Turning Up the Heat: Electricity Infrastructure, Temperature, and Poor Households[*]

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Abstract

Rising temperatures increase demand for electricity-intensive cooling, yet in many low- and middle-income countries individuals are making adaptation decisions in electricity markets characterized by subsidized prices, weak enforcement, and high distribution losses. We study how extreme heat interacts with these institutional distortions in Karachi, Pakistan, using feeder-level data on electricity supplied and billed, and losses, customer-level billing records, and high-resolution weather data. As temperatures rise, households increase both formal (billed) and informal (unbilled) electricity consumption, but unbilled consumption responds more strongly. Billed consumption exhibits bunching at tariff thresholds, consistent with strategic responses to increasing-block pricing. Heat shocks therefore expand a pre-existing fiscal distortion by increasing losses when system demand peaks. We examine the rollout of theft-resistant cables, which raise the effective cost of adaptation. Cable installation reduces unbilled consumption across temperature ranges, though less so during extreme heat; feeder-level billed consumption does not increase one-for-one, implying lower total electricity consumption and reduced cooling among poor households. At the same time, non-residential customers experience increased billed consumption consistent with improved reliability. These findings illustrate the complex tradeoffs between the adaption of poor households and broader society.

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1 Introduction

Extreme heat is increasing in frequency and intensity, raising the stakes of climate adaptation, particularly in developing countries where exposure is high and resources are limited (IPCC, 2023). Although air conditioning has substantially attenuated the effects of heat in high-income countries (Barreca et al., 2016), billions of people live in low and middle-income countries (LMICs) that have tropical climates without air conditioning (Biardeau et al., 2020). These populations are both exposed to extreme temperatures and too poor to adopt and use such energy-intensive appliances (Rode et al., 2021).

Household income and credit constraints alone do not determine adaptation, which occurs within the institutional structure of local electricity markets. In many developing countries, these markets are characterized by distortions that arise from social norms, institutions, and political influences: subsidized prices, high losses from unbilled electricity consumption, low cost recovery, electricity rationing, and under-investment (Burgess et al., 2020; McRae, 2015b; Mahadevan, 2024). While prior work documents how such distortions impair electricity provision in LMICs, little is known about how they affect climate adaptation.[1]

This paper studies the interaction between extreme heat and electricity market distortions in Karachi, Pakistan. A city of 20 million people, Karachi has some of the largest informal settlements in Asia. Karachi Electric, the distribution company serving the greater Karachi region, rations electricity via load shedding in response to high unbilled consumption (due to electricity theft) and low revenue recovery (Ahmad et al., 2025). Although Karachi is one of the most heat-exposed cities in the world (Biardeau et al., 2020), very few households in these poorest communities report having an air conditioner. Almost all households report owning fans (Ahmad et al., 2021).

To examine adaptation to extreme heat in this setting, we combine administrative

[1]There is research documenting how firms and their employees may adjust to higher temperatures (see, e.g., Adhvaryu, Kala and Nyshadham, 2020; Somanathan et al., 2021), but those do not focus on these distortions.

utility records, household survey data, and high-resolution weather data to identify adaptation margins rarely observed in existing work. Monthly feeder-line data on electricity supplied, billed, and lost allow us to directly measure unbilled consumption—an outcome typically unobserved. Complimentary customer-level billing records enable forensic analyses of strategic responses to nonlinear tariffs in the spirit of Mahadevan (2024). These data are merged with gridded temperature records to link heat exposure to both formal and informal electricity use.

A key innovation of this paper is to show that informal electricity consumption —commonly characterized as theft or unbilled consumption—serves as an important adaptation mechanism for poor households facing nonlinear tariffs and an electricity sector that historically weakly enforced the exclusion of non-payers. As temperatures rise, households increase electricity consumption through both formal and informal channels, but the response of unbilled consumption is substantially larger. This is at least partly driven by residential customers with formal grid connections responding strategically to increasing block tariffs, and shifting to unbilled consumption to avoid the higher marginal prices charged for additional electricity consumed via their formal connection. The marginal benefit of electricity increases with temperature, pushing households across tariff thresholds and into informal usage. Heat shocks therefore amplify a pre-existing fiscal distortion: as cooling demand rises, so do electricity losses.

We then examine a large-scale infrastructure intervention implemented by the utility: the replacement of bare wires with theft-resistant aerial bundled cables (ABCs). As documented in Ahmad et al. (2025), this intervention reduces unbilled consumption and improves cost recovery. In our setting, however, it also raises the effective price of informal adaptation. We assess how cable upgrades influence electricity outcomes under different temperature conditions. The staggered rollout of cable upgrades depends on pre-determined feeder-line losses and utility resource constraints, creating variation across locations and over time (Ahmad et al., 2025). Our identification strategy follows the spirit of a difference-in-differences approach, comparing the electricity consumption (both billed and unbilled) under different temperature conditions in treated and non-treated locations before and after cable upgrades. This permits us to examine the effects of an exogenous shock that increases the cost of adaptation.

This paper provides two additional key sets of results. First, our findings show that the cable intervention did reduce the informal electricity subsidy and increased the effective price of consuming electricity services to adapt to high temperatures. We show that ABC installation reduces unbilled electricity consumption across temperature bins, though the reduction attenuates at the highest temperatures when cooling needs are greatest, indicating that in extreme heat, the benefits from cooling services outweigh the additional costs induced by the cabling upgrade. Feeder-level billed consumption does not increase one-for-one with the decline in unbilled units, implying that total electricity consumption falls. For poor households, restricting informal access can reduce cooling hours and increase health expenditures.

Lastly, we consider the tradeoffs between utility finances, households' ability to adapt to extreme heat, and societal well-being more broadly. To do so, we extend the discussion to include key non-residential electricity customers, such as hospitals, schools, and religious sites, who are less likely to consume unbilled electricity, but may benefit from any positive spillovers that result from improved utility finances. A series of analyses illustrate how increasing the effective cost of electricity services for a subset of customers can not only improve the utility's finances, but help society more broadly. We show that the non-residential customers benefit from the cabling intervention, due to increases in electricity use that were enabled by reduced load shedding.

These results highlight a dynamic interaction between climate shocks and institutional equilibria. In the equilibrium described by Burgess et al. (2020), low cost recovery leads utilities to ration electricity, weakening the link between payment and supply. We show that extreme heat amplifies this distortion: as temperatures rise, households expand informal consumption, further eroding cost recovery and intensifying fiscal strain precisely when demand peaks. Infrastructure upgrades that close the informal margin partially restore the payment–supply link and improve reliability, but they simultaneously raise the private cost of adaptation for vulnerable households.

The paper makes three contributions. First, it advances the literature on climate adaptation by examining residential responses to extreme heat in a distorted electricity market. Prior work emphasizes income and wealth as central determinants of adaptation: temperature–electricity gradients are relatively flat in poorer settings with limited cooling adoption (Davis and Gertler, 2015; Rode et al., 2021), while rising incomes enable stronger adaptation through air-conditioning and other technologies (Auffhammer, 2014; Davis and Gertler, 2015; Davis, Martinez and Taboada, 2020; Randazzo, Pavanello and De Cian, 2023; Bai et al., 2026). We extend this framework by incorporating the institutional and political distortions pervasive in LMIC electricity sectors (McRae, 2015b; Burgess et al., 2020; Mahadevan, 2024). In settings characterized by nonlinear tariffs, weak enforcement, and rationing, adaptation decisions are shaped not only by household resources but also by the equilibrium structure of electricity provision. We document that adaptation to heat occurs along both formal and informal electricity margins within this environment.

Second, the paper contributes to the literature on distorted infrastructure equilibria by showing that climate shocks can expand the distortion margin. Burgess et al. (2020) describe a low-payment equilibrium in which payment and supply are delinked and utilities ration rather than price electricity. McRae (2015b) shows how subsidy design distorts investment incentives, and Mahadevan (2024) demonstrates that billing manipulation generates persistent price wedges. We show that extreme heat interacts with these mechanisms by increasing reliance on unbilled electricity consumption, thereby intensifying cost-recovery shortfalls precisely when system demand peaks. In equilibrium, adaptation behavior feeds back into fiscal and reliability constraints, reinforcing the same distortions that sustain underprovision. More broadly, the paper contributes to the emerging literature on the political economy of climate adaptation (Carleton et al., 2024*b*) by examining an intervention that raises the cost of one adaptation margin in order to correct fiscal distortions.

Third, the paper provides evidence on the impacts of exogenous changes to the price of adaptation. A growing literature—particularly in the health sector—studies policies that reduce the cost of protective services and thereby attenuate the effects of climate shocks (Björkman Nyqvist et al., n.d.; Banerjee and Maharaj, 2020; Gunnsteinsson et al., 2022; Mullins and White, 2020; Cohen and Dechezleprêtre, 2022). In contrast, we analyze an infrastructure reform that increases the effective price of electricity-based adaptation by restricting informal access. Leveraging quasi-experimental variation in the rollout of theft-resistant cables, we examine how raising the cost of one adaptation margin reshapes electricity consumption, cooling behavior, and associated health expenditures. This evidence highlights that adaptation margins are embedded in institutional settings where policy-induced price changes may constrain or expand households' ability to cope with climate risk.

2 Background on Study Setting

As one of the most heat-exposed countries in the world (Biardeau et al., 2020), Pakistan is a first-order setting for studying heat exposure, cooling demand, and electricity consumption. Recent estimates indicate that 21.6% of the country's population lives below the official poverty line (Barriga-Cabanillas et al., 2024).[2] Home to 20 million people, Karachi is the largest city in Pakistan and the twelfth largest city worldwide. Like most cities in the region, a significant proportion of Karachi's population lives below the poverty line.

[2]National poverty rate is 40% when using the global LMIC poverty line of $ 3.65 per day poverty line (World Bank, 2024).

2.1 Heat and Cooling Services

Karachi's residents are exposed to frequent and intense heat waves, a risk that has been exacerbated by climate change and rapid urbanization. The city's average recorded temperatures have increased by 2.25 degrees Celsius over the last 60 years (Ilyas, 2024*a*). Karachi has the 4th highest cooling degree day exposure, a measure of the need for cooling services, of any city in the world (Biardeau et al., 2020). There has also been a substantial increase in its built-up area due to the expansion of formal and informal settlements (Li et al., 2023). Together, rising temperatures and urbanization create the urban heat island effect, whereby heat gets trapped in urban areas due to reduced green spaces, heat-absorbing construction materials, and emissions from human activities (Amin, 2024). As a result, periods of extreme heat significantly impact residents' health and strain the city's power, water and health services infrastructure (Ilyas, 2024*b*).

Cooling, either with fans or air conditioners, is one of the most effective ways residents can mitigate the adverse impacts of heat. Among poor households surveyed in Karachi, almost all of them reported having fans, whereas only 3% reported having air conditioners (shown in Appendix Figure A1). Cooling using ACs and fans requires not only the upfront costs to purchase the appliance, but it also requires electricity. Yet, access to affordable and reliable electricity remains a persistent challenge in Karachi and the rest of Pakistan, as discussed more below.

2.2 Electricity Sector

2.2.1 Electricity Generation and Tariffs

Since the 1990s, Pakistan's power sector has experienced numerous reforms, including the development of the National Electric Power Regulatory Authority (NEPRA), the agency responsible for regulating the sector (Bacon, 2019). One aspect that did not dramatically change: Pakistan's electricity sector relies predominantly on fossil-fuel–based generation.

The country's thermal plants are predominantly fueled by imported resources such as liquefied natural gas (LNG), furnace oil, coal, and diesel accounting for a large share of total electricity supply. Because these fuels are imported, their prices are subject to substantial volatility driven by global commodity prices, exchange rate fluctuations, and supply-side shocks.

Electricity tariffs faced by the consumers are set at national level, and this tariff is the same for all residential customers across the country, regardless of DISCO through which they receive their electricity. There is a lifeline tariff for customers consuming less than 50 kWh per month. Beyond that, residential customers on the "normal" schedule face an increasing block price characterized by a handful of "slabs" or cutoffs at which the cost per kWh jumps in price; between January 2018 and June 2021 the cutoffs for price increases occur at 100, 200, 300, and 700 kWh per month (Table A1). Since at least 2008, the biggest jump in per unit price (as charged to the residential customers) occurs as monthly consumption exceeds 300 kWh in a given month.

Historically, electricity retail tariffs for households were set below production costs (Munasinghe, 1984), meaning subsidized electricity prices for substantial proportion of the population (Trimble et al., 2016). Yet, due to pressure from international organizations the tariffs have changed relatively frequently in recent years, including five changes during our study period (Table A1).[3]

Widespread informal electricity use and poor bill recovery also undermined the utility cost recovery. These structural problems lead to chronic loadshedding, overburdened infrastructure, financial losses, and accumulation of receivables throughout the supply chain (Younas and Ali, 2021).

[3]Ongoing reforms aim to eliminate electricity tariff subsidies and instead target support to low income households via the national social protection program (Profit, 2024).

2.2.2 Electricity Distribution

Electricity in Karachi is provided by Karachi Electric (KE), a vertically integrated private utility. KE owns in-house generation capacity; however, it purchases more than half of its electricity from the national grid. Its distribution tariffs are regulated and it faces significant financial losses due to informal usage and low bill payment rates. Unauthorized electricity connections, commonly known as *kundas*, are widespread in Karachi. Kundas are typically attached to low-tension service cables near the point of use. Although KE actively monitors and removes kundas, the bare wire infrastructure allows for quick reconnection. In many areas, residents secretly install kundas at night - especially during hot seasons when cooling needs increase - and remove them in the morning to avoid detection (Ahmad et al., 2025).

To combat electricity theft, KE introduced aerial bundled cables (ABCs) starting in 2015. These cables have a tightly bound design that prevents illegal tapping. After initial pilot testing, KE expanded ABC installations in 2018 to high-loss areas. The ABCs were primarily aimed at reducing electricity theft, rather than improving the system's resilience to normal weather damage or extreme weather events, or reducing technical losses (Ahmad et al., 2025). The spatial and temporal variation in ABC installation creates a natural experimental setting for studying formal and informal household electricity usage during hot temperatures.

3 Conceptual Framework and Hypotheses

We motivate our research hypotheses through a conceptual framework built around a household's choice to procure electricity either through formal or informal channels. We simplify our analysis by assuming the household is aware of the temperature when it makes its choice, in essence assuming that kunda usage is an ex-post choice (Carleton et al., 2024*a*). This assumption is without loss for our directional predictions: imperfect temperature forecasts would attenuate, but not overturn, the comparative statics derived below.[4]

For a household, let $b(e,t)$ be their total benefit when they consume e units of electricity and the temperature is t degrees. Further, assume that their benefit is increasing and concave in electricity usage, and decreasing in temperature, and that $b_{et} \geq 0$, i.e. when temperatures rise the marginal benefit of electricity increases. This is appropriate in our setting as Karachi is in a semi-arid tropical region and electricity is heavily used for cooling purposes, and at higher temperatures, electricity is more beneficial.

Given t, the agent must decide whether to consume electricity formally, at cost $c(e)$, or pay for a kunda, with cost, $K + ke$, to steal electricity.[5] During our study period, KE employed a marginal tariff structure, with multiple slabs.[6] We assume that formal cost follows a similar structure, where as consumption increases, the formal marginal cost of electricity also increases. Let $0 = e_0 < e_1 < e_2 \cdots < e_n$ be the slab cut-offs, and $c_1 < c_2 \cdots < c_n$ be the per-unit marginal cost for each preceding slab (i.e. c_i is the marginal cost between e_{i-1} and e_i). Finally, for kunda use, we assume it incurs both a fixed cost $K \geq 0$ to procure a kunda and then a constant variable cost k to use it. The latter cost can be viewed as capturing the increasing probability of a kunda being detected, which increases with time/units used.[7]

The agent would then choose to use a kunda, if kunda usage is cheaper than formal electricity. Let e_a be the first slab after which the formal marginal cost is higher than the

[4]This would be consistent with a model where the household plans usage for the coming month and has an estimate of the general temperature. We also do not model a constraint on maximum consumption as while interesting, it would not change any of our directional results. If the choice of appliance and other durable investments were of interest, one could incorporate the upper-bound of consumption as an ex-ante choice, however since our analysis is more short-run and we do not have reliable data on appliance ownership, we do not model this choice.

[5]We treat kunda use as a continuous margin once the fixed cost is paid, allowing households to optimally combine formal and informal electricity sources.

[6]For higher load households, there was also a time of use structure, with fixed marginal costs for peak and off-peak hours. As most of our households are not in this category, we only model the slab structure, though results for time of use customers would be similar.

[7]We note that costs could be different, but the intuition would still hold. Appendix Figure A2 plots the case where the marginal cost of formal as well as kunda use is increasing.

kunda's marginal cost ($k \in (c_a, c_{a+1})$), then the agent will begin using a kunda if they plan to use more electricity than $e_a + \Delta$, where Δ is implicitly defined by $c(e_a + \Delta) - c(e_a) = K$. That is to say, if the agent anticipates using enough electricity to cover both the fixed and variable costs of kunda use, they will begin augmenting formal usage with kunda usage.

The top panel of Figure 1 illustrates the agent's choice by plotting a simple case of marginal benefits and marginal costs, when there are 3 slabs, there is no fixed cost of kunda connections ($K = 0$) and $k \in (c_1, c_2)$, i.e the marginal cost of kunda use is lower after the first threshold is crossed.[8] MC^f then represents the marginal cost under the formal structure, while MC^e illustrates the effective cost structure in the presence of a kunda. Let MB represent the agent's marginal benefit once temperature is revealed (and assume it to be linear for expositional clarity). Then, in the absence of a kunda, the agent would have consumed $\hat{e}^f$, however, in their case, using a kunda is more cost effective, and so they consume at $e^t = e_1 + e^k$, a mix of both formal and informal consumption, with formal usage "stopping" at e_1. This would imply that for neighborhoods without ABCs, the distribution of formal consumption should exhibit peaks or "bunches" at tariff thresholds.[9]

Hypothesis 1. *In the absence of ABCs, the distribution of customer billed (formal) consumption should exhibit bunching at tariff thresholds.*

The additional marginal benefit curve (MB^l) helps illustrate some other patterns. Starting at MB^l, as temperatures rise, marginal benefits would shift rightwards and total usage would increase. Depending on household preferences, it would initially mean an increase in formal usage until $e_1 + \Delta$ after which, while total use would increase, formal use would remain constant at e_1.

At a population level then, where different households will have different preferences and cost structures, these results suggest, perhaps intuitively, that as temperatures rise, both electricity consumption and losses should rise. Throughout, we use utility-reported

[8] Appendix Figure A3 plots a case when $K > 0$.

[9] We note that due to the "step-wise" nature of MC under KE's tariff structure, there can be bunching in the presence of ABCs as well, however the model suggests bunching should reduce once ABCs are installed.

losses, which include both technical and non-technical components; however, the mechanisms emphasized here operate through changes in non-technical losses (electricity theft), with technical losses assumed to be largely fixed at the feeder level in the short run.

Hypothesis 2. *As temperatures rise, both formal and informal electricity consumption increase.*

Hypothesis 3. *As temperatures rise, utility losses increase.*

Consider now the effect of ABC wiring on electricity use, in particular the use of kundas. ABCs were deployed by KE with the intention of preventing kunda use. Due to their insulated structure, directly hooking to the low transmission wires is made impossible. However, they do not make theft impossible, households may switch to other methods of stealing, such as meter tempering, or even drilling holes into the wire before making a connection. While theft is still possible, ABCs do make them more costly, as alternative methods are more easily detectable (meter tempering, holes in low transmission wires), or simply more complex to undertake. This then would potentially raise both the fixed and marginal costs of stealing, and intuitively, reduce the amount of electricity pilfered.

The bottom panel of Figure 1 illustrates a case where the marginal cost of kunda use has increased for the original household in the top panel (reflected in the new effective marginal cost curve MC^{ne}. When marginal benefits are reflected by MB, stealing is no longer cost-effective, and the household's total use falls to $\hat{e}^f < e^t$, and it is all formal. The following hypothesis formalizes this result.[10]

Hypothesis 4. *At a given temperature, ABC wiring weakly increases formal usage (billed units) and reduces the level of losses in a feeder-line.*

Finally, our framework allows us to hypothesize the effects rising temperatures would have on the ability of ABC wires to limit theft. As temperatures rise (and MB rises, say to

[10]We note that an increase is not necessary, formal consumption may also stay constant. E.g. while we do not model a budget constraint, if for a household the budget is binding pre-installation, it is possible that the household's formal consumption remain unchanged.

MB^h), theft may once again become cost-effective, leading to increased losses at higher temperatures even in areas with ABC wiring.

Hypothesis 5. *As temperatures rise, the ability of ABCs to mitigate losses, falls.*

4 Data

The analyses utilize data from multiple sources. First, through a non-disclosure agreement, the utility shared extensive data at the feeder-line, transformer, and consumer levels. In addition, we collected survey data for a sample of utility customers, and utilize publicly available data on weather and temperature.

4.1 Utility Feeder-Line Outcomes and Cable Conversion

We assembled a comprehensive and unique dataset including estimates of feeder-level losses, percentage of billed amount paid, utility claims, consumer complaints, consumer numbers and date of cable conversions of transformers from KE.[11] Further details of the utility datasets are as follows:

Utility Financial Indicators. There are two variables that are primary indicators of utility financial health: *losses* and *revenue recovery*, respectively. The data on feeder-level monthly losses and revenue recovery cover all feeder-lines in Karachi from January 2018 to October 2020. Losses are measured as the difference between units sent out and units billed and then divided by units sent out. Losses, therefore, represent the proportion of the electricity sent out that is not billed. Note that this is essentially an estimate of total T&D losses, as there is no way to distinguish between unbilled consumption and technical losses. Revenue recovery is defined as the ratio of net credit to billing. In other words, it is proportion of billed electricity consumption that is actually paid.

[11]These outcomes obtained from utility's administrative records are measured at the feeder-line level. Transformer level data on these outcomes are not available during the period of our study.

Theft-Resistant Cable Installation. KE provided the dates when cables were upgraded at each transformer. We observe the installation record through January 2021. To match these data with feeder-level monthly variables, we create two measures for cable installation. First, we define a binary indicator for whether a feeder-line has at least one transformer where cables were upgraded. Second, we calculate the ratio of transformers with theft-resistant cables installed relative to the total number of transformers in a feeder-line.

4.2 Household Survey and Electricity Bills

In October and November 2021, we surveyed approximately 3,000 residential customers across 150 transformers. More details on survey design and implementation can be found in Ahmad et al. (2025). The questionnaire collects information on basic household characteristics, demographics, and other outcomes related to electricity consumption, e.g., appliance ownership and usage, as well as household expenditures. Among the surveyed households, almost all of them report having fans but only 3% report having air conditioners (Figure A1).

For this set of surveyed households, we obtain the corresponding customer-level billing records from KE. The sample covers the period between June 2018 and August 2021. In the data, we observe information on monthly billed units of electricity (both the kWh and the monetary amount), the amount and date of bill payments, and total monetary amount due to KE.

4.3 Weather

We utilize weather information from ERA5-Land reanalysis data provided by the European Center for Medium-Range Weather Forecasts (ECMWF). Reanalysis data are generated by combining atmospheric models with local observations. ERA5-Land provides global daily surface weather records on a $0.1° \times 0.1°$ grid (approximately 9×9 km) starting from 1950. We identify the grids in Karachi, Pakistan, and retrieve a series of weather variables, including temperature, precipitation, wind speed, direction, and more.

To combine the electricity and weather data, we match pole mounted transformers (PMTs) to weather records at the closest ERA5-Land grid node. For feeder-line-level analysis, we aggregate the PMT-level weather data to the feeder-line-level by taking the average over all PMTs within a feeder-line. For customer-level analysis, we match customers to weather records at the PMT to which they belong to. After constructing the daily weather data for PMTs and feeder-lines, we aggregate the data to monthly level by summing the number of days over each billing month. Figure A4 plots the distribution of daily temperature by calendar month in Karachi. During hot months, such as April to November, almost all the days have daily average temperatures above 24°C and the average daily maximum temperature can reach 35°C.

5 Empirical Strategy

We begin by estimating the relationship between temperature and electricity outcomes. Our empirical model leverages random variation in realized temperature for a given area and over time.

For feeder-line (or customer) i in billing month t, we estimate the following model:

$$y_{it} = \sum_{b \in B \setminus \{<21\}} \beta_b T_{bit} + \gamma \mathbf{X}_{it} + \alpha_i + \delta_{y(t)} + \phi_{q(t)} + \varepsilon_{it}, \tag{1}$$

where y_{it} is either the feeder-line-level electricity outcomes (including units sent out, billed and unbilled units, customer complaints, and infrastructure damage) or customer-level billed consumption. T_{bit} are binned measures of daily average temperature. We use this binned approach to capture potentially important nonlinearity in the electricity-temperature relationship (Auffhammer, 2022). Specifically, we sort daily average temperature (°C) into five bins $B = \{< 21, 21-24, 24-27, 27-30, > 30\}$. Then, for each i and billing month t, we count the number of days that daily average temperature falls into each bin $b \in B$ and denote this as T_{bit}. For the regression, since the number of days in a billing month is fixed, we omit one category (<21°C) and therefore β_b captures the change in electricity outcomes associated with having one additional day that daily average temperature falls into bin b in a billing month, relative to a day in the <21°C bin.

$\mathbf{X}_{it}$ is a vector of other weather conditions, including total precipitation and average wind speed in a billing month. We control for these variables using a second-order polynomial in all regressions to account for the nonlinearity in people's behavior change on rainy or windy days in ways that might also affect electricity consumption.

We include a set of fixed effects to control for unobservable confounding factors. α_i are feeder-line (or customer) fixed effects that account for time-invariant differences across feeder-lines (or customers) that might be tied to electricity outcomes. We have year fixed effects $\delta_{y(t)}$ and quarter-of-year fixed effects $\phi_{q(t)}$ to capture common trends and seasonality. Standard errors are clustered at the IBC level to account for serial correlation within IBC regions.

To examine how cable upgrades affect electricity outcomes under different temperature conditions, we estimate the following interaction model.

$$y_{it} = \sum_{b \in B \setminus \{<21\}} \beta_b T_{bit} + \sum_{b \in B} \eta_b T_{bit} \times \mathrm{ABC}_{it} + \gamma \mathbf{X}_{it} + \alpha_i + \delta_{y(t)} + \phi_{q(t)} + \varepsilon_{it}. \tag{2}$$

Compared to Equation 1, the above equation adds interactions between temperature bins (T_{bit}) and the indicator for cable upgrades (ABC_{it}). For the feeder-line-level analysis, ABC_{it} equals 1 if a feeder-line i already has at least one transformer with theft-resistant cables installed in month t. For the customer-level analysis, ABC_{it} equals 1 if the transformer that serves customer i already has theft-resistant cables installed in month t.

In this equation, β_b characterizes the relationship between temperature and electricity outcomes for the baseline scenario without cable upgrades. These coefficients are estimated relative to the omitted <21°C bin. η_b captures how cable upgrades change electricity outcomes for each temperature bin, relative to the baseline scenario without cable upgrades.[12] To interpret the results for a specific temperature bin b, the total effect under the cable upgrade scenario is $\beta_b + \eta_b$. This combined effect characterizes the electricity outcomes under different temperature conditions when theft-resistant cables have been installed, relative to the omitted <21°C bin without cable upgrades.

Recent work by Jones et al. (2026) suggests that bin-based temperature regressions can produce spurious U-shaped responses when predictable shifts in temperature exposure are correlated with outcome trends. We assess the robustness of our results using the counterfactual temperature control approach proposed by Jones et al. (2026). As shown in Appendix B, the estimated temperature effects remain stable, and our main findings are unchanged. Concerns about bias arising from bin-based temperature regressions are less relevant in our setting for two reasons. First, our analysis focuses on customers and feeder lines within a single city, where baseline climate variation across locations is minimal. Second, our sample spans a relatively short period (2018–2021), over which long-run warming trends are limited.

6 Evidence on Adaptation Among Poor Households

In this section, we document that poor, urban households are adapting to hot temperatures through both formal, billed electricity consumption and informal, unbilled electricity consumption.

[12]Unlike β_b, η_b is identified for all temperature bins, including the <21°C bin, because the timing of theft-resistance cable installation differs across transformers. Therefore, η_b for <21°C measures the change in electricity outcomes for a day with cable upgrades relative to a day without cable upgrades when the daily average temperature is below 21°C.

6.1 Adaptation through Formal Electricity Consumption

6.1.1 The Relationship between Temperature and Billed Consumption

Figure 2 shows the relationship between temperature and billed electricity consumption among formal electricity customers in our sample. Full regression results are reported in Appendix Table A2. The figure reveals a strong and monotonic relationship between heat exposure and formal electricity consumption. As the number of days in a billing month with higher average temperatures increases, both billed electricity units and billed amounts rise relative to the omitted category of days with average temperatures below 21°C.

Estimated coefficients increase steadily across temperature bins, indicating that customers consume more electricity – and incur higher bills – during hotter periods. This pattern is consistent across both outcome measures. The response is approximately linear at low and moderate temperature ranges; however, there is some attenuation at the highest temperature bin. While billed consumption continues to increase in months with more days above 30°C, the marginal increase relative to the preceding bin is smaller, particularly for billed units.

Overall, these results show that as temperatures rise, formally connected households respond by increasing billed electricity consumption. This pattern is consistent with heat-driven demand for electricity-intensive cooling services and mirrors temperature–electricity relationships documented in other low- and middle-income country settings.

6.1.2 Formal Consumption Responses and the Role of Tariff Incentives

Figure 5 presents the distribution of monthly billed electricity consumption for formally connected customers, separately for cool and hot months. Vertical dashed lines indicate the residential tariff thresholds implied by the increasing-block pricing schedule in effect during the study period. A detailed tariff schedule is presented in Appendix Table A1.

The figure provides additional evidence that households increase formal electricity consumption in response to higher temperatures. During cool months, billed consumption is concentrated at relatively low levels and the distribution is strongly right-skewed, with most households consuming between roughly 100 and 200 kWh per month. In contrast, during hot months the entire distribution shifts to the right. The modal range increases to approximately 200–300 kWh, and the right tail thickens substantially, with a nontrivial share of households consuming several hundred kilowatt-hours per month. As a result, many customers cross one or more tariff thresholds in hot months and are exposed to higher marginal prices on electricity consumption.

At the same time, the distribution reveals salient bunching at specific tariff cutoffs, most notably just below 300 kWh – the threshold associated with the largest discrete increase in the marginal electricity price. This bunching is visible in both cool and hot months. The presence of excess mass just below tariff thresholds suggests that households actively manage formal electricity consumption in response to nonlinear pricing, even when cooling needs are elevated. We interpret this pattern as consistent with financial constraints limiting households' ability to fully adapt to heat through formal electricity consumption alone. In particular, households may respond to higher marginal prices by curtailing formal usage or by shifting part of their electricity demand to informal connections, thereby keeping billed consumption just below tariff cutoffs. Similar bunching patterns in formal electricity bills have been documented in other contexts as indicative of strategic responses to electricity pricing and billing systems (e.g., Mahadevan, 2024).

In addition to the graphical evidence, we formally test for excess mass at tariff thresholds using density manipulation tests following Cattaneo, Jansson and Ma (2020), with results reported in Appendix Table A11. Consistently, these tests provide statistical evidence of bunching at key tariff cutoffs, particularly during hot months.

6.2 Adaptation through Informal Consumption

6.2.1 The Relationship between Temperature and Unbilled Electricity Consumption

We use feeder-line-level billing data to examine how temperature affects electricity flows and billing outcomes. Figure 3 reports coefficient estimates from regressions of feeder-line level outcomes on temperature bins, along with 95% confidence intervals. Full regression results are reported in Appendix Table A3.

Higher temperatures are associated with increases in electricity demand across all three outcomes. Total electricity sent out rises monotonically with temperature, with steadily increasing coefficient magnitudes across bins, indicating progressively higher electricity dispatch during hotter periods. Billed electricity consumption also increases as temperatures rise, but the response is smaller than that for total electricity sent out, particularly at higher temperature bins. As a result, the gap between electricity dispatched and electricity billed widens at high temperatures, suggesting that not all heat-driven increases in demand are captured through formal billing.

In contrast, unbilled electricity consumption exhibits a much stronger and more nonlinear response to temperature. Unbilled units are significantly higher than the omitted category across all temperature bins, with especially large increases in the two highest bins. These increases are larger than those observed for either total electricity sent out or billed units, indicating that a disproportionate share of additional electricity delivered during hot periods is absorbed through unbilled channels.

Taken together, these patterns imply that while higher temperatures raise overall electricity demand, a growing fraction of this demand is met through informal, unbilled consumption during hot periods. As temperatures increase, households become substantially more likely to rely on unbilled electricity, contributing to higher non-technical losses for the utility.

We also provide evidence that the observed increase in unbilled electricity consumption is not driven by technical losses. Appendix Figure A5 presents unbilled electricity separately for feeders serving industrial versus non-industrial customers (left panel), and for feeders with high versus low electrical load (right panel). Because industrial customers are less likely to engage in electricity theft and technical losses are typically more severe at higher load levels, these comparisons provide a useful diagnostic. The patterns in Appendix Figure A5 are inconsistent with a technical-loss explanation. In particular, unbilled electricity consumption responds more strongly to temperature in feeders serving non-industrial customers and in lower-load feeders, rather than in high-load feeders where technical losses would be expected to increase most sharply.

6.2.2 Evidence on Mechanisms of Unbilled Electricity Consumption

To shed light on the mechanisms underlying increases in unbilled electricity consumption, we examine data on the electricity utility's claims related to intentional consumer wire damage and meter damage. Figure 4 shows the estimated relationship between temperature and the number of reported damage incidents by temperature bin. Full regression results are reported in Appendix Table A4.

We find a significant increase in reported infrastructure damage during hot periods. In particular, claims related to both wire damage and meter damage rise sharply in the two highest temperature bins. Notably, the temperature effect on reported infrastructure damage closely mirrors the pattern observed for unbilled electricity consumption in Figure 3. In both cases, responses are modest at lower temperatures but exhibit large, discrete jumps in the highest temperature bins. This similarity supports the interpretation that increases in unbilled electricity consumption during hot periods reflect heightened electricity theft or tampering with the distribution system, rather than measurement error or billing practices alone.

We consider two broad classes of constraints – financial and technical – that could induce households to rely on informal electricity consumption, with distinct policy implications. First, households may face financial constraints that limit formal electricity consumption, particularly under nonlinear pricing. As discussed in Section 6.1.2, the discontinuities inherent in increasing-block tariffs create incentives to keep formal consumption below tariff cutoffs, which can be achieved by shifting some usage to informal connections. Second, households' formal electricity consumption may be technically constrained by their allowable connected load. If connected load limits prevent households from operating electricity-intensive cooling appliances, households may resort to theft in order to meet cooling needs during periods of extreme heat.[13] If this is true, one would expect stronger temperature responses in unbilled electricity consumption in feeder lines with a higher share of customers facing low connected-load constraints. We test this hypothesis in Figure A7 and find no evidence consistent with binding technical constraints. If anything, the temperature response of unbilled electricity consumption is more pronounced in feeder lines with fewer low-connected-load customers.[14]

6.2.3 The Cost of Adaptation via Informal Consumption to the Utility Company

As temperatures rise, households increasingly rely on informal electricity consumption, and this reliance manifests through observable damage to metering and distribution infrastructure. While such behavior may allow households to meet rising cooling needs during extreme heat, it also leads to higher non-technical losses and increased financial strain on the electricity utility.

To quantify the cost of household adaptation through informal electricity consumption borne by the utility, we estimate the increase in foregone revenue associated with unbilled electricity as temperatures rise. Table 1 summarizes the results of this calculation. We begin by computing the average number of days in a month in which the daily mean

[13] Connected loads below 1 kW typically support small appliances such as mobile phone chargers, laptops, and fans, whereas connected loads above 1 kW are required to operate appliances such as air conditioners, refrigerators, washing machines, and electric stoves. Figure A6 plots the distribution of customer connected load among all the feeder lines in our sample.

[14] Figure A7 uses logarithmic measures of electricity sent out, billed units, and unbilled units. Results using per-customer measures, shown in Figure A8, yield similar conclusions.

temperature falls within each temperature bin. Using our estimated relationship between feeder-line-level unbilled electricity consumption and temperature, we then calculate the additional unbilled electricity incurred under the observed temperature distribution, relative to a counterfactual in which all days in a month have average temperatures below 21°C, our reference category. Under this counterfactual comparison, the utility incurs an average cost of approximately 5.3 million PKR per feeder line per month, equivalent to 3,219 PKR per customer. Given that our sample includes 582 feeder lines in high-loss IBC regions, this implies a total monthly cost of approximately 3,084 million PKR, or about 11 million USD, borne by the utility as a result of heat-driven informal electricity consumption.

7 Effects of Increasing the Cost of Informal Adaptation

To address high electricity losses, the Karachi Electric implemented a cable upgrade program that replaced traditional bare wires with theft-resistant aerial bundled cables (ABCs). As shown in Ahmad et al. (2025), these upgrades substantially reduced unbilled electricity consumption and improved revenue recovery at the feeder-line level. Appendix Figure A9 replicates these results using the logarithm of total unbilled electricity units as the outcome variable, documenting large and persistent reductions in electricity losses following ABC installation.

While these infrastructure upgrades improve utility performance, they also increase the cost of informal electricity consumption and may alter how households adapt to heat. In the remainder of this section, we examine how theft-resistant cables affect households' adaptation via both formal and informal electricity consumption.

7.1 Effects on Adaptation through Formal Electricity Consumption

Theft-Resistant Cables and the Temperature–Billed Consumption Relationship. Figure 6 examines how the relationship between temperature and formal electricity consumption differs across feeder lines with and without theft-resistant cables. Using household billing data, we study two outcomes: the logarithm of billed electricity units (kWh) and the logarithm of billed amounts (PKR). Full regression results are reported in Appendix Table A9. All coefficients are interpreted relative to the omitted category of customers in feeder lines without ABC installation during months with average temperatures below 21°C.

Across both outcomes, billed electricity consumption increases with temperature, indicating greater electricity use during hotter periods. However, the magnitude and shape of this response differ sharply by cable type. Among customers in non-ABC feeder lines, billed electricity consumption rises gradually with temperature, with a modest increase in the 24–27°C range and some leveling off in the highest temperature bins.

In contrast, customers served by ABC-equipped feeder lines exhibit substantially larger increases in billed electricity consumption as temperatures rise. While billed units and amounts are significantly lower for ABC customers at low and moderate temperatures, this pattern reverses at higher temperatures. In the two hottest temperature bins, customers in ABC feeder lines consume significantly more billed electricity – and incur higher bills – than comparable customers in non-ABC areas. These differences are statistically significant and are mirrored across both billed units and billed amounts.

These patterns are consistent with theft-resistant cables limiting households' ability to rely on informal electricity consumption during hot periods. When informal connections become more costly or infeasible, households in ABC-equipped areas appear to rely more heavily on formal electricity to meet rising cooling needs, making heat-driven demand more visible in billing records. At the same time, the lower billed consumption observed in ABC areas at moderate temperatures is consistent with a form of "comfort smoothing," whereby households reduce discretionary electricity use in cooler periods in order to manage electricity expenditures and accommodate higher cooling needs during extreme heat.

Supporting Evidence from Bunching Analyses. To further examine how theft-resistant cables affect formal electricity use, Figure 8 presents the distribution of monthly billed electricity consumption by season and ABC status. Appendix Table A12 reports formal bunching tests at tariff cutoffs.

Before ABC conversion, we observe statistically significant bunching at multiple tariff thresholds. Among feeders that are ultimately converted but observed before conversion, we see significant excess mass appears at several tariff cutoffs during both cool and hot months. The 300 kWh cutoff, where the marginal price increase is largest, exhibits the most consistent and robust bunching. Following ABC conversion, the extent of bunching declines markedly and the estimated density differences are substantially smaller. This reduction in bunching suggests that theft-resistant cables limit households' ability to manipulate formal consumption around tariff thresholds, though they do not eliminate such behavior entirely. Taken together, ABC installation constrains informal electricity use and reduces strategic responses to nonlinear pricing. As a result, households in ABC-equipped areas are more likely to meet cooling demand through formal electricity consumption, particularly during periods of extreme heat.

7.2 Effects on Adaptation through Informal Electricity Consumption

Figure 7 examines how temperature and the installation of theft-resistant cables (ABCs) affect electricity outcomes at the feeder-line level. Full regression results, which make clearer the temperature bins in which the ABCs lead to statistically significantly different outcomes, are in the Appendix (Table A7). The reference group is the bin in which the daily average temperature is below 21°C and without cable upgrades, with the corresponding coefficient scaled to zero. Each temperature bin coefficient measures the effect of one additional day in that temperature range within a billing month.[15]

The top panel shows a strong increase in electricity sent out as temperatures rise. This pattern holds for both feeder types, indicating that aggregate demand responds similarly to heat regardless of cable type. ABC feeders have statistically significantly fewer units of electricity delivered in the three lowest temperature bins. However, in the hotter temperature bins when daily average temperature exceeds 27°C, the units sent out are comparable for the two types of feeders (i.e., there is not a statistically significant difference across cable types).

The middle and bottom panels of Figure 7 present the impacts on billed and unbilled electricity consumption, respectively. Consistent with the conceptual framework (Hypothesis 4), results indicate that cable upgrades significantly reduce unbilled electricity consumption across all temperature ranges, with the reduction being more pronounced on days with moderate temperatures (i.e., below 27°C). This suggests that cable upgrades effectively limit informal electricity consumption, particularly under moderate temperature conditions, where discretionary or informal consumption may be more elastic.

During hotter days (above 27°C), the reduction in unbilled electricity consumption diminishes. This suggest that at higher temperatures, most customers' threshold for informal usage is crossed. As a result, customers may turn to alternative informal methods, such as meter tampering, to meet their persistent electricity needs for cooling appliances. In line with Hypothesis 5 of our conceptual framework, while cable upgrades effectively reduce unbilled electricity consumption under moderate conditions, their impact may diminish during periods of high electricity demand driven by cooling needs.

In contrast to unbilled units, the middle panel shows no significant impact of cable upgrades on billed electricity consumption in any of the temperature bins. These findings,

[15] To fix ideas it is helpful to consider the magnitudes of the effect of an extra day in a given temperature bin for each of the three outcomes. For the non-ABC feeder lines, one additional day in the >30°C temperature bin increases electricity sent out by 2.6%, the electricity billed by 2.1%, and the unbilled electricity by 5.0%. In contrast, for an ABC feeder lines, one additional day in the >30°C temperature bin has essentially the same effect on electricity sent out and billed, but increases unbilled consumption by 4.1%.

in conjunction with the impacts on unbilled consumption, suggest that customers who previously relied on informal and unauthorized channels substantially reduce their overall electricity consumption, particularly during moderate temperature days. Because interactions on the logarithm of billed units are small/insignificant (see Table A7), the results indicate that ABCs do not simply convert all previously unbilled electricity into billed electricity one-for-one (at least not at the feeder-aggregate level captured here).

The aggregated feeder line response of billed consumption post-ABCs reflects the net effect arising from the heterogeneous responses of various types of customers. For example, primarily formal consumers that were rationed due to loadshedding, experience an increase in billed units post ABC, consistent with the results found in 6. While for consumers who consumed from both formal and informal sources, the unbilled units are eliminated, but there no change in their billed units, suggesting a very high price sensitivity of poor electricity consumers. Moreover, consumers who consumed primarily via informal channels might give up their consumption, or avoid formalization by migrating to non ABC areas. Thus, the overall effect is that ABCs primarily shrink the unbilled channel (losses) without producing an equally large, mechanically offsetting rise in billed units in these regressions. This suggests that higher costs and barriers to illegal connections introduced by cable upgrades result in a net reduction in electricity consumption.

Appendix Figure A10 and Appendix Table A8 report results using the raw (level) measures of these electricity outcomes and show patterns that are consistent with the log specifications. In addition, Table A10 examines heterogeneity in these effects by the intensity of ABC deployment at the feeder-line level. Consistent with the preceding results, the estimated effects are larger for feeder lines with higher ABC treatment intensity. Finally, the reduction in unbilled electricity following ABC installation is unlikely to be driven by changes in technical losses. As shown in Appendix Figure A11, the effects are concentrated among non-industrial feeder lines, with no corresponding effects observed for feeders serving industrial customers.

8 Welfare Implications

We have shown that ABCs raise the cost of informal electricity consumption and are associated with reductions in household electricity use, particularly during hot periods. At the same time, by reducing electricity losses, ABC installation may improve electricity supply and reduce load shedding in previously high-loss areas, potentially benefiting other users who do not rely on informal access. In this section, we examine these welfare implications by first considering the consequences for poor households and then assessing potential benefits for the broader society.

8.1 Implications for Poor Households

Our results suggest that theft-resistant cable installations reduce households' effective access to electricity by raising the cost of informal consumption, which may in turn constrain households' ability to cope with extreme heat. To provide a tractable welfare interpretation, we focus on two components rather than a full welfare analysis: (1) changes in health expenditures associated with reduced consumption of cooling services, and (2) changes in consumer surplus associated with reduced electricity consumption. We summarize the main implications here and present the full framework, assumptions, and calculations in Appendix Sections C1 and C2.

We begin with the cooling service consumption and health channel. Based on assumptions about appliance power usage, we convert the estimated decline in electricity consumption following ABC installation into implied changes in cooling service usage, focusing on fans and air conditioners. Using household survey data, we then estimate the relationship between health expenditure per capita and cooling appliance usage, controlling for a rich set of household characteristics (Appendix Table C1). Full details of these calculations and assumptions are provided in Appendix Section C1.

Table 2 summarizes the key results. Column (2) reports the estimated reduction in monthly electricity consumption per household following ABC installation, separately for the hot and cool seasons. In both seasons, households experience a decline of roughly 32–35 kWh per month. Columns (3) and (5) translate these reductions into implied changes in daily cooling service usage. Because fans are the dominant cooling technology in our sample, the implied reduction in fan usage is substantial – approximately 14 hours per day in the hot season and 13 hours per day in the cool season. In contrast, the implied reduction in air-conditioner usage is modest, at less than one hour per day in both seasons.

Columns (4) and (6) report the associated changes in monthly health expenditures per capita implied by these reductions in cooling service usage. In the hot season, if the forgone electricity consumption is assumed to have powered fan usage, the implied reduction in fan usage is associated with an increase in monthly health expenditures of approximately 230 PKR per capita. A similar pattern holds in the cool season. The corresponding estimates under the assumption that reduced electricity consumption reflects lower air-conditioner usage are much smaller, which might be due to the low self-reported rate of air-conditioner ownership in our household survey.

We also provide a complementary, demand-based estimate of the loss in consumer surplus associated with reduced electricity consumption following ABC installation, treating ABCs as increasing the effective price of electricity by restricting informal access. We estimate household electricity demand using feeder-line data and use ABC installation as an instrument for the average price. The resulting consumer surplus estimates, reported in Appendix Section C2, serve as a secondary benchmark relative to the health-expenditure channel. As shown in Table C5, the implied monthly loss in consumer surplus for an average household is approximately 735 PKR during the hot season and 253 PKR during the cool season.

8.2 Implications for the Society

While theft-resistant cable installations restrict informal electricity consumption among households and limit their adaptation options, they may generate benefits for non-residential customers who do not rely on informal access. By reducing distribution losses, ABC installation can allow the utility to reduce load shedding in areas that previously experienced high levels of unbilled consumption. Improvements in electricity reliability are particularly valuable for non-residential customers – such as commercial, industrial, and public-sector users – whose operations depend on consistent power supply and who are unlikely to engage in electricity theft. We therefore examine whether ABC installation leads to increased electricity consumption among non-residential customers, particularly during hotter months when cooling demand is highest.

Our analysis uses customer-level monthly billing records for non-residential customers from KE. Unlike residential households, these customers are unlikely to rely on informal electricity consumption, making them a useful group for assessing whether ABC installation improves electricity reliability and generates benefits for non-residential users. We provide supporting evidence for this assumption in Appendix D: billed electricity consumption for non-residential customers increases with temperature but does not exhibit the bunching patterns observed among residential users.

Figure 9 presents the estimated effects of temperature and ABC installation on billed electricity consumption for non-residential customers. Billed electricity consumption increases following ABC conversion, with the increase being more pronounced during hotter months. Because these customers do not typically engage in electricity theft, the observed increases in billed consumption are unlikely to reflect changes in billing compliance. Instead, the results are consistent with improvements in electricity reliability – such as reductions in load shedding – that enable non-residential customers to consume more electricity when cooling needs are highest.

Two additional pieces of evidence support this interpretation. First, feeder lines that experienced high levels of losses prior to ABC installation – where load shedding was more prevalent – exhibit clear improvements in electricity supply following conversion (Appendix Table D1). Second, consistent with these reliability gains, the increase in billed electricity consumption among non-residential customers is concentrated in these same high-loss feeder lines. As shown in Figure 9, non-residential customers served by high-loss feeders experience substantial increases in billed electricity consumption after ABC installation, whereas customers served by low-loss feeders exhibit little change.

These findings are robust across customer types. Appendix Figure D4 documents consistent patterns across eight non-residential customer categories, including commercial establishments, industrial users, and public-sector institutions. In particular, public-facing entities such as schools, hospitals, and religious institutions exhibit increases in billed electricity consumption following ABC installation, suggesting that improvements in electricity reliability extend to these essential public services.

9 Conclusions

Climate change is increasing exposure to extreme heat, yet much of the world's poor lack access to formal, reliable cooling technologies. This paper studies how poor urban households in a low-income setting adapt to heat in the presence of institutional frictions in electricity provision. Using detailed administrative data from Karachi, Pakistan, combined with household surveys and high-resolution weather data, we show that unbilled electricity consumption plays a central role in heat adaptation. As temperatures rise, households increase electricity use through both formal and informal channels, but the response of unbilled consumption is substantially larger, reflecting strategic behavior in the face of nonlinear tariffs and weak enforcement.

Household adaptation via informal electricity consumption imposes substantial costs on the utility. We examine how an exogenous infrastructure upgrade initiated by the utility – the replacement of bare wires with theft-resistant cables – alters these adaptation margins. The cabling intervention reduces unbilled electricity consumption across temperature ranges, raising the effective cost of electricity-based adaptation for households. While unbilled consumption declines less during periods of extreme heat, we find no corresponding increase in billed consumption at the feeder level, indicating that informal usage is not mechanically converted into formal consumption. Instead, households reduce overall electricity use, leading to fewer cooling hours and higher health expenditures. These results highlight how interventions designed to improve utility finances can affect households' capacity to cope with climate stress.

At the same time, reductions in electricity losses can generate benefits beyond residential households. For non-residential users, such as firms, schools, hospitals, and religious institutions, who are unlikely to rely on informal access, cable upgrades are associated with increased electricity consumption, particularly during hot periods and in previously high-loss areas. These gains are consistent with improvements in electricity reliability stemming from reduced load shedding. Taken together, our findings underscore that adaptation to climate change in low-income settings is shaped not only by income and technology, but also by institutional features of public service provision. Policies that improve utility performance may yield broad social benefits, while also reshaping households' adaptation options in ways that merit careful consideration as climate risks intensify.

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Figures and Tables

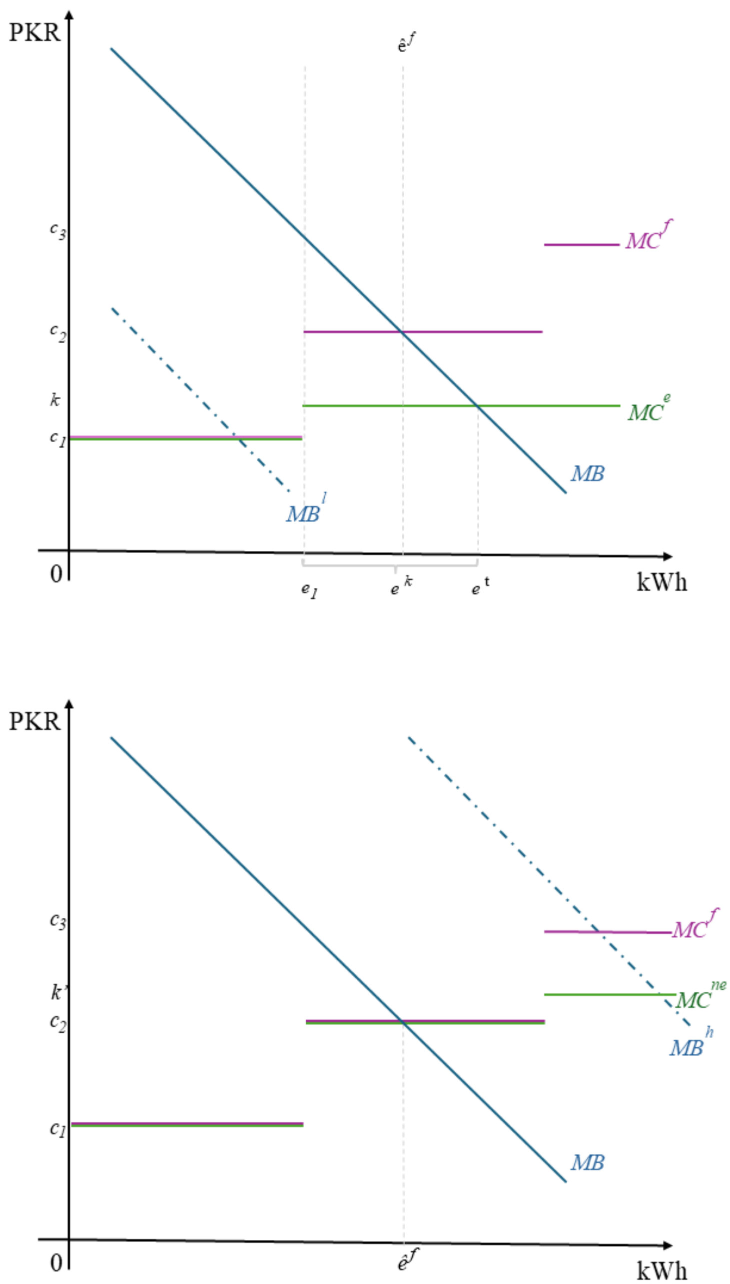

Figure 1: Household's choice of electricity usage.

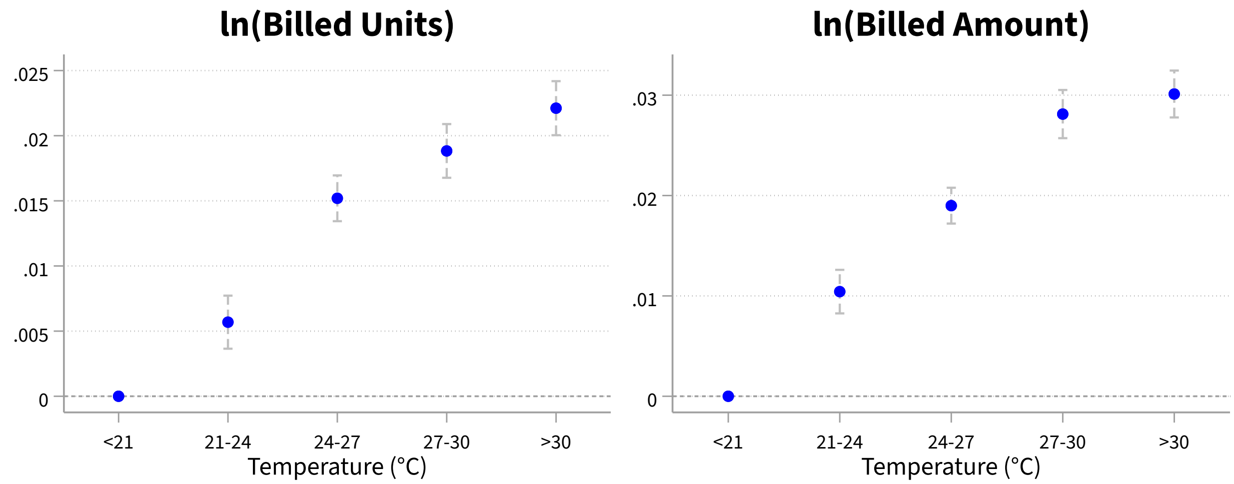

Figure 2: Heat and Billed Electricity Consumption of Formal Customers

Notes: This figure displays the estimated effect of temperature on billed electricity consumption (i.e., units and amount) of formal customers using the customer-level data. Formal customers in these analyses are the 3,000 customers that were in our survey for which we have the individual monthly billing data. These customers are always formal in our sample period. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. The omitted temperature category (<21°C) serves as the reference group for comparison. Blue dots are coefficient estimates. The coefficient estimates capture the change in electricity outcomes associated with having one additional day that daily average temperature falls into a given temperature bin in a billing month, relative to a day in the <21°C bin. Gray brackets are 95% confidence intervals centered on the estimated coefficient. The tabular results associated with these figures can be found in Appendix Table A2.

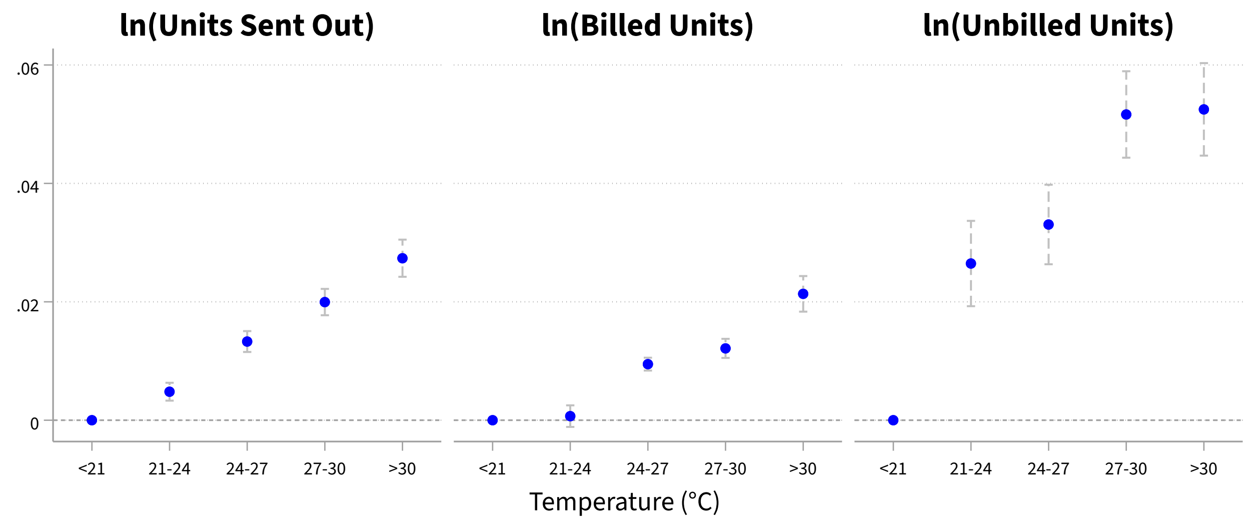

Figure 3: Heat and Electricity Consumption at the Feeder-Line Level

Notes: This figure displays the estimated effect of temperature on electricity outcomes, including total electricity sent out, billed units, and unbilled units, using the feeder-line-level data. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. The omitted temperature category (<21°C) serves as the reference group for comparison. Blue dots are coefficient estimates. The coefficient estimates capture the change in electricity outcomes associated with having one additional day that daily average temperature falls into a given temperature bin in a billing month, relative to a day in the <21°C bin. Gray brackets are 95% confidence intervals centered on the estimated coefficient. These results are also shown in tabular format in Appendix Table A3.

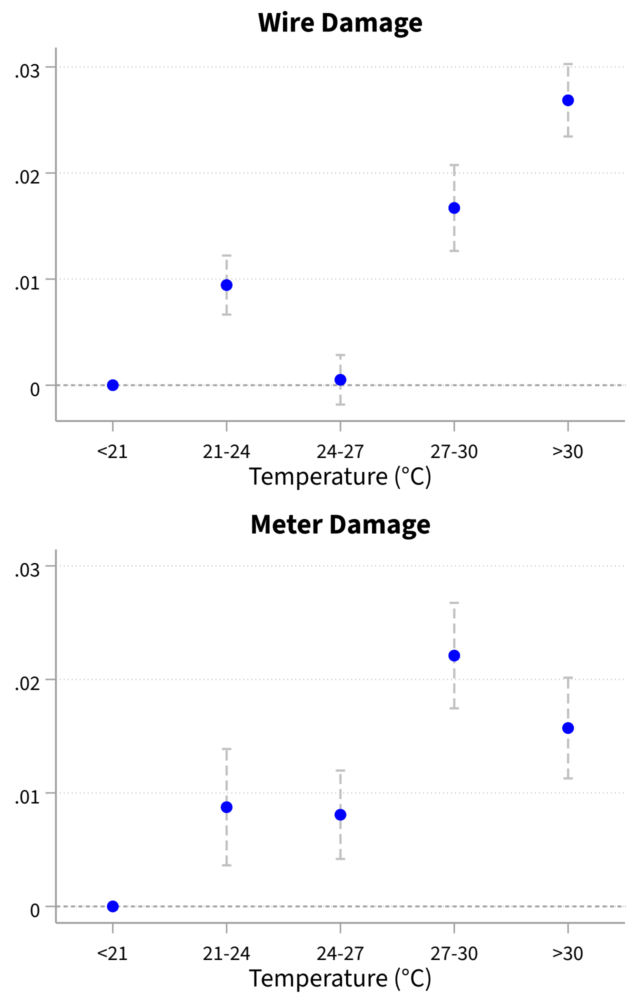

Figure 4: Heat and Infrastructure Damage

Notes: This figure displays the estimated effect of temperature on the number of the utility company's claims on infrastructure damage, using the feeder-line-level data. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. The omitted temperature category (<21°C) serves as the reference group for comparison. Blue dots are coefficient estimates from Poisson pseudo-likelihood regressions. Gray brackets are 95% confidence intervals centered on the estimated coefficient. These results are also shown in tabular format in Appendix Table A4.

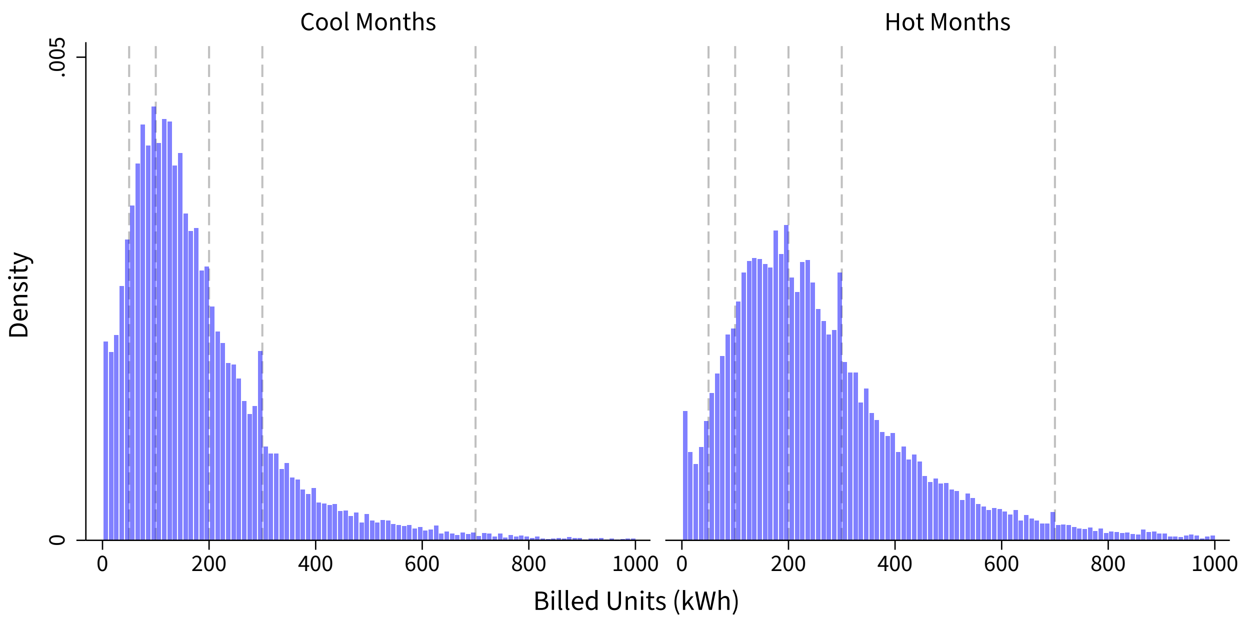

Figure 5: Distribution of Monthly Billed Units for Formally Connected Customers, by Cool and Hot Months

Notes: This figure presents the histogram of monthly billed electricity consumption units (in kWh), by cool and hot months, for customers who are formally connected with KE. The vertical dashed gray lines are the tariff cutoffs for residential customers. Hot months include May to September. The other calendar months are defined as cool months. Formal density manipulation test results are presented in Table A11.

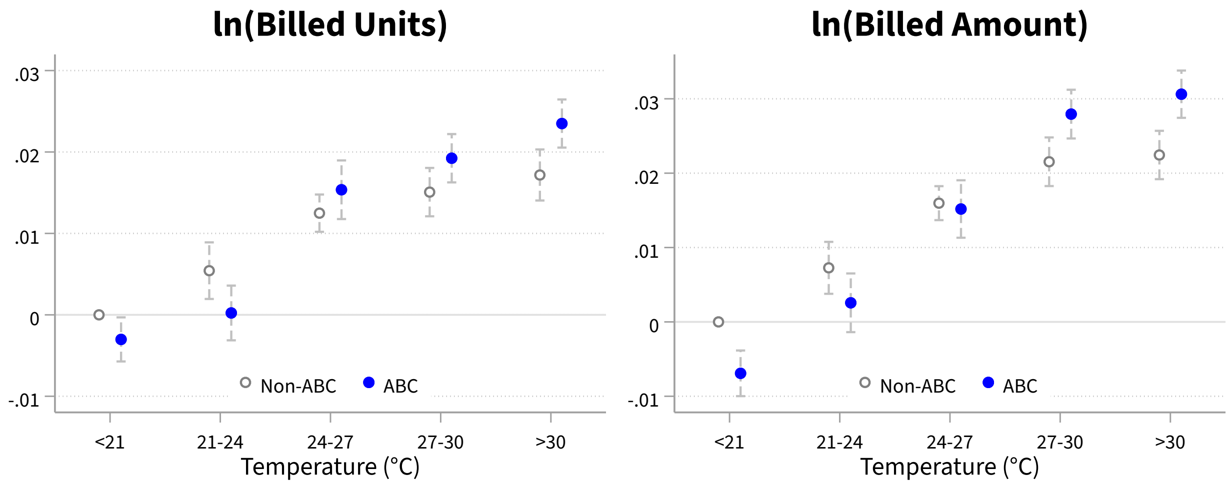

Figure 6: Heat, Theft-Resistant Cables, and Billed Consumption of Formal Customers

Notes: This figure displays the estimated effect of temperature and cable upgrades on on billed electricity consumption (i.e., units and amount) of formal customers using the customer-level data. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. Gray dots depict the estimated effect of temperature without cable upgrades. Blue dots depict the estimated effect of temperature with cable upgrades. Gray brackets are 95% confidence intervals. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison. These results are also shown in tabular format in Appendix Table A9.

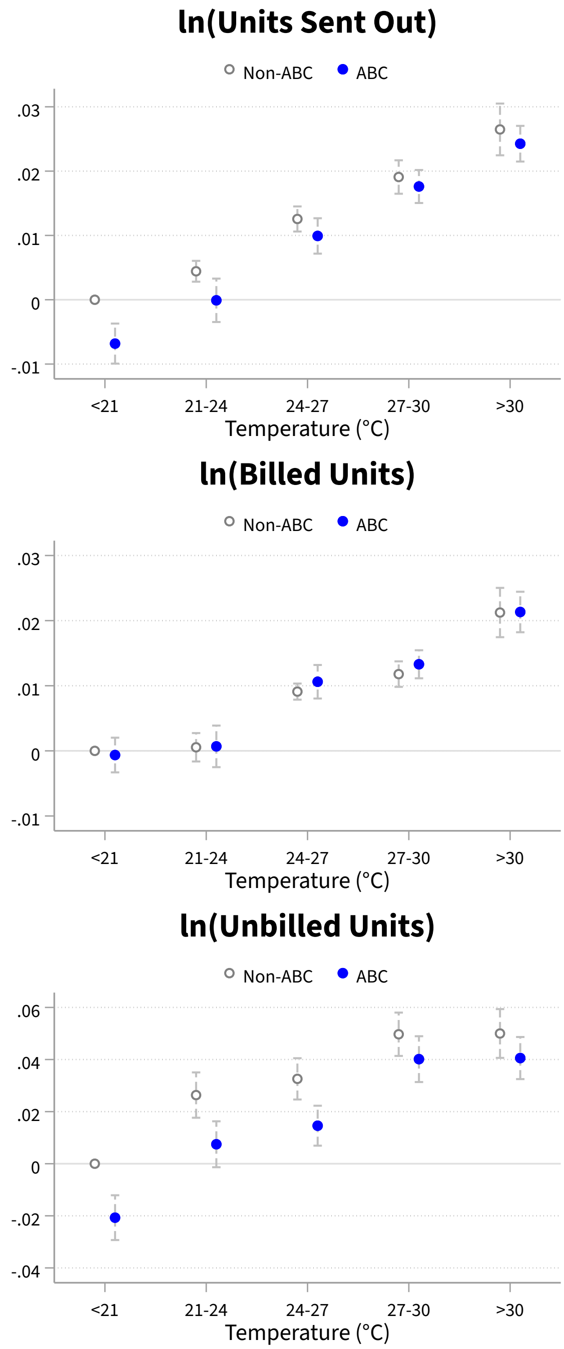

Figure 7: Heat, Theft-Resistant Cables, and Feeder-Line Electricity Consumption

Notes: This figure displays the estimated effect of temperature and cable upgrades on electricity outcomes, including total electricity sent out, billed units, and unbilled units, using the feeder-line-level data. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. Gray dots depict the estimated effect of temperature without cable upgrades. Blue dots depict the estimated effect of temperature with cable upgrades. Gray brackets are 95% confidence intervals. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison. These results in logs are also shown in tabular format in Appendix Table A7 and results in levels are in Appendix Table A8.

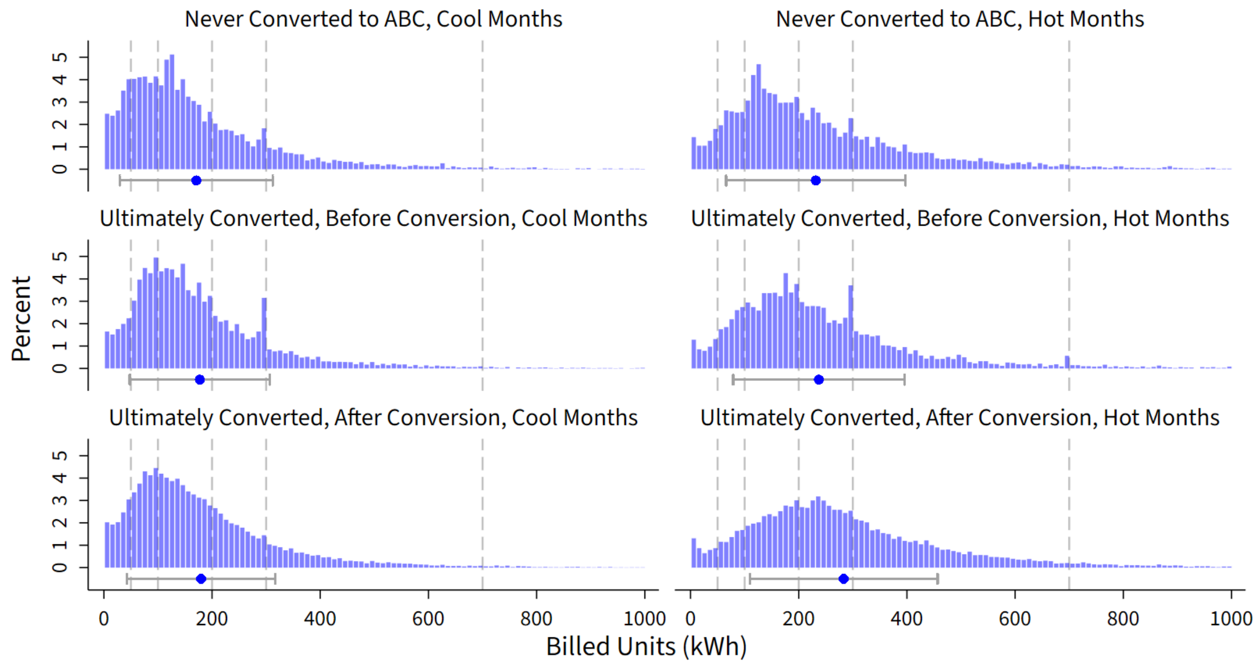

Figure 8: Distribution of Monthly Billed Units for Formally Connected Customers by Season and ABC Status

Notes: This figure presents the histogram of monthly billed electricity consumption units (in kWh) for customers who are formally connected with KE by season and ABC status. The vertical dashed gray lines are the tariff cutoffs for residential customers. Hot months include May to September and the other months in a day are defined as cool months. The blue circle at the bottom of each panel represents the mean and the gray segment represents the mean +/- one standard deviation. The associated density manipulation tests are in Appendix Table A12.

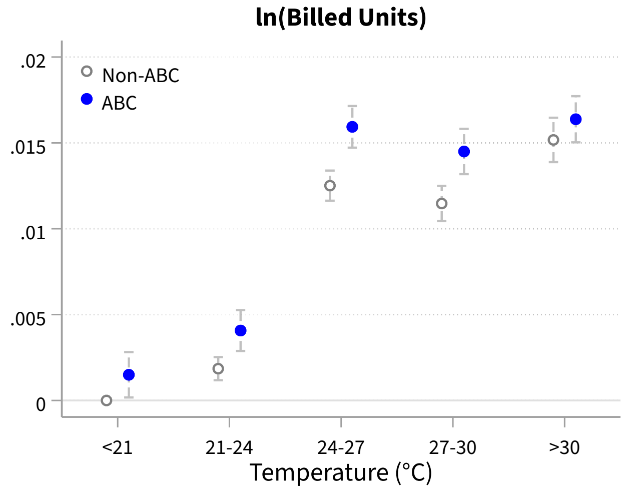

Figure 9: Temperature, ABC, and Billed Units for Non-Residential Customers

Notes: This figure displays the estimated effect of temperature and cable upgrades on on billed electricity consumption (kWh) of formal non-residential customers using the customer-level data. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. Gray dots depict the estimated effect of temperature without cable upgrades. Blue dots depict the estimated effect of temperature with cable upgrades. Gray brackets are 95% confidence intervals. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison.

Table 1: Cost to the Utility Company

Temperature Range	Percent Change in Monthly Unbilled Units	Average Number of Days in a Month	Change in Unbilled Units (kWh)	Cost to Utility Company (PKR)	Average Cost to Utility Company per Customer (PKR)
(1)	(2)	(3)	(4)	(5)	(6)
21-24	0.026	3.8	24,424	445,492	271
24-27	0.033	3.7	30,103	549,076	334
27-30	0.052	12.3	157,272	2,868,639	1,745
>30	0.053	6.0	78,354	1,429,182	869
Total			290,153	5,292,389	3,219

Notes: Column (2) reports the estimated percent change in monthly unbilled electricity units, taken from Column (5) of Table A3. Column (3) shows the average number of days per month in which the daily mean temperature falls within each temperature range over the sample period. The mean feeder-level unbilled electricity is 245,352 kWh. Column (4) is calculated by multiplying this mean by the percent change in Column (2) and the average number of days in Column (3). Column (5) reports the implied revenue loss to the utility, calculated by multiplying Column (4) by the average retail tariff of 18.24 PKR per kWh. Column (6) reports the average cost to the utility per customer, calculated by dividing Column (5) by the average number of customers per feeder line (1,644).

Table 2: Change in Cooling Appliance Usage Hours and Health Expenditure

Season	Monthly Consumption	Fan		AC	
		Daily Usage	Monthly Health Expenditure	Daily Usage	Monthly Health Expenditure
	(kWh / HH)	(hour)	(PKR / capita)	(hour)	(PKR / capita)
(1)	(2)	(3)	(4)	(5)	(6)
Hot	-34.70	-14.46	229.82	-0.96	24.21
Cool	-31.53	-13.14	208.85	-0.88	22.01

Notes: Change in monthly electricity consumption per household (Column 2) is calculated using the coefficient estimates of the interaction terms in Column (2) of Table C3 and the average number of days in a month with daily average temperature falling into each bin as shown in Table C4. Column (3) and (5) presents the estimated change in daily usage hours of the corresponding cooling appliance, assuming all the forgone electricity consumption would have been used for fan or air conditioner, respectively. Here, we assume the power of fan and air conditioner is 80W and 1,200W, based on the average estimate on KE webpage. Column (4) and (6) reports the calculated change in health expenditure as a result of decrease in cooling appliance usage, using coefficient estimates in Column (4) of Table C1.

ONLINE APPENDIX

Turning Up the Heat: Electricity Infrastructure, Temperature, and Poor Households

Husnain F. Ahmad Ayesha Ali Robyn C. Meeks
Zhenxuan Wang Javed Younas

A Additional Figures and Tables

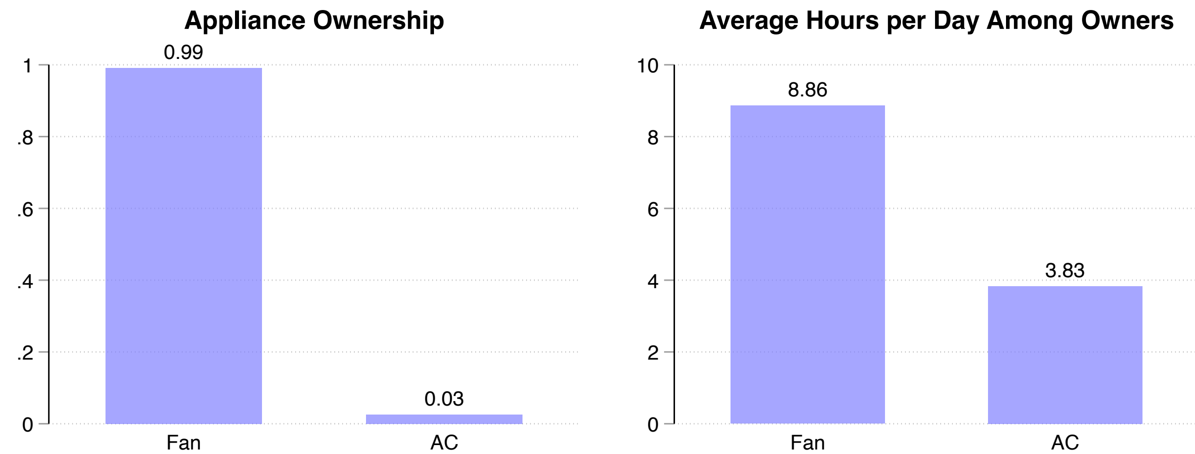

Figure A1: Self-Reported Cooling Appliance Ownership and Usage

Notes: This figure displays household self-reported ownership and usage patterns of fans and air conditioners. The data comes from our household survey conducted in Fall 2021. The left panel shows the share of households reporting to have these cooling appliances. The right panel shows the average usage hours in a typical day reported by households who claimed owning these appliances.

Table A1: Government of Pakistan's Residential Electricity Tariff: Jan 2018 - June 2021

Tariff Category	Units Consumed in Month (kWh)	Cost per Unit (PKR per kWh) A: Jan 2018 – – Dec 2018	B: Jan 2019 – – June 2019	C: July 2019 – – Sept 2019	D: Oct 2019 – – Nov 2019	E: Dec 2019 – – Jan 2021	F: Feb 2021 – – June 2021
Normal	001-100 Units	5.79	5.79	5.79	5.79	5.79	7.74
	101-200 Units	8.11	8.11	8.11	8.11	8.11	10.06
	201-300 Units	10.2	10.2	10.2	10.2	10.2	12.15
	301-700 Units	16	17.6	18.35	19.18	19.25	21.43
	Above 700 Units	18	20.7	21.45	22.28	22.35	24.53
Lifeline	Up to 50 Units	2	2	2	2	2	3.95

Notes: All tariffs are in PKR per kWh. All customers in the "Normal" tariff category have a peak load requirement that is less than 5 kW. Any residential customers with a peak load requirement that is more than 5 kW are placed on the time-of-use tariff (TOU). TOU customers are not included in our study sample, so we do not show their tariff prices here. The "normal" tariff is an increasing block tariff, meaning that customers are charged a uniform marginal price based on their total consumption in the billing period. The electricity tariff shown here includes a subsidy for lifeline and protected consumers, but excludes the monthly fuel charge adjustments, financing cost surcharges, sales tax, duties and other monthly fees. "Lifeline" consumers are those with consumption less than 100 units per month in each of the past 12 months. As a result of the uncertainty around future costs of imported fossil fuel, there is a gap between ex ante tariffs—set on the basis of projected fuel prices and generation mixes—and ex post realized costs faced by generation companies and power purchasers. To manage this gap, the government employs tariff adjustment mechanisms that pass realized fuel cost deviations through to consumers, primarily through Fuel Cost Adjustments (FCAs). FCAs are determined on a monthly basis by NEPRA, to reflect actual variations in fuel prices, the generation mix, and overall power purchase costs. The FCA is not included in the prices in the table above. The FCA is charged separately on consumers' monthly electricity bills, based on units consumed during the relevant fuel month, and can be either positive or negative depending on whether average fuel costs per kilowatt-hour exceed or fall below the reference level embedded in the tariff.

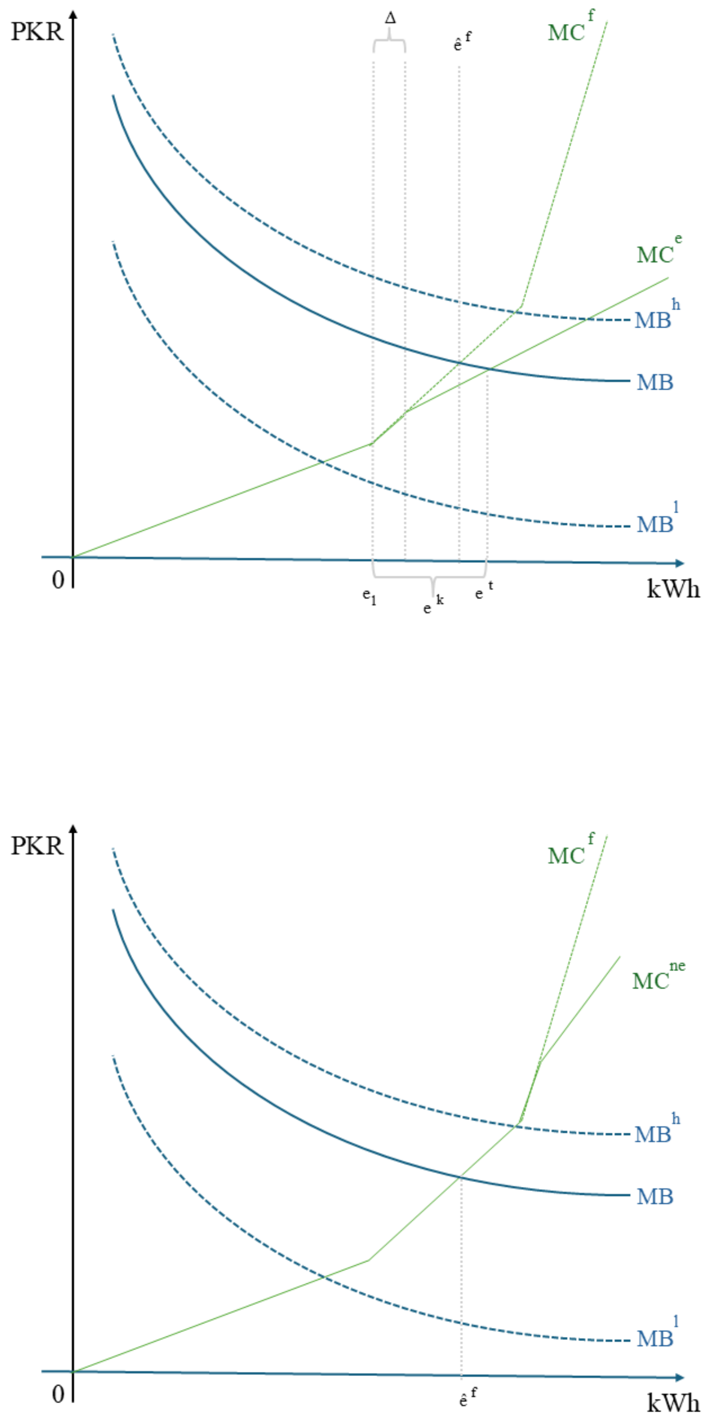

Figure A2: Household's Choice of Electricity Usage with Increasing MC and Kunda Cost

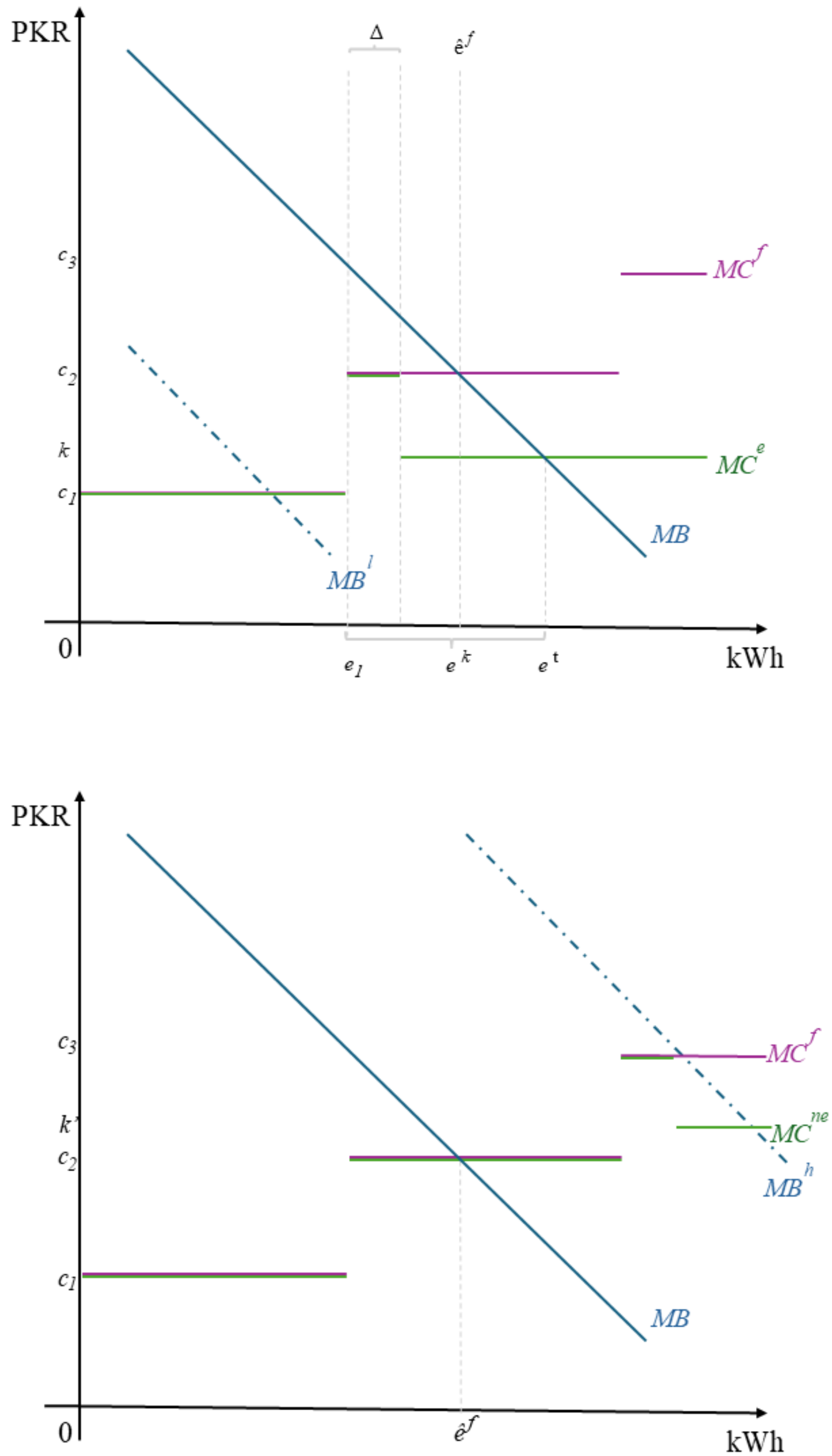

Figure A3: Household's Choice of Electricity Usage with Fixed Cost to Acquire a Kunda

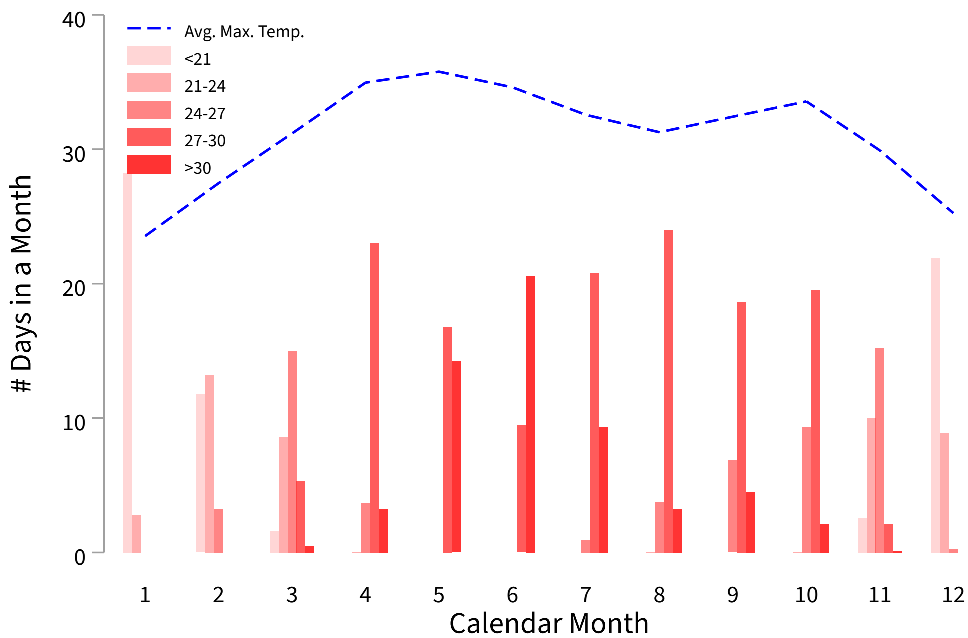

Figure A4: Distribution of Daily Temperature by Month

Notes: This figure displays the distribution of daily temperature (°C) in Karachi by calendar month. The red bars represent the average number of days per calendar month, over the 2018-2021 sample period, with daily average temperature falling within specific ranges. The dashed blue line illustrates the average maximum temperature for each calendar month.

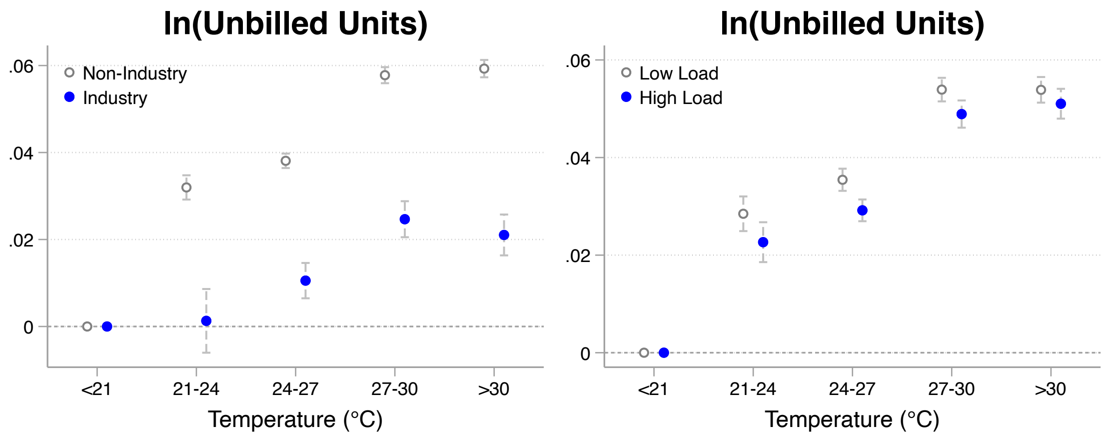

Figure A5: Evidence that the Effect on Unbilled Units Is Not Driven by Technical Losses

Notes: This figure displays the estimated effect of temperature on unbilled units, using the feeder-line-level data, differentiating by whether the feeder primarily serves industry versus non-industry customers (left panel) or whether it primarily serves low versus high load customers. The coefficient estimates capture the change in electricity outcomes associated with having one additional day that daily average temperature falls into a given temperature bin in a billing month, relative to a day in the <21°C bin for that type of feeder line (i.e., industry or no-industry, high load or low load).

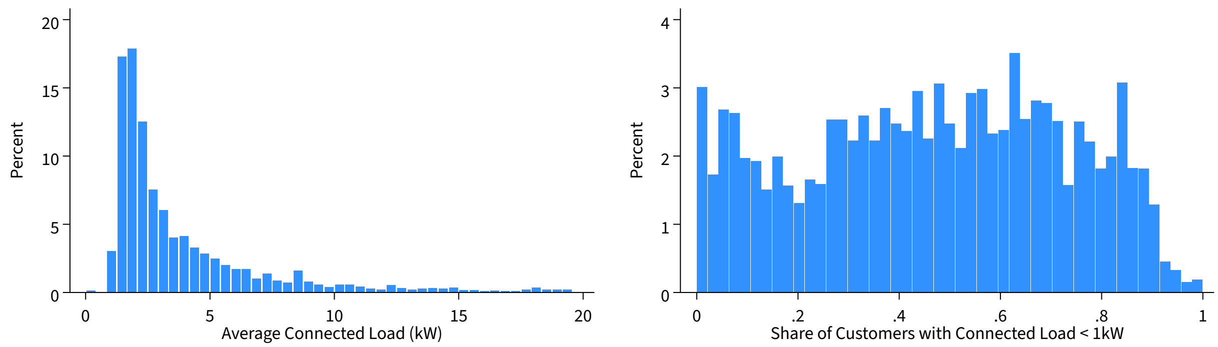

Figure A6: Distribution of Connected Load at Feeder Line Level

Notes: For each feeder line, we calculate the average connected load over all customers and the share of customers with connected load below 1kW. Then, we plot the distribution for the average connected load and share of customers among all the feeder lines.

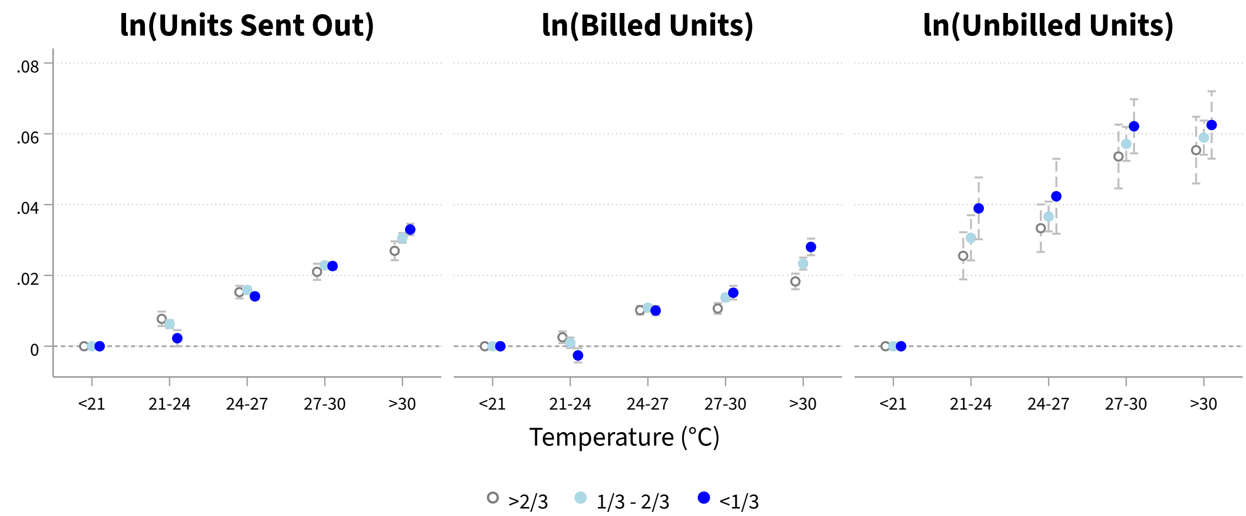

Figure A7: Heterogeneity of Temperature Effects by Feeder-Line Customer Connected Load

Notes: Averages calculated at the feeder line level. For these analyses, we exclude feeder lines with average connected load > 20kW, which are likely to mainly serve non-residential customers. Connected loads < 1kW can power energy efficient devices and small appliances, such as mobile phone charges, laptops, small fans, food mixers, etc. Connected loads > 1 kW are needed to power appliances such as air conditioners, refrigerators, washing machines, microwaves, and electric stoves. These results are also shown in tabular format in Appendix Table A5.

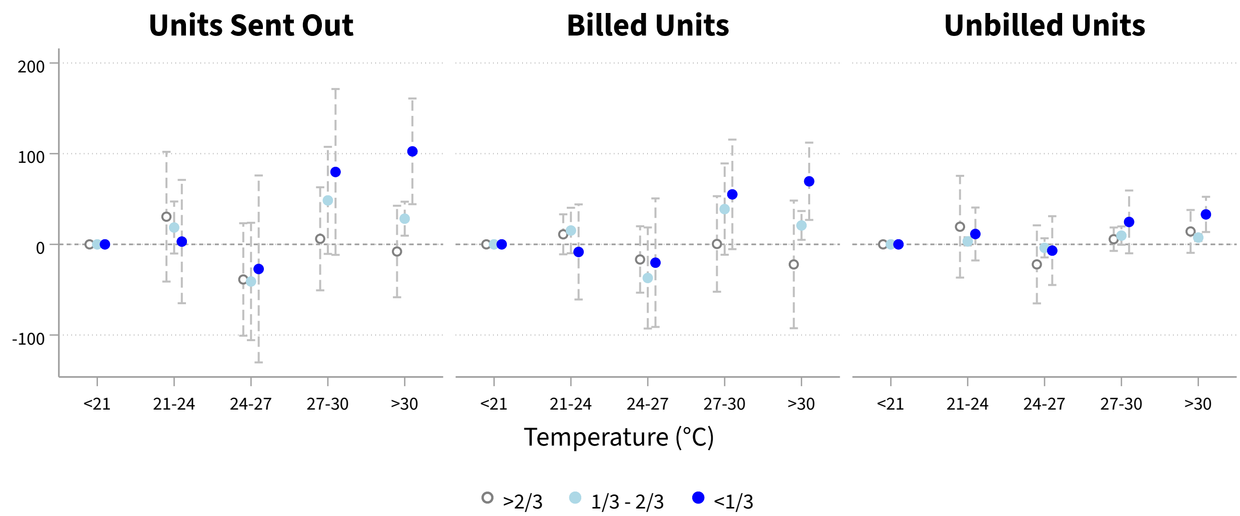

Figure A8: Heterogeneity of Temperature Effects by Feeder-Line Customer Connected Load - Per-customer Outcome Measures

Notes: This figure displays the estimated effect of temperature on per-customer electricity outcomes, including total electricity sent out, billed units, and unbilled units, using the feeder-line-level data and differentiating by the share of the feeder line with a connected load of < 1kW. Averages calculated at the feeder line level. The color of dots gets darker as the feeder line has a larger proportion of higher connected (> 1kW) load customers. For these analyses, we exclude feeder lines with average connected load > 20kW, which are likely to mainly serve non-residential customers. Connected loads < 1kW can power energy efficient devices and small appliances, such as mobile phone charges, laptops, small fans, food mixers, etc. Connected loads > 1 kW are needed to power appliances such as air conditioners, refrigerators, washing machines, microwaves, and electric stoves. These results are also shown in tabular format in Appendix Table A5.

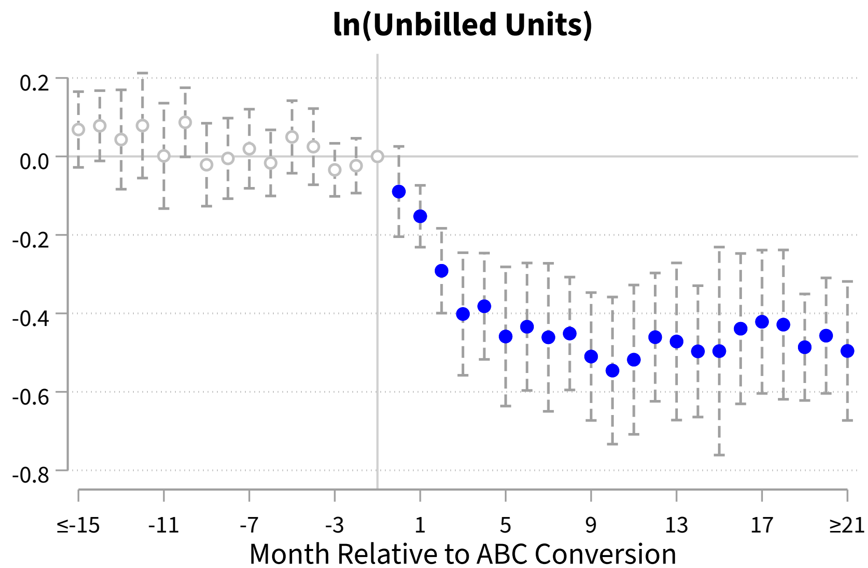

Figure A9: Dynamic Impacts of Theft-Resistance Cables on Unbilled Electricity Units

Notes: This figure displays the coefficients and their 95% confidence intervals from an event-study regression estimating the impact of theft-resistance cable installation on logarithm of unbilled electricity units, following Ahmad et al. (2025). Data are at the feeder level on a monthly basis. Regressions include IBC-by-month and feeder fixed effects. One month prior to the installation (-1) is the reference group, and the corresponding coefficient is normalized to zero. Standard errors are clustered at the feeder level.

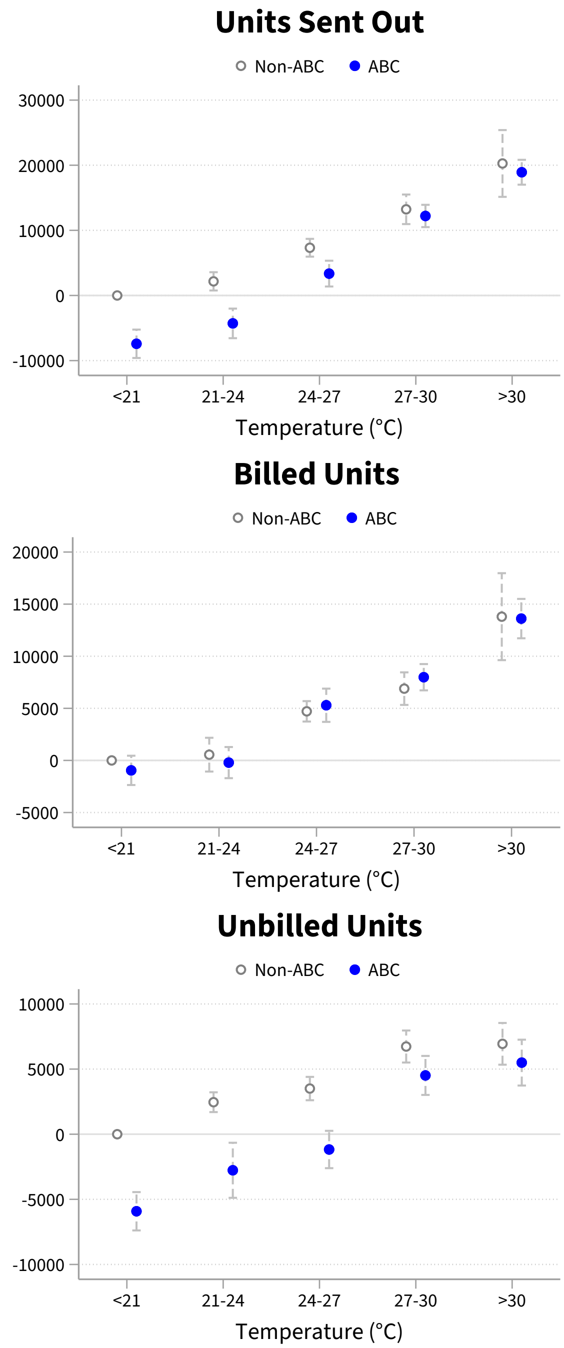

Figure A10: Heat, Theft-Resistant Cables, and Feeder-Line Electricity Consumption

Notes: This figure displays the estimated effect of temperature and cable upgrades on electricity outcomes, including total electricity sent out, billed units, and unbilled units, using the feeder-line-level data. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. Gray dots depict the estimated effect of temperature without cable upgrades. Blue dots depict the estimated effect of temperature with cable upgrades. Gray brackets are 95% confidence intervals. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison. These results are also shown in tabular format in Appendix Table A8.

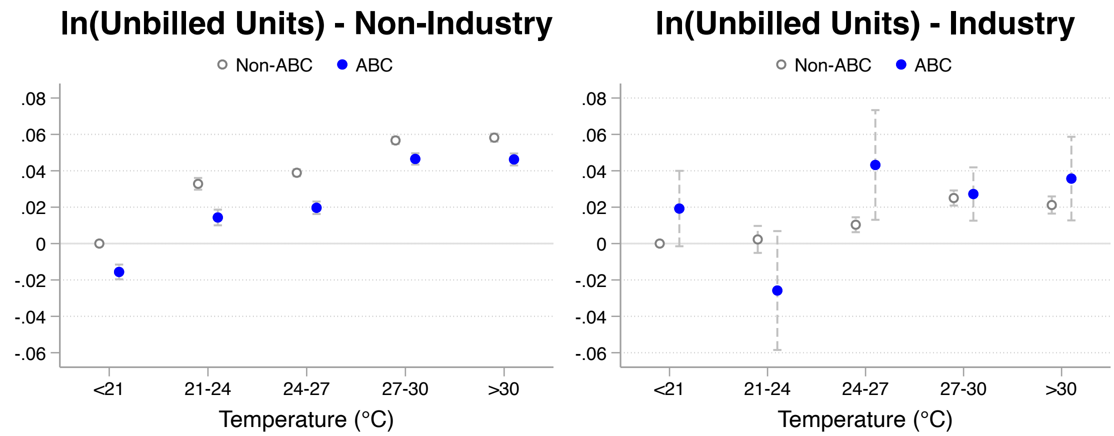

Figure A11: The Effect of ABC on Unbilled Units by Industry vs Non-Industry Feeder Lines

Notes: This figure displays the estimated effect of temperature and cable upgrades on unbilled units, using the feeder-line-level data. The graph on the left is for feeder lines that serve non-industry consumers and the graph on the right is for feeder lines that serve industry consumers. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. Gray dots depict the estimated effect of temperature without cable upgrades. Blue dots depict the estimated effect of temperature with cable upgrades. Gray brackets are 95% confidence intervals. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison.

Table A2: Temperature and Billed Consumption for Formal Customers

VARIABLES	(1) lnUnit	(2) lnAmount
tavgbin24	0.006***	0.010***
	(0.001)	(0.001)
tavgbin27	0.015***	0.019***
	(0.001)	(0.001)
tavgbin30	0.019***	0.028***
	(0.001)	(0.001)
tavgbin40	0.022***	0.030***
	(0.001)	(0.001)
Observations	88,300	88,300
Outcome Mean	241.04	3368.97
HH FE	Y	Y
Year FE	Y	Y
QoY FE	Y	Y

Notes: This table presents the same results represented in Appendix Figure 2. These regressions estimate effect of temperature on the monthly billed electricity consumption (i.e., units and amount) of formal customers using the customer-level data. The independent variables are the interactions between temperature bins (T_{bit}). The omitted category, i.e., daily average temperature below 21°C , serves as the reference group for comparison. Standard errors in parentheses are clustered at the PMT level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Temperature and Feeder-Line Electricity Outcomes

VARIABLES	(1) lnSendOut	(2) lnSendOut	(3) lnBill	(4) lnBill	(5) lnUnbill	(6) lnUnbill
tavgbin24	0.005***	0.011***	0.001	0.007**	0.026***	0.030***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.004)	(0.007)
tavgbin27	0.013***	0.015***	0.009***	0.011***	0.033***	0.034***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.006)
tavgbin30	0.020***	0.021***	0.012***	0.012***	0.052***	0.055***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.004)	(0.008)
tavgbin40	0.027***	0.027***	0.021***	0.020***	0.053***	0.057***
	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)	(0.010)
Observations	66,651	66,651	66,651	66,651	58,210	58,210
Outcome Mean (kWh)	891,032	891,032	682,936	682,936	245,352	245,352
Feeder FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
QoY FE	Y		Y		Y	
MoY FE		Y		Y		Y

Notes: This table contains the results represented in Figure 3. Regressions use monthly feeder line level data from Karachi Electric for the city of Karachi from January 2018 to October 2020. The dependent variables are the natural log of total electricity sent out to a given feeder line (lnSendOut), the number of billed units for the feeder line (lnBill), and difference between those two, which is the unbilled units (lnUnbill). β_b captures the change in electricity outcomes associated with having one additional day that daily average temperature falls into bin b in a billing month, where the bins are $\{< 21, 21 - 24, 24 - 27, 27 - 30, > 30\}$ relative to a day in the omitted temperature bin, which is <21°C bin in these regressions. Standard errors in parentheses are clustered at the IBC level. The odd columns are used for Figure 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Temperature and KE Claims of Damage to Infrastructure

VARIABLES	KE Claims	
	Meter Damage	Wire Damage
	(1)	(2)
tavgbin24	0.009***	0.009***
	(0.003)	(0.001)
tavgbin27	0.008***	0.001
	(0.002)	(0.001)
tavgbin30	0.022***	0.017***
	(0.002)	(0.002)
tavgbin40	0.016***	0.027***
	(0.002)	(0.002)
Observations	30,976	34,034
Outcome Mean	.65	2.72
Feeder FE	Y	Y
Year FE	Y	Y
QoY FE	Y	Y

Notes: This table presents the same results shown in Figure 4. The outcome variables, which are obtained from utility's administrative records and measured at the feeder-line level by month, are the number of the utility company's claims on two types of infrastructure damage, meter damage (column 1) and wire damage (column 2). The unit of the outcome variables is number per month. β_b captures the change in electricity outcomes associated with having one additional day that daily average temperature falls into bin b in a billing month, where the bins are $\{< 21, 21-24, 24-27, 27-30, > 30\}$ relative to a day in the omitted temperature bin, which is <21°C bin in these regressions. Standard errors in parentheses are clustered at the IBC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Temperature and Feeder-Line Electricity Outcomes by Connected Load

VARIABLES	lnSendOut			lnBill			lnLoss		
Share of <1kW Customers	>2/3	1/3 - 2/3	<1/3	>2/3	1/3 - 2/3	<1/3	>2/3	1/3 - 2/3	<1/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
tavgbin24	0.008***	0.006***	0.002*	0.003***	0.001	-0.003**	0.026***	0.031***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)
tavgbin27	0.015***	0.016***	0.014***	0.010***	0.011***	0.010***	0.033***	0.037***	0.042***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.003)	(0.002)	(0.005)
tavgbin30	0.021***	0.023***	0.023***	0.011***	0.014***	0.015***	0.054***	0.057***	0.062***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.004)	(0.002)	(0.004)
tavgbin40	0.027***	0.031***	0.033***	0.018***	0.023***	0.028***	0.055***	0.059***	0.062***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.002)	(0.005)
Outcome Level Mean (kWh)	952,043	1,006,525	767,937	628,551	737,062	634,957	344,188	299,587	167,753
NFeeder	333	518	476	333	518	476	332	518	476
NCustomer	2,777	2,591	1,295	2,777	2,591	1,295	2,780	2,597	1,323
Observations	13,981	21,462	18,935	13,981	21,462	18,935	13,234	19,632	15,840
R-squared	0.798	0.801	0.839	0.764	0.777	0.821	0.641	0.564	0.555
Feeder FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
QoY FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents the same results represented in Figure A7. Regressions use monthly feeder line level data from Karachi Electric for the city of Karachi from January 2018 to October 2020. The dependent variables are the natural log of total electricity sent out to a given feeder line (lnSendOut), the number of billed units for the feeder line (lnBill), and difference between those two, which is the unbilled units (lnLoss). We estimate the temperature effect separately for feeder lines with over 2/3, between 1/3 and 2/3, and less than 1/3 of customers whose connected load is below 1kW. β_b captures the change in electricity outcomes associated with having one additional day that daily average temperature falls into bin b in a billing month, where the bins are $\{< 21, 21-24, 24-27, 27-30, > 30\}$ relative to a day in the omitted temperature bin, which is <21°C bin in these regressions. Standard errors in parentheses are clustered at the IBC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Temperature and Feeder-Line Electricity Outcomes by Connected Load (Per Customer Outcomes)

VARIABLES	SendOutpc			Billpc			Unbilledpc		
Share of <1kW Customers	>2/3	1/3 - 2/3	<1/3	>2/3	1/3 - 2/3	<1/3	>2/3	1/3 - 2/3	<1/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
tavgbin24	30.492	18.565	3.038	11.049	15.251	-8.379	19.443	3.314	11.417
	(34.747)	(13.905)	(32.700)	(10.708)	(12.145)	(25.226)	(27.243)	(2.195)	(14.027)
tavgbin27	-38.754	-40.952	-27.142	-16.671	-37.094	-20.239	-22.083	-3.857	-6.903
	(30.119)	(31.361)	(49.569)	(17.795)	(27.003)	(34.079)	(20.892)	(5.113)	(18.246)
tavgbin30	6.105	48.488	79.839*	0.430	38.870	55.119*	5.676	9.618*	24.720
	(27.588)	(28.605)	(43.976)	(25.599)	(24.405)	(29.059)	(6.264)	(4.901)	(16.657)
tavgbin40	-7.901	28.300***	102.579***	-22.147	20.827**	69.549***	14.245	7.473***	33.031***
	(24.500)	(9.076)	(28.023)	(34.188)	(7.710)	(20.498)	(11.466)	(1.812)	(9.335)
Observations	10,205	15,902	13,988	10,205	15,902	13,988	10,205	15,902	13,988
R-squared	0.194	0.038	0.152	0.127	0.038	0.193	0.198	0.039	0.071
Outcome Mean	1,682	810	2,179	932	635	1,680	750	175	499
NFeeder	315	494	456	315	494	456	315	494	456
NCustomer	2777	2591	1295	2777	2591	1295	2777	2591	1295
Feeder FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
QoY FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents the same results represented in Figure A7. Regressions use monthly feeder line level data from Karachi Electric for the city of Karachi from January 2018 to October 2020. The dependent variables are per-customer total electricity sent out to a given feeder line (SendOutpc), the number of billed units for the feeder line (Billpc), and difference between those two, which is the unbilled units (Losspc). We estimate the temperature effect separately for feeder lines with over 2/3, between 1/3 and 2/3, and less than 1/3 of customers whose connected load is below 1kW. β_b captures the change in electricity outcomes associated with having one additional day that daily average temperature falls into bin b in a billing month, where the bins are $\{<21, 21-24, 24-27, 27-30, >30\}$ relative to a day in the omitted temperature bin, which is <21°C bin in these regressions. Standard errors in parentheses are clustered at the IBC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Temperature, ABCs, and Feeder-Line Electricity Outcomes (Logs)

VARIABLES	(1) lnSendOut	(2) lnBill	(3) lnLoss
tavgbin24	0.004***	0.001	0.026***
	(0.001)	(0.001)	(0.004)
tavgbin27	0.013***	0.009***	0.033***
	(0.001)	(0.001)	(0.004)
tavgbin30	0.019***	0.012***	0.050***
	(0.001)	(0.001)	(0.004)
tavgbin40	0.026***	0.021***	0.050***
	(0.002)	(0.002)	(0.005)
c.tavgbin21#c.ABC	-0.007***	-0.001	-0.021***
	(0.002)	(0.001)	(0.004)
c.tavgbin24#c.ABC	-0.005**	0.000	-0.019***
	(0.002)	(0.002)	(0.004)
c.tavgbin27#c.ABC	-0.003**	0.002	-0.018***
	(0.001)	(0.001)	(0.003)
c.tavgbin30#c.ABC	-0.001	0.002	-0.010***
	(0.001)	(0.001)	(0.002)
c.tavgbin40#c.ABC	-0.002	0.000	-0.009***
	(0.002)	(0.002)	(0.003)
Observations	66,651	66,651	58,210
R-squared	0.814	0.786	0.604
Outcome Level Mean (kWh)	891,032	682,936	245,352
Feeder FE	Y	Y	Y
Year FE	Y	Y	Y
QoY FE	Y	Y	Y

Notes: This table presents the same results represented in Figure 7. This presents the estimated effect of temperature and cable upgrades on electricity outcomes, including the natural log of total electricity sent out, billed units, and unbilled units, using the feeder-line-level data. The independent variables are the interactions between temperature bins (T_{bit}) and the indicator for cable upgrades (ABC_{it}). For the feeder-line-level analysis, ABC_{it} equals 1 if a feeder-line i already has at least one transformer with theft-resistant cables installed in month t. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison. Standard errors in parentheses are clustered at the IBC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Temperature, ABCs, and Feeder-Line Electricity Outcomes (Levels)

VARIABLES	(1) SendOut	(2) Bill	(3) Unbill
tavgbin24	2,169.464***	551.695	2,458.276***
	(684.946)	(791.547)	(370.922)
tavgbin27	7,326.688***	4,711.733***	3,505.220***
	(667.578)	(478.358)	(437.353)
tavgbin30	13,231.090***	6,890.585***	6,733.097***
	(1,108.425)	(762.873)	(600.287)
tavgbin40	20,269.680***	13,796.836***	6,938.702***
	(2,502.348)	(2,037.077)	(782.232)
c.tavgbin21#c.ABC	-7,417.715***	-954.601	-5,915.948***
	(1,063.090)	(686.289)	(718.502)
c.tavgbin24#c.ABC	-6,455.784***	-760.078	-5,227.781***
	(1,282.169)	(1,083.357)	(962.520)
c.tavgbin27#c.ABC	-3,969.883***	582.816	-4,679.054***
	(1,298.107)	(1,008.899)	(744.870)
c.tavgbin30#c.ABC	-1,023.028	1,096.159	-2,220.127***
	(1,405.441)	(1,063.753)	(714.558)
c.tavgbin40#c.ABC	-1,348.151	-184.621	-1,442.065
	(2,774.463)	(2,212.342)	(1,083.260)
Observations	66,651	66,651	58,210
R-squared	0.717	0.704	0.594
Outcome Level Mean (kWh)	891,032	682,936	245,352
Feeder FE	Y	Y	Y
Year FE	Y	Y	Y
QoY FE	Y	Y	Y

Notes: This table presents the estimated effect of temperature and cable upgrades on electricity outcomes, including the total electricity sent out, billed units, and unbilled units, using the feeder-line-level data. The independent variables are the interactions between temperature bins (T_{bit}) and the indicator for cable upgrades (ABC$_{it}$). For the feeder-line-level analysis, ABC$_{it}$ equals 1 if a feeder-line i already has at least one transformer with theft-resistant cables installed in month t. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison. Standard errors in parentheses are clustered at the IBC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Temperature, ABCs, and Formal Customers' Billed Consumption

VARIABLES	(1) lnUnit	(2) lnAmount
tavgbin24	0.005***	0.007***
	(0.002)	(0.002)
tavgbin27	0.012***	0.016***
	(0.001)	(0.001)
tavgbin30	0.015***	0.022***
	(0.001)	(0.002)
tavgbin40	0.017***	0.022***
	(0.002)	(0.002)
c.tavgbin21#c.ABC	-0.003**	-0.007***
	(0.001)	(0.002)
c.tavgbin24#c.ABC	-0.005***	-0.005**
	(0.002)	(0.002)
c.tavgbin27#c.ABC	0.003*	-0.001
	(0.002)	(0.002)
c.tavgbin30#c.ABC	0.004***	0.006***
	(0.001)	(0.001)
c.tavgbin40#c.ABC	0.006***	0.008***
	(0.001)	(0.001)
Observations	88,300	88,300
R-squared	0.493	0.558
Outcome Level Mean	241.04 kWh	3368.97 PKR
HH FE	Y	Y
Year FE	Y	Y
QoY FE	Y	Y

Notes: This table presents the same results represented in Figure 6. These regressions estimate effect of temperature and cable upgrades on the monthly billed household electricity consumption (i.e., units and amount) of formal customers using the customer-level data. The independent variables are the interactions between temperature bins (T_{bit}) and the indicator for cable upgrades (ABC_{it}), where ABC_{it} equals 1 if the transformer that serves customer i already has theft-resistant cables installed in month t. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Temperature, ABCs, and Feeder-Line Electricity Outcomes (Logs) by ABC Ratio

VARIABLES	lnSendOut			lnBill			lnLoss		
ABC Ratio	0 - 0.4	0.4 - 0.8	0.8 - 1	0 - 0.4	0.4 - 0.8	0.8 - 1	0 - 0.4	0.4 - 0.8	0.8 - 1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
tavgbin24	0.004***	0.004***	0.004***	0.000	0.000	0.000	0.026***	0.026***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)
tavgbin27	0.012***	0.012***	0.012***	0.009***	0.009***	0.009***	0.033***	0.033***	0.033***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
tavgbin30	0.019***	0.019***	0.019***	0.012***	0.012***	0.012***	0.050***	0.050***	0.051***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.005)
tavgbin40	0.027***	0.027***	0.027***	0.022***	0.022***	0.022***	0.050***	0.050***	0.051***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
c.tavgbin21#c.ABC	-0.002	-0.008***	-0.011***	0.000	-0.001	-0.002	-0.003	-0.021***	-0.035***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.006)	(0.005)	(0.005)
c.tavgbin24#c.ABC	-0.002	-0.003*	-0.007***	-0.001	0.002	-0.001	-0.009	-0.019***	-0.026***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.004)	(0.004)
c.tavgbin27#c.ABC	-0.000	-0.003**	-0.004***	-0.000	0.002	0.002	-0.007**	-0.019***	-0.026***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)
c.tavgbin30#c.ABC	-0.001	-0.000	-0.003*	-0.002	0.003**	0.002	-0.003	-0.008***	-0.014***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
c.tavgbin40#c.ABC	-0.002	-0.001	-0.003	-0.005*	0.002	0.002	-0.001	-0.009***	-0.014***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	54,276	56,188	55,337	54,276	56,188	55,337	46,392	48,237	47,441
Outcome Level Mean (kWh)	854,489	865,231	858,021	678,803	682,360	682,372	213,817	221,043	212,975
Feeder FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
QoY FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This presents the estimated effect of temperature and cable upgrades on electricity outcomes, including the natural log of total electricity sent out, billed units, and unbilled units, using the feeder-line-level data. We run subsample regressions by the ratio of PMTs with ABC conversion in a feeder line. For each subsample, we include feeder lines that did not have any PMT with ABC conversion and feeder lines whose ABC conversion ratio is between 0-0.4, 0.4-0.8, or above 0.8, respectively. The independent variables are the interactions between temperature bins (T_{bit}) and the indicator for cable upgrades (ABC_{it}). For the feeder-line-level analysis, ABC_{it} equals 1 if a feeder-line i already has at least one transformer with theft-resistant cables installed in month t. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison. Standard errors in parentheses are clustered at the IBC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Data Manipulation Test at Tariff Cutoffs - by Season

Season:	Cool	Hot
Tariff Cutoffs:		
50	0.0001	0.0000
	(0.7256)	(0.9009)
100	0.0008	-0.0003
	(0.0303)	(0.2531)
200	0.0002	0.0006
	(0.2199)	(0.0025)
300	0.0017	0.0007
	(0.0000)	(0.0000)
700	0.0000	0.0000
	(0.3001)	(0.4186)

Notes: This table shows the results from density manipulation tests at the electricity tariff cutoffs. These correspond to the histograms in Figure 5. We perform the manipulation tests using local polynomial density estimators as described by Cattaneo, Jansson and Ma (2020). Each cell displays the difference between the estimated density just to the left of the cutoff and the density just to the right. The p-values for the associated tests are reported in parentheses.

Table A12: Density Manipulation Test at Tariff Cutoffs - by Customer Group and Season

Customer Group:	Never Converted		Ultimately Converted, Before Conversion		Ultimately Converted, After Conversion	
Season:	Cool	Hot	Cool	Hot	Cool	Hot
Tariff Cutoffs:						
50	0.0004	0.0007	0.0002	0.0000	0.0004	0.0001
	(0.4856)	(0.0644)	(0.6166)	(0.8943)	(0.3262)	(0.6826)
100	0.0020	0.0000	0.0014	-0.0004	0.0006	-0.0003
	(0.0000)	(0.9538)	(0.0431)	(0.3931)	(0.1804)	(0.2174)
200	0.0001	0.0011	0.0008	0.0006	-0.0001	0.0007
	(0.7402)	(0.0150)	(0.0071)	(0.0847)	(0.5967)	(0.0071)
300	0.0013	0.0011	0.0044	0.0015	0.0005	0.0004
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0041)	(0.1630)
700	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000
	(0.6482)	(0.5987)	(0.9999)	(0.0001)	(0.5317)	(0.4136)

Notes: This table shows the results from density manipulation tests at the electricity tariff cutoffs. These correspond to the histograms in Figure 8. We perform the manipulation tests using local polynomial density estimators as described by Cattaneo, Jansson and Ma (2020). Each cell displays the difference between the estimated density just to the left of the cutoff and the density just to the right. The p-values for the associated tests are reported in parentheses.

B Counterfactual Temperature Control Correction

Jones et al. (2026) show that bin-based temperature regressions can generate spurious U-shaped responses when predictable shifts in temperature exposure – driven by long-run warming and baseline climate differences across locations – are correlated with differential outcome trends. The relevance of this concern is more limited in our setting for two reasons. First, our analysis focuses on feeder lines and customers within a single city, where baseline difference in climate conditions is small, removing the cross-location variation in baseline temperature that is central to the bias mechanism emphasized by Jones et al. (2026). Second, our sample spans a short time horizon (2018–2021), over which long-run warming trends are minimal.

Nonetheless, to assess whether predictable exposure patterns could influence our estimates, we conduct robustness checks for our main results using the counterfactual temperature control approach proposed by Jones et al. (2026). We construct expected bin exposures for each month and include these counterfactual exposures as additional controls in our regressions. As shown in Figures B1–B4, the estimated temperature effects remain stable, and our main findings are unchanged.

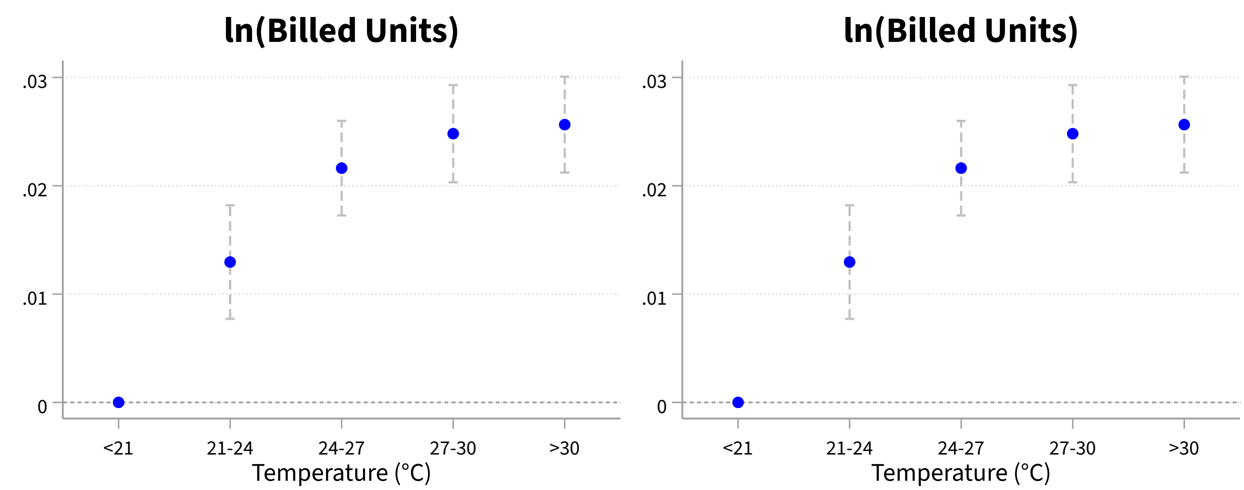

Figure B1: Temperature and Billed Consumption for Formal Customers - with Counterfactual Control Correction

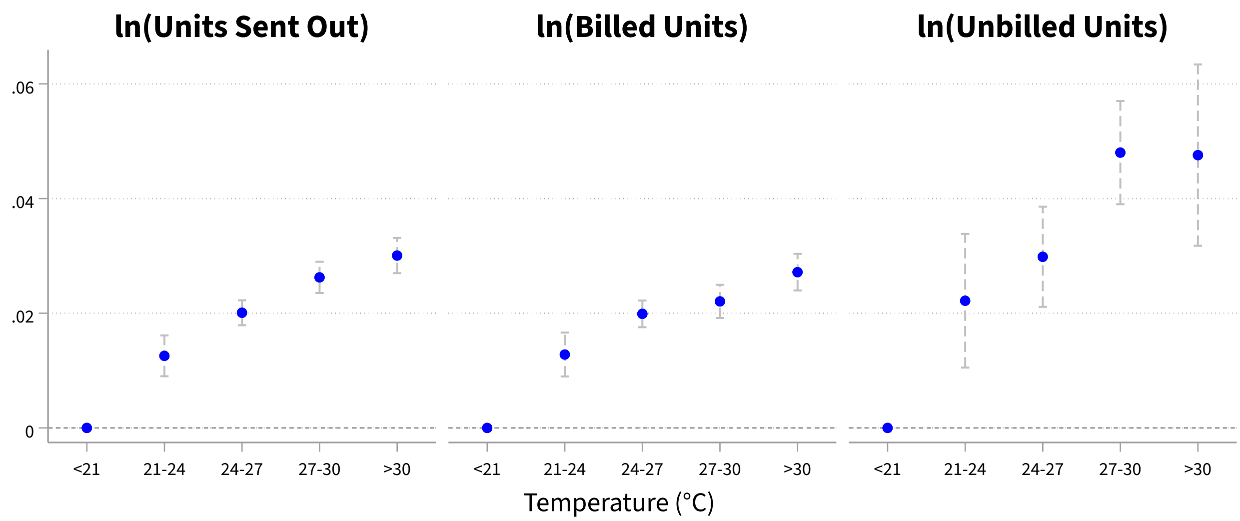

Figure B2: Temperature and Feeder-Line Electricity Outcomes - with Counterfactual Control Correction

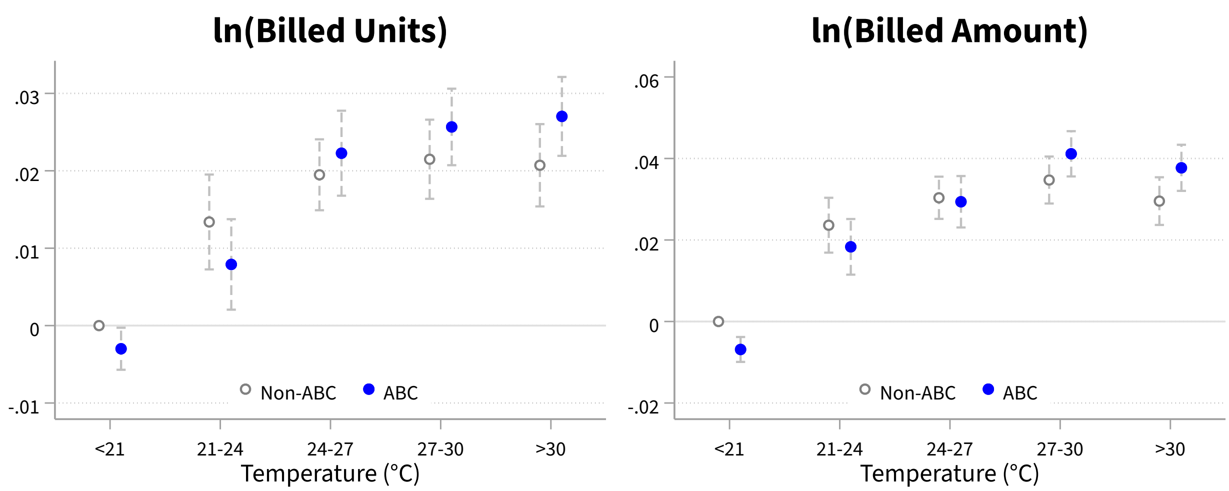

Figure B3: Temperature, ABC, and Billed Consumption for Formal Customers - with Counterfactual Control Correction

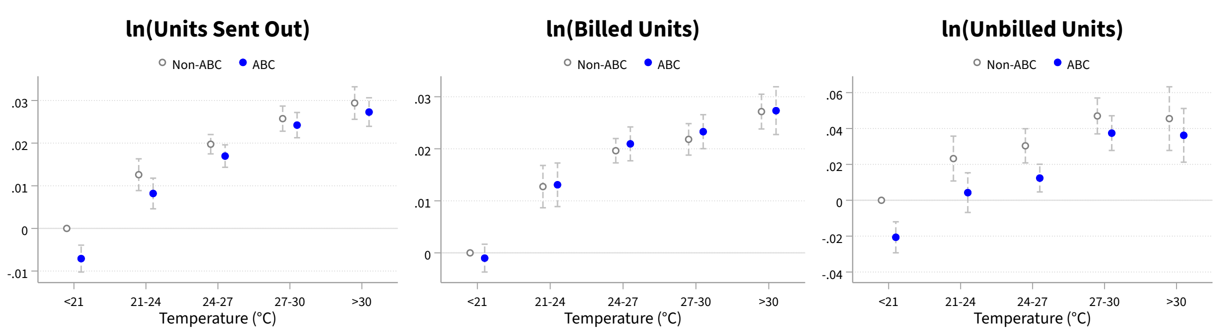

Figure B4: Temperature, ABC, and Feeder-Line Electricity Outcomes - with Counterfactual Control Correction

C Welfare Analysis of ABC Installation on Households

Our empirical results suggest that ABC installations reduce household electricity consumption and may impose additional burdens to household ability to adapt to hot temperatures. This section develops a framework to measure the welfare impacts of ABC installation for poor households in Karachi. The installation of ABCs has been linked with several impacts on residential customers. Rather than performing a full welfare analysis, we focus on two key components: (1) increase in health expenditures due to reduced cooling appliance usage and (2) decrease in consumer surplus due to reduced electricity consumption.

C1 Change in Cooling Service Consumption and Health Expenditures

ABC installations raise average price of electricity, leading to a decrease in electricity consumption and cooling appliance usage. This may constraint households ability to cope with heat stress during extreme temperature conditions and negatively affect their health outcomes. To translate the decrease in electricity consumption into health consequences, we first calculate the implied change in cooling appliance usage and then estimate the relationship between household health expenditure and cooling appliance usage.

Step 1: Calculating the Change in Cooling Appliance Usage. Column (2) of Table 2 shows the decrease in household monthly electricity consumption due to ABC installation that we calculated in the previous section. We convert these decreases in electricity consumption into decline in cooling appliance usage, assuming all the forgone electricity consumption would have been used for fan or air conditioner, respectively. Here, we assume the power of fan and air conditioner is 80W and 1,200W, based on the average estimate provided by KE.[16] On average, daily fan usage decreases by 13-14 hours and daily AC usage decreases by less than 1 hour.

Step 2: Estimate the Change in Health Expenditure. To translate the change in cooling appliance usage into change in health consequences, we estimate the relationship between health expenditure and cooling appliance usage and ownership, using the household survey data. Table C1 presents the estimation results. We link health expenditure per capita with household ownership and usage of three types of cooling appliances – fan, air cooler, and air conditioner. To account for differences in household wealth and electricity consumption, we add a rich set of control variables: an indicator for house ownership,

[16] K-Electric. Energy Consumption Calculator.

indicator for owning financial accounts, indicator for owning cars, number of rooms, duration of ABC conversion, electricity expenditure per capita, and indicators for self-reported income levels. The coefficient estimates for cooling appliance usage are all negative, suggesting more hours of cooling appliance usage is associated with less household health expenditures. The coefficient estimate for fan indicates that one more hour of fan usage is associated with 15 PKR decline in health expenditures. The coefficient estimate is not statistically significant for air cooler and air conditioner, but we note that the self-reported adoption rate of these cooling appliances is very low in our sample. In the last column, we restrict the sample to households that ever reported positive health expenditures and document similar estimates.

To quantify the change in health expenditures associated with less cooling hours, we apply the coefficient estimates in Column (4) of Table C1. Column (4) and (6) of Table 2 shows the calculation results, assuming the decrease in cooling appliance usage hours as indicated in Column (3) and (5). In hot season, the 14 hour decline in fan usage in day is associated with 229 PKR increase in health expenditures.

C2 Change in Consumer Surplus

ABCs make thefts more difficult. As is shown in our empirical analysis, there is a decrease in total electricity sent out and unbilled units. We therefore characterize the ABC installation as an informal tax on consumers for their electricity usage. Figure C1 provides an illustration of the change in consumer surplus. After ABC installation, the average electricity price rises from AP_0 to AP_1, leading to a decrease in electricity consumption from Q_0 to Q_1. The blue area captures the corresponding decrease in consumer surplus. We take the following steps to quantify the change in consumer surplus.

Step 1: Calculating Average Price and Electricity Consumption. We start with calculating the electricity consumption per household and average electricity price, i.e., the key variables that are needed for demand estimation. To account for household total electricity consumption that are billed and unbilled (due to theft), we leverage the electricity operation data at the feeder-line level. We assume an 8% technical loss rate of electricity distribution following NEPRA's report. Then, the total electricity consumption in each feeder line is calculated by excluding the technical losses from the total electricity sent out. For each feeder line, we define the average electricity price as the total billed amount divided by total electricity consumption. Electricity consumption per household is calculated using the total electricity consumption divided by the number of customers

Table C1: Cooling Appliance Usage and Health Expenditure

VARIABLES	Health Expenditure per Capita (PKR)				
	(1)	(2)	(3)	(4)	(5)
Daily Hours: Fan	-15.854***			-15.897***	-19.197**
	(5.628)			(5.617)	(7.803)
Ownership: Fan	168.357			167.723	-134.444
	(208.509)			(208.846)	(450.370)
Daily Hours: Air Cooler		-61.747		-63.601	-96.598
		(62.725)		(62.382)	(67.790)
Ownership: Air Cooler		325.586		337.512	356.736
		(393.971)		(395.354)	(426.890)
Daily Hours: AC			-25.387	-25.124	24.528
			(23.950)	(23.450)	(105.567)
Ownership: AC			103.271	107.330	183.674
			(230.592)	(234.826)	(254.524)
HH Controls	✓	✓	✓	✓	✓
Observations	2,945	2,945	2,945	2,945	1,816

Notes: The analysis uses household survey conducted in 2021 Fall. The outcome variable is health expenditure per capita (PKR). The independent variables include the ownership of cooling appliances and self-reported daily hours of usage. In Column (5), we restrict the sample to households that report positive health expenditures. All regressions include a set of household controls: an indicator for house ownership, indicator for owning financial accounts, indicator for owning cars, number of rooms, duration of ABC conversion, electricity expenditure per capita, and indicators for self-reported income levels. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

served by each feeder line. For feeder lines that ultimately have ABC conversion, we use the average number of customers in the post-ABC period. For feeder lines that never have ABC conversion during our sample period, we use the average number of customers over the whole sample period. Since one feeder line can serve non-residential customers, we restrict our sample to non-industrial feeder lines and exclude the feeder lines with more than 100 industrial customers or less than 100 total customers so that the electricity consumption and the number of customers we capture here are mainly residential customers. We focus our analysis on high-loss IBC regions where most of the ABC installations occur.

Step 2: Estimating Electricity Demand. Once we have the data on average price (AP) and electricity consumption per household (Q), we estimate the demand function for a representative household, using the ABC installation as an instrumental variable for the

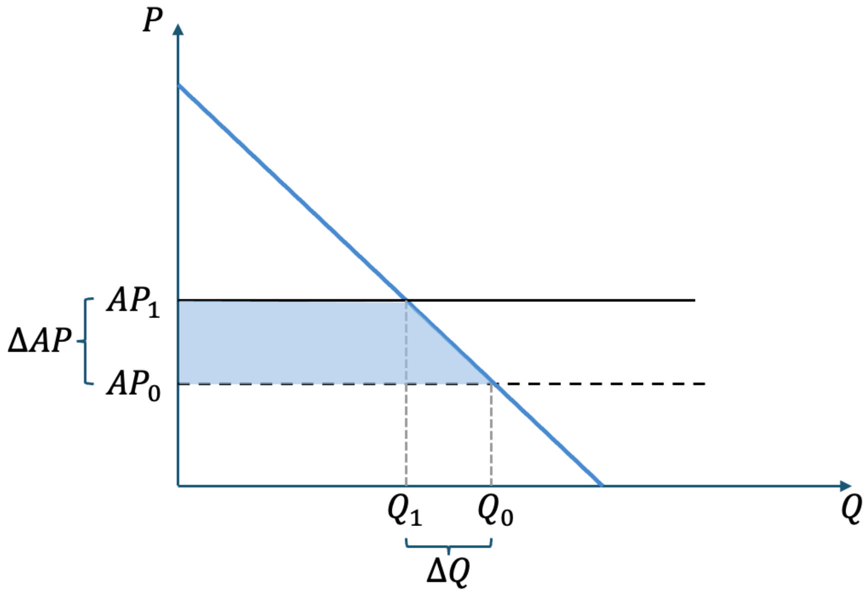

Figure C1: Illustration of the Change in Consumer Surplus

Notes: This graph shows the change in consumer surplus arising from ABC installation. We characterize the ABC installation as imposing an informal tax on consumers for their electricity usage. Therefore, it leads to an increase in average price from AP_0 to AP_1. Consequently, electricity consumption decreases from Q_0 to Q_1. The blue area represents the loss in consumer surplus as a result of ABC installation.

average price. For feeder-line i in IBC region j in month t, the regressions are:

$$AP_{it} = \gamma \text{ABC}_{it} + \alpha_i + \delta_{j(i)t} + \varepsilon_{it}$$
$$Q_{it} = \beta \widehat{AP}_{it} + \phi_i + \kappa_{j(i)t} + u_{it}$$

The regressions include feeder-line fixed effects and IBC-by-month fixed effects. The coefficient β captures the marginal effect of average price increase on household electricity consumption.

Table C2 presents the estimation results. We estimate the demand function using the full sample and by cool versus hot season. Hot season includes May to September. All other months are classified as cool season. Column (1)-(3) reports the first-stage estimation results, showing statistically significant increases in average price by 0.970 to 1.951 PKR per kWh. Column (4)-(6) shows the second-stage estimation results. On average, 1 PKR increase in average price leads to a 28 kWh reduction in electricity consumption per household. The implied price elasticity is -0.685. When separating by season, the consumption response is more sensitive in cool season compared to hot season.

Table C2: Estimation of Electricity Demand

Dep. Var.:	Average Price (PKR)			Consumption per Household (kWh)		
	All	Cool Season	Hot Season	All	Cool Season	Hot Season
	(1)	(2)	(3)	(4)	(5)	(6)
ABC	1.365***	0.970***	1.951***			
	(0.209)	(0.214)	(0.260)			
Avg. Price				-28.139***	-39.188***	-21.924***
				(5.069)	(8.514)	(4.627)
Observations	11,536	6,163	5,372	11,536	6,163	5,372
F-stats	42.53	20.60	56.14			
Elasticity				-0.685	-1.197	-0.416

Notes: This table presents the estimation of electricity demand, using monthly data at the feeder-line level. The analysis focuses on high-loss IBCs. To make sure the feeder lines in our sample mainly serve residential customers, we drop feeder lines with more than 100 industrial customers or less than 100 total customers. The total electricity consumption at each feeder line is measured by the electricity sent out $\times$ (1 - technical loss rate). Here, we assume an 8% technical loss rate based on NEPRA's estimation. Average price is defined as total billed amount divided by total electricity consumption. Consumption per household is defined as total electricity consumption divided by the number of customers served by each feeder line. For feeder lines that ultimately have ABC conversion, we use the average number of customers in the post-ABC period. For feeder lines that never have ABC conversion during our sample period, we use the average number of customers over the whole sample period. ABC is a binary indicator that equals 1 when the feeder line has transformers with ABCs installed. Columns (1)-(3) report the first-stage regression results where we estimate the effect of ABC on average price. Columns (4)-(6) report the second-stage regression results where we estimate the relationship between average price and electricity consumption using ABC as the instrumental variable. All regressions control for feeder-line and IBC-by-month fixed effects. Standard errors in parentheses are clustered at the feeder-line level. Hot season includes May to September. The other months are classified as cool season. The bottom row shows the implied price elasticity based on the coefficient estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Step 3: Estimating Decrease in Electricity Consumption. We estimate the change in electricity consumption per household in different temperature conditions given the ABC installation status by applying the regression model in Equation 2 to our restricted sample. The estimation results are shown in Table C3. Column (1) presents coefficient estimates from an unweighted regression. In Column (2), we weight the regression using the number of customers in each feeder line. The results are similar across these two columns, showing statistically significant decline in electricity consumption after ABC installation across various temperature conditions. These coefficients captures how temperature distribution in each month and the ABC status will affect electricity consumption. To predict the average change in electricity consumption during the cool and hot season, we multiple the coefficients of the interaction terms with the distribution of daily average temperature in a month as shown in Table C4. The calculation results are presented in Column (2) of Table C5. On average, household monthly electricity consumption decreases by 34.7 kWh in hot season and by 31.53 kWh in cool season.

Step 4: Calculating the Change in Consumer Surplus. Table C5 reports the calculated change in consumer surplus. Column (3) presents the relationship between electricity consumption and average price, corresponding to Column (5) and (6) in Table C2. Column (4) reports average electricity consumption per household for the pre-ABC period (i.e., Q_0 in Figure C1). Column (5) shows the change in consumer surplus per household per month, corresponding to the blue area in Figure C1, which we calculated using $\frac{1}{2} \times (Q_0 + Q_0 + \Delta Q) \times \frac{\Delta Q}{\partial Q / \partial AP}$.

Table C3: Electricity Consumption, Temperature, and ABC

Dep. Var.:	Consumption per Household	
	Unweighted	Weighted
	(1)	(2)
tavgbin24	1.970***	1.396
	(0.469)	(1.121)
tavgbin27	4.282***	3.044***
	(0.328)	(0.863)
tavgbin30	6.289***	3.878**
	(0.374)	(1.301)
tavgbin40	9.304***	5.296***
	(0.536)	(1.555)
c.tavgbin21#c.ABC	-0.668**	-0.956***
	(0.244)	(0.193)
c.tavgbin24#c.ABC	-1.049**	-1.000***
	(0.417)	(0.291)
c.tavgbin27#c.ABC	-1.444***	-1.587***
	(0.344)	(0.308)
c.tavgbin30#c.ABC	-0.719*	-0.761**
	(0.378)	(0.270)
c.tavgbin40#c.ABC	-1.813***	-1.493***
	(0.518)	(0.418)
Observations	16,717	16,717

Notes: The analysis uses monthly data at the feeder-line level, focusing on high-loss IBCs. To make sure the feeder lines in our sample mainly serve residential customers, we drop feeder lines with more than 100 industrial customers or less than 100 total customers. The total electricity consumption at each feeder line is measured by the electricity sent out $\times$ (1 - technical loss rate). Here, we assume an 8% technical loss rate based on NEPRA's estimation. Consumption per household is defined as total electricity consumption divided by the number of customers served by each feeder line. For feeder lines that ultimately have ABC conversion, we use the average number of customers in the post-ABC period. For feeder lines that never have ABC conversion during our sample period, we use the average number of customers over the whole sample period. ABC is a binary indicator that equals 1 when the feeder line has transformers with ABCs installed. The independent variables, tavgbin, capture the number of days in a month with daily average temperature falling into each bin (<21, 21-24, 24-27, 27-30, >30). Standard errors in parentheses are clustered at the IBC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C4: Summary Statistics of Temperature Bins

Temperature Range	Average Number of Days in a Month	
	Cool Season	Hot Season
<21	7.95	0.00
21-24	6.68	0.00
24-27	5.70	1.32
27-30	9.17	15.20
>30	0.82	14.09

Notes: Hot season includes May to September. Cool season includes the other months.

Table C5: Change in Consumer Surplus

Season	Monthly Consumption (kWh / HH)	$\partial Q/\partial AP$	Average Consumption without ABC (kWh / HH)	ΔCS (PKR / HH)
(1)	(2)	(3)	(4)	(5)
Hot	-34.70	-21.92	481.53	-734.61
Cool	-31.53	-39.19	331.00	-253.64

Notes: Change in monthly electricity consumption per household (Column 2) is calculated using the coefficient estimates of the interaction terms in Column (2) of Table C3 and the average number of days in a month with daily average temperature falling into each bin as shown in Table C4. Column (3) presents the relationship between electricity consumption and average price, corresponding to Column (5) and (6) in Table C2. Column (4) reports average electricity consumption per household for the pre-ABC period. Column (5) shows the calculated change in consumer surplus.

D The Benefits of ABC Installation on Non-Residential Customers

In this section, we examine how the installation of theft-resistant cables (ABCs) affects non-residential customers. By reducing electricity theft, ABC installation lowers distribution losses and may allow the utility to implement less load shedding in areas that previously experienced high levels of unbilled consumption. As a result, non-residential customers—who are unlikely to consume electricity informally—may benefit from improved electricity reliability.

Our analysis uses customer-level billing records from KE. We exclude all customers on residential tariffs, as well as those whose recorded premise types are houses, flats, or shops. The remaining customers primarily consist of commercial, industrial, and public-sector users, who are substantially less likely to rely on informal electricity consumption.

We begin by establishing that this group of customers does not exhibit patterns consistent with informal electricity use. Figure D1 plots the distribution of monthly billed electricity consumption (kWh) by season and ABC status. Among customers served by PMTs that are ultimately converted to ABCs but observed prior to conversion, we find little evidence of bunching at tariff thresholds. In contrast to residential customers, the distribution of billed consumption for non-residential users appears smooth, with no salient excess mass around tariff cutoff points.

We next examine the effect of temperature on electricity consumption for these non-residential customers. Figure D2 shows that billed electricity consumption increases with temperature, indicating higher electricity use during hotter periods. Figure D3 further examines this relationship separately across eight common categories of non-residential customers identified in our data. For most categories, billed electricity consumption rises as temperatures increase, consistent with greater demand for cooling and related services. One notable exception is schools, for which electricity consumption decreases at the two highest temperature bin, likely due to reduced operations during summer break.

Figure 9 estimates the effects of temperature and ABC installation on billed electricity consumption for non-residential customers. We find that billed electricity consumption increases following ABC conversion, with the increase being more pronounced during hotter months. Figure D4 shows that this pattern is broadly consistent across the eight non-residential customer categories in our sample. Because these customers are unlikely to rely on informal electricity consumption, the observed increases in billed electricity are unlikely to reflect changes in theft behavior. Instead, the results are consistent with improvements in electricity reliability – such as reductions in load shedding – which enable

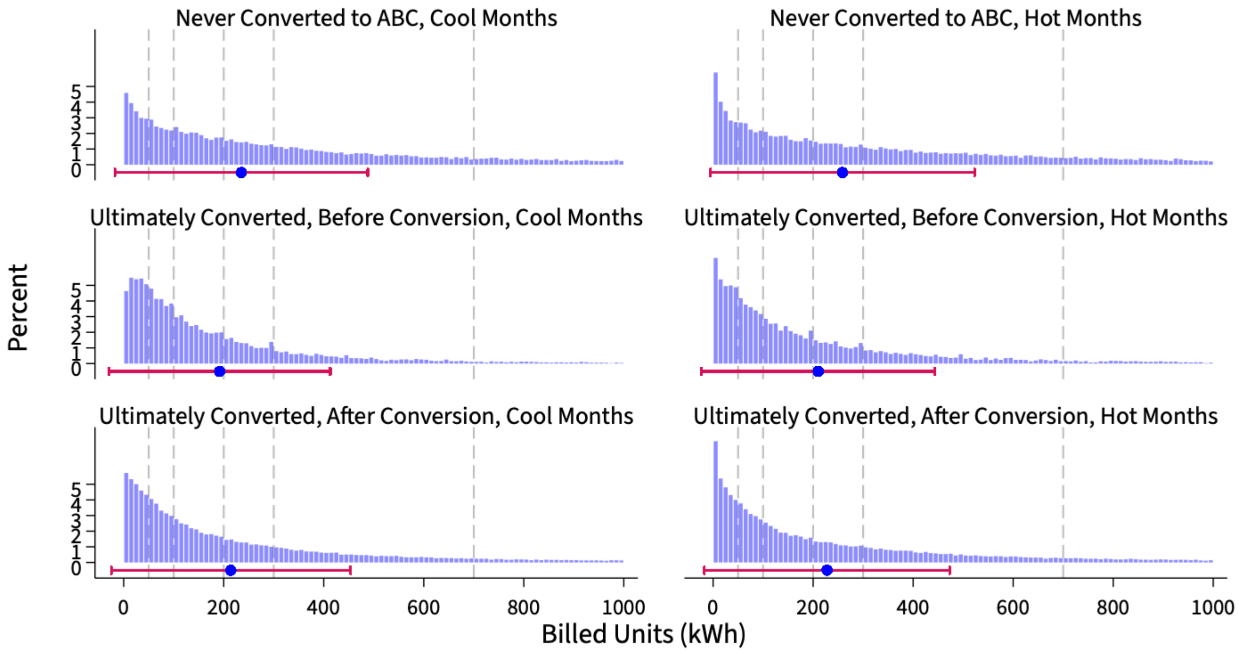

Figure D1: Histogram of Billed Units (kWh) of Non-Residential Customers

Notes: This figure presents the histogram of monthly billed electricity consumption units (in kWh), by cool and hot months and by ABC status, for non-residential customers who are formally connected with KE. The vertical dashed gray lines are the tariff cutoffs for residential customers. Hot months include May to September. The other calendar months are defined as cool months. Formal density manipulation test results are presented in Table.

higher electricity usage, particularly during periods of elevated cooling demand.

We provide two additional pieces of evidence in support of this interpretation. First, we show that planned daily hours of electricity supply increase following ABC installation in feeder lines that previously experienced high losses and more frequent load shedding. Table D1 reports these estimates. Using KE's administrative records, we classify feeder lines into high-loss and low-loss categories and examine how planned supply hours change across monthly load-shedding categories. Relative to low-loss feeder lines, high-loss feeder lines receive fewer hours of electricity supply. Following ABC installation, daily electricity supply increases by approximately 0.3 to 0.4 hours in these high-loss feeder lines.

Second, we show that the increase in billed electricity consumption among non-residential customers is concentrated in feeder lines that experienced the largest improvements in reliability. As shown in Figure 9, the post-ABC increase in billed electricity consumption occurs primarily in high-loss feeder lines. These feeders experienced more frequent load shedding prior to ABC installation and therefore exhibit larger gains in electricity service provision afterward. In contrast, low-loss feeder lines – many of which were covered by ABCs as part of KE's ring-fencing strategy – experienced relatively little

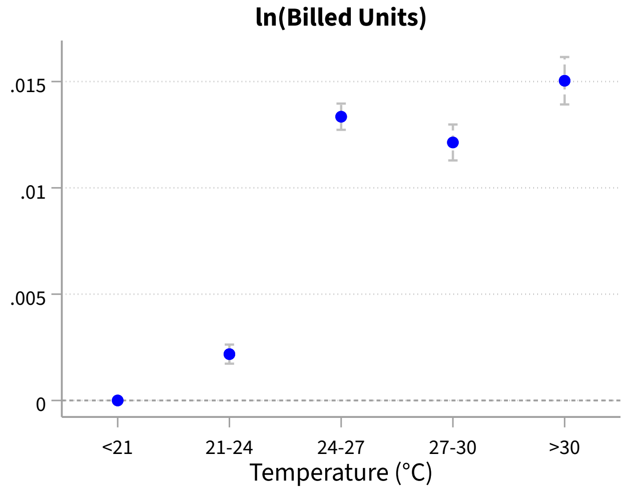

Figure D2: Temperature and Billed Units for Non-Residential Customers

Notes: This figure displays the estimated effect of temperature on billed electricity consumption (kWh) of formal non-residential customers using the customer-level data. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. The omitted temperature category (<21°C) serves as the reference group for comparison. Blue dots are coefficient estimates. The coefficient estimates capture the change in electricity outcomes associated with having one additional day that daily average temperature falls into a given temperature bin in a billing month, relative to a day in the <21°C bin. Gray brackets are 95% confidence intervals centered on the estimated coefficient.

load shedding prior to ABC installation and consequently display smaller improvements in electricity supply and billed consumption.

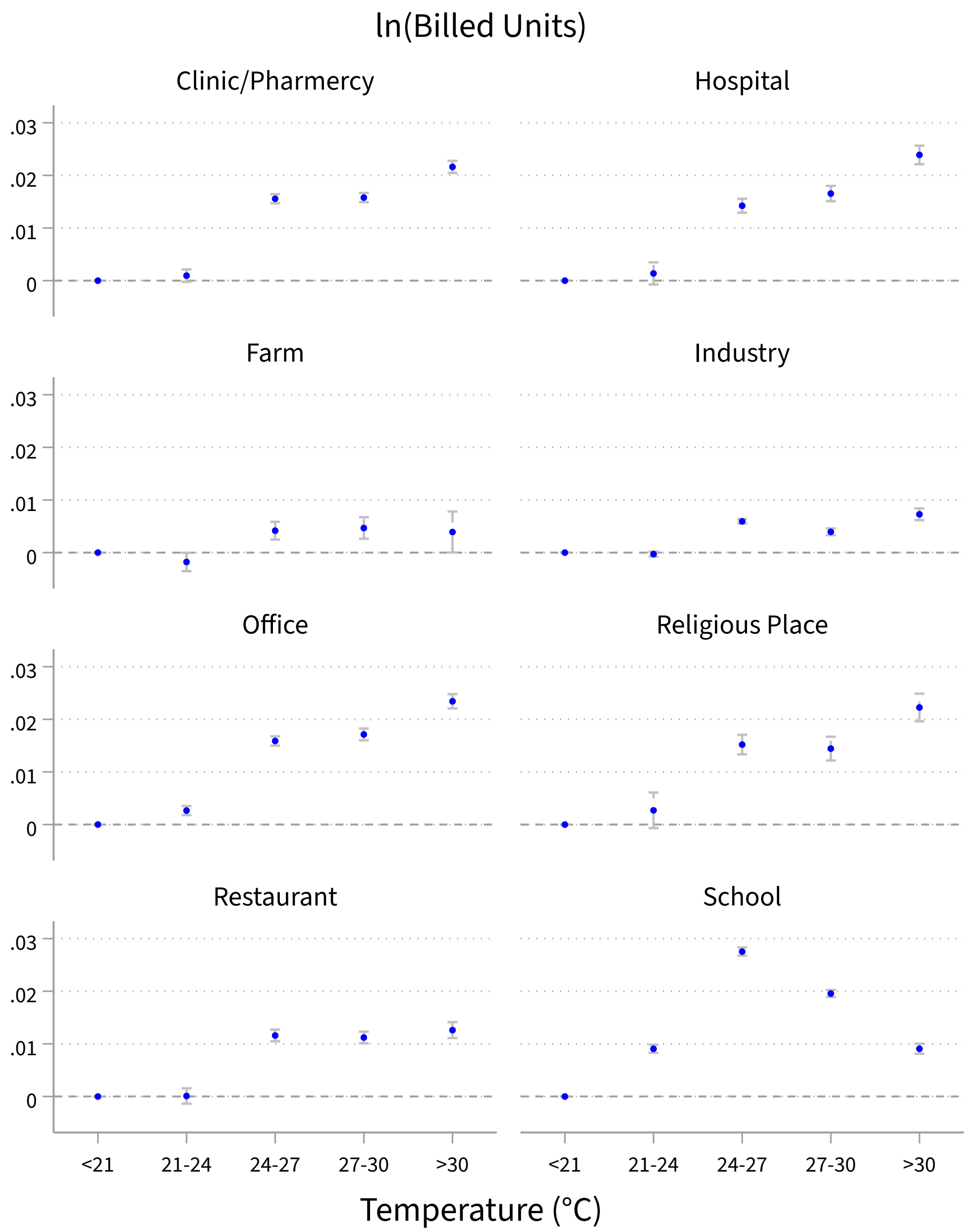

Figure D3: Temperature and Billed Units for Non-Residential Customers by Type

Notes: This figure displays the estimated effect of temperature on billed electricity consumption (kWh) of formal non-residential customers by type of customers. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. The omitted temperature category (<21°C) serves as the reference group for comparison. Blue dots are coefficient estimates. The coefficient estimates capture the change in electricity outcomes associated with having one additional day that daily average temperature falls into a given temperature bin in a billing month, relative to a day in the <21°C bin. Gray brackets are 95% confidence intervals centered on the estimated coefficient.

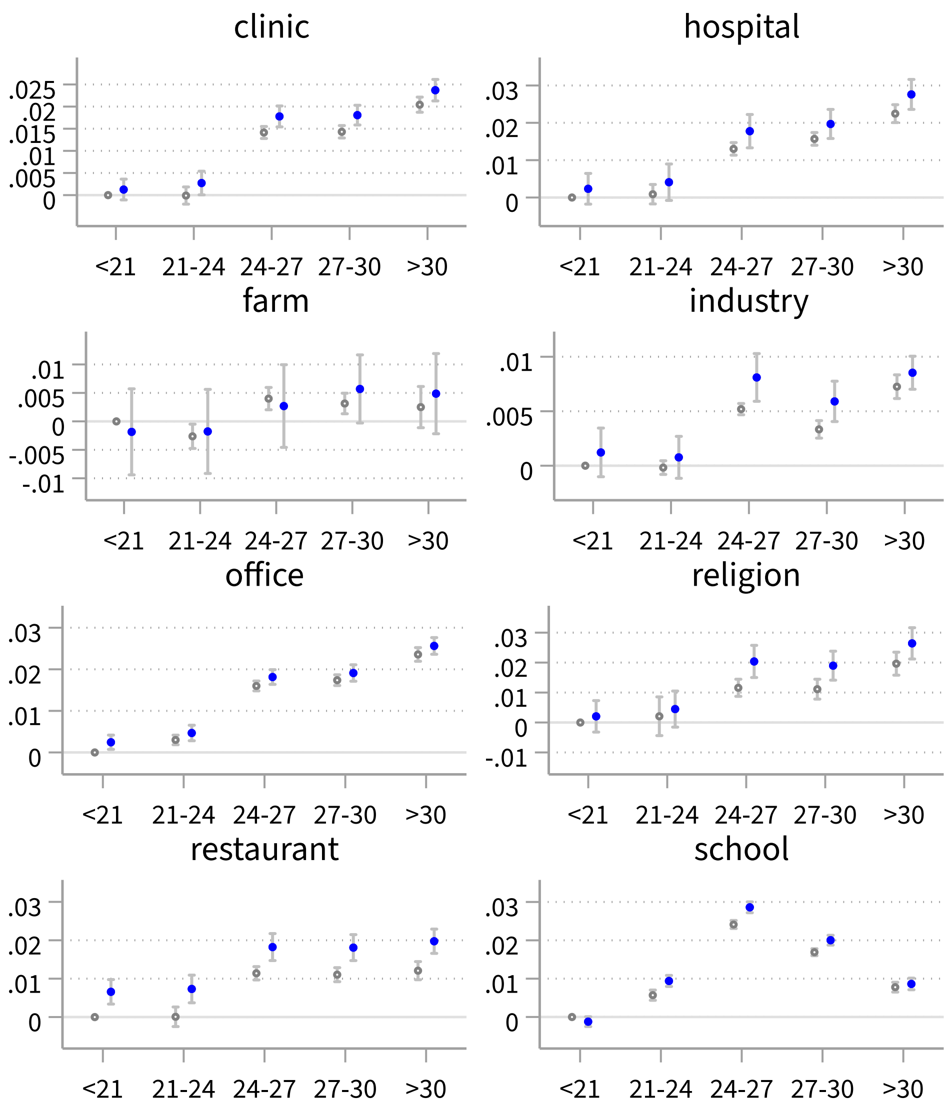

Figure D4: Temperature, ABC, and Billed Units for Non-Residential Customers by Type

Notes: This figure displays the estimated effect of temperature and cable upgrades on on billed electricity consumption (kWh) of formal non-residential customers by type. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. Gray dots depict the estimated effect of temperature without cable upgrades. Blue dots depict the estimated effect of temperature with cable upgrades. Gray brackets are 95% confidence intervals. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison.

Table D1: The Effect of ABC Installation on Feeder-Line-Level Electricity Supply

VARIABLES	SupplyHour				lnSupplyHour			
Feeder Loss Category	Low	Low	High	High	Low	Low	High	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ABC	-0.469	0.086	0.441***	0.314***	-0.023	0.006	0.023***	0.017***
	(0.333)	(0.383)	(0.084)	(0.083)	(0.016)	(0.018)	(0.004)	(0.004)
Supply Hours	22.14	22.15	18.06	18.06	22.14	22.15	18.06	18.06
Observations	22,285	22,228	17,817	17,809	22,285	22,228	17,817	17,809
Feeder FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y		Y		Y		Y	
IBC-Year-Month FE		Y		Y		Y		Y

Notes: The table presents the estimated effect of ABC installation on average daily hours of electricity supply using monthly feeder-line-level load shedding categories from KE. The outcome variable is the raw level or the logarithm of daily electricity supply hours. The independent variable, ABC, is a binary indicator that equals 1 when the feeder line has transformers with ABCs installed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

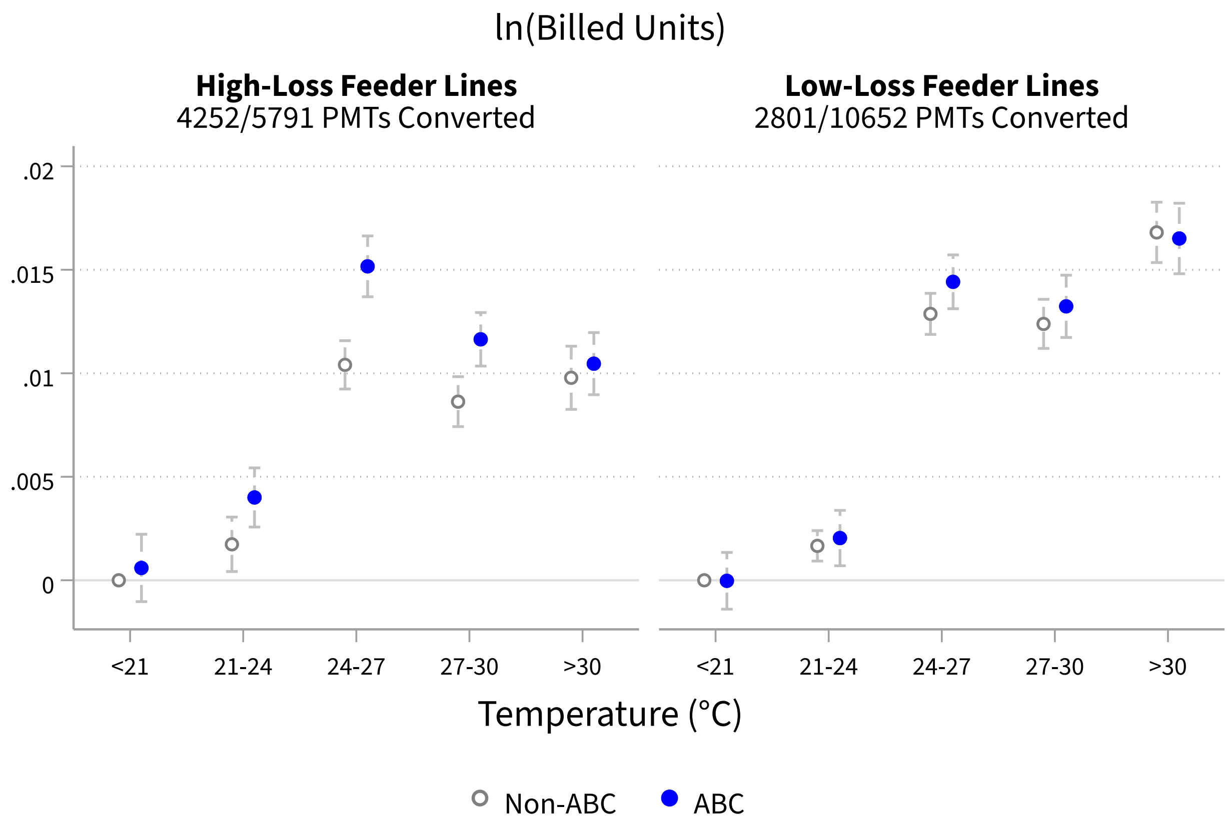

Figure D5: Temperature, ABC, and Billed Units for Non-Residential Customers by Feeder Loss Category

Notes: This figure displays the estimated effect of temperature and cable upgrades on on billed electricity consumption (kWh) of formal non-residential customers using the customer-level data. We run subsample regressions for customers in high-loss feeder lines vs low-loss feeder lines classified by KE. The horizontal axis represents the number of days in a billing month with daily average temperature falling into specific ranges. Gray dots depict the estimated effect of temperature without cable upgrades. Blue dots depict the estimated effect of temperature with cable upgrades. Gray brackets are 95% confidence intervals. The omitted category, i.e., daily average temperature below 21°C without cable upgrades, serves as the reference group for comparison.

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