationship depends on the elasticity of electricity demand (Clements, 2019). The source material explicitly identifies electricity for household use as a good with relatively inelastic price elasticity. This implies that higher tariffs may reduce consumption, but not in proportion, since households still require basic electricity services. Hence, the theoretical expectation is not that higher tariffs eliminate electricity consumption. Rather, they should increase the likelihood that households reduce discretionary consumption and avoid higher consumption categories.

Price discrimination theory offers another basis for analyzing non-linear electricity tariffs. Consumers in a tariff system are not paying a uniform price for electricity. Rates vary according to consumption blocks and time of use. The regulatory authority charges different prices for different consumption levels and peak hours. This leads to a nonlinear pricing environment. Block pricing is discrimination on the quantity of consumption. Time-of-use pricing discriminates by time of consumption, where the same electricity service has different prices depending on when it is consumed. From this perspective, electricity-price discrimination can have a demand-management function (Ding & Zhang, 2021; Simshauser & Whish-Wilson, 2017). The tariff structure is designed to encourage consumers to change their behavior by making high monthly consumption or peak-period use more expensive.

The theoretical framework thus predicts three hypotheses:

H1: Stronger signals of electricity block-tariff are correlated with lower household electricity-consumption categories.

H2: Household electricity consumption in higher categories is associated with weaker peak-hour price signals.

H3: Stronger peak-hour duration signals for lower household electricity-consuming categories.

Methodology

The study used a quantitative cross-sectional household-survey design. The target population is households in District Quetta, Pakistan. The study used a systematic random-sampling procedure to select households. Systematic sampling is a structured method of selecting observations at regular intervals after identifying a random starting point (Atinafu et al., 2023). The source's sampling procedure aligns with established guidance on probability sampling and survey research (Malhotra et al., 2017; Sekaran & Bougie, 2016). The sampling frame comprised 218,662 households in Quetta District. Cochran's sampling procedure exhibited a minimum requirement of 385 households (Cochran, 1977). To improve reliability and account for possible non-response, the study selected 515 households. The systematic sampling interval was calculated by dividing the household population by the target sample, which resulted in an interval of about 425. The researchers chose a random starting point and visited every 425th household. In the end, they obtained 497 complete and usable responses. The data collection took place from January to March 2024.

The dependent variable is the monthly household electricity consumption. Instead of a continuous measure, we categorize electricity consumption into eight ordered groups, which correspond to the tariff slabs used by the electricity provider:

Table 1 Electricity price block tariffs

Tariff Blocks (Electric unit: KW/h)	Year 2022 (Price in PKR)	Year 2023 (Price in PKR)	Percent Change
001-100 Units	13.48	20.85	54.67
101-200 Units	18.95	27.32	44.17
201-300 Units	22.14	31.51	42.32
301-400 Units	25.53	38.41	50.45
401-500 Units	27.74	41.62	50.04
501-600 Units	29.16	43.04	47.60
601-700 Units	30.3	44.18	45.81
Above 700 Units	35.22	49.1	39.41

Source: National Electric Power Regulatory Authority. (NEPRA, 2023)

The categories provide a natural ordering from very low to very high electricity consumption. According to the source, the thresholds align with QESCO electricity billing slabs and were not created arbitrarily for statistical analysis. This study used ordered logit regression to measure the effects of all three electricity tariff types on household electricity consumption. Equation 1 below provides the ordered logit regression estimation.

Equation 1 Ordered logit regression

$$\mathbf{Pr}\ (Y_i > J)Y_i^* = \frac{exp\ (aj+XiBj)}{1+[exp\ (aj+XiBj)]}$$

Where J = 0-7

$Y_i^* = x_i'\beta + e_i$

$$Y_i^* = \beta_0 + \beta_1 PBT + \beta_2 PHT + \beta_3 PDT + \beta_4 HHSize + \beta_5 HHIncome + \varepsilon_i$$

$e_i \sim (0,1)$, i = 1,2,……., N

The eight categories for the dependent variable (electricity consumption) were defined based on the electricity billing slabs used by the local electricity distribution company (QESCO). Where $E(e_i/x_i) = 0$ and $Var(e_i/x_i) = 1$. The observable variable, Y_i, is treated as an ordinal variable with J number of response categories and as a representation of the theoretical random variable, $Y_i^* = J$, and $\mu = \mu{-1}\, \mu_0\, \mu_1 \ldots \mu_J$ defined as a vector of unobservable threshold parameters, with the relation between the observable and the latent variable expressed as; $Y_i = J$ if $\mu_J - 1 < Y_i^* \leq \mu_J$, J = 0, 1, 2, ..., J Where $\mu{-1} = -\infty$, $\mu 0 = 0$, $\mu J = \infty$ and $\mu{-1} < \mu 0 < \mu 1 < \cdots < \mu_J$. The probability can be written as: $Prob[Y_i = J] = Prob[\mu j{-1} < Y_i^* \leq \mu_J] = Prob[\mu_J{-1} - x_i'\beta < e_i \leq \mu_J - x_i'\beta]$ which can be written as $\Phi(\mu_J - x_i'\beta) - \Phi(\mu_{J-1} - x_i'\beta)$. Where J is the categories of responses to electricity consumption and $\Phi(\bullet)$ is the standard normal cumulative distribution function = $\frac{\partial Prob[Demand\ J]}{\partial x_i}[\phi(\mu_{J-1} - x_i'\beta) - \phi(\mu_J - x_i'\beta)]$ x Where $\phi(\bullet)$ is the standard normal density function. However, ordered-logit coefficients alone do not tell us how to interpret a variable's effect on the probability of being in each category. The study therefore computes marginal effects and predicted probabilities. Marginal effects show how the probability of membership in each consumption category changes with a change in an explanatory variable. Predicted probabilities offer a complementary representation by estimating the distribution of households across consumption levels at different tariff values.

The model fitness statistics were checked using the test of parallel lines, VIF values, and Goodness-of-Fit statistics. Multicollinearity was evaluated using variance inflation factors. The VIF values reported range from 1.829 to 4.200, with an average VIF of 2.764. The authors conclude that multicollinearity is not serious enough to endanger the model estimates. The pseudo-R^2 of the ordered-logit model is 0.2288. Fitting the model yielded a chi-square of 2179.08, df = 6, p <.001. The parallel-lines test produces chi^2=36.776 (p=.432), and the Brant test produces chi^2=29.71(p=.481). Both proportional-odds tests are nonsignificant, so their numerical results do not provide evidence against the proportional-odds assumption.

Results

The final sample is 497 households. All eight categories receive a monthly electricity consumption allocation. 7.9% of households (79 households) consume 1-100 units per month. Seventy-seven (15.5%) households consume 101-200 units, and 109 (21.9%) households consume 201-300 units. Ninety-four households (18.9%) use between 301 and 400 units, and 78 households (15.7%) use 401–500 units. Twenty-eight households (5.6%) use 501–600 units, 40 households (8.0%) use 601–700 units, and 32 households (6.4%) use above 700 units. Thus, more than half of the sample is in the 201–500 unit range, and extremely high consumption is limited to a smaller proportion of households. The block-tariff measure has a mean of 3.69 and a standard deviation of 1.16. Peak-hour price has a mean of 3.78 and a standard deviation of 1.16. Peak-hour duration has a mean of 3.76 and a standard deviation of 1.23. The average family size is 5.81 persons.

Marginal effects

The marginal-effects results show a clear redistribution of consumption probabilities as tariff variables increase. Table 2 presents the marginal-effects results.

Table 2 ***Marginal Effects of Electricity Tariffs and Household Characteristics on Monthly Electricity Consumption Categories***

Variable	1–100 Units	101–200 Units	201–300 Units	301–400 Units	401–500 Units	501–600 Units	601–700 Units	Above 700 Units
Electricity Block	.0570	.0684	.0166	−.0458	−.0470	−.0044	−.0093	−.0353

Tariff								
Electricity Peak-Hour Price Tariff	.0339	.0407	.0098	−.0272	−.0280	−.00264	−.0055	−.0210
Electricity Peak-Hour Duration Tariff	.0476	.0572	.0139	−.0383	−.0393	−.0037	−.0078	−.0295
Household Size	−.0070	−.00847	−.0020	.0056	.0058	.0005	.0011	.0043
Household Income								
Average Income	.0097	.0113	.0023	−.0079	−.0076	−.0006	−.0014	−.0058
High Income	−.0371	−.0573	−.0339	.0296	.0514	.0073	.0049	.0349

Note. $p < .10$. $p < .05$. $p < .01$.

Block tariffs have the largest marginal effects among three pricing mechanisms. A one-unit increase in the block-tariff measure increases the probability of a household falling in the 1–100 unit category by 5.70 percentage points. The largest positive change is 6.84 percentage points for the 101- 200-unit group. The probability of being in the 201- 300-unit category rises by a more modest 1.66 percentage points. Above this level, all marginal effects are negative. The probability of consuming 301–400 units falls by 4.58 percentage points, and the probability of consuming 401–500 units falls by 4.70 percentage points. For the households with the highest level of consumption (>700 units), the estimated probability decreases by 3.53 percentage points. Overall, the pattern is consistent with the hypothesis that the stronger the block-tariff signal, the stronger the redistribution away from higher electricity use and toward lower consumption categories.

Peak-hour prices show the same directional pattern, but with smaller changes. An increase in the peak-hour price variable increases the probability of consuming between 1 and 100 units by 3.39 percentage points and between 101 and 200 units by 4.07 percentage points. The probability of consuming 201-300 units rises by around 0.98 percentage points. For higher consumption, the effect is negative. The chance of being in the 301-400 category drops by 2.72 percentage points, and the 401-500 category drops by 2.80 percentage points. 2.10 percentage-point increase reduces the probability of consumption above 700 units. These results imply that households that respond to peak pricing tend to be in the lower categories of monthly electricity consumption.

The peak-hour duration variable produces larger effects than the peak-hour price variable in several categories. The probability of consuming 1-100 units increases by 4.76 percentage points and the probability of consuming 101-200 units increases by 5.72 percentage points. The increase for the 201-300 unit group is 1.39 percentage points. The effect is reversed in higher categories. The probability of consuming 301–400 units decreases by 3.83 percentage points, and the probability of consuming 401–500 units decreases by 3.93 percentage points. The probability of being in the above-700 unit category decreases by 2.95 percentage points. The results show that peak-period length has an independent impact on peak-hour price.

Predicted probabilities

Predicted probabilities provide additional support for movement across the consumption distribution. Table 3 provides details of predicted probabilities.

Table 3 ***Predicted Probabilities of Monthly Electricity Consumption Categories***

Predictor and	1–100	101–200	201–300	301–400	401–500	501–600	601–700	Above 700

Level	Units	Units	Units	Units	Units	Units	Units	Units
Electricity Block Tariff								
1	.0046	.0151	.0532	.1431	.3473	.1562	.1653	.1152
2	.0255	.0726	.1784	.2500	.2737	.0883	.0798	.0316
3	.1228	.2143	.2554	.1860	.1526	.0388	.0238	.0064
Electricity Peak-Hour Price Tariff								
1	.0143	.0432	.1232	.2186	.2987	.0995	.1121	.0902
2	.0385	.0994	.2038	.2337	.2221	.0740	.0830	.0450
3	.0971	.1832	.2431	.1883	.1600	.0568	.0518	.0192
Electricity Peak-Hour Duration Tariff								
1	.0067	.0217	.0727	.1734	.3441	.1365	.1450	.0994
2	.0280	.0782	.1844	.2468	.2616	.0858	.0810	.0337
3	.1049	.1959	.2533	.1933	.1646	.0469	.0317	.0091
Household Size								
1	.0970	.1769	.2292	.1744	.1379	.0546	.0775	.0520
2	.0738	.1517	.2257	.1922	.1540	.0558	.0819	.0645
3	.0555	.1265	.2154	.2073	.1735	.0580	.0850	.0784
Family Income								
1	.0745	.1525	.2266	.1914	.1511	.0544	.0809	.0682
2	.0843	.1639	.2289	.1834	.1435	.0538	.0794	.0624
3	.0374	.0952	.1926	.2210	.2026	.0618	.0859	.1031

Note. $p < .10$. $p < .05$. $p < .01$.

The predicted probability of consuming only 1-100 units for the lowest block-tariff level is 0.46%, and the probability of consuming 401-500 units is 34.73%. The probability of consumption above 700 units is 11.52%. At the highest block-tariff level, the predicted distribution differs substantially. The probability of 1-100 unit consumption increases to 12.28%, the probability of 101-200 units increases to 21.43%, and the probability of 201-300 units reaches 25.54%. Meanwhile, consumption above 700 units drops to 0.64%. At the lowest peak-hour price level, the probability of consuming between 1 and 100 units is 1.43%, 29.87% in the 401- 500 unit category, and 9.02% above 700 units. At the highest peak-price level, the probability of 1–100 units increases to 9.71%, whereas the probability of 101–200 unit consumption increases to 18.32% and the 201–300 unit consumption to 24.31%. Above 700 units, consumption drops to 1.92%. At the lowest peak duration level, only 0.67% of households are expected to be in the 1–100 unit category, 34.41% in the 401–500 unit category, and 9.94% consume more than 700 units. At the highest duration level, the probability of consuming 1–100 units increases to 10.49%, 101–200 units to 19.59%, and 201–300 units to 25.33%. The probability of consuming more than 700 units is only 0.91%. Combined, these predicted probabilities reinforce the marginal effects results that stronger tariff signals are systematically associated with movements to lower electricity-consumption categories.

Discussions

The results show that the three dimensions of electricity prices studied in this research are significantly related to households' electricity consumption patterns. Block tariffs, peak-hour prices, and peak-hour duration all increase the probability of households being in the lower consumption categories and decrease the probability of high consumption. The findings therefore support the general proposition that price structures can manage electricity demand. This is consistent with studies that have found electricity tariffs to be relevant instruments for promoting household conservation (Albatayneh et al., 2022; Lin & Lan, 2023; Sun & Lin, 2013). However, the three mechanisms do not produce equally strong effects simultaneously. Block tariffs produce the biggest marginal shifts for most categories of consumption. This result is economically reasonable, as block pricing directly ties the tariff to total electricity consumption. Unlike peak-hour pricing, which applies only to a certain time period, block pricing is based on the household's cumulative monthly electricity consumption. This therefore provides a permanent incentive for consumers not to move up to more expensive, higher consumption levels. This result is consistent with the overall rationale of increasing-block tariffs discussed by Sun and Lin (2013) and Lin and Lan (2023). If the pricing is on an increasing-block basis, high levels of electricity use will be considerably more expensive, while modest levels of use will be relatively cheaper. The predicted-probability results show the size of this pattern. At the lowest block tariff level, the probability mass is in relatively high consumption categories. At the highest level, the distribution shifts strongly toward 101–300 units, and extreme consumption is relatively rare. This is an important contribution because it shows that tariff responsiveness is not reflected only in a lower average level of electricity consumption. Instead, it shifts the probability mass across the entire consumption distribution. Peak-hour price tariffs are also significantly related to electricity consumption, but the effects are smaller than under block tariffs. The results are consistent with the rationalization of time-of-use pricing. During designated peak periods, higher electricity prices give households a financial incentive to reduce or reschedule electricity-consuming activities.

While Freier and von Loessl (2022) stress the importance of well-designed dynamic tariffs for private households, Kiguchi et al. (2021) show the heterogeneous effects of time-of-use tariff structures. The relatively smaller peak-price effect found here may reflect the essential nature of some household electricity consumption. Households may cut back on discretionary appliance use, but cooling, heating, lighting, and food preservation may be difficult to defer. This possibility is especially relevant in a city like Quetta, where climatic conditions create substantial heating and cooling needs. Thus, a price incentive does not imply that households have unlimited flexibility to shift electricity demand. One of the most interesting findings is the role of peak-hour duration. The marginal effects of peak-hour duration exceed those of peak-hour price in several categories. For example, the probability of consuming 101-200 units increases by 5.72 percentage points, rather than 4.07 percentage points, under peak-hour duration. Likewise, the probability of consuming more than 700 units decreases by 2.95 percentage points under duration, compared with 2.10 percentage points under peak price. This suggests that the temporal structure of peak pricing matters.

Higher peak prices increase the financial cost of electricity consumed during the peak. By extending the period, households face that cost for longer. This may limit households' ability to sit out a short, costly spell. The shift from four to six peak hours thus may strengthen the tariff signal by reducing the nearby off-peak time available to shift consumption. This means that electricity regulators should not assess time-of-use tariffs solely on the difference between peak and off-peak prices. The tariff window's period, start hour, end hour, and total duration could also affect household demand. The large tariff effects found here do not undermine previous studies that find low or heterogeneous elasticities of electricity prices. Lanot and Vesterberg (2021) find that households respond less to marginal price incentives, but Balarama et al. (2020) find a large heterogeneity in price elasticity. Andruszkiewicz et al. (2020) also show seasonal differences in elasticity. These findings are consistent with the literature. Electricity consumption shows statistically significant changes across consumption categories, even when tariffs are not highly elastic.

Limitations and future directions

Several limitations should be considered. The first is about the geographical scope. The study is based on households in Quetta. Elsewhere, climatic conditions, electricity infrastructure, income distribution, building characteristics, and household consumption practices can vary greatly. Second, the study relies on self-reported data. Survey respondents may misreport electricity-consumption patterns or tariff responses. Social desirability and recall bias may therefore affect some measures. The third limitation is the study's cross-sectional design. Household electricity consumption is dynamic and affected by weather, income, household composition, appliance ownership, tariff reforms, or electricity availability. Cross-sectional evidence cannot explain these temporal changes. Fourth, the analysis categorizes consumption into tariff blocks rather than high-frequency continuous electricity-consumption records. This suits ordered-logit estimation and policy-relevant tariff categories, but does not identify the precise timing of within-day load shifts. Future studies should thus correlate survey information with electricity-billing data or smart-meter records. Panel studies could track the same households before and after tariff reform. Such designs would enable researchers to estimate whether household responses increase, decrease, or persist over time.

Conclusion

The research investigated the relationship between electricity tariff structures and household electricity consumption patterns in Quetta, Pakistan. It identifies three tariff design elements: electricity block tariffs, peak-hour price tariffs, and peak-hour duration tariffs. Using data from 497 households and an ordered-logit framework, the analysis finds that all three tariff dimensions are significantly associated with movement toward lower consumption categories. Duties on blocks cause the greatest changes in probability. As the block-tariff measure increases, the probability of being in the 1–100 and 101–200 unit categories increases by 5.70 and 6.84 percentage points, respectively. Conversely, the likelihood of consumption over 700 units decreases by 3.53 percentage points. The directional pattern for peak-hour price tariffs is similar but with smaller marginal effects. Another major disincentive to high consumption is the length of peak hours. It has a larger effect than peak-hour price alone in several categories.

The predicted probabilities support these results. With tariff measures, the probability mass shifts from high consumption to lower and moderate electricity use. The results show that the electricity-pricing policy is more than a notional unit price. The form of price change, price levels, and the length of the price period affect household electricity demand patterns. Developing electricity systems involves more than setting tariffs. Tariff structures should instead penalize overconsumption while protecting households for whom consumption reflects basic needs. Progressive block pricing, carefully designed peak-hour tariffs, and judiciously chosen peak-period durations can thus supplement demand-side management. This study provides household-level evidence from an energy-constrained developing urban setting and shows the importance of disaggregation of tariff components. At the same time, given the cross-sectional design, interpret the results as strong associations rather than definitive causal effects of tariff reform. Future research using billing records, smart-meter data, longitudinal designs, and policy-based natural experiments could provide stronger evidence of the causal effects of tariff changes and help identify which households respond most strongly to particular pricing mechanisms.

References

1. Ahmad, N., Abbasi, A., Khalid, H. A., & Rehman, H. (2025). A dynamic pricing and clustering scheme for efficient home energy management system in a microgrid. *IEEE Access, 13*, 50411–50427.

2. Albatayneh, A., Juaidi, A., Abdallah, R., Peña-Fernández, A., & Manzano-Agugliaro, F. (2022). Effect of the subsidized electrical energy tariff on residential energy consumption in Jordan. *Energy Reports, 8*, 893–903. https://doi.org/10.1016/j.egyr.2021.12.019

3. Ali, M., & Shafiq, M. (2021). Revealing expert perspectives on challenges to electricity demand-side management in Pakistan: An application of Q-methodology. *Utilities Policy, 70*, 101216. https://doi.org/10.1016/j.jup.2021.101216

4. Andruszkiewicz, J., Lorenc, J., & Weychan, A. (2020). Seasonal variability of price elasticity of demand of households using zonal tariffs and its impact on hourly load of the power system. *Energy, 196*, 117175. https://doi.org/10.1016/j.energy.2020.117175

5. Atinafu, B. T., Tarekegn, F. N., & Kebede, W. M. (2023). Assessment of the level of social support and associated factors among cancer patients in the Comprehensive Cancer Center in Ethiopia: Ordinal logistic regression analysis of the level of social support and associated factors among cancer patients. *Heliyon, 9*(5), e15688. https://doi.org/10.1016/j.heliyon.2023.e15688

6. Balarama, H., Islam, A., Kim, J. S., & Wang, L. C. (2020). Price elasticities of residential electricity demand: Estimates from household panel data in Bangladesh. *Energy Economics, 92*, 104937. https://doi.org/10.1016/j.eneco.2020.104937

7. Chung, Y. M., Kang, S., Jung, J., Chung, B. J., & Kim, D. S. (2022). Residential electricity rate plans and their selections based on statistical learning. *IEEE Access, 10*, 74012–74022. https://doi.org/10.1109/ACCESS.2022.3190892

8. Clements, K. W. (2019). Four laws of consumption. *Economic Record, 95*(310), 358–385. https://doi.org/10.1111/1475-4932.12491

9. Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.

10. Ding, S., & Zhang, S. (2021). Pricing mechanism of charging pile power supply market—Based on RTP theory and price discrimination model. *E3S Web of Conferences, 275*, 0–5. https://doi.org/10.1051/e3sconf/202127501073

11. Evans, G. H. (1967). The law of demand—The roles of Gregory King and Charles Davenant. *The Quarterly Journal of Economics, 81*(3), 483–492.

12. Fischer, C. (2008). Feedback on household electricity consumption: A tool for saving energy? *Energy Efficiency, 1*(1), 79–104. https://doi.org/10.1007/s12053-008-9009-7

13. Fraija, A., Agbossou, K., Henao, N., Kelouwani, S., Fournier, M., & Hosseini, S. S. (2022). A discount-based time-of-use electricity pricing strategy for demand response with minimum information using reinforcement learning. *IEEE Access, 10*, 54018–54028. https://doi.org/10.1109/ACCESS.2022.3175839

14. Freier, J., & von Loessl, V. (2022). Dynamic electricity tariffs: Designing reasonable pricing schemes for private households. *Energy Economics, 112*, 106146. https://doi.org/10.1016/j.eneco.2022.106146

15. Gorman, W., Barbose, G., Baik, S., Miller, C., & Carvallo, J. P. (2025). Backup power or bill savings? How electricity tariffs impact residential solar-plus-storage usage in the United States. *Utilities Policy, 96*, 102035. https://doi.org/10.1016/j.jup.2025.102035

16. Govaerts, N., Bruninx, K., Le Cadre, H., Meeus, L., & Delarue, E. (2023). Signaling future or historical distribution grid costs via tariffs? A welfare analysis of long-run incremental cost pricing. *Utilities Policy, 82*, 101537. https://doi.org/10.1016/j.jup.2023.101537

17. Jaffar, M., Jogezai, N. A., Abdul Latiff, A. R., Baloch, F. A., & Khilji, G. K. (2024). University teachers at the crossroads: Unpacking their intentions toward ChatGPT's instructional use. *Journal of Applied Research in Higher Education.*

18. Jaffar, M., & Latiff, A. R. A. (2024). Pro-environmental conservation behavior through the lens of norm activation model: A systematic review (2018–2023). *PaperASIA, 40*(2b), 1–11.

19. Jia, J.-J., Xu, J.-H., & Fan, Y. (2018). Public acceptance of household energy-saving measures in Beijing: Heterogeneous preferences and policy implications. *Energy Policy, 113*, 487–499. https://doi.org/10.1016/j.enpol.2017.11.024

20. Kiguchi, Y., Weeks, M., & Arakawa, R. (2021). Predicting winners and losers under time-of-use tariffs using smart meter data. *Energy, 236*, 121438. https://doi.org/10.1016/j.energy.2021.121438

21. Klug, T. W., Beyene, A. D., Meles, T. H., Toman, M. A., Hassen, S., Hou, M., Klooss, B., Mekonnen, A., & Jeuland, M. (2022). A review of impacts of electricity tariff reform in Africa. *Energy Policy, 170*, 113226. https://doi.org/10.1016/j.enpol.2022.113226

22. Lanot, G., & Vesterberg, M. (2021). The price elasticity of electricity demand when marginal incentives are very large. *Energy Economics, 104*, 105604. https://doi.org/10.1016/j.eneco.2021.105604

23. Lin, B., & Lan, T. (2023). Progress of increasing-block electricity pricing policy implementation in China's first-tier cities and the impact of resident policy perception. *Energy Policy, 177*, 113544. https://doi.org/10.1016/j.enpol.2023.113544

24. Lin, B., & Wang, Y. (2020). Analyzing elasticity and subsidies to reform residential electricity tariffs in China. *International Review of Economics & Finance, 67*, 189–206. https://doi.org/10.1016/j.iref.2020.01.005

25. Maestri, C. O. N. M., & Andrade, M. E. M. C. (2022). Priorities for tariff compensation of distributed electricity generation in Brazil. *Utilities Policy, 76*, 101374. https://doi.org/10.1016/j.jup.2022.101374

26. Malhotra, N. K., Nunan, D., & Birks, D. F. (2017). *Marketing research: An applied approach* (5th ed.). Pearson Education Limited.

27. Manoharan, M., Srinivasan, P., Selvaraju, M., & Kumar, G. K. (2026). A comprehensive review of smart metering design, demand side management and load forecasting in smart grid. *AIP Conference Proceedings, 3422*(1), 030001. https://doi.org/10.1063/5.0334488

28. National Electric Power Regulatory Authority. (2023). *National Electric Power Regulatory Authority*. Islamic Republic of Pakistan, Power Division.

29. Nelson, T., McCracken-Hewson, E., Whish-Wilson, P., & Bashir, S. (2018). Price dispersion in Australian retail electricity markets. *Energy Economics, 70*, 158–169. https://doi.org/10.1016/j.eneco.2017.12.026

30. Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). Wiley.

31. Simshauser, P., & Whish-Wilson, P. (2017). Price discrimination in Australia's retail electricity markets: An analysis of Victoria & Southeast Queensland. *Energy Economics, 62*, 92–103. https://doi.org/10.1016/j.eneco.2016.12.016

32. Sun, C., & Lin, B. (2013). Reforming residential electricity tariff in China: Block tariffs pricing approach. *Energy Policy, 60*, 741–752. https://doi.org/10.1016/j.enpol.2013.05.023

33. Wang, J., Hassan, M. S., Alharthi, M., Arshed, N., Hanif, I., & Saeed, M. I. (2022). Inspecting non-linear behavior of aggregated and disaggregated renewable and non-renewable energy consumption on GDP per capita in Pakistan. *Energy Strategy Reviews, 39*, 100772. https://doi.org/10.1016/j.esr.2021.100772

34. Weidenbörner, V., Gleue, M., Feldhaus, C., & Werthschulte, M. (2025). Which tariff to choose? How individual attitudes and preferences explain demand for flexible electricity tariffs in Germany. *Energy Research & Social Science, 121*, 103978. https://doi.org/10.1016/j.erss.2025.103978

35. Wesseh, P. K., & Dogah, K. E. (2022). Dynamic tariffs and climate policy interaction: An economic analysis of welfare implications in retail electricity markets. *Energy Research & Social Science, 90*, 102679. https://doi.org/10.1016/j.erss.2022.102679