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 utility customers have little incentive to conserve. It also means electricity distribution companies have less to invest in infrastructure maintenance, modernization, and technical upgrades. 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 infrastructural intervention that made illegal electricity connections physically more difficult in Karachi, Pakistan. We find that this infrastructure improvement reduced non-technical losses, increased revenue recovery, and led to lower electricity delivered to the distribution system, a proxy for generation. This translates into a reduction in CO2 emissions that is between 0.10% to 1.19% of Pakistan's emissions within a year. Losses fall due to an increase in formal utility customers and greater billed consumption among the existing formal customers. Consumers report fewer service outages, as well as greater appliance ownership and use after the infrastructure upgrade. The improvement in infrastructure also provided the utility with some technical resilience to the disruptions caused by the COVID-19 pandemic, protecting against an uptick in non-technical losses.

Keywords: Electricity, Infrastructure, Losses
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1 Introduction

Fiscal challenges pervade the electricity sector in many countries. Electric power and distribution losses – losses between the points of electricity generation and the distribution companies' end-consumers – are substantial contributors to the sector's problems. These losses disproportionately affect utilities in low-income and lower-middle-income countries[1] and have important ramifications for the environment and development. First, the higher the losses, the more electricity must be generated per unit delivered to end-consumers. Further, non-technical losses – electricity theft and bill non-payment – mean people are not paying the full cost of electricity services consumed, which reduces their incentives to conserve. When electricity generation is dominated by fossil fuels, as in Pakistan, these factors translate into higher CO2 emissions, which have negative implications for the environment.

Even before accounting for the costs to society of excess CO2 emissions, these losses are crippling. Non-technical losses are estimated to cost utilities $96 billion per year worldwide (Bellero, 2017). These losses lead to unreliable electricity service delivery via load shedding (Burgess et al., 2020) and result in fewer investments in infrastructure maintenance, modernization, and technical upgrades. Further, unreliable and poor quality electricity services can limit the benefits from electrical grid connections (Pargal and Ghosh Banerjee, 2014; Samad and Zhang, 2016; Timilsina, Sapkota and Steinbuks, 2018; Meeks et al., 2022). An estimated 1 billion people worldwide receive electricity through grids that provide services with frequent outages and voltage fluctuations (World Bank, 2020). Unreliable electricity service is particularly problematic in South Asia, a region that has more power outages than anywhere else in the world (Zhang, 2018).

We study the effects of one infrastructure improvement, aerial bundled cables (ABCs), in Karachi, Pakistan. ABCs are an expensive upgrade from basic bare electrical wires,

[1] Losses are approximately three times higher in low-income and lower-middle-income countries, at 16 and 18% respectively, than those in high-income countries (IEA/OECD, 2018).

which are cheap 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 power utility 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 CO2 emissions within the country.

We use differences in the introduction of this infrastructure upgrade across Karachi over time to measure its effects on economic and environmental outcomes relevant to both the electricity utility and its customers. For the utility, we estimate the impacts of ABCs on two important measures of financial health, losses and revenue recovery, using a feeder level monthly panel dataset that covers the period between January 2018 to late 2020. With the exogenous shock of COVID-19 in early 2020, we also assess the extent to which ABCs helped mitigate the pandemic's impacts on these outcomes. Further, we investigate whether impacts on losses translate into changes in carbon emissions due to effects on the quantity of electricity generated.

On the consumer-side, we estimate customer responses to ABCs using individual residential customer-level panel data on billing-related outcomes over the same time period. We also use cross-sectional survey data, which we collected in Fall 2021, for these same utility customers, to complement the utility's administrative data and better understand consumer responses. Given electricity expenditures likely comprise a larger proportion of lower-income households' overall expenditures, we also assess whether ABCs had different impacts for the poorest households in comparison to the less-poor.

Our analysis provides a number of key findings on the impacts of electricity distribution infrastructure improvements. First, the installation of ABCs reduced losses and increased revenue recovery. The conversion of distribution lines to ABCs had the greatest impacts on losses (revenue recovery) in the feeders with the highest losses (lowest revenue recovery) prior to the intervention. These results indicate not only that ABCs improved on financial measures, but that gains were highest for areas that were the worst performing prior to the intervention. We find that the number of formal utility customers significantly increased with ABC installation. 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.

Second, the ABC roll-out appears to have provided some technical resilience to the disruptions caused by the COVID-19 pandemic. Losses, which are a function of the technical infrastructure, appear not to have been effected by the pandemic in feeders with ABCs (relative to those without ABCs). This suggests that the pandemic did not lead to an uptick in theft in areas with ABC wiring. Revenue recovery, which is a function of consumers' ability to pay bills, however was impacted by the onset of the pandemic even in areas in which ABCs were installed. Together these suggest that the ABCs increased utility resilience to electricity theft, but not bill non-payment.

In addition to ABC installations growing the number of formal utility customers, they also led to meaningful changes among the utility's residential consumers. Residential consumers responded to ABC installations with significant increases in both billed units (kWh) and the billed monetary amount, as well as reductions in documented theft and irregular billing. Our household surveys permit a better understanding as to how these intensive margin changes in theft influenced residential consumers. Customers in areas with ABCs report experiencing significantly fewer blackouts (locally known as *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. However, even with this better electricity service quality, these households are no more likely to report trusting the utility; in fact, they are significantly less likely to believe their electricity bills accurately reflect their consumption.

Lastly, although ABCs led to an increase in both the total number of utility customers and billed units (kWh) per customer, we find evidence that electricity generation (proxied 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 CO2 emissions associated with Pakistan's electricity generation mix, we find that the reduction in CO2 emissions per year from ABC installations is equivalent to between 0.10% and 1.19% of the country-wide emissions within a year.

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 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.

In line with earlier literature (see, Meeks et al., 2022), we show that infrastructure improvements increase service reliability – in this case via load shedding – and lead to an increase in bill payments. However, although diminished, losses do persist. Further, the improvements do not translate into increased trust in utility or confidence in billing. These findings emphasize the need for further work to understand determinants of willingness to pay in contexts where electricity (and other basic utilities) is subsidized.

In addition to finding positive impact on utility finances and reduction in load shedding, our results highlight an additional channel through which such programs can be beneficial. Specifically we find that ABCs have a positive environmental externalities.

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, while Section 6 addresses the consumer response to their installation. We extend the analysis to illustrate the implications for CO2 emissions and climate change in Section 7. 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 enormous 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. Although the power sector underwent major reforms such as allowing independent private producers, unbundling the monolithic utility company, establishing a regulatory entity, and offering a generous subsidies program, the country has continued to suffer from frequent blackouts.[2]

Given these challenges, cost efficiency of all three segments – generation, transmission and distribution – is an essential prerequisite for achieving the desired goals of reliable and affordable availability of electricity. In this paper, we focus on the the issue of transmission and distribution (T&D) losses, which were as high as 19.1% for Karachi Electric in 2019 (NEPRA, 2021).

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]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 CO2 from the burning of fossil fuel and contamination of waterways due to the waste water discharged by power plants (NEPRA, 2021).

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 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]

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.

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.

2.4 COVID-19 and Electricity Distribution

In February 2020, the first cases of COVID-19 were identified in Karachi. Shortly afterwards, Karachi was put under lockdown from March 21 until May 9.[6] During this period meter reading activities were suspended, and bills were calculated on the basis of average consumption of the past 11 months or consumption in the same month of the previous year.[7] Other field and in-person operations including infrastructure improvements were also halted (Ahmad et al., 2021).

[6]Vakeel Rao, Hafeez Tunio, Tufail Ahmed, "Sindh decides to go into COVID-19 lock down". The Express Tribune. 21 March 2020, retrieved Aug 2021; Rizwan Shehzad, "Countrywide lockdown stretched till May 9", 24 April 2020, The Express Tribune, retrieved Aug 2021.

[7]Salman Siddiqui, "K-Electric consumers get high average bills" The Express Tribune, retrieved Aug 2021.

As most industrial and commercial activities were closed down, there were severe local economic effects, especially in lower and middle income urban areas, where many people were forced out of work (Ahmad et al., 2021). The government introduced a moratorium on disconnecting non-paying electricity customers and announced bill relief programs for lower income and small and medium enterprises. Residential customers consuming less than 300 kwh per month could pay their billed amount during the months of March to May in three equal instalments, which were added to their bills between June and November.[8] Small and medium industrial and commercial customers were also eligible to receive bill waivers for three months.[9] Although these programs offered immediate relief to customers, they also negatively affected utility revenues. We capture these effects in Section 6.2. Moreover, despite these support programs, phone surveys conducted in June and November 2020 show that households were most likely to miss electricity payments, with more than half of the households reporting having missed an electricity payment during this period (Asad et al., 2020).

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.

[8] The News, "Below 300 units, KE customers can avail three monthly instalments", April 22, 2020, retrieved Aug 2021.

[9] Commercial customers with sanctioned load up to 5kW and industrial consumers with sanctioned load up to 70kW received a subsidy of Rs100,000 and Rs450,000 in their electricity bills, respectively, which was applied in six months starting from May 2020. See Dawn, "KE announces relief for SMEs through prepaid bills", May 19, 2020, retrieved Aug 2021.

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 Research Design and Econometric Model

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:

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

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. 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.

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 A1, 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 A1, 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 A1, 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 The Impacts 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 utility's claims of damage or the number of consumers.

5.1 Losses and Revenue Recovery

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 important results. First, there is no evidence of differential pre-trends with respect to both losses and revenue recovery across the treated and untreated groups in the months prior to ABC installation. Second, these illustrate a negative effect on losses and a positive effect on revenue recovery from ABC 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 Table1, Panel B. These analyses are performed using both monthly and quarterly losses and revenue recovery data as outcome measures. All regressions include feeder fixed effects.

Results in both panels provide 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. 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. Results are robust to the inclusion of various fixed effects; coefficient are similar in magnitude, regardless of whether we include month (quarterly) fixed effects or IBC-by-month (IBC-by-quarter) fixed effects. Additional estimates, included in the Appendix, provide some evidence of non-linearities in the effect of ABC installation intensity (Table A2), specifically we find diminishing returns to the fraction of PMTs covered by ABC installations within feeders.

Prior to the intervention, some areas of the distribution system suffered from higher losses and lower revenue recovery rates than other areas. We investigate whether ABCs had differential impacts based on pre-intervention feeder loss (revenue recovery) level (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.

The COVID-19 pandemic caused major disruptions in the utilities operations, and COVID related lock-downs and social distancing protocols also had major economic consequences for the utility's customers. Given that ABC roll-outs continued to take place on both sides of the pandemic, it is difficult to disentangle the effects of infrastructure upgrades and the pandemic. However, our data allows us to make some basic comparisons, leveraging differences at the feeder level across time. Table 3 presents potential evidence of ABC's providing some resilience against the pandemic's exogenous shock in the technical domain.

Losses, which are a function of the technical infrastructure appear to have not been effected by the pandemic in feeders with ABCs (relative to those without ABCs), suggesting that the pandemic did not lead to an uptick in theft in areas with ABC wiring. However, this resilience does not extend to revenue recovery, which is to be expected as recovery is not just a function of the distribution network, but also of consumer's ability to pay back their bills. Moreover, we expect a greater fraction of consumption in ABC feeders to be metered and billed relative to non-ABC feeders. Thus, bill recoveries in ABC feeders might be affected more by shocks to income relative to non-ABC feeders. Restricting the sample of feeders to only those in high loss IBCs (columns 3 and 4) gives similar estimates for both losses and revenue recovery, indicating that ABC and non-ABC feeders in low loss areas are not driving the results.

5.2 Mechanisms for Loss Reduction

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). We find no 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 4. 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 Utility Legal Claims of Damage

With ABCs making it difficult to connect illegally, we see an increase in the number of consumers above. Of interest is whether ABCs yield higher levels of consumer resentment, especially given the local context and resistance to such infrastructural upgrades. One source of this may be intentional damage to KE equipment, which would yield a higher number of claims made by KE.

If consumers try to illegally connect to the distribution grid after the installation of the ABCs, damage to either the ABCs or other parts of the electrical grid may result. When there is damage to the distribution company's infrastructure or property, the utility files a claim against the suspected party. We find that overall, utility claims against customers fell after ABC installation (Table 5), though there is an uptick in ABC related claims. The latter is only natural as feeders without ABCs would be ineligible for such claims. Overall, we find that complaints fall, even when accounting for ABC damage, suggesting that ABC installation results in a more robust distribution system.

6 Consumer Response to ABCs

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.

6.1 Consumer Response: Billing Panel Data

Event studies in Figure 5 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 6 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.

6.2 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 utility feeder line data on consumer complaints, and the type of complaints filed, to estimate impacts of ABCs on these outcome measures. Regressions results are presented in Table 7, 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 estimates in Panel B show no evidence on any of the complaint types. These results suggest that although consumer complaints increase, it seems to be a function of the number of customers also increasing. When we account for the customer increase, there is no significant impact of the ABC conversion on complaints.

6.3 Understanding Consumer Response via Survey Data

We use our household survey data to help us better understand the mechanisms through which the ABC impacts may have occurred. The residential consumer survey is cross-sectional, therefore, we interpret these results as correlational relationships. To understand if these mechanisms potentially differ according to how well-off households are, we report the results for the interactions of the ABC indicator with the Below2 and Above2 indicators.

Historically, the electricity utility has targeted load shedding according to feeder-line level losses. Given losses fell and revenue recovery increased with the ABC (Table 1), we would expect to see less load shedding in these ABCs relative to other high loss areas that had not had ABCs installed. Table 8 presents differences in reported service quality for households covered by ABC, that are above the $2 per day expenditures per capita and those that are below. We see no significant differences for either of these groups, relative to the households not covered by ABCs, in the reported appliance damages (column 1) or voltage fluctuations in summer (column 2) or winter (column 3). This indicates that, when electricity is delivered, the perceived quality of those electricity services is not different across ABCs and non-ABCs areas.

There are, however, significantly fewer hours per day of reported load shedding in both the summer (column 4) and winter (column 5) 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 our survey sample is 7.6 hours per day in the summer and 5.6 hours in the winter.

With fewer hours of load shedding (Table 8), 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 present correlation results to this effect in Table 9. Regarding the household total number of appliances (column 1), the Below2 households in ABC areas have a significantly greater total number, compared to the non-ABC areas. The Above2 households in ABC areas have a positive coefficient, but with a larger standard error the difference is not statistically significant. Consistent with less load shedding and greater appliance ownership, households in ABC areas report significantly more total hours of appliance usage per day than the non-ABC areas (column 2). The survey collected ownership information on specific appliances, we report differences in percentage ownership of some of the appliances for illustrative purposes in columns 3 through 5.

Our panel analysis of utility consumer billing data showed that ABCs increased billed monetary amount and the ratio of the billed amount paid, suggesting we could also see changes in the household reported expenditure. Differences in expenditures, as reported in the household survey, are in given in Table 10. ABC households below the \$2 per day per capita expenditures have significantly higher electricity expenditures than their non-ABC counterparts (column 3). It is not obvious ex-ante whether higher electricity expenditures would mean lower non-electricity expenditures or just overall higher total expenditures. We see evidence of the latter, but not of the former among this below the \$2 per day per capita expenditures group of ABC houses. The expenditures data for the above \$2 per day per capita expenditures group are noisier and there are no significant differences for this group.

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, reliability, benefits, and subsidies. Results are presented in Figure 6. Interestingly, there are no differences in the proportion of households that believe the utility is responsive to the customers' needs, that the utility is trustworthy, or that the utility cares about its customers; however, households in ABC areas are, on average, less likely to believe that their electricity bills accurately reflect their consumption. ABC households below the \$2 per day per capita expenditures are less likely to report that they would pay their bill on time, in both situations in which they have funds and when their financial resources are low; however, these household are also more likely to believe that the government subsidizes electricity.

The survey also asked respondents to list the three most serious problems with respect to electricity service provided by the utility and differences in these beliefs are reported in Figure 7. Households in ABC areas are, on average, significantly less likely to say electricity shortages and load shedding are serious problems, while also more likely to say that bill errors are a problem. These are consistent with the other beliefs reported above. Only a subset of these households – those that are also in the Above2 expenditure group – are also significantly more likely to report thinking voltage fluctuations and an inability to power large appliances are a serious problem, a difference that could be the result of differences in large appliance ownership.

7 Implications for Climate Change

Ex-ante, the implications of the ABC intervention for electricity generation and, therefore, CO2 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 CO2 emissions.

In this section, we explore the implications of the infrastructure upgrade for climate change 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 CO2 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 CO2 emissions. Lastly, to provide some prospective, we compare these estimates to the annual CO2 emissions for Pakistan.

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. [10] 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 in Table 11 show that ABCs led to a decrease in generation of 97,213.3 kWh per feeder line

[10] 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 CO2 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.

per month (column 1). In logs, the intervention led to a 10.2% decrease in generation per feeder line per month (column 2).

To translate these generation reductions per month into avoided CO2 emissions, we perform calculations of the estimated reduction in CO2 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" consititutes 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 CO2 per kWh reduction of electricity services consumed to be 0.76 kg CO2/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 CO2/kWh and 1.06 kg CO2/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 12. In column 1, we present the result of multiplying each of these estimated changes in CO2 per kWh change in generation by the estimated reduction in generation: 97,213.3 kWh per feeder line per month (column 1 of Table 11). This provides us with a range of estimated reductions in CO2 emissions per year per feeder line, by fuel source of the marginal generator. We can aggregate these numbers to all high loss feeders (column 2) and compare them the estimated CO2 emissions for Pakistan in a year (column 3). As can be seen, regardless of the blend used, the reduction in CO2 emissions is non-trivial, with the most conservative reduction in emissions due to high-loss IBCs accounting for almost a tenth of a percent of Pakistan's total CO_2 emissions, increasing to 0.17% for the responsive blend, and up to .24% if the highest polluting power plants are brought offline first.

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 reduced monthly losses by 6 to 8.2 percentage points and increased recoveries by 5 percentage points. 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 led to an increase in the total number of metered customers and a reduction in utility claims of damage to the distribution infrastructure. 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. We also find evidence of ABC's providing some resilience against the pandemic's exogenous shock in the technical domain, as losses are not deferentially affected by the pandemic in feeders with ABCs (relative to those without ABCs), suggesting that the pandemic did not lead to an uptick in theft in areas with ABC wiring. However, revenue recovery is negatively impacted which reflects negative shocks to consumer's ability to pay back their bills.

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 environment perspective, it is encouraging to see that 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 CO2 emissions from ABC installations to be between 0.10% and 1.19% of the country's total emissions within a year. In a country that depends on thermal power plants to produce 70% of the total electricity, the carbon-reducing impact of ABCs is clearly non-trivial.

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Figures and Tables

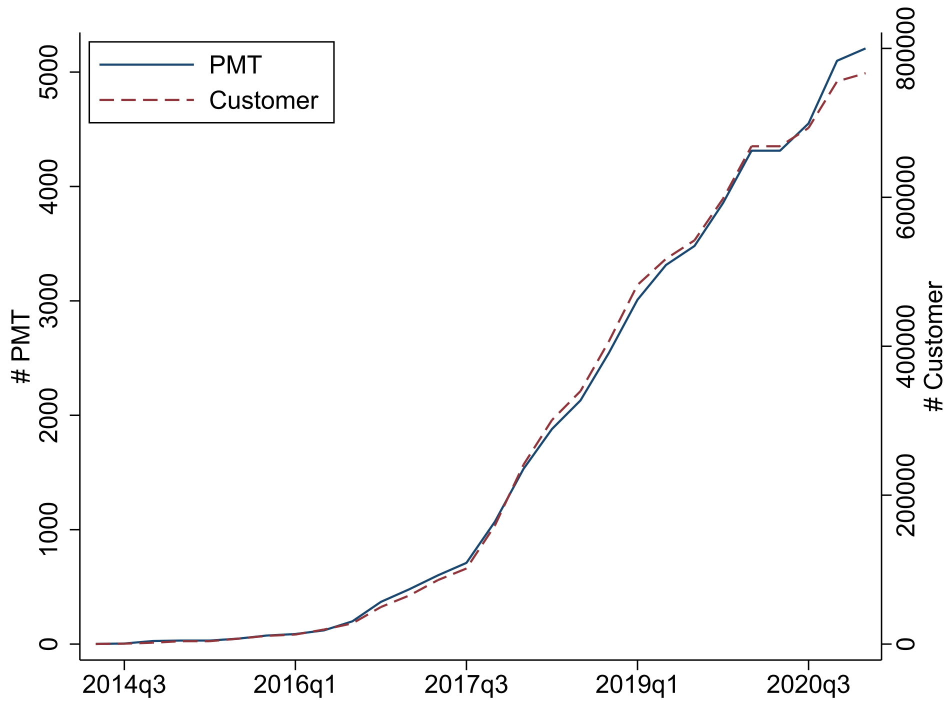


Figure 1: Trend of ABC Installation

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

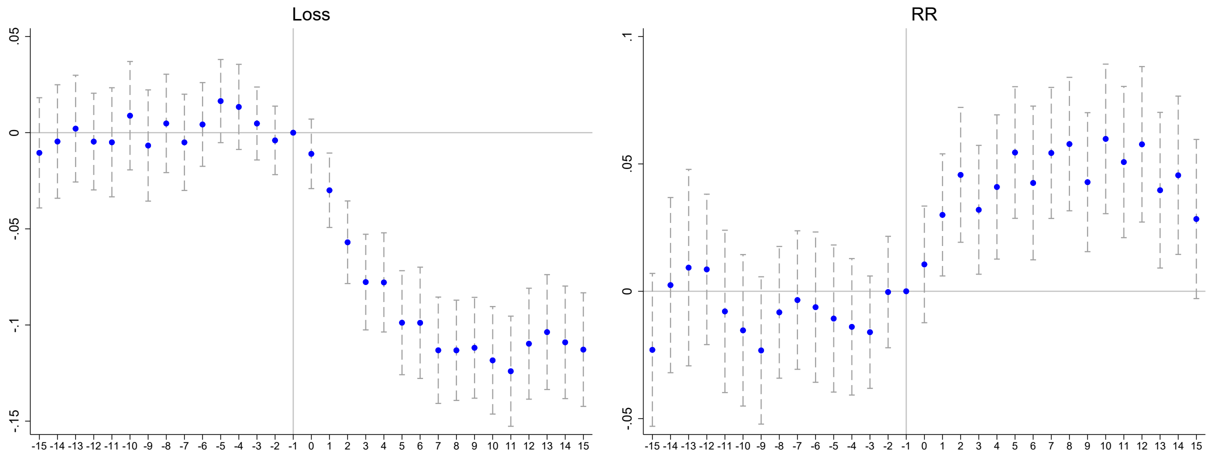


Figure 2: Event Study Estimates of the ABC Impact on Losses and Revenue Recovery

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Resilience of ABC Impact to COVID

	All IBCs		High-Loss IBCs	
	Loss	RR	Loss	RR
	(1)	(2)	(3)	(4)
ABC	-0.081***	0.055***	-0.084***	0.056***
	(0.009)	(0.009)	(0.009)	(0.009)
ABC $\times$ COVID	-0.007	-0.025*	-0.013	-0.032**
	(0.011)	(0.014)	(0.012)	(0.015)
Outcome Mean	0.260	0.792	0.324	0.701
Observations	47,575	37,353	13,919	11,721
Feeder FE	✓	✓	✓	✓
IBC-Month 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. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

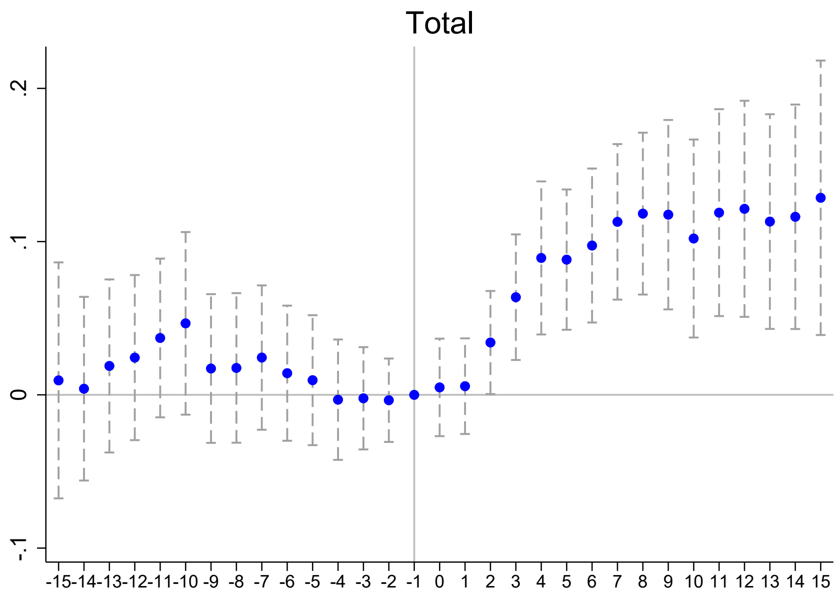


Figure 3: Event Study Estimates of the ABC Impact on the Number of Consumers

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 4: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

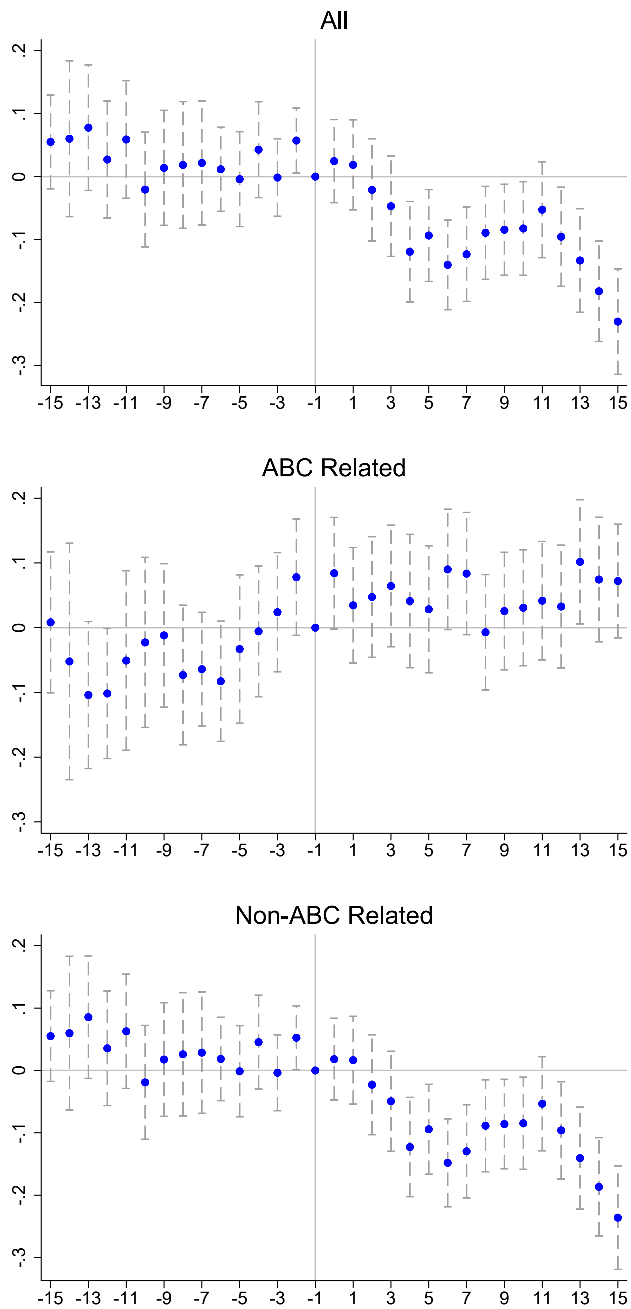


Figure 4: Event Study Estimates of the ABC Impact on KE Claims

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 5: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

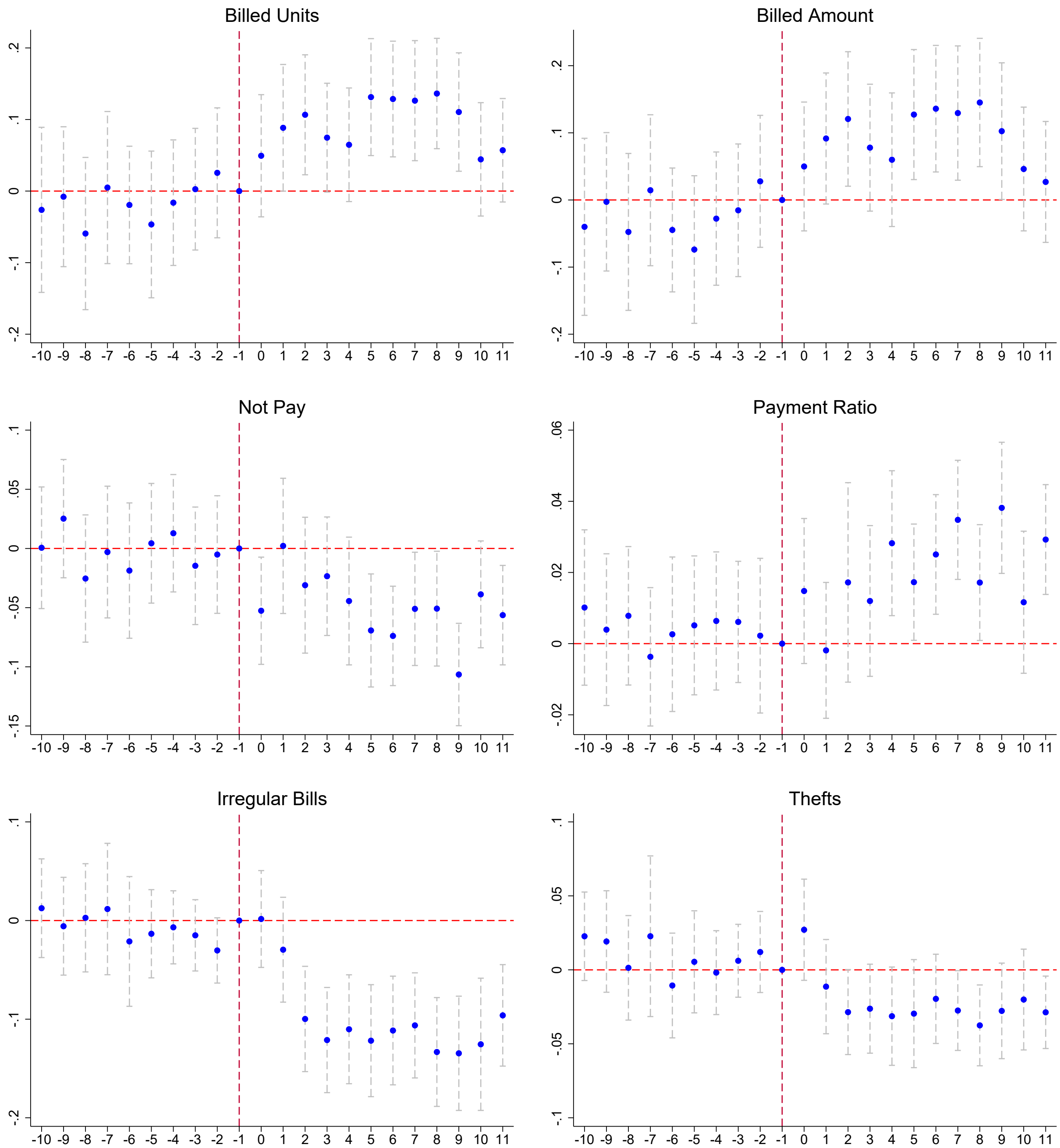


Figure 5: Event Study: Effect of ABC on Customer Behavior

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 6: 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 7: 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 8: Effect of ABC on Household-Reported Service Quality

	Appliance Damages	Weekly Number of Voltage Fluctuations		Daily Hours of Load Shedding/Power Cuts	
		Summer	Winter	Summer	Winter
	(1)	(2)	(3)	(4)	(5)
ABC × Below2	0.009	-0.150	-0.022	-1.173***	-1.015***
	(0.028)	(0.313)	(0.220)	(0.260)	(0.322)
ABC × Above2	0.072	0.926*	0.300	-1.479***	-0.984**
	(0.059)	(0.511)	(0.437)	(0.532)	(0.476)
Control Mean	0.248	1.237	0.699	8.541	6.872
Observations	3,068	2,882	2,887	3,068	3,068
R-squared	0.038	0.062	0.035	0.125	0.302
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. 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. Standard errors are clustered at the PMT level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of ABC on Appliance Ownership

	Total Number of Appliances	Total Hours of Daily Usage	% Own Sewing Machine	% Own TV	% Own Water Dispenser
	(1)	(2)	(3)	(4)	(5)
ABC × Below2	0.506***	3.487***	0.014	0.131***	0.004*
	(0.156)	(0.847)	(0.014)	(0.029)	(0.002)
ABC × Above2	0.121	4.336***	0.071***	0.032	0.006
	(0.376)	(1.607)	(0.019)	(0.069)	(0.006)
Control Mean	6.833	18.409	0.038	0.378	0.001
Observations	3,068	3,068	3,068	3,068	3,068
R-squared	0.372	0.198	0.028	0.149	0.005
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. 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. Standard errors are clustered at the PMT level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Effect of ABC on Household Expenditures

	Total Expenditures	Non-Electricity Expenditures	Electricity Expenditures
	(1)	(2)	(3)
ABC × Below2	1,604.285*	573.110	1,016.532***
	(838.381)	(796.270)	(229.586)
ABC × Above2	-8,916.708	-5,059.016	-3,854.354
	(8,444.901)	(7,005.919)	(3,674.562)
Outcome Mean	31,798	27,613	4,244
Observations	3,068	3,052	3,052
R-squared	0.360	0.316	0.088
Control	✓	✓	✓
IBC FE	✓	✓	✓

Notes: Expenditures are in Pakistani rupees and the exchange rate at the time was approximately 1 USD = 170 rupees. 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. 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. Standard errors are clustered at the PMT level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

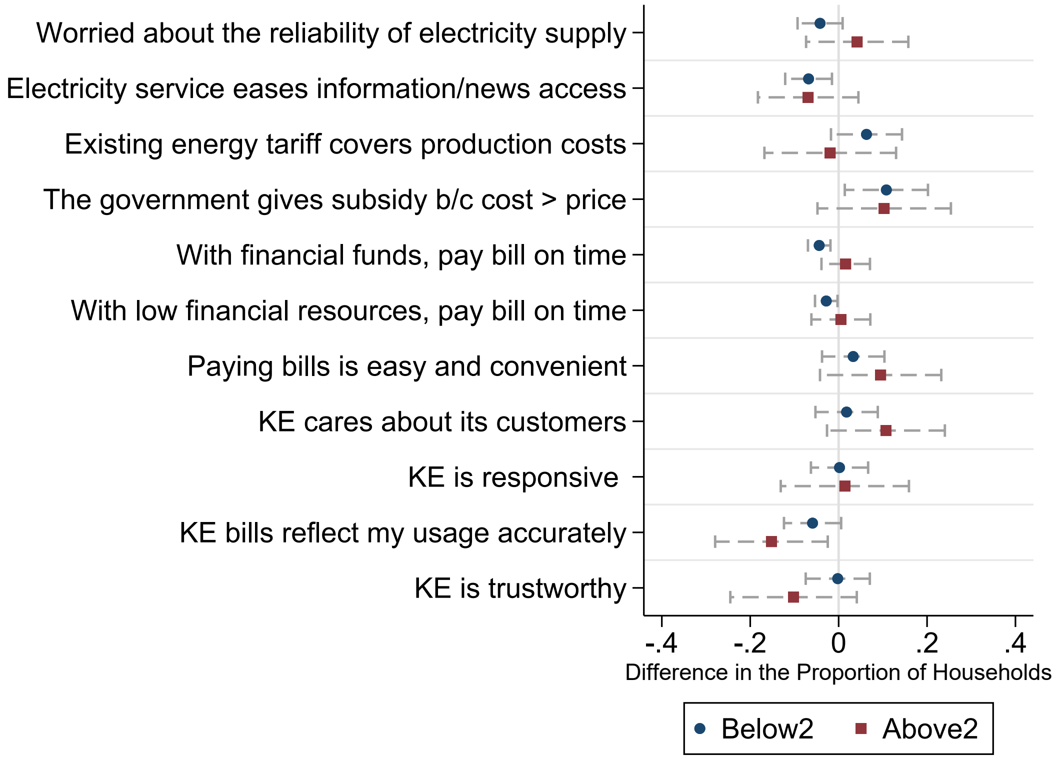


Figure 6: Effect of ABC on Household Beliefs

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.

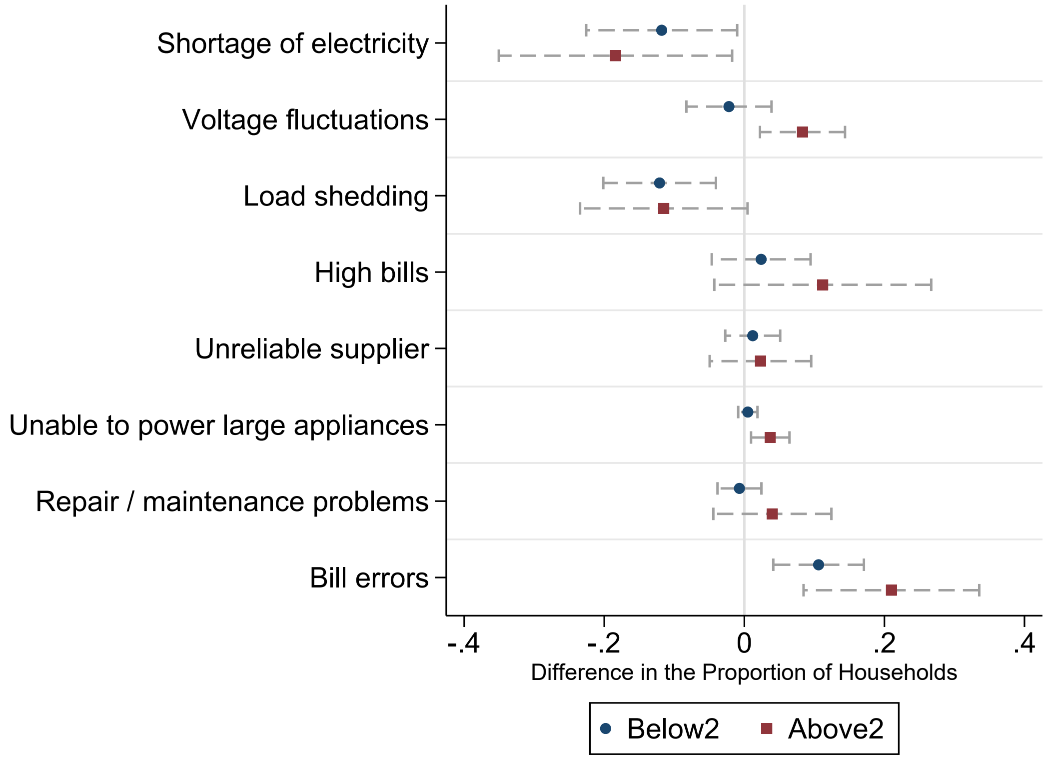


Figure 7: Effect of ABC on Household-Reported Serious Problems

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. They are the response to the question, "Thinking about your issues with the electricity utility, what is your most serious problem you face with the electricity service?" The outcome variables are binary indicators for whether the household lists the corresponding issues as one of their top 3 issues. 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, and indicators for having financial accounts. Standard errors are clustered at the PMT level.

Table 11: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

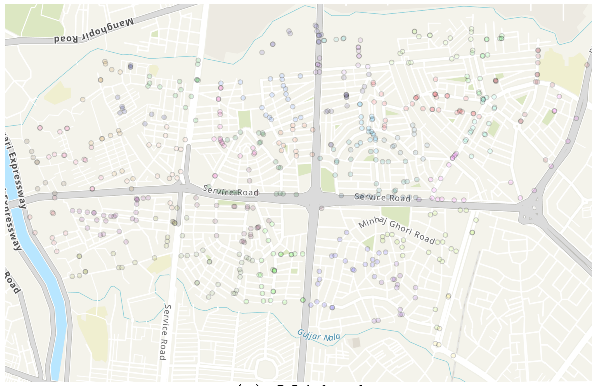
Table 12: Change in CO2 Emissions per Change in Electricity Generated, by Generation Fuel Type

Generation Fuel(s)	Δ in CO2 emissions (tons) per year per feeder (1)	Δ in CO2 emissions (tons) per year for all high loss feeders (2)	High loss feeders: % of Pakistan's annual CO2 emissions (3)
Natural gas	- 536.6	- 213,574	0.10%
Responsive blend	- 886.6	- 352,861	0.17%
Residual fuel oil	- 1236.6	- 492,148	0.24%

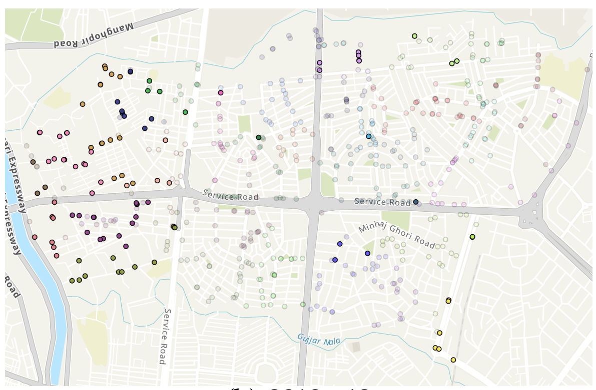
Notes: Numbers for column 1 are based on calculations in Appendix A3 and regression results in column 1 of Table 11. Column 2 assume 398 high loss feeders. Columns 3 is calculated by dividing the number in column 2, by the 2018 estimated CO2 emissions for Pakistan (208,370 kt). Pakistan's CO2 emissions include "carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring." The emissions data for Pakistan are from the World Open Data, which is sourced from the 2020 CAIT data from ClimateWatch.

APPENDIX: FOR ONLINE PUBLICATION

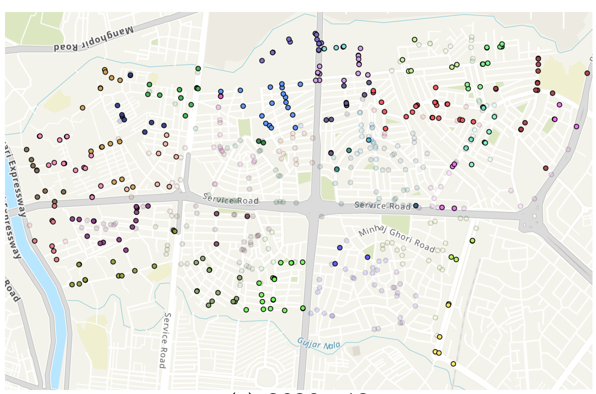
A1 ABC Installation Over Time by PMT



(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: 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 A2: 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 A3: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A3 Calculations: Reduction in CO_2 per kWh Reduction in Electricity Generated

To calculate the approximate reduction in CO_2 per kWh reduction of electricity services consumed, we undertake a multi-step calculation. We use information specific to Pakistan, based on NEPRA's 2021 Annual State of the Industry Report.

We first calculate the proportion of generation attributed to each of the fuels potentially responding to the changes in demand. We use details on the generation mix in Table A4 and assume that LNG is same as natural gas throughout the calculations.

Table A4: Generation Mix for Pakistan, 2021

Fuel	Generation Quantity (GWh)	Percent of Generation
Natural gas	17,917.02	12.6%
Liquefied natural gas (LNG)	31,761.81	22.3%
Residual fuel oil (RFO)	10,596.06	7.4%
Coal	28,000.78	19.7%
Hydro	38,800	27.3%
Nuclear	10,871	7.6%
Other renewables (solar, wind)	4,322	3.0%
Total	142268.67	100%

Source: NEPRA (2021)

Further, we assume that the fossil fuel (natural gas, residual fuel oil, and coal) generation is responding to the changes in demand and that this response is proportional, based on their contributions to generation. It is a safe assumption 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%

Next, we calculate the average emissions intensity by fuel type of generation. We assume a plant efficiency and apply an emissions factor to estimate the kg of CO_2 per MWh reduction. We multiply the average heat rate for the [natural gas/RFO/coal] power plants in Pakistan, based on NEPRA's reports (NEPRA, 2021), and multiple these times 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 plant efficiency.

The average emissions intensity for each of the fossil fuel sources of generation are as follows:

Natural gas: (8.7 MMBtu/MWh) X (52.9 kg CO_2/MMBtu) = 460 kg CO_2/MWh

Residual fuel oil: (14.1 MMBtu/MWh) X (75 kg CO_2/MMBtu) = 1,060 kg CO_2/MWh

Coal: (97 kg CO_2/MMBtu) X (12 MMBtu/MWh) = 1,170 kg CO_2/MWh

To achieve our 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 X 56%) + (1060 X 12%) + (1170 X 32%) = 760 kgCO_2/MWh = 0.76 kg CO_2/kWh

This calculation provides our basic estimation of the reduction in CO_2 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 answer would be lower. This calculation also ignores upstream fuel effects, like natural gas leakage, which would make the answer 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 A5 below.

Table A5: Change in CO2 emissions per change in electricity generated, by fuel

Fuel(s)	Change in CO2 per generation change (kg CO2/kWh)
Natural gas	0.46
Blended generation fuels	0.76
Residual fuel oil	1.06

Source: We use these numbers in our calculations in Section 7 of the paper.