The Economic and Environmental Effects of Infrastructure Improvements: Evidence from Pakistan's Electricity Sector*

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Abstract

Fiscal challenges pervade the electricity sector in many developing countries. Low bill payment and high theft mean that utility customers do not pay the official tariff rate, leading distribution companies to ration supply via load shedding. The resulting low quality electricity services can impair economic benefits from connections to the electrical grid. Using differences in intervention timing across space, we study the impacts of an infrastructure intervention that made illegal electricity connections physically more difficult in Karachi, Pakistan. We find that the installation of aerial bundled cables reduced non-technical losses and increased revenue recovery, due to an increase in formal utility customers and greater billed consumption among the existing formal customers. The intervention led to lower electricity delivered to the distribution system, a proxy for generation, which translates into a reduction in CO_2 emissions that is 1.7 % and 4.3% of the electricity utility's annual emissions. Changes in consumer surplus vary depending on the cost previously paid for illegal grid connections.

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1 Introduction

Fiscal challenges pervade the electricity sector in many developing countries. Electric transmission and distribution losses – losses between points of generation and end-consumers – are three times higher in low-income and lower-middle-income countries than in high-income countries (IEA/OECD, 2018). A subset of these losses, comprised of electricity theft and bill non-payment, cost utilities an estimated $96 billion per year worldwide (Bellero, 2017) and often result in a low payment, low quality equilibrium, in which distribution companies either ration electricity supply via load shedding (Burgess et al., 2020) or make insufficient investments to maintain infrastructure and meet growing demand (Carranza and Meeks, 2021). These losses negatively affect consumers as well. An estimated 1 billion people worldwide receive electricity through grids providing services disrupted with frequent outages (World Bank, 2020), and such low quality electricity services impede consumers' economic benefits from connections to the electrical grid (Fried and Lagakos, 2022).

Given the burning of fuels for electricity and heat is the largest single source of global greenhouse gas emissions, the environmental impacts of losses are noteworthy. The higher the losses, the more electricity that must be generated per unit sold to end-consumers. Further, non-technical losses mean individuals are not paying the full cost of electricity services consumed, which reduces their incentives to conserve. When electricity generation is dominated by fossil fuels – such as in low and middle income, where 71% of electricity production is generated from burning oil, gas, and coal sources (OECD/IEA, 2014) – these factors translate into higher CO_2 emissions.

We study the effects of an infrastructure improvement, aerial bundled cables (ABCs), in Karachi, Pakistan. ABCs are an infrastructure upgrade from basic bare electrical wires, which are relatively low-cost but also exposed and easily tapped by illegal connections. With ABCs, the cables are twisted together and insulated, characteristics that impede "weathering, abrasion, tearing, cutting, and chemicals" and make illegal connections to the distribution system more difficult (USAID, 2009). Karachi Electric (KE), the distribution company serving the greater Karachi area, introduced ABCs within its distribution network starting in 2015 in an effort to reduce losses. Conversions to ABC wiring increased in intensity during 2018, when KE adopted the strategy of targeting high and very high loss feeder lines. The installation work typically began by gathering community support to carry out ABC conversion at the Pole Mounted Transformers (PMTs) level. Once installations began, a ring fencing strategy was used in order to convert the closest PMTs to ensure complete geographical coverage of ABCs within a feeder line.

Pakistan provides a suitable location to study both electricity losses and carbon emissions from electricity generation. As of 2014, electric power transmission and distribution losses in the country were an estimated 17% of output (EIA-OEA, 2018). The National Power and Regulatory Authority (NEPRA) reports that in 2019-20, all 10 major distribution companies faced losses above 9%, with all but 4 reporting losses above 15%. Karachi Electric, the distribution company we study reported transmission and distribution losses of 19.1%, allowing substantial room for reductions. With 63% of electricity generation, as of 2015, from oil, gas, and coal sources (EIA-OEA, 2018), these losses contribute to CO_2 emissions within the country. Further, unreliable electricity service is particularly problematic in South Asia, a region that has more power outages than anywhere else in the world (Zhang, 2018).

In this paper we investigate whether infrastructure upgrades can alleviate economic and environmental challenges of the electricity sector affecting producers and consumers. On the producer-side, we estimate the effects of ABC conversion on two important measures of utility financial health, losses and revenue recovery, and the channels through which those effects occur. We investigate whether these effects translate into positive implications for the environment, in terms of a reduction in electricity generation and thereby CO_2 emissions. Lastly, we estimate the effects of the infrastructure improvement on consumer welfare.

Using differences in the introduction of this infrastructure upgrade across Karachi over time, we measure its effects on economic and environmental outcomes relevant to both the electricity utility and its customers. We use a unique combination of datasets provided by the electricity utility – three years of feeder-level data for financial outcomes, as well as individual household-level panel data on billing-related outcomes over the same time period – and complement those administrative data with consumer-level data that we collected via a survey of 3,000 utility customers in Fall 2021.

Our analyses provides key insights into the impacts of electricity distribution infrastructure improvements on producers (the electricity utility), consumers (residential customers), and the environment. First, the ABCs had economically meaningful and statistically significant impacts on utility financial measures. The conversion of distribution lines to ABCs significantly reduced utility losses and increased revenue recovery and the greater the intensity of lines converted to ABCs the larger the larger the effects. This effect persists for at least 30 months post-installation. The infrastructure upgrade had the greatest impacts on losses (revenue recovery) in the feeders with the highest losses (lowest revenue recovery) prior to the intervention, indicating that gains greatest in the worst-performing areas pre-intervention.

Second, we find evidence that these financial gains come via two channels: the formalization of customers previously informally (illegally) connected and imrpovement in payment behaviors among the existing consumers. In support of the former channel, we find that the number of formal utility customers significantly increased with ABC installation, an effect driven by residential customers. The timing of that increase, a few months following ABC installation, suggests that households previously using illegal connections learned relatively quickly that their prior method of accessing grid electricity was less feasible. In support of the latter channel, ABC installations led to significant increases both in billed units (kWh) and monetary value. Customers are more likely to paye their bills and pay a higher ration of their bills. Reductions in evidence of theft and irregular billing are also documented.

Third, we fine that the improvements in billing outcomes translate into benefits to the environment. Although ABCs led to an increase in both the total number of utility customers and billed units (kWh) per customer, losses (unbilled consumption) fall. We find evidence that electricity generation (proxied for by electricity transmitted to feeder lines within the distribution system) decreased following ABC installation. Using this estimated reduction in electricity ”sent out”, along with our calculations of the CO_2 emissions associated with Pakistan’s electricity generation mix, we find that the reduction in CO_2 emissions per year from ABC installations is equivalent to between 1.67% and 4.26% of the utility’s annual emissions from electricity generation.

What does this mean for consumers? Ex ante, we expect consumers to be worse off given the ABCs result in higher bills from the electricity utility, on average. Yet, households using “kundas” – the illegal connections (or hooks) to the low-tension cables within the electric grid – are not receiving electricity at a zero cost. Typically, an informal group facilitates kundas within a given region of the city and a household or business must pay an upfront cost for the kunda and then a monthly fee for continued use.[1] We calculate the change in consumer surplus for a range of kunda prices and find a decrease between 1 USD and 2.60 USD per month. We supplement these consumer surplus calculations with evidence from our household survey that suggests potential benefits from the reduction in losses and increase in revenue recovery. Customers in areas with ABCs report experiencing significantly less load shedding than areas without ABCs and, consistent with that, these households also have more appliances and a greater number of reported hours of appliance use per day.

In estimating the impacts of ABCs on the utility’s non-technical losses and revenue recovery, the paper contributes to a literature on public sector financing (Pomeranz, 2015; Kumler, Verhoogen and Frías, 2020; Khan, Khwaja and Olken, 2016; Carrillo, Pomeranz

[1] During focus groups held in Fall 2021 by our research team in Karachi, this was commonly acknowledged and kunda prices between 3 to 15 USD per month were discussed.

and Singhal, 2017), as well as more targeted research on improving the finances of electricity and water utilities (Szabó and Ujhelyi, 2015; McRae, 2015a; Jack and Smith, 2020; Ali, Gaibulloev and Younas, 2018). Our paper is the first to provide evidence on the impacts of ABCs, which can help control electricity losses in contexts where smart metering or prepaid metering might be difficult to implement due to customer and employee resistance. With analyses of not only revenue recovery (i.e., the proportion of billed consumption that is paid) but losses (i.e., consumption that is not billed) at the feeder line, we can add to the literature that assesses technological impacts of meters on bill payment (McRae, 2015a; Jack and Smith, 2020) and capture the impacts of a technology on a common source of leakage in the electricity sector.

The rest of the paper proceeds as follows. Section 2 provides background information on electricity distribution in Karachi, recent infrastructure improvements, as well as information on COVID-19 and its role in electricity service delivery. Section 3 details the data, both from Karachi Electric and from our household survey, employed in our analyses. Section 4 describes the empirical models underpinning our estimations. Section 5 presents results on the impacts of ABCs on utility-level outcomes. We extend the analysis to illustrate the implications for CO_2 emissions and climate change in Section 6. Section 7 addresses changes in consumer surplus in response to the infrastructure upgrade. Section 8 concludes.

2 Background on Electricity in Pakistan

2.1 Electricity Sector in Pakistan and Generation

Pakistan's power sector has long been beset with challenges, frustrating the core goals of providing affordable and reliable electricity (Younas and Ali, 2021). High per unit production costs, overburdened infrastructure, unsustainable transmission and distribution losses, intermittent load shedding, and growing circular debt are some of the major problems due to which the sector is trapped in a sub-optimal equilibrium. Since the early 1990s, the power sector has undergone major reforms, such as allowing independent private producers, unbundling the country's vertically integrated power company, and establishing a regulatory entity – National Electric Power Regulatory Authority (NEPRA). Yet the sector has continued to suffer from financial challenges and frequent blackouts.[2] A major source of financial concern for the sector is transmission and distribution (T&D) losses.

T&D losses have been exacerbated by the outdated transmission infrastructure from the powerhouse to the customers. High T&D losses due to rampant theft of electricity and non-payment of bills take a heavy toll on the balance sheets of the utility companies. As a result of the financial crunch, they are unable to make significant investments in infrastructure upgrades.[3]

From an environmental perspective, Pakistan's high-cost and largely non-renewable generation mix means that any reduction in generation would yield both lower costs and CO2 emissions. As of June 2021, the share of the installed capacity due to non-renewable sources stood at close to 70%.[4]

2.2 Electricity Distribution in Karachi

The context of our research is electricity distribution in the city of Karachi, which is the largest and most densely populated city in Pakistan. KE, which is a vertically integrated

[2] Bacon (2019) provides excellent anecdotal analysis of the various power sector reform initiatives in Pakistan and challenges thereof.

[3] Studying the effect of a unique reward-reprimand policy in curbing losses by Karachi Electric, Ali, Gaibulloev and Younas (2018) find that the policy was successful in reducing average monthly distributional losses across and within feeders by 3.1% to 6.6%.

[4] Renewable energy power plants (hydel, wind, solar and bagasse) in the generation mix was around 30% with 12,062 MW, while the share of non-renewable thermal power plants (gas, oil, coal and nuclear) was around 70% with 27,711 MW (NEPRA, 2021). During fiscal year 2020-21, the share of gas, Regasified Liquefied Natural Gas (RLNG), Residue Furnace Oil (RFO), coal and High-Speed Diesel (HSD) based generation in total thermal generation stood at 20.20%, 35.82%, 11.96%, 31.59% and 0.45%, respectively. The heavy reliance on thermal generation would clearly be contributing to the environmental pollution due to the release of CO_2 from the burning of fossil fuel and contamination of waterways due to the waste water discharged by power plants (NEPRA, 2021).

and privately-owned power utility is the sole provider of electricity services in Karachi. The utility has a distribution network spanning an area of 6500 square kilometers, covering 2.5 million customers including residential, commercial, industrial, and agricultural consumers.

This distribution network is divided into local offices, known as Integrated Business Centers (IBCs), which handle electricity distribution, billing, and collection in their respective areas. Out of a total of 30 IBCs within the utility's network, 12 IBCs are categorized as high loss with average distribution losses exceeding 30% and bill payment rates below 80%. These areas have a large fraction of lower income customers residing in semi-formal to informal settlements. "Kundas" or illegal connections to the main electricity cables are a common sight in many communities.[5] When a house or business connects via a kunda, it is not at a zero cost. Typically, an informal group facilitates kundas within a given region of the city. Commonly customer pays an upfront cost for the kunda and then a monthly fee for continued kunda use.[6]

One of the key challenges in high loss IBCs is a culture of non-payment of electricity bills, which is a product of local political, economic, and social conditions (Ahmad et al., 2021). There are some pockets in the city with particularly poor law enforcement where it is difficult to remove illegal connections or disconnect defaulters due to the influence of local mafias. There are many other communities where it is acceptable to use electricity through temporary "kundas," which are put in place at night especially in the hot summer season and are removed early in the morning to avoid detection. Historically, KE also installed temporary informal connections to extend the network to commercial establishments and residential complexes where service did not exist. Later these "kundas" became difficult to take down due to local resistance. In addition to illegal usage, many

[5]The local distribution infrastructure typically consists of a sub-station (receiving electricity from the grid station), a 11 Kv feeder line carrying electricity from the sub-station to a pole mounted transformer (PMT) and low-tension cables (220-440V) carrying electricity from the PMT to the customers. A "kunda" is usually hooked on the low-tension cables originating from the PMT.

[6]This was commonly acknowledged and discussed during focus groups held by our research team in Karachi during Fall 2021.

of the consumers connected through formal connections, find it difficult to pay their bills fully and on time, as they are employed in daily wage work, low skilled jobs, and small businesses, and thus face fluctuating economic conditions.

Another challenge is that consumers have low trust in the utility to deliver reliable and affordable electricity services. High loss areas face up to 6 to 7.5 hours of planned outages daily. Unplanned outages due to infrastructure faults are also not uncommon. There is a common perception of over-billing by KE due to faulty meters and billing errors. Thus, the everyday experience of electricity service provision in the high loss areas is far from ideal. Low trust in the utility and the acceptability of using electricity without paying for it, leads to a vicious cycle of high electricity and financial losses, overloaded infrastructure, and unreliable electricity services.

2.3 Infrastructure Improvements: Aerial Bundled Cables

In an effort to decrease illegal electricity usage, the main infrastructure initiative launched by KE was the conversion of cables at the Pole Mounted Transformer (PMT) level to Aerial Bundled Cables (ABCs). Due to their intertwined cable design, ABCs are difficult to connect to using "kundas". ABC conversion began in 2015 as pilot intervention in a handful of PMTs, and was then expanded to a few IBC regions in Karachi.

There are two factors affecting the roll-out of ABC conversion. First, it is determined by KE's business strategy. Initially, ABC budgets were set by strategic department which included targets for the number of PMTs which had to be converted to ABC. Since a major part of the ABC Project was outsourced, these budgets were specifically set keeping in view the execution capacity of outsourced manpower. Those selected PMTs were considered as low hanging fruit to serve as proof of concept and to simultaneously allow KE to gain quick recoveries and meet their financial targets. After 2018, the budgets were decentralized down to the IBC level, which consequentially allowed the IBCs to set up practical targets depending on their resource and community realities after consultation with KE's strategy department. At that time, KE adopted the policy of targeting ABC conversion to PMTs in high and very high loss feeders.

Second, the roll-out of ABC conversion is subject to resource constraints. Before the project could be implemented at a specific PMT site, the designated IBC/area had to be assessed for material and human resource availability, the extent of infrastructure planning development and the level of community resistance anticipated. KE prioritized the project in areas which had comparatively less resource and administrative constraints to meet targets set by strategy or IBC management.

Figure 1 shows the increased coverage of ABCs, both in terms of infrastructural coverage (number of PMTs) and customer coverage (number of customers), over time between 2016 and 2020. Additionally, appendix maps (see Figure A1) depict the installation across one IBC in Karachi over time.

Although ABC conversion made it very difficult to connect illegally to electricity cables, new ways of installing "kundas" emerged with the passage of time, which involved puncturing of ABC. Thus it was unclear to what extent this infrastructure improvement alone would be sufficient to address the problem of illegal usage.

3 Data

The analysis utilizes data collected from two sources. First, the utility shared extensive data at the feeder line, PMT, and consumer levels. In addition, we collected survey data for a sample of utility customers.

3.1 Utility Feeder line Data

We have assembled a comprehensive and unique dataset including feeder level losses, revenue recovery, utility claims, consumer complaints, and consumer number from KE. The final dataset is aggregated to the feeder and monthly level, which covers 2163 feeder lines in Karachi.

Loss and Revenue Recovery. 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. Revenue recovery is defined as the ratio of net credit to billing.

Claims and Complaints. We collect utility claims from January 2018 to October 2020. Utility claims happen when there is damage against KE infrastructure/property (e.g., PMT, service cable, etc.). KE then ends up filing an official claim against the suspected party or institution. Police then investigate the claim.

We also assemble a dataset on consumer complaints from January 2018 to June 2021. Consumer complaints are tickets submitted by KE customers regarding a variety of issues, such as billing, technical problems, and service concerns for the contract account. For each claim or complaint, we observe information on its topic, creation time, and the corresponding feeder line. The data is then aggregated to the feeder level on a monthly basis.

Consumer Number. For each feeder line in Karachi, we collect monthly data on the number of active consumers in each category, including agricultural, bulk, commercial, industry, and residential during the period between January 2018 and March 2021.

ABC Installation. KE provides dates when each PMT has ABC installed. We observe the installation record till January 2021. To match this data with feeder-level monthly variables, we create two measures for ABC adoption. First, we define a binary indicator for whether a feeder line has at least one PMT with ABCs installed. Second, we calculate the ratio of the number of PMTs with ABCs installed relative to the number of total PMTs in a feeder line.

3.2 Household Survey Data

In October and November 2021, we surveyed approximately 3,000 residential customers across 150 PMTs. To select consumers to survey, we randomly selected households from the utility's roster of consumers in a multiple-step process. We restrict the sampling to high-loss feeders within 8 of Karachi Electric's IBC offices. Within these high loss feeder lines, we restrict to PMTs with a minimum of 80 customers and a maximum of 500 customers, to both ensure we have sufficient households to allow for replacement and to avoid outlier transformers with particularly large number of customers. This leaves us with more than 1,500 PMTs from which to select. We randomly select 150 PMTs, ensuring PMTs both with and without ABCs are represented in the list. Selected PMTs serve, on average, 202 residential customers each. Within PMTs, we limit our sample to residential customers with active accounts and then randomly select 20 customers per PMT to survey.

The questionnaire collects information on basic house characteristics, household demographics, and other outcomes related to electricity consumption. We collect data on appliance ownership and use, as well as household expenditures (both electricity and non-electricity related). Questions also cover household perceptions about their neighbors theft and payment practices, as well as respondents' beliefs about the utility, electricity service quality (both load shedding and voltage fluctuations), tariff, billing and payment practices.

3.3 Utility Residential Consumer Data

For each surveyed residential customer, we obtain the corresponding individual-level data on billing and payment behaviors from KE. The sample covers the period between June 2018 and August 2021. In the data, we observe information on monthly billed electricity units and amount, the amount and date of payment, total due to KE, and the billing category mode (BCM). These data allow us to check whether a customer paid their bill in a billing cycle or not.

The BCM variable allows us to observe whether billing occurred in a normal manner or whether there are irregular bills. If a consumer has a normal BCM, it means that the meter functioned properly and there were no errors in billing. There will be irregular bills if the meter stops working, or becomes faulty, or if there are other errors in recording units or calculating bills. Irregular bills also occur when there is a case of theft or kunda detection by KE. According to the BCM classifications, we are able to identify customers with irregular bills or those alleged by the utility to have engaged in thefts in a month.

4 Empirical Strategy

4.1 Utility Losses and Revenue Recovery

To estimate the economic effect of infrastructure improvements, our research design leverages differences in time and space within the ABC conversion process in Karachi. The adoption of ABCs follows a staggered process, the timing of which mainly depends on KE's business strategy. Since the roll-out of ABCs creates variations across feeder lines and over time, we employ a staggered difference-in-differences (DID) approach to identify the causal effect of ABC conversion on feeder-level losses and revenue recovery.

For feeder line i of IBC region j in month t, we estimate the following regression model throughout our main analysis.

$$y_{ijt} = \beta \mathrm{ABC}_{it} + \alpha_i + \delta_{jt} + \varepsilon_{ijt}. \tag{1}$$

The outcome variable includes losses and revenue recovery ratios, both measured in percentage points. The variable of key interest, ABC_{it} is a binary indicator for whether a feeder line i already had at least one PMT with ABC installed in month t.

We add a rich set of fixed effects to control for unobservable determinants for losses and revenue recovery. We include feeder fixed effect α_i to capture feeder-level time-invariant unobservable factors that may affect the outcome. We also control for IBC-specific time fixed effect δ_{jt} to account for regional policy shocks or potentially different time trends across IBCs. The standard errors are clustered at the feeder line level.

In an alternative model specification, we explore the intensity impact of the ABC installation by replacing the ABC dummy with ABC ratio, which, as previously defined, is the ratio of the PMTs that have been converted to ABCs in a feeder line.

4.2 Validity of Identification Strategy

Our identification strategy takes advantage of variations in outcome measures specific to feeder lines with ABC conversion relative to feeder lines without ABC conversion, and in periods before and after the conversion. Based on KE's business strategy, the roll-out of ABC conversion depends on pre-determined feeder line characteristics in terms of loss categories, resource constraints, and local resistance. By including our fixed effects, the model can account for a range of omitted variables that could otherwise bias the estimates. The feeder line fixed effect controls for time-invariant differences across feeder lines, such as loss categories, available resources, and community resistance. The IBC-by-month fixed effects capture any IBC-level policies and efforts that might affect ABC conversion and losses, such as change in IBC management, allocation of budgets, revision of targets, etc. After adjustment for these fixed effects, the roll-out time is conditionally independent of unobservable factors that may affect losses and revenue recovery.

Parallel Trends Assumption. The DID approach requires parallel trends in the outcome variable between the treatment group and the control group in the absence of the ABC conversion. To provide evidence that the assumption holds prior to treatment, we estimate the dynamics of losses and revenue recovery using the event-study framework. Specifically, we include leads and lags of the ABC conversion dummy in the baseline regression to trace out the month-by-month effects:

$$Y_{ijt} = \sum_{\substack{-15 \leq k \leq 15 \\ k \neq -1}} \beta_k \mathbb{1}[t - \tau_i = k] + \alpha_i + \delta_{jt} + \varepsilon_{ijt}. \tag{2}$$

The dummy variables, $\mathbb{1}[t - \tau_i = k]$, jointly represent the ABC conversion events. Specifically, τ_i denotes the first month when feeder line i started deploying ABCs at its PMTs, and k measures the gap between the current month and the initial deployment month τ_j. A negative k represents the pre-conversion month while a positive k represents the post-conversion month. Controlling for leads allows us to examine the pre-treatment effects as a test for the parallel trends. Controlling for lags enables us to trace the effects in the periods after the initial conversion. Note that the dummy for $k = -1$ is omitted from Equation (2) so that the estimated effects are relative to one month prior to the conversion. If the results show that the estimated coefficients for the leads of ABC-conversion dummy are small in magnitude and statistically indistinguishable from zero, then there is no evidence of meaningfully differential trends in losses or revenue recovery ratio in advance of the ABC conversion. This would provide support for the parallel trends assumption.

4.3 Consumer Bill Analyses

To complement the analysis of the utility level impacts, we investigate the consumer level response to ABCs using panel data on residential customers' billing-related outcomes.

We conduct both event studies and difference-in-differences regression analyses of ABCs impacts on residential customers. For residential consumer i served by PMT j in month t, we estimate the following regression model:

$$y_{ijt} = \beta \text{ABC}_{jt} + \alpha_i + \delta_t + \gamma_{j\tau(t)} + \varepsilon_{ijt}. \tag{3}$$

The outcome variables include different consumer-level measures on billed electricity consumption, payment behavior, and thefts. The variable of key interest, ABC_{jt} is a binary indicator for whether PMT j already has ABC installed in month t. We add consumer fixed effect (α_i), month fixed effect δ_t, and PMT by month-of-year fixed effect $\gamma_{j\tau(t)}$ to capture unobservable factors. Standard errors are clustered at the PMT level.

5 The Effects of ABC Installations

In this section, we present results from our baseline model that suggest that infrastructure improvements, in the form of ABC installation, resulted in reduced losses and increased revenue recovery. To understand the channels through which these impacts occurred, we also investigate whether ABCs installation affected the number of utility customers or customer bill payment behaviors.

5.1 Utility Losses and Revenue Recovery

5.1.1 Main Results

We investigate the effects of ABC installations through both event studies and regression analyses. The event studies in Figure 2 estimate the difference between the feeders that were "treated" via installation of ABCs on at least one PMT and those that were not (the "untreated"), controlling for both IBC-by-month and feeder fixed effects.

These event studies provide two key results. Figure 2 shows that the estimated coefficients for the leads of ABC-conversion dummy are small in magnitude and statistically indistinguishable from zero. Hence, there is no evidence of meaningfully differential trends in losses or revenue recovery ratio in advance of the ABC conversion, which provides support for the parallel trends assumption. The lack of differential trends in both losses and revenue recovery provides support for the parallel trends assumption. Second, these reults illustrate a significant negative effect on losses and positive effect on revenue recovery from ABC installation. These effects persist for the duration of the study period, which lasts 30 months post-installation.

We further investigate this relationship through difference-in-differences analysis, as depicted in Equation 1. Results showing the estimated impact of ABCs – using the binary variable indicative of ABC installation on at least one PMT on a feeder line – on losses are provided in Table 1, Panel A. Results from regressions using our other measure of treatment – the intensity of ABC installation within a feeder – are presented in Panel B of Table 1. These analyses are performed using both monthly and quarterly losses and revenue recovery data as outcome measures. All regressions include feeder fixed effects and an some form of IBC-time fixed effect, depending on whether the analyses are at the monthly or quarterly-level.

The results in both panels tell a consistent story. ABC installation, whether measured as a binary indicator or as treatment intensity, led to significant reductions in losses and increases in revenue recovery. In Panel A, the estimates in column 1 and 3 suggest that losses were lower by 6.2 to 8.2 percentage points in feeders with ABC wiring. This is a reduction of 26% to 32% of the average loss level in non-ABC feeders. Similarly, the estimates in column 2 and 4 suggest that revenue recovery was improved by 5 to 5.2 percentage points, which is an increase of 6% of the average recovery in non-ABC feeders. Panel B provides evidence that fully replacing all lines within a feederline with ABCs leads to even larger improvements in loss reduction and revenue recovery. more intense treatment. However, supplemental evidence is indicates non-linearities in the effect of ABC installation intensity, specifically we find diminishing returns to ABCs for revenue recovery (Table A4).

Addtitionally, we investigate whether the ABCs have heterogeneous effects, depending on the severity of the losses and revenue recovery problem prior to the upgrade. We classify the initial losses or revenue recovery rate (the monthly average losses or revenue recovery rate over 2018m1 and 2018m6) of the feeder line into three percentiles, low, medium, and high. The ABC indicator is then interacted with binary indicators for whether the feeder line falls into certain loss or RR categories. Results from these analyses are presented in Table 2. We find that the effects of ABC installation are increasing in the level of losses pre-intervention. In other words, losses decreased more in the feeders that had higher levels of losses at baseline. Similarly, revenue recovery increased more amongst the feeders with medium and low levels of baseline revenue recovery.

5.1.2 Robustness Checks

The results presented in Table 1 are robust to a number of checks (Table A3).

Contemporary Loss Mitigation Policies. Our estimated impact of ABC conversion might be confounded by contemporary loss mitigation policies. While national- or regional-level policies are common shocks to different feeder lines and therefore will be absorbed by the IBC-by-month fixed effects, feeder-level time-variant factors however, present a major challenge. First, there might be contemporary efforts or policies that only targets high-loss feeder lines within IBCs. Second, seasonal patterns might differ across feeder lines. For example, KE might spend more efforts on maintenance during peak seasons and these might be more frequent for high-loss feeder lines. To mitigate these concerns, we include IBC-by-loss-category-by-month or feeder-by-calendar-month fixed effects to capture feeder-level policies within each IBC. The results, shown in Panel A and B of Table A3, are similar to those from our baseline estimates.

Stable Unit Treatment Value Assumption. Another key identification assumption is that there is no spillover effect on feeder lines in our control group. Specifically in our setting, it means ABC conversions by one feeder line do not affect others that haven't yet adopted ABCs. This is perhaps mostly likely to occur in feeder lines that are very close to each other. Concerns arise when there are spillovers of thefts or internal migration into neighboring non-ABC feeder lines. In response to these concerns, KE adopted the "ring fencing" strategy – once ABC conversion starts, they tried to cover neighboring regions to prevent these negative spillovers. To further address this issue, we exclude from our sample feeder lines that are very close to each other. Specifically, we identify the center point of each feeder line area by averaging the GPS coordinates of its PMTs, and calculate the distance between each pair of feeder line areas. We then re-estimate the baseline model by dropping the feeders lines that have at least one nearby feeder line within its 100m/300m/500m buffer zone. As reported in Panel C–E of Table A3, we get similar coefficient estimates.

Heterogeneity-Robust DID Estimator. Recent literature shows the potential estimation bias of the two-way fixed effects (TWFE) estimator with varied treatment timing (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). Under a setting with multiple periods and staggered treatment timing, the bias arises from the comparison between later treated units and earlier treated units that instead serve as the control. The event study model usually generates reliable estimates as it breaks down treatment effects in different periods (Sun and Abraham, 2021). To further mitigate this concern, we employ a heterogeneity-robust DID estimator proposed by Callaway and Sant'Anna (2021). This estimator only compares treated units with never-treated ones serving as controls, hence excluding all the "bad" comparisons. In Panel F of Table A3, we report the aggregated estimates of the average treatment effect on the treated (ATT) for all timing groups across all periods. The coefficient estimates have the same sign and similar magnitudes with the ones from our baseline model.

5.2 Mechanisms for Utility Effects

Reductions in losses could come via multiple channels. We find evidence that the reductions in losses came with both an increase in the total number of customers and a reduction in utility claims of damage to the distribution infrastructure. Together, these results are indicative of ABCs making kundas more difficult and as a result, more consumers becoming formal customers of the utility. Further, customers would be more likely to avoid disconnections due to bill non-payment in the absence of informal substitutes for electrification, theoretically increasing revenue recovery.

5.2.1 Effects of ABC Installation on Customer Numbers

Losses could fall due to increased formalization of customers. Customers previously connecting to the grid via informal, illegal connections may shift to formal connections at the time of ABC installation. We investigate this channel for loss reduction through event studies and regression analyses.

We perform an event study in which the outcome variable is the inverse hyperbolic sine of number of all types of consumers on a feeder line over time. Figure 3 provides no evidence of a statistically significant difference in pre-trends between the ABC "treated" and "untreated" feeder lines. We do see a statistically significant increase in the number of customers following the ABC installation. Interestingly, the increase occurs approximately 2 months after the installation of the ABCs, suggesting that customers previously using illegal connections learn in the few months after ABC installation that kundas are more difficult to connect with the ABCs and therefore switch to legal connections.

Like before, we implement two forms of regression analyses to estimate the impact of ABCs on the number of consumers, one using the binary indicator of ABC installation as the treatment variable, the other using the proportion of PMTs in a feeder covered by ABCs as the measure of treatment intensity. Results are in Table 3. In Column 1, the outcome variable is the inverse hyperbolic sine of number of consumers – of all types – in each feeder line. We see a significant effect of ABCs on total consumers in both Panel A (using the ABC binary treatment indicator) and Panel B (using the treatment intensity variable). Columns 2 through 6 in the table show the estimated impacts of ABCs on different categories of consumers (agricultural, bulk, commercial, industrial, and residential). We find that ABC installation led to a 6.5% increase in total number of customers at the feeder line level. Column 6 suggests that these changes were driven primarily by an increase in residential consumers.

5.2.2 Consumers' Payment for Electricity Services

Event studies in Figure 4 indicate that, following the installation of ABCs, both residential consumers' quantity of billed units and the monetary billed amount significantly, both of which are consistent with a reduction in kundas and an increase in consumption of electricity services through formal connections to the grid. These came with reductions in the probability of customers not paying their bill and an increase in the payment ratio (the proportion of the billed amount paid for the month), coinciding with the increases in revenue recovery found in the feeder-level analysis. Lastly, there is evidence of a reduction in irregular billing and billing following detection of theft.

The difference-in-differences regression analyses in Table 4 provide further insights. Panel A shows the average treatment effects of ABCs, similar to those in the event studies. With our binary treatment variable "ABC", we interpret these coefficients as the impact of a PMT being upgraded from the old distribution wires to ABCs. In columns 1 and 2, the outcome variables are the inverse hyperbolic sine of billed units (kWh) and billed monetary amounts (rupees). Results indicate the ABC conversion led to a 9% increase in kWh of billed units (column 1) and a 9.8% increase in billed amount (column 2). In addition, the probability of a customer not paying one's monthly electricity bill on-time decreased by 5.2 percentage points (column 3) and the ratio of monthly billed quantity paid increased by 1.6 percentage points (column 4). Finally, the probability of a meter related issue within a month and whether there were thefts during a month reduced by 11.1 and 3.8 percentage points, respectively.

Panel B shows heterogeneity by expenditure group. Interestingly, the effects of the ABCs on the low expenditure and high expenditure groups are of similar magnitude for all outcomes except one. In column 5, the group with expenditures greater than $2 per day are significantly less likely to have irregular bills within a month than those households with expenditures less than $2 per day. This might be reflective of relatively better metering infrastructure, metering, and billing practices in richer neighborhoods covered by ABC installations.

6 Implications for Climate Change Mitigation

Ex-ante, the implications of the ABC intervention for electricity generation and, therefore, CO_2 emissions are not obvious. If anything, our results to this point suggest that emissions may increase as a result of infrastructure upgrades: ABCs led to an increase in both the total number of utility customers and billed units (kWh) per customer, which together indicate an increase in electricity supplied and therefore electricity generated. In a setting such as Pakistan, where 62% of electricity generation is via fossil fuels (NEPRA, 2021), an absolute increase in electricity generation likely means an increase in CO_2 emissions.

6.1 Estimating Reductions in Emissions

In this section, we explore the implications of the infrastructure upgrade for climate change mitigation through a multi-step process. First, we estimate the impacts of ABCs on a proxy for electricity generation. Then, we calculate the marginal changes in CO_2 emissions per kWh change in electricity generated. Third, using the results of the prior two steps, we perform back-of-the envelope calculations to estimate ABCs' influence on CO_2 emissions. Lastly, to provide some prospective, we compare these estimates to the CO_2 emissions from Karachi Electric's annual generation.

For the first step, given generation occurs at a higher level than the ABC intervention, we use the quantity of electricity "sent out" (kWh) to a feeder line per month (in other words, the quantity delivered to a feeder line) to proxy for generation per feeder line.[7] To estimate the impact of ABCs on electricity generation, we run regressions akin to those described in Equation 1, but with the quantity "sent out" as the outcome variable. Results

[7] Electricity sent out includes metered consumption, unmetered (illegal) consumption as well as technical losses. A reduction in technical losses can be considered a pure welfare gain as CO_2 emissions are averted but consumption is not reduced. However, a reduction in in metered or unmetered consumption might have welfare consequences for consumers which we are unable to capture in this calculation.

in Table 5 show that ABCs led to a decrease in generation of 97,213.3 kWh per feeder line per month (column 1). In logs, the intervention led to a 10.2% decrease in generation per feeder line per month (column 2). These results indicate that not only did ABCs reduce losses, they also reduced the total electricity delivered, and therefore, the quantity generated.

To translate these generation reductions per month into avoided CO_2 emissions, we perform calculations of the estimated reduction in CO_2 emissions per kWh reduction of electricity generated that are specific to Pakistan's generation mix. Details of these calculations are in Appendix A3, though broadly speaking, we create a mix of fuels that would most likely be used to respond to changes in demand. This "responsive mix" constitutes mostly of generation attributed to fossil fuels, as these technologically allow for changes relatively easier changes in production, when compared to other sources. Our calculations indicate that the reduction in CO_2 per kWh reduction of electricity services consumed to be 0.76 kg CO_2/kWh for our responsive mix.

Note that the above estimates is one of many alternatives. If, alternatively, if we assume that marginal production takes place solely through natural gas (the least carbon intensive of Pakistan's fossil fuel generation mix) or residual fuel oil (the most carbon intensive of the country's fossil fuel generation mix), our estimates change to 0.46 kg CO_2/kWh and 1.06 kg CO_2/kWh, respectively. Our responsive mix then is a conservative estimate, between both bounds, though we provide estimates using all three.

Finally, we calculate the change in CO2 emissions per change in electricity generated by generation fuel type and, to put these numbers in perspective, we compare them to Pakistan's annual CO2 emissions. Results are in Table 6. In column 1, we present the result of multiplying each of these estimated changes in CO_2 per kWh change in generation – according to fuel type of natural gas, residual fuel oil, coal, and a responsive blend of the three fuels – by the estimated reduction in generation: 97,213.3 kWh per feeder line per month (from column 1 of Table 5). This provides us with a range of estimated reductions in CO_2 emissions per year per feeder line, by fuel source of the marginal generator. We can aggregate these numbers to all high loss feeders (column 3) and compare them the estimated CO_2 emissions from Karachi Electric's generation in a year (column 4). This reduction in CO_2 emissions is non-trivial, equal to roughly 1.67% to 4.26% of Karachi Electric's annual emissions due to generation.

6.2 Comparing ABCs with with Energy Efficiency

To provide a sense of magnitude for these calculations, we compare the ABCs' reductions in billed electricity consumption with the technologically feasible reductions from other technologies. To do so, we convert the ABCs' feeder-line level reductions into residential consumer-level reductions. From our regressions, we know that ABCs reduced the feeder line level quantity "sent out" by 97,213.3 kWh per feeder line per month. We divide that by the number of residential consumers per feederline (1,685), which provides an ABC-induced reduction in electricity consumption of 57.7 kWh per residential customer per month.

To put this reduction in perspective, we perform back of the envelope calculations for electricity savings that would occur if a household replaced 3 incandescent light bulbs with more efficient LED light bulbs. We perform these calculations based on Carranza and Meeks (2021), who through a randomized experiemnt in the Kyrgyz Republic found that in the absence of positive spillovers, the reductions in electricity consumption due to a randomized energy efficient light bulb intervention, performed close to those predicted in engineering models.

First, we calculate the power reduction (kW) per household from making this switch to LEDs. We assume households would replace a 100 W incandescent with a 100 W equivalent LED. Actual wattage listed for LEDs is typically 10 W for a 100W equivalent bulb. Therefore for each incandescent bulb replaced by a LED, there is a reduction of 90 W (100 W - 10 W). If the household has 3 lightbulbs and replaces all of them, this is a power reduction of 270 W or 0.27 kW.

We use that estimated reduction to calculate three scenarios – for winter, spring/fall, and summer – for expected reduction in billed electricity (kWh) per month. We use these to estimate the expected reductions (Table A14). Given lighting is used differently over the course of a year, we make these calculations by season. These three scenarios place the per household kWh reduction due to switching 3 incandescent light bulbs to LEDs at between 24.3 and 44.55 kWh per month, which is just below the 57.7 kWh per month ABC-induced reduction we calculated per consumer. Therefore, the reduction from ABCs is equivalent to that of lighting efficiency.

7 Changes in Consumer Surplus

7.1 Conceptual framework

In the preceding sections we analysed the effect of ABC installation on the utility's bottom-line, showing that it reduced losses and increased revenue, suggesting that the intervention raised producer surplus. In this section we look at the effects ABC had on consumers, and analyse it from two angles; first we estimate changes in consumer surplus, and government subsidies. Second, we extend the discussion of effects beyond quantitative measures, and report evidence of improvements in the quality of electricity services.

When calculating changes in consumer surplus, we note that given our previous results, in particular the decrease in units sent out and increase in billed units, we expect consumer surplus to fall. This is because for any decreasing demand function, we would anticipate that a switch from kundas to formalised connections would increase the effective price of electricity and reduce consumption, and therefore lower consumer surplus.

However there are two important caveats to this results. The presence of kundas effects the ”price” the consumers pay for electricity, indeed they allow consumers to access electricity at zero marginal cost. For simplicity we assume that the kunda price is a lump-sum transfer from consumers to kunda operators,[8] then the decrease in consumer surplus also incorporates a decrease in these lump-sum transfers. In our calculations then, we separate out these effects.

Second, we note that as ABC installation does not change the pricing structure for pre-existing formal customers, any fall in consumer surplus is driven by consumers who were previously using kundas to bypass billing. In such a case, while it is true that ABCs decrease CS, it is driven by a switch from informal to formal consumption. It is then reasonable to assume that it lowers the cross-subsidisation of consumption of electricity from formal to informal consumers, and may indeed yield higher quality of service for the utility's formal customers, such as lower incidence of load-shedding and voltage fluctuations. These latter quality effects are not captured by our surplus calculations.

Finally, a note on total welfare. We note that with fewer units sent out, the amount of subsidy paid by the government falls. This would under a perfectly competitive market result in an increase in welfare, but a utility is the quintessential natural monopoly, and in the presence of market power, welfare may increase or decrease, depending on whether the subsidy causes the utility to over or under-produce relative to the optima. While we find evidence that total surplus falls, we must highlight that the results reported on welfare do not account for externalities such as carbon emissions from production, and that the decrease in technical losses is a pure welfare gain.

7.2 Empirical Evidence

We now quantify the welfare impacts of ABC installation. We measure the costs to the subsidized consumers, the benefits to the electric utility, and the change in government expenditures. We restrict our analysis to the high-loss IBCs and amoung the feeder lines that ultimately have ABCs installed.

[8] Which is also in line with our focus group discussions and other work (see for example Haider (2020)), that suggests kunda operators charge a fixed monthly fee for the kunda.

ABCs make illegal electricity connections or thefts more difficult. As is shown in previous sections, there is an increase in consumers' billed amount and payment ratio after the ABC installation. Hence, we characterize the ABC installation as an informal tax to consumers for their electricity usage. The change in billed amount and payment ratio can be approximated by an average price increase faced by consumers in feeder lines with ABC installed. Therefore, for tractability, we consider the tax as a price tax.

To measure the change in consumer surplus, we need to estimate price elasticities of electricity demand. We leverage the monthly feeder-level data on electricity sent-out, bill payment, and the number of customers to conduct the estimation. For each feeder line, We first calculate the average electricity consumption per consumer (y_{it}) as the total consumption divided by the average number of customers in the post-ABC period.[9]

The average electricity price (p_{it}) faced by consumers is measured as the total expenditure on electricity usage divided by the total consumption. Consumers' expenditures on electricity usage include the amount they pay to KE (for legal connections).[10]

With the calcuated average electricity consumption and average electricity price, we estimate the price elasticity of electricity demand using the 2SLS approach. For feeder line i in IBC region j in month t, the first and second stage regressions are:

$$\ln(p_{ijt}) = \gamma \mathrm{ABC}_{it} + \alpha_i + \delta_{jt} + \varepsilon_{ijt}$$
$$\ln(y_{ijt}) = \beta \ln(\hat{p}_{ijt}) + \phi_i + \kappa_{jt} + u_{ijt}.$$

In the above equations, γ captures the change in electricty price after the ABC installation and β captures the price elasticity of electricity demand. With these parameters, we can calculate the change in consumer surplus as a result of average price increase induced by

[9]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. Implicitly, we assume a balance between the electricity supply and demand.

[10]As kunda pricing is considered a lump-sum transfer, we ignore them for the purposes of calculating the average price.

the ABC installation.

The changes in consumer surplus calculated above contain with them the lump-sum transfers made to kunda-operators pre-ABC. To account for this we estimate the amount of transfer using results from our household survey. According to the household survey, we assume the proportion of households using Kunda is 10% and test different Kunda price assumptions ranging from 0 to 3500 PKR. Then, we calculate the total payment for Kunda usage by multiplying the Kunda price with the number of households using Kunda in each feeder line. Note that we assume consumers are no longer paying for Kunda for the post-ABC period since illegal connections will be terminated.

The change in producer surplus is measured by the change in consumer payment to KE. We first estimate the average change in the proportion of electricity paid relative to the electricity sent-out (R_{it}) after the ABC installation.[11] The total change in consumer payment is then calculated by multiplying R_{it} with the average electricity sent-out per feeder line, average electricity price, and the number of feeder lines.

Lastly, the change in government subsidies is calculated by multiplying the change in electricity consumption per customer with the average subsidy rate (i.e., 4.7 PKR according to KE) and the total number of customers.

Table 7 presents the welfare calculations under different Kunda price assumptions.

7.3 Supporting Evidence

We supplement these consumer surplus calculations with evidence from our household survey that suggests potential benefits from the reduction in losses and increase in revenue recovery. Customers in areas with ABCs report experiencing significantly less load shedding than areas without ABCs and, consistent with that, these households also have more appliances and a greater number of reported hours of appliance use per day.

[11] The proportion of electricity paid relative to the electricity sent-out is calculated by RR$\times$(1-Loss) where RR is the revenue recovery ratio and Loss is the loss rate. We then estimate the average change by regression this outcome variable on ABC dummy controlling for feeder line and IBC-by-month fixed effects.

7.3.1 Consumer Complaints

With ABCs making illegal connections more difficult to achieve, consumers might make more frequent complaints to the utility (e.g., complaints regarding deterioration of service quality or disputes of bills), which we investigate here. We use the utility's feeder line level data on consumer complaints, and the type of complaints filed, to estimate impacts of ABCs on these outcome measures. Regression results are presented in Table 8, with Panel A reporting results where the outcome variable is the number of complaints and Panel B normalising these to be relative to the number of consumers at a feeder line. Estimated impacts across the two panels suggest that the rise in complaints was proportional to the increase in consumers. Panel A indicates an increase in total complaints, which is the result of an increase in bill complaints and service requests in combination with a decrease in arrears disputes. In contrast, after dividing the total complaints by the number of consumers provided services within the feeder, the magnitude of the estimates in Panel B are smaller. These results suggest that consumer complaints overall decrease with the ABCs; it appears to be a function of a significant reduction in technical complaints, which is consistent with improvements in service quality.

7.3.2 Suggestive Evidence from Survey Data

We use our household survey data to help us better understand the mechanisms through which the ABC impacts may have occurred. Given our residential consumer survey is cross-sectional, we interpret these results as correlational and supplemental to our main results. Historically, the electricity utility has targeted load shedding according to feeder-line level losses. Given the utility's financial indicators improved – losses fell and revenue recovery increased – with ABCs (Table 1) and the utility links load shedding to losses, we expect to see less load shedding in these ABCs relative to other high loss areas that had not had ABCs installed. Table 9 presents differences in reported service quality for households covered by ABC, relative to those not yet covered by ABCs. There are significantly fewer hours per day of reported load shedding in both the summer (column 1) and winter (column 2) among the ABC areas, relative to the non-ABC areas. This suggests that the utility is reducing the hours of load shedding within these areas, possibly because losses have decreased following the ABC conversion. The estimated reduction in load shedding is approximately one fewer hour of load shedding in areas with ABCs, depending on the season and the expenditure group. Notably, the mean load shedding in the control group is 8.5 hours per day in the summer and 6.9 hours in the winter. With fewer hours of load shedding, household appliance ownership and use may differ across ABC and non-ABC areas as households can use the appliances more when there are more hours of electricity available. We see great number of both appliances (column 3) and hours of daily appliance usage (column 4).

Lastly, we use data from a number of survey questions designed to elicit respondents' beliefs and perceptions to understand if there are differences across ABC and non-ABC households with respect to the electricity utility, load shedding, and bills/bill-payment. Results are presented in Figure 5. Households in ABC areas are, on average, less likely to believe that their electricity bills accurately reflect their consumption and more likely to report that bill errors are a concern; however, they are also less likely to believe electricity quality issues (both electricity shortages and load shedding) are problems.

8 Conclusions

High T&D losses and low revenue recovery are major impediments in providing reliable and high quality electricity services in a sustainable manner. We study the effectiveness of an infrastructure improvement program targeted to high loss areas in Karachi, Pakistan. The program involved an extensive and fairly rapid conversion of bare electric service wires by Aerial Bundled Cables, beginning in 2015. ABCs, due to their thick insulated covering and intertwined design, ABCs make hooking illegal connectors to them more difficult. We use the variation in timing of ABC installations at feeder lines, together with administrative and customer-level survey data to identify the impact of ABCs using an event study and difference-in-differences approach. The intensity of the ABC roll-out over time was dependent on the business strategy of the utility, while the placement of ABCs began in neighborhoods with least anticipated community resistance. However, we find that there are no significant differences in the trends in losses, revenue recoveries, and customer outcomes prior to ABC installation.

Differences in the timing of infrastructure upgrades across space allow us to use panel data techniques to measure their impact on relevant outcome variables. Complementing our analysis of KE's administrative data, we also estimate individuals' responses to ABCs using residential customer-level data, which we collected in Fall 2021.

We find that ABC conversion both significantly reduced monthly losses and increased revenue recoveries. ABCs yielded greatest impact on losses (revenue recovery) in the feeders with the highest loss (lowest revenue recovery) levels prior to the intervention. We find evidence that ABCs achieved these impacts by increasing the total number of formal metered residential customers, increasing the quantity of billed units (and therefore the billed monetary amounts) as well as the payment ratio, while decreasinf irregular bull payments and indicators of theft. Together, these results are indicative of ABCs making illegal connections to the distribution wires more difficult and, as a result, more customers becoming formal customers of the utility.

The results from our household surveys are mostly consistent with our findings from the data provided by the utility. Customers in areas with ABCs reported considerably less load shedding than those in areas without ABCs. However, there is no significant difference in levels of trust in the utility across the intervention. In fact, we find that households in areas with ABCs are less likely to think that utility billing is accurate. It is difficult to draw a clear connection between infrastructure upgrades and trust in the utility, as it is likely to be a function of customer beliefs about how much they should be paying for electricity, which will depend on the economic, social and political context.

From the environmental perspective, despite an increase in both the total number of customers and the billed units per customer, the amount of electricity sent out over the distribution system decreased after ABC installation. We estimate that the reduction in CO_2 emissions from ABC installations to be between 1.7% and 4.3% of the utility's annual emissions from electricity generation. In a country that depends on thermal power plants to produce 70% of the total electricity, the carbon-reducing impact of ABCs is non-trivial.

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Figures and Tables

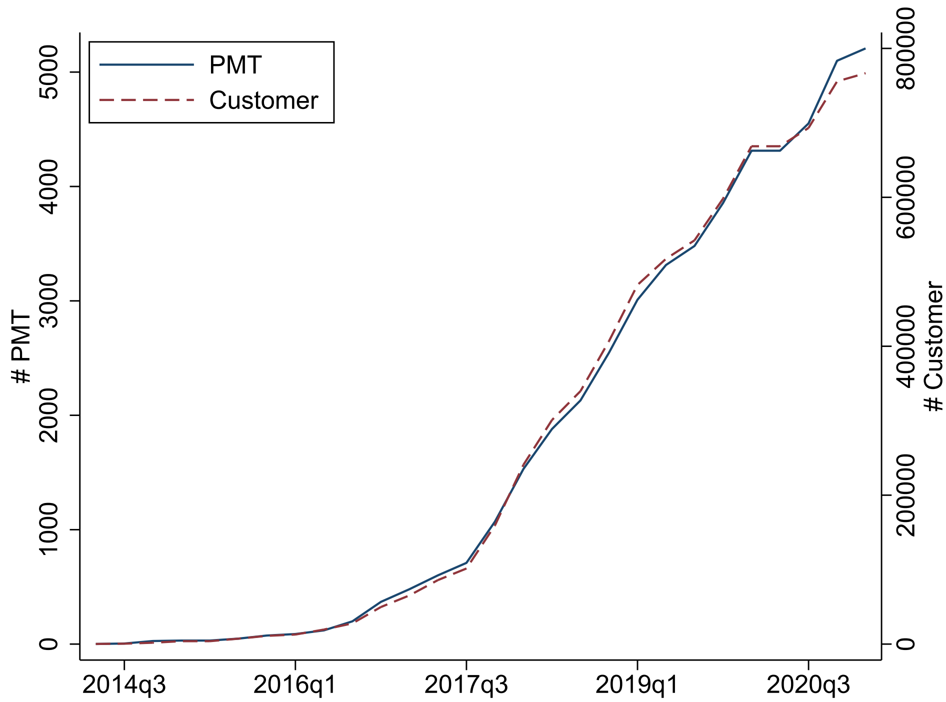


Figure 1: Trend of ABC Installation

Notes: This figure shows the cumulative number of PMTs (pole mount transformers) and customers covered by ABCs over time in Karachi, Pakistan.

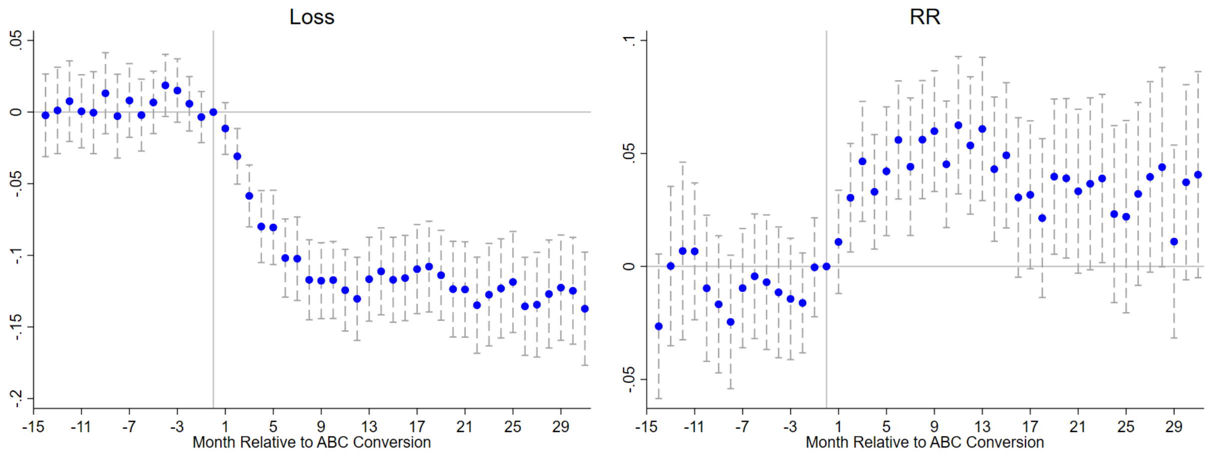


Figure 2: Event Study Estimates of the ABC Impact on Losses and Revenue Recovery

Notes: Figure shows the coefficients and their 95% confidence intervals from an event-study regression estimating the ABC impact on losses and the revenue recovery rate. Data are at the feeder level on a monthly basis. Regressions include IBC-by-month and feeder fixed effects. One month prior to the ABC installation (-1) is the reference group and the corresponding coefficient is normalized to zero. Standard errors are clustered at the feeder level.

Table 1: Impact of ABC Installation on Losses and Revenue Recovery

	Monthly		Quarterly	
	Loss	RR	Loss	RR
	(1)	(2)	(3)	(4)
Panel A: DID Estimates				
ABC	-0.082***	0.052***	-0.062***	0.050***
	(0.009)	(0.009)	(0.008)	(0.009)
Panel B: Intensity of Treatment				
ABC Ratio	-0.176***	0.090***	-0.175***	0.105***
	(0.013)	(0.013)	(0.013)	(0.013)
Control Mean	0.260	0.792	0.243	0.813
Observations	47,575	37,353	18,219	15,157
Feeder FE	✓	✓	✓	✓
IBC-Month FE	✓	✓		
IBC-Quarter FE			✓	✓

Notes: Data are at the feeder line level. There are 2163 feeder lines in Karachi during the study period. ABC is a binary indicator that equals 1 when the feeder line has PMTs with ABC installed, and equals zero otherwise. ABC Ratio is defined as the number of PMTs with ABC installed divided by the number of total PMTs in a feeder line. All regressions include feeder and IBC-by-month or IBC-by-quarter fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Heterogeneous Impacts by High/Low Loss Feeders

	Monthly		Quarterly	
	Loss	RR	Loss	RR
	(1)	(2)	(3)	(4)
ABC	-0.024*	-0.033***	-0.006	-0.024***
	(0.014)	(0.010)	(0.014)	(0.009)
ABC × Medium Loss	-0.061***		-0.057***	
	(0.016)		(0.016)	
ABC × High Loss	-0.135***		-0.126***	
	(0.030)		(0.029)	
ABC × Mediam RR		0.098***		0.073***
		(0.013)		(0.014)
ABC × Low RR		0.182***		0.153***
		(0.022)		(0.023)
Control Mean	0.260	0.792	0.243	0.813
Observations	43,041	23,461	16,495	9,635
Feeder FE	✓	✓	✓	✓
IBC-Month FE	✓	✓		
IBC-Quarter FE			✓	✓

Notes: Data are at the feeder line level. There are 2163 feeder lines in Karachi during the study period. ABC is a binary indicator that equals 1 when the feeder line has PMTs with ABC installed, and equals zero otherwise. We classify the initial losses or revenue recovery rate (the monthly average losses or revenue recovery rate over 2018m1 and 2018m6) into three percentiles, low, medium, and high. The ABC indicator is then interacted with binary indicators for whether the feeder line falls into certain loss or RR categories. All regressions include feeder line and IBC-by-month fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

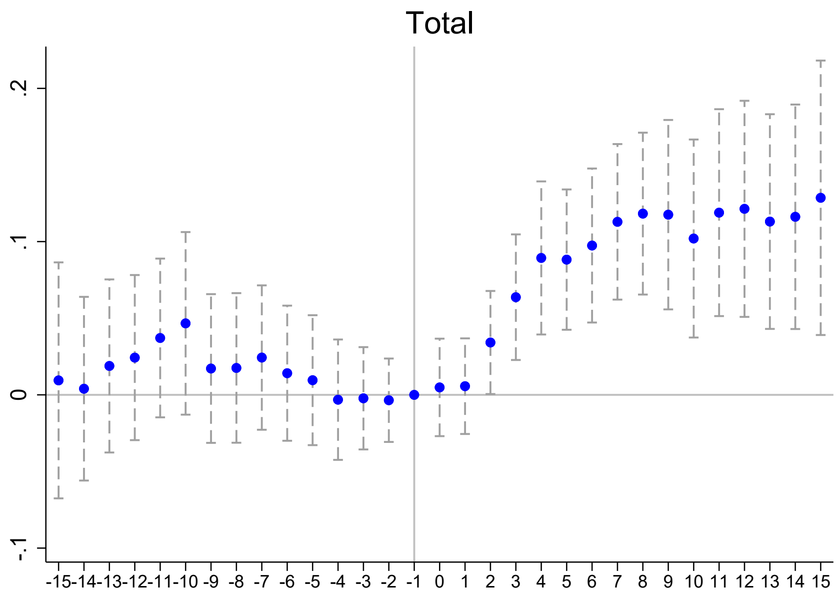


Figure 3: Event Study Estimates of the ABC Impact on the Number of Consumers

Notes: Figure shows the coefficients and their 95% confidence intervals from an event-study regression estimating the ABC impact on the number of consumers measured in inverse hyperbolic sines. Data are at the feeder level. From the top to the bottom, the figure shows the number of all claims, ABC-related claims, and non-ABC-related claims. Regressions include IBC-by-month and feeder fixed effects. One month prior to the ABC installation (-1) is the reference group and the corresponding coefficient is normalized to zero. Standard errors are clustered at the feeder level.

Table 3: Impact of ABC on Consumer Number

VARIABLES (IHS)	Total	Agriculture	Bulk	Commerce	Industry	Resident
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DID Estimates						
ABC	0.065***	-0.002	-0.004	-0.023	-0.009	0.064**
	(0.022)	(0.019)	(0.006)	(0.029)	(0.035)	(0.028)
Panel B: Intensity of Treatment						
ABC Ratio	0.138***	0.005	-0.008	-0.053	-0.015	0.159***
	(0.033)	(0.009)	(0.008)	(0.047)	(0.052)	(0.043)
Outcome Mean	1,582.96	1.24	0.09	263.41	11.71	1,306.51
Observations	67,602	67,602	67,602	67,602	67,602	67,602
Feeder FE	✓	✓	✓	✓	✓	✓
IBC-Month FE	✓	✓	✓	✓	✓	✓

Notes: The outcome variable is the log number of consumers in each feeder line. Columns 2-6 refers to different consumer categories. ABC is a binary indicator that equals 1 when the feeder line has PMTs with ABC installed, and equals zero otherwise. ABC Ratio is defined as the number of PMTs with ABC installed divided by the number of total PMTs in a feeder line. All regressions include feeder line and IBC-by-month fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

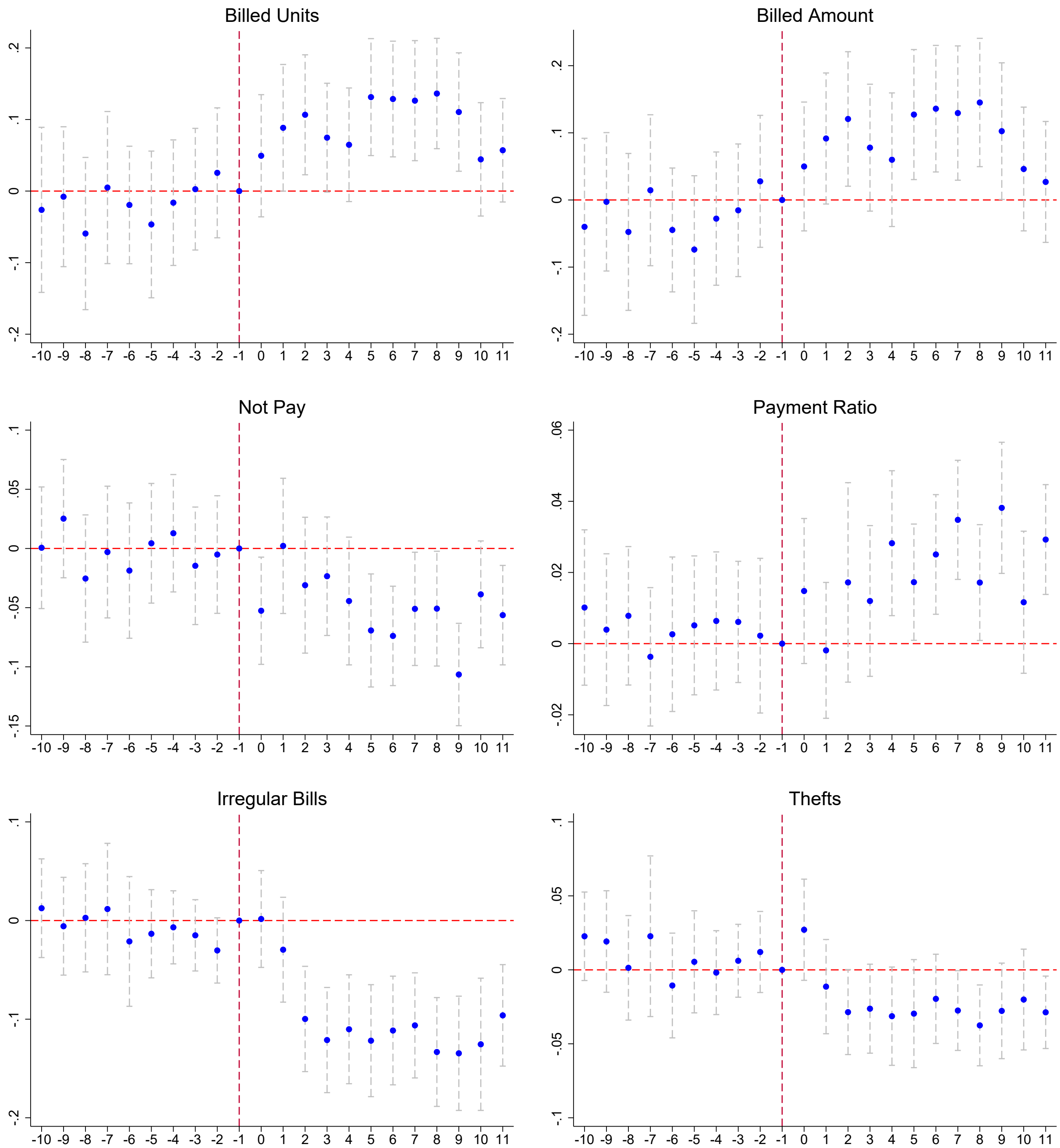


Figure 4: Event Study: Effect of ABC on Customer Behavior

Notes: Figure plots coefficients and their 95% confidence intervals from the event study estimates of the ABC effect. The outcome variables include billed electricity units (in inverse hyperbolic sine), billed electricity amount (in inverse hyperbolic sine), an indicator for whether the customer does not pay electricity bills on time, the proportion of payment relative to the total dues to KE (payment ratio), an indicator for whether there are irregular bills in that month, and an indicator for whether there are thefts in that month. All regressions include customer, month, and PMT-by-Month-of-Year FEs. Standard errors are clustered at the PMT level.

Table 4: Effect of ABC on Customer Behaviors

	IHS Billed Units	IHS Billed Amount	Not Pay	Payment Ratio	Irregular Bills	Thefts
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Treatment Effect						
ABC	0.090***	0.098***	-0.052***	0.016***	-0.111***	-0.038***
	(0.024)	(0.029)	(0.012)	(0.005)	(0.021)	(0.008)
Panel B: Heterogeneity by Expenditure Groups						
ABC $\times$ Below2	0.090***	0.096***	-0.050***	0.017***	-0.106***	-0.038***
	(0.024)	(0.030)	(0.012)	(0.005)	(0.020)	(0.008)
ABC $\times$ Above2	0.087	0.118*	-0.076***	0.014	-0.159***	-0.039***
	(0.060)	(0.070)	(0.027)	(0.011)	(0.041)	(0.015)
Outcome Mean	241.05	3,369.08	0.33	0.20	0.20	0.05
Observations	88,296	88,296	88,296	88,296	88,296	88,296
Number of HHs	3047	3047	3047	3047	3047	3047
Customer FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓
PMT-MoY	✓	✓	✓	✓	✓	✓

Notes: Customer-level data are provided by KE. The outcome variables include billed electricity units (in inverse hyperbolic sine), billed electricity amount (in inverse hyperbolic sine), an indicator for whether the customer does not pay electricity bills on time, the proportion of payment relative to the total dues to KE (payment ratio), an indicator for whether there are irregular bills in that month, and an indicator for whether there are thefts in that month. ABC is a binary dummy that equals 1 if the household is served by a PMT that has ABCs installed already. Above2 = 1 if the household's expense per capita is above $2 each day and Below2 = 1 if the household's expense per capita is below $2 each day. All regressions include customer, month, and PMT-by-month-of-year FEs. Standard errors are clustered at the PMT level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of ABC on Electricity Sent-Out

	Quantity Sent Out (kWh per month)	
	Level	IHS
	(1)	(2)
ABC	-97,213.292***	-0.102***
	(18,433.656)	(0.023)
Outcome Mean Level	920,981	920,981
Observations	47,575	47,575
Feeder FE	✓	✓
IBC-Month FE	✓	✓

Notes: Data are at the feeder line level. ABC is a binary indicator that equals 1 when the feeder line has PMTs with ABC installed, and equals zero otherwise. All regressions include feeder line and IBC-by-month fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Change in CO_2 Emissions per Change in Electricity Generated, by Generation Fuel

			Aggregated: High-loss feeders	
Generation Fuel(s)	Δ in CO_2 (t CO_2) / Δ generation (MWh) (1)	Δ in CO_2 emissions per feeder (tons) (2)	Δ in CO_2 emissions per year (tons) (3)	% of KE's annual CO_2 emissions from generation (4)
Natural Gas	- 0.46	- 536.6	- 213,574	1.67%
Responsive Blend	- 0.76	- 886.6	- 352,861	2.77%
Residual Fuel Oil	- 1.06	- 1,236.6	- 492,148	3.86%
Coal	- 1.17	- 1,364.9	- 543,190	4.26%

Notes: The steps leading to these results are detailed in Appendix A3. Column 1 is based on the numbers reported in Table A12. Column 2 is calculated by multiply the values in column 1 by -97,213 kWh per month, which is the reduction estimated in Table 5, as the reduction in quantity sent out to a feeder line per month as a result of the ABC installation. Column 3 is calculated by multiplying Column 2 by 398, based on the utility's 398 "high loss" feeders. Column 4 is calculated by dividing column 3 by 12,754,639 tons of CO_2, which was our estimate for the total CO2 emissions for generating the KE units of electricity purchased per year.

Table 7: Effect of ABCs on Welfare

Kunda Price (1)	ΔCS per Consumer (2)	ΔCS Total (3)	ΔKunda Revenue (4)	ΔPS (5)	ΔSubsidy (6)	ΔWelfare (7)
0	-682	-473,548,704	0	331,708,768	-133,894,840	-7,945,079
750	-607	-421,442,915	-52,105,772	331,708,768	-133,894,840	-7,945,079
1500	-532	-369,337,143	-104,211,544	331,708,768	-133,894,840	-7,945,079
2000	-482	-334,599,962	-138,948,725	331,708,768	-133,894,840	-7,945,079
2500	-432	-299,862,781	-173,685,906	331,708,768	-133,894,840	-7,945,079
3500	-332	-230,388,418	-243,160,269	331,708,768	-133,894,840	-7,945,079

Notes: All values are in Pakistani Rupees. Exchange rate during this period was approximately 1 USD = 150 PKR. Kunda prices are based on prices reported in our focus groups in summer and fall 2021. The change in total consumer surplus is calculated by multiplying the per customer change (column 2) by the number of customers in high loss areas following the ABC intervention (694,743 customers). The change in producer surplus is measured by the change in the amount of customer payment to KE. ΔSubsidy is measured by the change in government subsidies for electricity. Details for the calculation is described in Section 7.2.

Table 8: Impact of ABC on Consumer Complaints

VARIABLES (IHS)	All	Bill Complaints	Service Requests	Technical Complaints
	(1)	(2)	(3)	(4)
Panel A: Total Measures				
ABC	-0.079***	0.223***	-0.126***	-0.238***
	(0.023)	(0.031)	(0.041)	(0.032)
Outcome Mean	85.58	5.48	1.73	12.32
Panel B: Per Consumer Measures				
ABC	-0.016***	0.001***	0.002*	-0.018***
	(0.002)	(0.000)	(0.001)	(0.002)
Outcome Mean	0.264	0.011	0.086	0.166
Observations	71,918	71,918	71,918	71,918
Control	✓	✓	✓	✓
Feeder FE	✓	✓	✓	✓
IBC-Month FE	✓	✓	✓	✓

Notes: Data are at the feeder line level. The outcome variable is the inverse hyperbolic sine of the number of consumer complaints, including all types of complaints, bill complaints, service request. In panel A, We add consumer number as control variable. In panel B, we use per consumer measures defined as the number of complaints divided by the number of consumers covered by a feeder line. All regressions include feeder line and IBC-by-month fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Evidence on ABCs, Household-Reported Service Quality, and Appliances

	Daily Hours of Load Shedding/Power Cuts		Total Number of Appliances	Total Hours of Daily Usage
	Summer (1)	Winter (2)	(3)	(4)
ABC	-1.173***	-1.015***	0.506***	3.487***
	(0.260)	(0.322)	(0.156)	(0.847)
Control Mean	8.541	6.872	6.833	18.409
Observations	3,068	3,068	3,068	3,068
R-squared	0.125	0.302	0.372	0.198
Control	✓	✓	✓	✓
IBC FE	✓	✓	✓	✓

Notes: Outcome variables are collected via our household survey implemented in late 2021. ABC is a binary dummy that equals 1 if the household is served by a PMT with ABCs installed. Control variables included are: total number of family members, number of rooms, years in the neighborhood, indicators for house owners, indicators for owning a car, and indicators for having financial accounts. Standard errors are clustered at the PMT level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

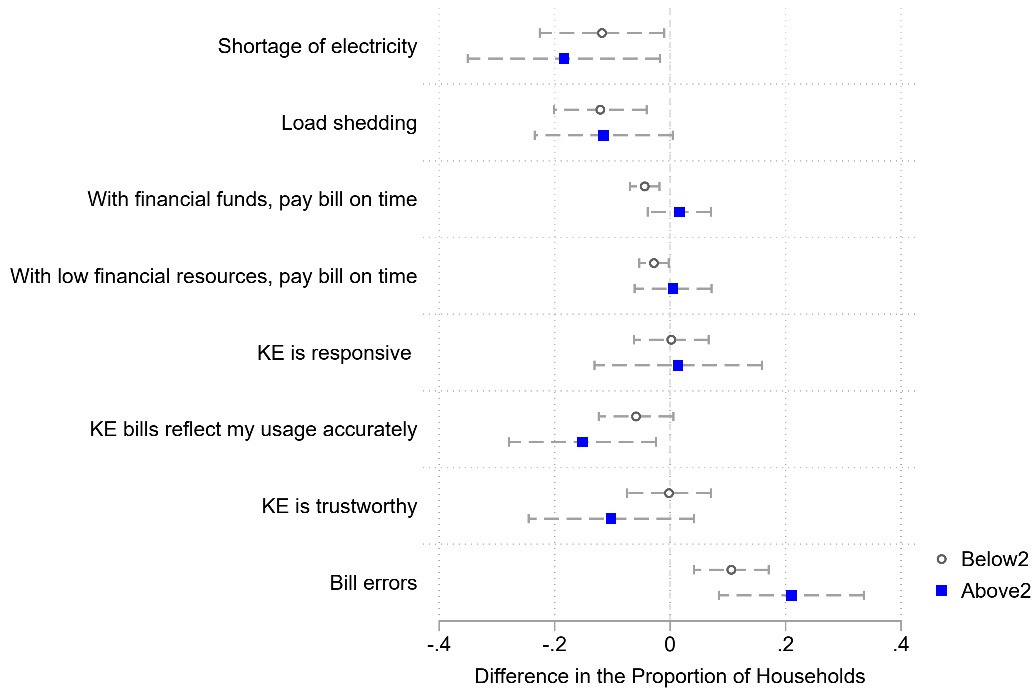
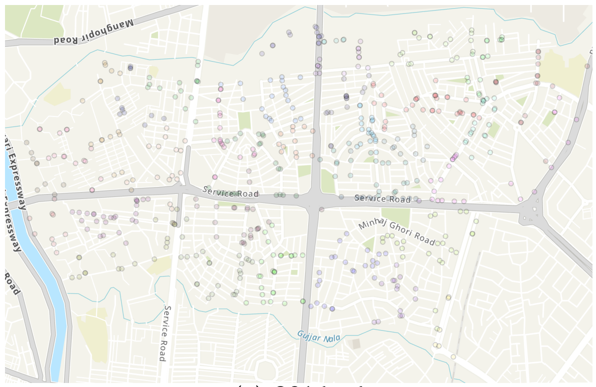


Figure 5: Effect of ABC on Household Beliefs

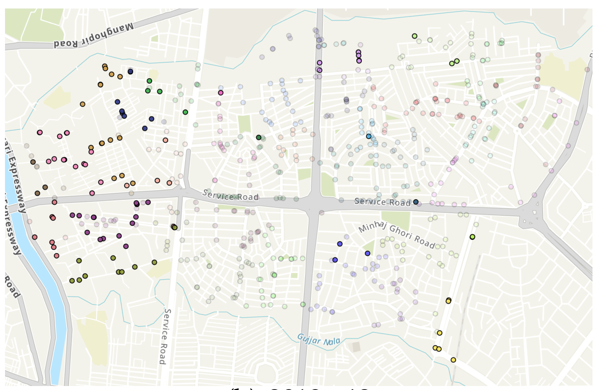
Notes: Figure plots coefficients and their 95% confidence intervals from regressing outcome variables on the interactions between ABC (a binary dummy that equals 1 if the household is served by a PMT with ABCs installed) and two categorical income variables (Above2 and Below2). Above2 = 1 if the household's expense per capita is above \$2 each day and Below2 = 1 if the household's expense per capita is below \$2 each day. Data were collected via our household survey implemented in late 2021 in response to questions asking respondents to indicate whether they agreed or disagreed with the belief statement. The outcome variables here are binary indicators equaling 1 if the respondent indicated some level of agreement (between mildly to strongly agree) with the statement and zero otherwise. Regressions include control variables: total number of family members, number of rooms, years in the neighborhood, indicators for house owners, indicators for owning a car, indicators for having financial accounts, expenditures on food items, and binary indicators for household income categories. Standard errors are clustered at the PMT level.

APPENDIX: FOR ONLINE PUBLICATION

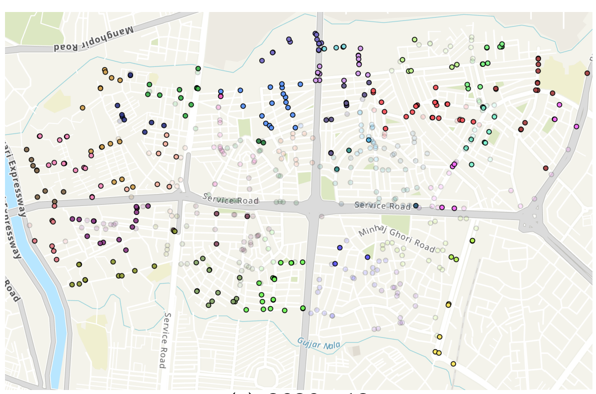
A1 ABC Installation Over Time by PMT



(a) 2016m6



(b) 2018m12



(c) 2020m12

Figure A1: ABC Installation at PMTs

Notes: The figures show the location of PMTs in one of the IBCs with high losses. Light colored circles indicate PMTs without ABCs, and darker colored circles indicate PMTs that have been converted to ABCs..

A2 Additional Figures and Tables

Table A1: Summary Statistics: General Household Characteristics

Variable	mean	sd	min	max
Household Characteristics				
Number of Adults	4.34	2.84	1	46
Number of Children	2.66	2.35	0	27
Total Number of People	7.00	4.06	1	47
Years in the Neighborhood	22.37	18.53	1	80
% Housing Owners	0.79	0.41	0	1
% Housing Renters	0.21	0.41	0	1
House Characteristics				
Number of Rooms	2.71	1.33	1	12
% Pakka	0.76	0.42	0	1
% Katcha	0.19	0.39	0	1
% Both Pakka and Katcha	0.05	0.21	0	1
Connectivity				
% Cellphone	0.60	0.49	0	1
% Mobile Internet	0.60	0.49	0	1
Expenditures				
Total Monthly Expenditures	33426.02	25095.02	0	418300
Expenditure on Food	18543.54	13283.91	0	300000
Expenditure on Electricity	5001.27	8851.94	0	250000
Expenditure on Water	983.88	1939.43	0	40000
Expenditure on House Rent	1759.76	4427.53	0	90000
Expenditure on Other Rent	257.70	1259.82	0	22000
Expenditure on Other Utilities	250.19	878.24	0	25000
Expenditure on Durables	80.57	1450.02	0	50000
Expenditure on Transportation	2221.53	4502.02	0	90000
Expenditure on Other Recurring	175.48	1097.79	0	30000
Expenditure on Healthcare	2747.38	11354.45	0	350000
Expenditure on Education	2557.88	6811.91	0	200000
Asset Ownership and Financial Accounts				
% Own Vehicles	0.04	0.19	0	1
% Own Motorcycles	0.59	0.49	0	1
% Own Land	0.05	0.22	0	1
% Financial Account	0.32	0.47	0	1

Notes: Statistics are calculated from our household survey conducted in 2021.

Table A2: Summary Statistics: Electricity-Related Household Characteristics and Reports

Variable	mean	sd	min	max
Electricity Connection Details				
Years with KE Connection	20.98	19.04	1	80
% Households Paying KE for Electricity	0.87	0.33	0	1
% Households Paying Other Entity for Electricity	0.09	0.28	0	1
% Meter Installed	0.96	0.19	0	1
% Meter Calculating Peak Consumption	0.19	0.39	0	1
% Households Checking Meter Regularly	0.06	0.23	0	1
% Share Meter with Other Households	0.01	0.11	0	1
Summer Monthly Electricity Expense (PAK)	5,635.48	6,988.37	500	200000
Winter Monthly Electricity Expense (PAK)	3,885.55	7,812.55	300	250000
Lighting Sources				
% Use Candle	0.12	0.32	0	1
% Use Lantern	0.01	0.09	0	1
% Use Kerosene Oil	0.01	0.11	0	1
% Use Battery Light	0.34	0.47	0	1
% Use Solar Powered Light	0.14	0.35	0	1
% Use Generator	0.06	0.23	0	1
% Use Mobile Light/Torch	0.06	0.24	0	1
Electricity service quality				
Summer Outage/Load Shedding Hours per Day	7.63	2.72	0	24
Winter Outage/Load Shedding Hours per Day	5.62	3.08	0	24
% Experience Appliance Damages	0.27	0.45	0	1
% Use Device to Protect Against Voltage Fluctuation	0.38	0.49	0	1
% Report Electricity Shortage	0.46	0.50	0	1
% Report Voltage Fluctuation	0.12	0.33	0	1
% Report Unplanned Load Shedding	0.73	0.45	0	1
% Report High Expense Electricity	0.72	0.45	0	1
% Report Frequent Billing Errors	0.28	0.45	0	1
Appliance ownership				
% Own Refrigerator	0.75	0.43	0	1
% Own Microwave Oven	0.01	0.10	0	1
% Own Washing Machine	0.72	0.45	0	1
% Own Air Conditioner	0.03	0.16	0	1
% Own TV	0.48	0.50	0	1
% Own Electric Water Pump	0.69	0.46	0	1
Total Number of Appliances	7.41	3.01	0	37
Light bulb Types				
% Use Incandescent	0.01	0.07	0	1
% Use CFLs	0.26	0.44	0	1
% Use LEDs	0.84	0.36	0	1

Notes: Statistics are calculated from our household survey conducted in 2021.

Table A3: Robustness Checks of ABC Impacts on Losses and Revenue Recovery

	Loss	RR
A. Feeder & IBC-by-Loss-Category-by-Month FE	-0.066***	0.048***
	(0.008)	(0.009)
B. Feeder-by-Calendar-Month & IBC-by-Month FE	-0.092***	0.053***
	(0.010)	(0.010)
C. Keep Feeders with >100m Distance from Others	-0.081***	0.053***
	(0.009)	(0.009)
D. Keep Feeders with >300m Distance from Others	-0.088***	0.053***
	(0.010)	(0.010)
E. Keep Feeders with >500m Distance from Others	-0.095***	0.046***
	(0.017)	(0.015)
F. Heterogeneity-Robust DID Estimator	-0.073***	0.066***
	(0.013)	(0.012)

Notes: Data are at the feeder line level. The coefficient estimate in each cell is from a separate regression. In Panel A, we control for Feeder and IBC-by-Loss-Category-by-Month FEs. In Panel B, we control fro feeder-by-calendar-month and IBC-by-month FEs. In Panel C–E, we only keep the feeder lines with at least 100m/300m/500m distance from its nearest neighbors. In Panel F, we report the aggregated ATT for all the timing groups across all periods using the heterogeneity-robust DID estimator proposed by Callaway and Sant'Anna (2021). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Nonlinearity in Impacts of ABCs

	Monthly		Quarterly	
	Loss	RR	Loss	RR
	(1)	(2)	(3)	(4)
ABC Ratio	-0.159***	0.176***	-0.130***	0.185***
	(0.030)	(0.039)	(0.035)	(0.041)
ABC Ratio^2	-0.019	-0.092**	-0.048	-0.086**
	(0.032)	(0.042)	(0.037)	(0.043)
Control Mean	0.260	0.792	0.243	0.813
Observations	47,575	37,353	17,626	14,664
Feeder FE	✓	✓	✓	✓
IBC-Month FE	✓	✓		
IBC-Quarter FE			✓	✓

Notes: Data are at the feeder line level. ABC Ratio is defined as the number of PMTs with ABC installed divided by the number of total PMTs in a feeder line. All regressions include feeder line and IBC-by-month/quarter fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Impact of ABC on Consumer Number: Before and After COVID

VARIABLES	Total	Agriculture	Bulk	Commerce	Industry	Resident
	(1)	(2)	(3)	(4)	(5)	(6)
ABC	0.074***	0.000	-0.006	0.032	0.017	0.072***
	(0.021)	(0.019)	(0.006)	(0.025)	(0.035)	(0.025)
ABC $\times$ COVID	-0.045	-0.015	0.013	-0.279***	-0.132**	-0.041
	(0.041)	(0.012)	(0.012)	(0.074)	(0.063)	(0.053)
Outcome Mean	1,582.96	1.24	0.09	263.41	11.71	1,306.51
Observations	67,602	67,602	67,602	67,602	67,602	67,602
Feeder FE	✓	✓	✓	✓	✓	✓
IBC-Month FE	✓	✓	✓	✓	✓	Yes

Notes: The outcome variable is the number of consumers in each feeder line, measured in inverse hyperbolic sine. Columns 2-6 refers to different consumer categories. ABC is a binary indicator that equals 1 when the feeder line has PMTs with ABC installed, and equals zero otherwise. COVID is a binary indicator for the post-COVID period (i.e., after March 2020). All regressions include feeder line and IBC-by-month fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

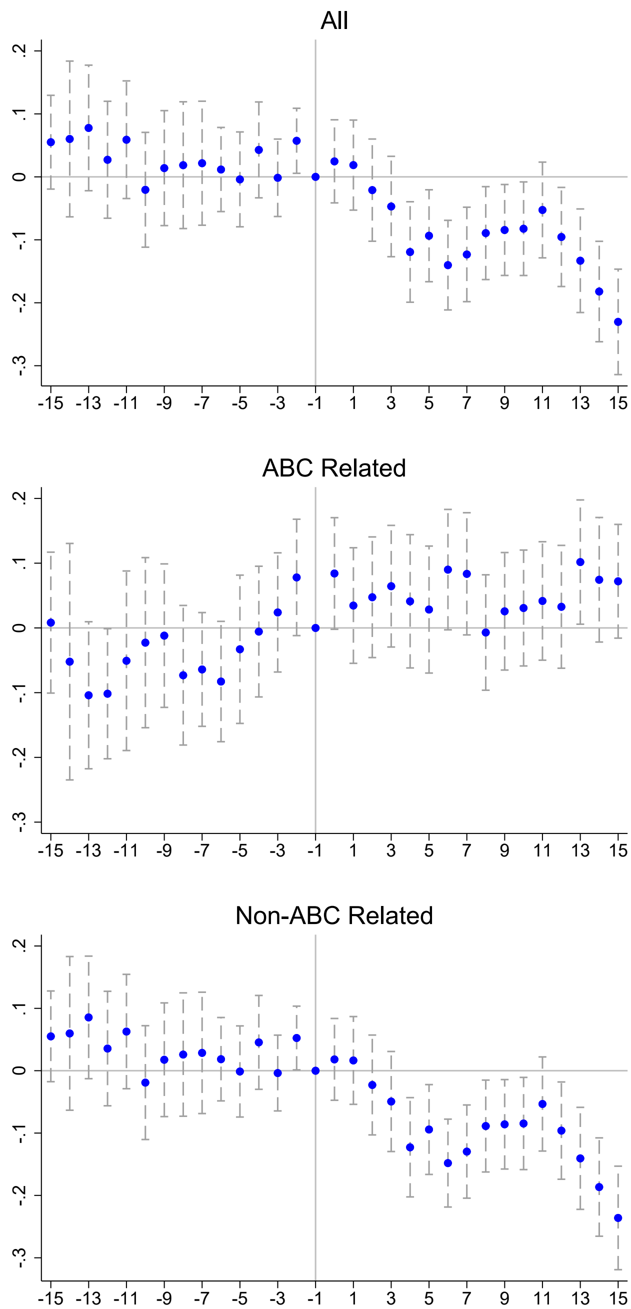


Figure A2: Event Study Estimates of the ABC Impact on KE Claims

Notes: Figure shows the coefficients and their 95% confidence intervals from an event-study regression estimating the ABC impact on the number of KE claims measured in inverse hyperbolic sines. Data are at the feeder level. From the top to the bottom, the figure shows the number of all claims, ABC-related claims, and non-ABC-related claims. Regressions include IBC-by-month and feeder fixed effects. One month prior to the ABC installation (-1) is the reference group and the corresponding coefficient is normalized to zero. Standard errors are clustered at the feeder level.

Table A6: Impact of ABC on KE Claims

VARIABLES (IHS)	All	ABC Related	Non-ABC Related
	(1)	(2)	(3)
Panel A: DID Estimates			
ABC	-0.058***	0.063**	-0.063***
	(0.018)	(0.024)	(0.018)
Panel B: Intensity of Treatment			
ABC Ratio	-0.170***	0.051	-0.175***
	(0.029)	(0.033)	(0.029)
Outcome Mean	9.278	0.159	9.118
Observations	41,536	41,536	41,536
Feeder FE	✓	✓	✓
IBC-Month FE	✓	✓	✓

Notes: The outcome variable is the number of KE claims, including all types of claims, ABC-related claims, and non-ABC-related claims, all measured in inverse hyperbolic sine. These claims happen when there is damage against the KE infrastructure/property and then KE files a claim against the public or an individual for damage, and then the police investigates the claim. ABC is a binary indicator that equals 1 when the feeder line has PMTs with ABC installed, and equals zero otherwise. ABC Ratio is defined as the number of PMTs with ABC installed divided by the number of total PMTs in a feeder line. All regressions include feeder line and IBC-by-month fixed effects. Standard errors in parentheses are clustered at the feeder line level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A3 Calculations: Reductions in CO_2 Emissions

In this section, we detail the steps involved in calculations pertaining to CO_2 emissions and the impacts of ABCs on them. First, we calculate the CO_2 emissions produced for all electricity generated and delivered to the service area covered by Karachi Electric. Second, we estimate the reduction in CO_2 per kWh reduction of electricity services consumed, in order to estimate the reduction in CO_2 emissions resulting from the introduction of the ABCs. Lastly, we use these two calculations together to compare the CO_2 emissions reductions from ABCs with the overall emissions from electricity purchased for the KE territory.

These calculations are conducted using information specific to Pakistan, from NEPRA's 2021 Annual State of the Industry Report (NEPRA, 2021).

A3.1 Part 1: CO_2 Emissions for Units of Electricity Purchased by Karachi Electric

We first calculate the CO_2 emissions for all units purchased for KE's service territory. NEPRA's report provides information on Karachi Electric system generation, as well as the purchases KE makes from the Central Power Purchasing Agency (CPPA-G). As shown in Table A7, the generation mix differs accross the two sources.

Table A7: Generation Mix for Pakistan, 2021

Fuel	KE Generation: Generation Quantity (GWh)	KE Generation: Percent (%)	CPPA-G Generation: Generation Quantity (GWh)	CPPA-G Generation: Percent (%)
Natural gas	3,420.59	26.08	14,496.43	11.22
Liquefied natural gas (LNG)	4,778	36.43	26,983.81	20.89
Residual fuel oil (RFO)	4,265	32.52	6,331.06	4.90
Coal	453	3.45	27,547.78	21.33
Hydro	0	0.00	38,800	30.04
Nuclear	0	0.00	10,871	8.42
Other renewables (solar, wind)	200	1.52	4,122	3.19
Total	13,116.6	100%	129,152.1	100%

Source: Data in this table are from the 2021 NEPRA annual report (NEPRA, 2021).

In FY 2020-21, Karachi Electric procured a total of 19,486 GWh. This was comprised of electricity generated within the KE system (13,116 GWh), as well as outside purchases from CPPA-G (6,370 GWh) (NEPRA, 2021).

We calculate the average emissions intensity by generation fuel type. We assume a plant efficiency and apply an emissions factor to estimate the kg of CO2 per MWh. We assume that LNG is same as natural gas throughout the calculations. We multiply the average heat rate for the [natural gas/RFO/coal] power plants in Pakistan, based on NEPRA's reports (NEPRA, 2021) by the carbon intensity of the [natural gas/RFO/coal] fuel. These calculations allow us to account not only for the generation fuel type, but also the efficiency of plants operating in Pakistan.

These calculations of emissions intensities are shown in Table A8.

Table A8: Average Plant Heat Rates and Emissions Intensities on Fuels

Generation Fuel	Power Plants' Average Heat Rate (MMBtu/MWh)	Carbon Intensity of Fuel (kg CO_2/MMBtu)	Emissions Intensity (kg CO_2/MWh)
Natural gas	8.7	52.9	460
RFO	14.1	75	1,060
Coal	97	12	1,170

We use these emissions intensities by fuel type, in conjunction with the generation mix information in Table A7, to calculate the emissions for KE.

We first do so for the units KE purchased from its own generation basket. This is quite straightforward to calculate as we can know the quantities generated by fuel type for the KE system generation. We multiply these by the emissions intensities from above. Results are presented in Table A9.

Table A9: Emissions from KE system electricty generation

Generation Fuel	Contribution to KE (GWh)	Contribution to KE (MWh)	Emissions intensity (kg CO_2/MWh)	Emissions total by fuel (kg CO_2)
Natural gas	8198.59	8198590	460	3,771,351,400
RFO	4,265.00	4265000	1060	4,520,900,000
Coal	453.00	453000	1170	530,010,000
Sum				8,822,261,400

Calculating the emissions from generation of the electricity purchased from CPPA-G requires a few additional steps. First, we assume that the generation mix of the units purchased from CPPA-G matches the proportions of the CPPA-G's overall generation. We calculate those proportions, still assuming that LNG is the same as natural gas. Results are in Table A10.

Table A10: CPPA-G Generation

Generation Fuel	CPPA-G generation (GWh)	proportion of CPPA-G's generation
Natural gas	41,480.24	0.321
RFO	6,331.06	0.049
Coal	27,547.78	0.213
(Hydro)	38,800	0.300
(Nuclear)	10,871	0.084
(Renewables)	4,122	0.032

We know from the NEPRA report (NEPRA, 2021) that KE purchased 6,370 GWh from CPPA-G in the 2020-21 FY. We assume that these units that KE purchased from CPPA-G were generated according to the overall CPPA-G mix shown in Table A10. With this information, we can calculate the CO_2 emissions from the electricity units that KE purchased from CPPA-G. We multiply the proportions in the far right column of Table A10 with 6,370 GWh and get results in Table A11.

Table A11: Emissions from the electricity generation of KE's purchases from CPPA-G

Generation Fuel	Contribution to KE (GWh)	Contribution to KE (MWh)	Emissions intensity (kg CO_2/MWh)	Emissions total by fuel (kg CO_2)
Natural gas	1,964.94	1,964,940.16	460	903,872,472
RFO	299.91	299,905.55	1,060	317,899,879
Coal	1,304.95	1,304,952.41	1,170	1,526,794,320
Sum				2,748,566,671

We next sum the emissions from the electricity units purchased from KE (8,822,261,400 kg CO_2) in Table A9 and the emissions from the electricity units purchased from CPPA-G (2,748,566,671 kg CO_2) in Table A11. We then convert this total of 11,570,828,071 kg CO_2 to tons, resulting in an estimated 12,754,639 tons of CO_2 per year from the generation of the electricity units purchased by Karachi Electricity.

A3.2 Part 2: CO2 Emissions Avoided due to ABC Installation

We first calculate the proportion of generation attributed to each of the fuels potentially responding to the changes in demand. First, we assume that the marginal units purchased are from the Karachi Electric generation basket, not CPPA-G. Further, we assume that the fossil fuel (natural gas, residual fuel oil, and coal) generation in the KE generation is responding to the changes in demand and that this response is proportional to their generation mix. It is reasonable to assume that nuclear and renewables are not responding. Hydro could be the marginal responder, but it is very unlikely; the zero marginal cost of hydropower makes it much cheaper than oil, coal or gas generation.

Based on these assumptions, we calculate the proportion of responding generation that is contributed by each of these fossil fuels:

Natural gas: (17.9+31.8)/(17.9+31.8+10.6+28.0) = 49.8/88.3 = 56%
Residual fuel oil: 10.6/88.3 = 12%
Coal: 28.0/88.3 = 32%

We then deploy the average emissions intensity for each of the fossil fuel sources, as shown in Table A8.

To calculate a blended estimate of the reduction in CO_2 per kWh reduction of electricity services consumed, we assume that the marginal generators are proportional to the generation from oil, coal and gas and weight these according to the proportion that each fuel contributes to the generation mix, as follows:

$$= (460 \text{ X } 56\%) + (1060 \text{ X } 12\%) + (1170 \text{ X } 32\%) = 760 \text{ kgCO2/MWh} = 0.76 \text{ kg } CO_2 \text{ / kWh}$$

This calculation provides our basic estimation of the reduction in CO2 per kWh reduction of electricity services consumed: 0.76 kg CO_2 /kWh.

There are some caveats to this calculation. As mentioned above, this assumes plants generating with fossil fuels respond. If hydro responds, the emissions response would be lower. This calculation also ignores upstream fuel effects, like methane leakage, which would make the result higher if included. Further, it is possible that the generation response is not proportional across the fossil fuels.

To provide upper and lower bound estimates of the reduction in CO_2 per kWh reduction of electricity services consumed, we can alternatively assume that the marginal generation is either strictly natural gas (the least carbon intensive of the three fuels) or residual fuel oil (the most carbon intensive of the three fuels). This provides us with the range of estimates in Table A12.

We use these calculations to estimate the change in the CO_2 emissions from electricity generated, depending on which of these fuels in the marginal fuel: natural gas, residual fuel oil, coal, or the responsive blend calculated earlier. We present these calculations in Table 6.

Table A12: Change in CO_2 emissions per change in electricity generated, by fuel

Fuel(s)	Change in CO_2 per generation change (kg CO_2 /kWh)
Natural gas	0.46
Blended generation fuels	0.76
Residual fuel oil	1.06
Coal	1.17

Source: We use these numbers in our calculations in Section 6 of the paper.

We know from Table 5 that the change in the quantity sent out per feed line as a result of the ABC intervention is -97,213 kWh per month. We multiply that amount by the change in the CO_2 per kWh generated via each fuel, and convert to metric tons of CO_2 per feeder line per year. To aggregate these avoided CO_2 emissions up, we mutiply the per feeder line numbers by either the 398 high loss feeder lines in Karachi (our conservation estimate) or the 2000 total feeder lines in Karachi (an upper bound estimate), providing us with two estimates of the aggregates tons per year in avoided CO_2 emissions in Karachi, as a result of the intervention. Lastly, we compare these reductions to the overall emissions that are from the electricity units purchased by Karachi Electric, as calculated above in Section A3.1.

We see in Table 6 that the reduction in CO_2 emissions resulting from the approximately 400 high-loss feeder lines being converted to ABCs, would result in a reduction of CO_2 emissions somewhere between 1.67% and 4.26% of the emissions due to electricity generated for KE.

Table A13: Change in CO_2 Emissions per Change in Electricity Generated, by Generation Fuel

			Aggregated: High-loss feeders	
Generation Fuel(s)	Δ in CO_2 (t CO_2) / Δ generation (MWh) (1)	Δ in CO_2 emissions per feeder (tons) (2)	Δ in CO_2 emissions per year (tons) (3)	% of KE's annual CO_2 emissions from generation (4)
Natural Gas	- 0.46	- 536.6	- 213,574	1.67%
Responsive Blend	- 0.76	- 886.6	- 352,861	2.77%
Residual Fuel Oil	- 1.06	- 1,236.6	- 492,148	3.86%
Coal	- 1.17	- 1,364.9	- 543,190	4.26%

Notes: Column 1 is based on the numbers reported in Table A12. Column 2 is calculated by multiply the values in column 1 by -97,213 kWh per month, which is the reduction estimated in Table 5, as the resuction in quantity sent out to a feeder line per month as a result of the ABC installation. Column 3 is calculated by multiplying Column 2 by 398, based on the utility's 398 "high loss" feeders. Column 4 is calculated by dividing column 3 by 12,754,639 tons of CO_2, which was our estimate for the total CO2 emissions for generating the KE units of electricity purchased per year (see end of Section A3).

Table A14: Scenarios of expected household reductions in monthly electricity bill, by season

		Winter	Spring/Fall	Summer
(a)	kW reduction per household	0.27	0.27	0.27
(b)	Average hours of bulb use per day	5.5	4.5	3
(c)	Days in month	30	30	30
	Expected LED savings per month (kWh) = a $\times$ b $\times$ c	44.55	36.45	24.30

Notes: Average hours per day are based on differences in sunrise and sunsets across seasons.