Impacts of Electricity Quality Improvements: Experimental Evidence on Infrastructure Investments*

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Abstract

Hundreds of millions of households depend on electricity grid connections providing low quality and unreliable services. Understanding the impacts of and consumer response to electricity quality improvements is important for development and the environment. We investigate this in the Kyrgyz Republic through the randomized installation of smart meters; a technology that can improve electricity service quality. Treated households experience significantly fewer voltage fluctuations per day, an indicator of improved electricity quality post-intervention. Treated households' billed consumption of electricity services increased during peak months post-intervention, with renters' increase approximately 3 times that of homeowners. Consistent with this, treated households, particularly renters, significantly increased ownership of electric heaters. Treated households invested more in energy efficiency, potentially mitigating their electricity bill increases post-intervention.

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1 Introduction

Although electricity access has increased during the 21st century, poor electricity service quality remains a persistent problem in many developing countries (Zhang, 2018; Burgess et al., 2020; Carranza and Meeks, 2021). This impedes development, as low-quality and irregular electricity services limit consumption and attenuate the economic benefits from grid connections, affecting firms both in the short-run (Fisher-Vanden et al., 2015; Allcott et al., 2016; Cole et al., 2018; Hardy and Mccasland, 2019; Mahadevan, 2021) and in the long-run general-equilibrium (Fried and Lagakos, Forthcoming).

Understanding residential consumers' responses to changes in electricity quality is also important. Pro-poor growth in developing countries is expected to result in greater household appliance ownership and increased residential electricity demand (Wolfram et al., 2012). Yet hundreds of millions of households depend on grid connections that provide low-quality and unreliable electricity services (Day, 2020) and variable service quality introduces important heterogeneity potentially affecting households' benefits from electrification (Chakravorty et al., 2014; Samad and Zhang, 2016, 2017; Hashemi, 2022).[1] Recent evidence indicates a substantial willingness-to-pay for improved electricity service quality (Alberini et al., 2020; Deutschmann et al., 2021; Meles et al., 2021; Hashemi, 2021) and models indicate households likely respond to such improvements via their appliance ownership (McRae, 2010). If improvements in electricity quality result in greater residential consumption of electricity services, there are implications not only for household well-being, but for the environment as well (Jayachandran, 2021) as 71% of electricity production in low and middle income countries is generated from burning oil, gas, and coal (IEA/OECD, 2018). Yet little evidence exists on the impacts of – and response to – electricity quality improvements among residential consumers.

This paper reports results from the first randomized experiment designed to provide

[1]The cost of generators is typically prohibitively high for residential consumers. In contrast, firms can adapt to low service quality through such investments in self-generation (Steinbuks and Foster, 2010).

exogenous variation in electricity service quality. Our experiment does so through the random installation of residential smart meters in the Kyrgyz Republic, a lower-middle-income country in Central Asia with electricity quality issues common to many developing countries. We ask: what are the impacts of improved service quality on residential billed electricity consumption? To understand the mechanisms through which these effects occur, we estimate the impacts on household appliance ownership and energy efficiency investments. Lastly, given that renters often do not incur the full cost of changes in electricity bills (e.g., as is common in this setting, renters often pay a fixed monthly sum to landlords that covers utility bills), we investigate heterogeneous responses by home ownership.[2]

Transitioning to "smart grids," electricity utilities in many countries increasingly install smart meters.[3] These investments can address a number of sector challenges, including facilitating improvements in reliability (i.e., reduce frequency of outages) and power quality (i.e., eliminate fluctuations above or below a standardized voltage range).[4] To do so, the technology provides high-frequency energy readings (i.e., readings occur often) and alarms that help the utility identify and locate outages, as well as monitor for voltage fluctuations (U.S. Department of Energy, 2016). Additionally, these meters cut consumers' grid connections when voltage drops below or spikes above the safe engineering range, protecting appliances from damage and destruction.

Estimating the relationship between electricity service quality and household outcomes is typically challenging for multiple reasons. First, service quality is often endogenous to a neighborhood. For example, utilities may target planned outages (i.e., load

[2]The analysis of renter-owner heterogeneity was not pre-specified prior to the experiment and therefore exploratory; however, ex post we found this to be an important source of heterogeneity.

[3]China leads smart meter installations, with 469 million units installed as of 2017 (Largue, 2018). The 86 million smart meters installed in the United States covered roughly half of the country's electricity customers in 2018 (U.S. Energy Information Administration, 2019b). More recently, additional countries have announced smart meter plans; for example, India plans to install 250 million meters (Singh, 2020).

[4]These claims are discussed by sector experts (Sprinz, 2018), electricity utilities (see, e.g., Duke Energy Progress, 2020; BC Hydro, 2016), government entities (U.S. Department of Energy, 2014), and multi-lateral development banks (ESMAP, 2019).

shedding) to neighborhoods with low rates of bill payment (see, e.g., Ali et al., 2018). Conversely, neighborhoods with powerful residents (e.g., those powerful for political, financial, or other reasons) or entities providing important services (e.g., hospitals) may be spared such outages. Second, measuring changes in outages and voltage fluctuations is difficult due to common data limitations. Utilities may not record outages and/or voltage fluctuations and, if they do, they may lack incentives to share such data. As a result, most prior economics research on electricity quality has either employed data on self-reported electricity quality or used electricity shortages as a proxy for outages. We overcome these two challenges through our study's novel experiment and data collection processes.

In collaboration with an electricity utility, 20 neighborhoods were selected within one city. Each neighborhood receives electricity services via a transformer, the component in the distribution system that converts high-voltage electricity to usable, low-voltage electricity for household use (Glover et al., 2011). These 20 transformers, and the approximately 1,600 households that they serve, were randomly assigned to treatment or control status. At the end of summer 2018, smart meters were installed at all 798 houses in the treatment group. These replaced the houses' old meters, which did not provide two-way communication with the utility, send alerts of poor service quality events, or automatically shutdown household connections when voltage fluctuates. The control houses, 846 in total, retained their old meters. Electricity prices remained the same across both groups during the study period.

We measure electricity service quality using multiple data sources. First, we obtain data at frequent intervals from additional smart meters installed at all transformers in the study area. These data provide objective outcome measures for both the treatment and control groups that are separate and distinct from the house-level intervention. In addition, baseline and follow-up surveys provide self-reported measures of households' electricity service quality, as well as data on household appliances and energy efficiency investments. These datasets are complemented by utility data on monthly household billed electricity consumption.

This focus on a metering intervention to improve electricity quality differs from prior economics research. In developed countries, researchers have investigated smart meters as a vehicle for other interventions, such as facilitating time-varying electricity prices or providing households with real-time information on their electricity consumption through in-home displays (see, e.g., Wolak, 2011; Jessoe and Rapson, 2014; Ito et al., 2018). In developing countries, research has addressed the impacts of metering interventions on utility finances and consumer bill payment (McRae, 2015a; Jack and Smith, 2020). In our study setting, there are no changes in pricing or in-home displays to provide additional consumer information as in the former studies, nor is this a new transition from unmetered to metered consumption or a shift in the timing of bill payment (from post- to pre-payment) as in latter studies. Further, the utility did not integrate the smart meters into the billing system, so meter readers continued to both read and deliver bills throughout the study. As a result, the primary impacts expected from this intervention ex ante were electricity quality improvements.[5]

We begin by documenting an electricity service quality improvement following the smart meter installation: the intervention led to fewer incidences of voltage fluctuations per day. We corroborate results using transformer smart meter data with additional analyses employing panel survey data. Next, we estimate the consumer responses to these service quality improvements. Treated households' monthly billed electricity consumption significantly increased, by 50.6 kWh per month during peak demand months (November to March), when many households use electric heaters. In comparison to the baseline control group mean of 806.2 kWh per month, this increase is technically and statistically significant. Billed electricity consumption did not significantly change during off-peak months (April to October). Billed electricity consumption increased almost 5

[5]Our original research proposal to the IGC intended to investigate the impacts of smart meters on electricity quality and losses; however, we learned during the intervention roll-out that the utility was not using the meter functionalities that would affect losses or theft.

times more among renters than homeowners, indicative of differential responses to the service quality improvements.

These increases in peak months are consistent with unmet demand prior to the intervention, followed by improved electricity service quality and greater consumption thereafter. Pre-intervention electricity quality issues occurred most frequently during months of peak demand, so these months have the room for the greatest quality improvements. Post-intervention households consume a greater quantity of electricity services during peak demand months due to electricity being available for more hours per day within the standard voltage range.

We investigate the channels through which service quality affects billed electricity consumption, as well as the heterogeneous responses by home ownership status. The increase during peak months could result from greater use of existing appliances (due to the additional hours of quality services sufficient to power those appliances) or investments in new appliances (i.e., more appliances purchased and used). We find evidence of the latter.[6] Treated households' ownership of electric heaters significantly increased after the electricity quality improvement and, consistent with the billed electricity consumption results, that increase in electric heaters was 2.4 times greater among home renters than it was among homeowners. Further, treated households were also more likely than control households to have made an energy efficiency improvement – window replacements, which can increase a building's retention of heat in the winter. This home weatherization, in conjunction with the common residential use of electric heating, implies that the increase in peak season billed electricity consumption would have been even larger in the absence of increased energy efficiency.

The paper makes several important contributions. Broadly, this paper contributes to experimental research on the impacts of improving public service delivery in developing countries (Duflo et al., 2012; Dhaliwal and Hanna, 2017; Callen et al., 2016; Banerjee et

[6] Without appliances individually monitored, we cannot rule out the former explanation.

al., 2018; Muralidharan et al., 2018) and a small body of experimental research on infrastructure service quality (Gonzalez-Navarro and Quintana-Domeque, 2016). Differences in electricity service quality are important given the low returns to electrification found in some settings (Lee et al., 2020; Burlig and Preonas, 2016), but not others (Dinkelman, 2011; Lipscomb et al., 2013; Rud, 2012; Van de Walle et al., 2013; Kassem, 2021; Meeks et al., 2021). Our experimental design provides an exogenous variation in electricity quality improvements and our data collected – separating incidences of outages from voltage fluctuations – adds nuance to the discussion of electricity service quality and increases attention to voltage fluctuations, which are an understudied yet pervasive problem. By investigating energy efficiency as a channel for household response, the paper contributes to research on both the impacts of residential energy efficiency (see, e.g., Davis et al., 2014, 2020; Carranza and Meeks, 2021) as well as the drivers of energy efficiency investments in developing countries (Fowlie and Meeks, 2021; Beattie et al., 2022).

Beyond electricity quality, our study underscores an additional source of heterogeneity in understanding the role of electricity services in development: differential responses by home ownership. A homeowner-renter gap in electric appliance ownership and energy efficiency investments is documented in developed countries (see, e.g., Davis, 2012, 2021a), but less so in developing countries.

The paper proceeds as follows. Section 2 explains electricity quality and demand for electricity services, as well as the role of smart meters. Section 3 details the study setting and the experimental design. Section 4 describes data sources and presents baseline checks. Section 5 presents the estimated impacts of smart meters on electricity service quality and the consumer response. Section 6 presents estimates of the returns to consumers from the electricity service quality improvements and discusses generalizing results to other settings. Section 7 concludes.

2 Conceptual Framework: Electricity Quality and Demand

A household's demand for electricity services is determined by the demand for services from each of the household's electrical devices. In this section, we provide a conceptual framework, which is informed by existing literature (see, e.g., Klytchnikova and Lokshin, 2009; McRae, 2010), as to how electricity quality changes affect demand for electricity services. We consider two main types of poor electricity service: unreliable service due to outages and low service quality due to voltage fluctuations. Both outages and voltage fluctuations can affect the appliances owned, the extent to which the appliances are used, the quantity of electricity services consumed, and the electricity bill.

An outage is a complete stoppage within the distribution system, preventing end users' consumption of electricity services. Outages can be planned or unplanned. Planned outages are either for regular repairs and maintenance, which are typically of limited duration and scheduled for off-peak months, or for electricity rationing.[7] Unplanned outages are typically due to infrastructure breakage, malfunction, and overloaded distribution systems.[8] These unplanned outages can be lengthy in duration, lasting until replacement parts are purchased and repairs are completed. Absent back-up generation (i.e., via diesel generators) or battery storage, electrical appliances cannot be powered during an outage.

Beyond the inability to use appliances during the outage itself, customers may respond to frequent outages in additional ways that further suppress the quantity of electricity services consumed. They may avoid purchasing certain appliances (e.g., an electric heater), if they believe that frequent outages will prevent their regular use. Alternatively, consumers may unplug appliances that they own (e.g., refrigerators) due to concerns that the appliance may be damaged.

[7] Rationing (also know as "load shedding"), which distribution companies employ when generation does not meet demand (Burgess et al., 2020), did not occur during our study period and therefore is not further discussed.

[8] For example, transformers can overload. Each transformer can transfer a certain maximum electricity load at any given time, and exceeding that load may cause breakage (Glover et al., 2011).

Consumer response to improvements in electricity quality may vary, making it ambiguous ex ante as to whether their electricity bills will increase or decrease in response. First, in response to more hours of electricity services available, consumers may use the appliances that they already own more than previously. They may also purchase and use additional electrical devices. Both of these responses would lead to increases in their electricity bills. Alternatively, if consumers replace devices with more energy efficient models, invest in other forms of energy efficiency (e.g., weatherization), or change other electricity saving behaviors following improvements in service quality, then their bills may decrease. Further, consumer responses may be dynamic and change over time. The net effect of these responses on their electricity bills will depend on the magnitude of the energy-saving behaviors relative to the electricity service consumption increases.

Whether the customers are renters versus homeowners contributes additional potential heterogeneity in the response to electricity quality changes, as the two groups differ in at least two important ways. First, they are less likely to invest in any durables for the home, unless those goods are portable (i.e., the appliance or investment can be moved with them to their next dwelling). For example, one may increase their home's winter comfort level by investing either in an electric heater or new windows that better retain heat. New windows may be a more cost effective way to achieve a level of home comfort, but they are not portable like an electric heater. Second, renters are more likely to pay a fixed fee for the electricity services consumed (e.g., if they agree to pay the homeowner a certain standard monthly amount with their rent), which means that they pay a zero marginal cost for additional units of electricity consumed. In contrast, homeowners will pay the tariff charged by the utility, which is an increasing block price.

Voltage fluctuations – a spike above or a drop below the standard acceptable voltage range – can result from faulty and old distribution infrastructure, insufficient maintenance and repairs, or demand that exceeds the infrastructure's capacity. Voltage fluctuations can negatively affect the quantity of electricity services consumed via multiple channels, most of which operate through the same mechanisms as outages;[9] however, given some appliances may still function at lower voltages, they may affect electricity service consumption somewhat differently than outages. For example, a light bulb may provide services at low voltages, but the lighting quality is dimmer than with standard voltage. In such cases, appliances consume fewer kWh per minute of use.

3 Randomized Experiment with Smart Meters

With a history of poor quality electricity services, the Kyrgyz Republic provides a suitable setting for a randomized experiment to test the consumer response to electricity quality improvements. In this section, we provide background information on the country's electricity sector and explain the randomized experiment.

3.1 Electricity Sector in the Kyrgyz Republic

Nearly 100% of Kyrgyzstan's population is connected to the electrical grid, the result of large-scale infrastructure construction during the former Soviet Union. Much of the existing electricity infrastructure dates back to that time (Zozulinsky, 2007).

After 1992, the country's electricity sector was restructured. Kyrgyzenergo, the state-owned power company, was incorporated as a joint stock company, with the Kyrgyz government owning approximately 95% of the shares. By 2000 the sector was unbundled by functionality – generation, transmission, and distribution – resulting in one national generation company, one national transmission company, and four distribution companies (World Bank, 2017a). The distribution companies (DISCOs) each cover distinct territories, purchasing electricity from the national transmission company and delivering it to residential, commercial, and industrial consumers.

[9] First, low voltage can mean that power is insufficient to run certain appliances. Second, knowing voltage spikes can damage appliances, households may choose not to purchase and use certain appliances. A household could purchase equipment, such as a stabilizer, to protect the appliance should voltage fluctuate; however, we do not see much evidence of this occurring in our data.

Government regulations dictate the relationship between the DISCOs and the electricity customers (Government Decree 576, "Regulations on the Use of Electric Energy"). When a new customer connects to the electrical grid, they sign a contract with the DISCO with specific requirements regarding service quality and payment. The DISCO commits to deliver reliable electricity service at a consistent voltage (220/280 volts) and installs a meter at the customer's location to track their consumption. The customer commits to pay for the electricity services consumed – as calculated based on monthly meter readings – by a specified date. If there are any deviations from the electricity quality standards, customers can report them and any resulting material damages to the government oversight body. In theory, this allows the customer to recover from the DISCO any damages that resulted from a service interruption or voltage fluctuation; however, in practice these were historically difficult for customers to prove.

Electricity consumption has changed since the country's independence in 1991. The percentage of total electricity consumption comprised by the residential sector steadily increased, reaching 63% by 2012 (Obozov et al., 2013). These changes are consistent with low electricity prices and increasing appliance ownership.[10] Winter consumption is approximately three to four times that of summer, which is indicative of electric heating in the winter and the absence of air conditioning in the summer.

Unreliable and low-quality electricity services are pervasive, caused by the poor condition of the energy sector assets, intensive electricity use, and large seasonal variations in demand (Carranza and Meeks, 2021). Between 2009 and 2012, distribution companies reported an average of two outages per hour within their coverage areas (World Bank, 2017b). When electricity is delivered, voltage fluctuations are frequent. In a 2013 survey, more than 50% of respondents reported voltage problems, and approximately one-fifth reported damage to electrical appliances from poor electricity quality (World

[10] Residential consumers face a two-tiered increasing block price with a non-linearity in the price at 700 kWh per month. Below the cutoff, consumers pay 0.77 Kyrgyz soms (KGS) per kWh. Above the cutoff, consumers pay 2.16 KGS per kWh. The exchange rate was 69 KGS = 1 USD as of September 1, 2018. Residential consumers rarely exceed the threshold of the first tier during the summer months.

Bank, 2017a). The impacts of poor service quality on consumption of electricity services are compounded by the timing: service quality is typically the worst during the peak months, when demand for services are highest.

Prior to this randomized experiment, smart meters were not new to the country. A substantial number of smart meters were previously installed in other cities within the country. A survey of employees across 3 of the country's DISCOs – all with smart meters installed to some extent within their distribution network – revealed that the majority of respondents believed smart meters mitigated appliance breakage due to voltage problems and reduce consumer complaints (Isaev et al., 2022).

3.2 Randomized Experiment

The experiment was implemented in one city, which had no smart meters previously installed, in collaboration with the DISCO serving the territory. In this city, the mean temperature during the winter is between negative 10 and 15 degrees Celsius.

The randomized design focused on the last two steps in the electricity distribution system: neighborhood transformers and residential electricity consumers (illustrated in Appendix Figure A1).[11] Twenty transformers, which each serve a neighborhood of households, were selected for the project. A map of the 20 transformers shows that they are all located within a two-square-mile area (Appendix Figure A2). As shown in Figure 1, transformers were randomly assigned to treatment or control status, with 10 neighborhood transformers in each group. As randomization is at the transformer level, standard errors are clustered by transformer throughout our analyses. Additionally, due to the limited number of transformers, we use wild-bootstrapping and randomization inference to compute alternative p-values for coefficients in our main results.

The treatment occurred at the household level. Houses served by the transformers in the treatment group (798 houses) received smart meters and those served by the control

[11] Residential consumers were identified as those consumers being charged the residential tariff rate.

transformers (846 houses) retained their old meters. The utility replaced the old meters with smart meters during July and August 2018. The smart meters are comparable in size to the old meters (Appendix Figure A3) and were affixed in the place of those old meters, either on the outside of the home or in the shared stairwells of apartment buildings (Appendix Figure A4).

Prices and consumption salience were unaffected by the treatment. Electricity prices remained constant across the treatment and control groups. The smart meters did not come with any additional in-home display that could increase consumption information or price salience.

The study's residential electricity consumers live in either multistory apartment buildings or single-family dwellings. Eighty percent of these dwellings are owner occupied. The average house in the sample has three rooms. Houses are typically individually metered. Sixty-five percent of households use electricity for winter heating. Houses had only modest investments in energy efficiency at the outset, with 20% and 21% of households using energy-efficient light bulbs and insulation, respectively. Households did report electricity quality issues, with 47% reporting one or more outage per week and 71% reporting one or more voltage fluctuation per week during the winter prior to the intervention. Twenty-one percent of households reported prior appliance damage due to the poor electricity quality; however, almost no households had equipment to protect against poor electricity quality, such as electricity generators or stabilizers.

4 Data and Baseline Checks

We employ data from several sources, including baseline and follow-up survey data, utility transformer and billing records, and data from smart meters installed at transformers.

4.1 Primary and Secondary Data Sources

The analyses employ primary and secondary data, which vary in the timing of their coverage relative to the smart meter intervention (Appendix Figure A5).

4.1.1 Transformer Smart Meter Data

During summer 2018, approximately 2 to 3 months before the intervention, smart meters were installed at all 20 project transformers, both treatment and control. These transformer-level smart meters are independent and distinct from the intervention smart meters installed at houses. These meters were installed for data collection purposes and they provide high-frequency objective indicators of electricity quality for both the treatment and control groups, regardless of individual household meter status. These smart meters record "event alarms" indicating problematic events within the neighborhood covered by the transformer. Alarms can be activated for a number of reasons, including signs of electricity theft and indicators of poor service quality.[12]

We create transformer-level variables measuring the incidence of different types of problems (i.e., poor quality, outages, and theft). We also create a variable comprising "other" alarms to capture those events that are not indicative of our main outcomes and that we do not anticipate to be impacted by the intervention. The categorization of alarm event types is based on documentation provided by the meter manufacturer. The incidence measure provides a measure of interruptions akin to the System Average Interruption Frequency Index (SAIFI), a standardized measure used in the United States for interruptions in electricity service delivery. The smart meter alarms data also provides a measure of voltage fluctuations, which is additional information beyond the SAIFI measure. A limitation of the transformer data is that it does not capture event duration, which prevents us from creating a measure comparable to the System Average Interruption Du-

[12]For example, alarms are activated if power is detected going from a distribution line to a consumer without a formal connection (an indication that someone is bypassing the meter), if an over-voltage event (a voltage spike above the standard range) is detected, or if a power failure (outage) is detected.

ration Index (SAIDI).

The incidence of alarms in our data varies greatly by event type (Appendix Table A1). Of the transformer alarms recorded after the intervention, approximately 60% indicated electricity voltage problems, 22% indicated power outages, 6% indicated theft, and the remaining 12% were in the "other" category. The high number of voltage-related alarm events underscores the extent to which electricity quality is a problem.

4.1.2 Baseline and Follow-up Survey Data

Baseline and follow-up survey data were collected in July 2018 and May 2019, respectively. In each survey round, we sought to survey all 1,644 households within the treatment and control groups. Survey respondents totaled 1,143 for the baseline survey and 1,125 for the follow-up survey. When we include only the households that responded to both survey rounds the panel dataset includes 880 households.

The baseline survey was brief, designed to limit interaction with households. The follow-up survey was more extensive, resulting in greater breadth of variables available for the period after the smart meter installation. Both surveys asked questions on characteristics of the home, quality of electricity services, the set of home appliances owned, and overall household expenditures, among others. Importantly, both survey rounds collected data on perceived electricity quality during the previous winter (January and February), providing panel data on household perceptions of outages and voltage fluctuations during the peak season.

4.1.3 Utility Data

The electricity utility provided several datasets. First, transformer-level data were provided. These include cross-sectional information on transformer characteristics (age of transformer, capacity, etc.) and monthly panel data that start in January 2017 and continue for 33 months, including dates of overhaul maintenance, repairs, and replacements for all project transformers. Second, the utility provided household-level monthly billed electricity consumption data from January 2017 through March 2020. These billed consumption data cover periods of approximately 18 months before and after the intervention. The period of analysis ends in March 2020 due to various interruptions associated with the onset of the COVID-19 pandemic.

4.2 Non-Compliance and Attrition

Non-compliance is not an issue in this study. Treatment assignment was at the transformer level, and all houses within the treatment group had smart meters installed by the utility. By law, all electrical connections are required to be metered, the meters – whether smart meters or the old meters – are legally owned by the electricity distribution company, and consumer consent is not required for meter changes.

We check the response rates for the treatment and control groups in the baseline and follow-up surveys and find no differential attrition across groups. Attrition rates between the baseline and follow-up surveys are 24.3% and 21.7% in the treatment and control groups, respectively (Appendix Table A2). We also check for differences in the baseline characteristics of the attritors (i.e., those households in the baseline survey but not the follow-up survey) and non-attritors (i.e., those households in both the baseline and the follow-up surveys) and find no significant differences (Appendix Table A3).

4.3 Baseline Balance Tests

We test for baseline balance between treatment and control groups using transformer-level utility data, household monthly billed electricity consumption data, and baseline survey data.

Table 1 compares the control and treatment groups on characteristics important to electricity quality. Panel A compares treatment and control transformers across various characteristics. The transformers are similar with respect to the average number of houses served, their average capacity (an average of 381 versus 406 kVA), and their age. Differences between treatment and control transformers are not statistically significant. The age of the transformers is reflective of the country's overall aging infrastructure.

Table 1 Panel B compares the treatment and control households at baseline. There are no statistically significant differences in households' reported electricity quality, house size, use of insulation and energy-efficient light bulbs, heating fuel used, and the use of technologies to protect against poor electricity quality (e.g., generators and stabilizers). These comparisons are limited to the 880 households in the balanced panel; however, similar comparisons for the full 1,143 households surveyed at baseline provide similar results (Appendix Table A4).

Comparing the results in panels A and B is also helpful to alleviate potential concerns regarding baseline differences. Although the differences between the treatment and control transformers in Panel A are not statistically significantly, we acknowledge that the treatment transformers serve slightly fewer customers (85 versus 80 households) and are marginally newer (33 versus 28 years) and this might raise concerns that the service quality prior to the intervention was already better in the treatment transformers than the control transformers. To alleviate these concerns, we note that in Panel B there were no significant differences in the baseline household reports of outages and voltage fluctuations during the winter pre-intervention; if anything, the treatment households actually were more likely to report appliance damage, although this difference is also not statistically significant. The lack of differences in electricity quality across the treatment and the control transformers pre-intervention is further supported by an event study analysis checking for differences in the pre-treatment transformer-level smart meter alarms using the three months of available data (May, June and July of 2018). We find no pre-intervention differences between the treatment and control transformers with respect to the monthly number of event alarms (Appendix Figure A6).

Lastly, we also test for balance across treatment and control houses using monthly household billed electricity consumption data. Figure 2 graphs pre-treatment billed electricity consumption. The top panel plots the month-by-month differences between average electricity bills in the treatment and control groups, without controlling for any other variables. Both groups have similar seasonal consumption patterns; the average monthly electricity consumption in the winter is approximately three times that in the summer, which is indicative of households using electric heating during the winter, but not air conditioning in the summer. The graph shows no significant differences in monthly electricity bills before the intervention. The bottom panel plots the month-by-month average electricity bills for the treatment and control households. To address potential concerns that the baseline winter billed consumption was slightly higher (albeit insignificantly so) for the treatment households, we will show that results using the billed consumption data are robust to controlling for earlier periods of pre-intervention electricity consumption.

5 Effects on Electricity Quality and Consumer Response

In this section, we first confirm that the smart meter installation led to an improvement in electricity service quality and then present estimates of the consumer response to smart meters and the electricity quality improvements, including billed electricity consumption, household expenditures, and energy efficiency investments.

5.1 The Effects on Electricity Quality

5.1.1 Electricity Quality Results

To estimate the intervention's effect on indicators of electricity quality, we employ the data on event alarms from the transformer-level smart meters during the post-intervention period. The outcome measures are the number of transformer-level events per day indicating either voltage fluctuations or power outages. We estimate the following equation:

$$E_{gt} = \alpha \text{Treat}_g + \delta' \mathbf{X}_g + \gamma_t + \epsilon_{gt}, \tag{1}$$

where E_{gt} is the number of times per day either voltage fluctuations or outage events are recorded by the transformer smart meter g in time period t. Treat_g is an indicator of transformer treatment status equaling 1 for those randomly assigned to the treatment status. $\mathbf{X}_g$ is a vector of transformer characteristics that could affect electricity service quality (i.e., the number of households served by the transformer and the transformer's technical capacity), and γ_t are month-by-year fixed effects. Standard errors are clustered at the transformer level.

Results are presented in Table 2. In column 1, the number of voltage fluctuations per day is the outcome variable. There are significantly fewer voltage fluctuations per day in the treatment group than in the control group following the intervention, controlling for transformer characteristics and time fixed effects. The mean number of voltage events for the control group was 2.3 voltage fluctuations per day. Comparing the coefficient on Treat_g with the control group mean – our estimate of the counterfactual – we see that these alarms are essentially eliminated within the treatment group.

Power outages are the outcome variable in column 2. There are no significant effects on outages; however, the control group mean of 0.518 outages per day indicates that outages were less problematic than voltage events in the counterfactual, leaving less room for improvement. This lack of an outage effect may be tied to the post-intervention increase in billed electricity consumption, which we discuss in the section on consumer responses.

In addition, we show that the treated households experienced an electricity quality improvement (Table A18), as measured by self-reported electricity quality measures. These analyses, which are described in more detail in Appendix A2, highlight that both the objective and subjective measures of electricity quality showed improvement following the smart meter installation. The results in Appendix A2 also provide evidence regarding the mechanisms through which electricity quality improves: the information provided by the *household-level* smart meters direct the utility's attention to the locations with the worst quality (i.e., with the greatest need for improvements). Due to the limited number of transformers included in the study, we interpret this evidence on mechanisms as suggestive; however, it is supported by qualitative reports that household complaints to the electricity utility were frequent – but typically not acted upon – prior to the intervention. Households reported that the smart meters made it such that the utility had to address service quality problems.[13]

5.1.2 Addressing Potential Threats

We address the potential threats to identification in a randomized design such as the one employed in this experiment.

First, there are twenty transformers in the study, which means there are a small number of clusters. To address this design limitation, we present wild-bootstrapped standard errors and show that both the voltage and outage results hold (Appendix Table A5).

Second, sample standard errors may be unduly influenced by extreme values of individual observations (Young, 2019). To address this potential concern, we present p-values from randomization inference with 500 permutations of the treatment status (Appendix Table A5) to demonstrate that the results hold.

Third, if the intervention in the treatment transformers directed utility effort away from the control transformers SUTVA would be violated. We argue that, since this specific utility covers a territory with 7,633 transformers, of which approximately 700 are in this one city, any additional attention provided to the 10 treatment transformers are unlikely to substantially affect the 690 remaining untreated transformers in that city.

[13]To the extent that the *transformer-level* smart meters – which were installed on both the treatment and the control transformers for data collection purposes – are also providing information to the utility and directing their efforts, this would likely downward bias our estimated electricity quality improvements.

5.1.3 Supporting Evidence on Electricity Quality

To check that the voltage fluctuation and outage events – as measured by the transformer-level smart meters – are indeed picking up variations in the electricity quality, we perform two additional robustness checks. First, we test the correlation between the transformer-level smart meter voltage fluctuation and outage events and the household reported electricity quality measures, which were collected via the follow-up survey implemented at approximately the same time. Transformer smart meter events indicating electricity quality problems are indeed negatively and significantly correlated with better household-reported electricity reliability (Appendix Table A6). As expected, theft events are not correlated with households' reported electricity quality.

Second. we check the correlation between the transformer smart meter events (our outcome measures in Table 2) and events captured by the household smart meters. This is only feasible for the treated households, where the intervention smart meters are installed. These two measures should not be perfectly correlated, for multiple reasons. First, household and transformer meters do not capture exactly the same things. Second, heterogeneity in electricity quality across households within a transformer's service area is expected, as households located closer to or farther from a transformer experience voltage fluctuations differently.[14] Alternatively, an outage may impact one or all houses served by a single transformer. These two levels of smart meter alarms, however, should be positively correlated, and they are (Appendix Table A7).

5.2 Consumer Responses to Electricity Quality Changes

As detailed in Section 2, electricity quality improvements could impact billed electricity consumption in multiple ways, which determine the extent to which consumers benefit from smart meter installation.

[14]For example, those close to the transformer may be more likely to experience voltage spikes, whereas those far from the transformer may be more likely to experience voltage drops.

5.2.1 Billed Electricity Consumption

We estimate the impact of smart meters on household billed electricity consumption as follows:

$$\text{Bill}_{igt+1} = \beta_1 \text{Treat}_g \times \text{Post}_t + \lambda_i + \delta_t + \epsilon_{igt}, \tag{2}$$

where Bill_{igt+1} is the monthly billed electricity consumption by household i in transformer g in month $t+1$, because the bill in $t+1$ reflects the electricity consumption in t. Treat_g is the indicator of transformer treatment status, equaling 1 if the household is treated with a smart meter and 0 otherwise. The binary variable, Post_t, is an indicator equaling 1 for months after the intervention. Standard errors are clustered at the transformer level.

We run the regressions separately for the heating (November to March) and non-heating (April to October) months, given the seasonality in both consumption and service quality. November to March is the period of peak electricity consumption and also the time when electricity quality problems are worst.

We then assess the extent to which the treatment had differential impacts depending on home ownership status. To do so, we modify the equation above to include the interaction of Treat_g times Post_t with Owner_i, which is a binary indicator variable that equals 1 if the respondent's family owns the home and 0 otherwise (i.e., if the respondent's family rents the house).

Table 3 presents results. Household billed consumption significantly increased during the heating season (Column 1). The increase is consistent with better service quality (i.e., fewer voltage fluctuations), as shown in Section 5.1. Billed electricity consumption is not significantly impacted in the non-heating season (Column 2), which is consistent with baseline seasonal differences in electricity quality.

Additional tests support these results. We show with wild-bootstrapping and randomization inference to compute p-values for the coefficients (Appendix Table A8). Further, an event study analysis (Appendix Figure A7) illustrates the impacts on monthly billed electricity consumption and over time, showing a statistically significantly higher billed electricity consumption in treatment households, relative to control households, during the post-intervention peak months.

To alleviate potential concerns that households with different consumption patterns pre-intervention respond differently to the installation of smart meters, we perform an additional robustness check. We re-run the regressions, controlling for monthly billed electricity consumption in 2017 (well before the smart meter installation). Results are robust to including these controls (Appendix Table A9).

We interpret the increase in billed consumption as the result of the improvements in electricity service quality. If the smart meters made consumers more attentive to their electricity consumption, we might see similar effects in their bills. When an increasing block price was introduced in Kyrgyzstan several years before our intervention, the regulator implemented information campaigns to inform residential consumers how different appliances contributed to their bills and a monthly consumption of 700 kWh, the cutoff for the increasing block price (see example in Appendix Figure A8). If the smart meters induced consumers to monitor their consumption more closely, then treated households would likely have more bunching just below the 700kWh cutoff. We check for differential bunching around the tariff discontinuity at 700kWh and find no evidence of this behavior (Appendix Figure A9).

Households can adapt to the improved service quality either behaviorally (e.g., reducing their use of appliances or increasing the amount of electricity stolen) or technologically (e.g., increasing the efficiency of their appliances or homes). We investigate these household adaptations further in the following subsection.

5.2.2 Electrical Appliances

To better understand households' responses to the improvements in electricity quality, we utilize household survey data, which asked about electrical appliance ownership and purchase timing, providing a panel dataset of these variables.[15] The timing of survey implementation is important for understanding household changes; these follow-up data were collected after the households experienced the first post-installation peak (winter heating) season, but before the second.

We estimate the impact of treatment on household appliance ownership as follows:

$$\text{Appliance}_{igt} = \beta_1 \text{Treat}_g \times \text{Post}_t + \beta_2 \text{Post}_t + \lambda_i + \epsilon_{igt}, \tag{3}$$

where Appliance_{igt} is household ownership of items such as refrigerators, water heaters, and electric heaters. The indicator variables, Treat_g and Post_t, as well as household fixed effects, are defined as before. Standard errors are clustered at the transformer level. We also run these regressions with the interaction of treatment and home ownership, as we did with the previous analysis.

Table 4 presents the corresponding results, with Westfall-Young step-down adjusted p-values for multiple hypothesis testing reported. In Panel A, we see a statistically significant increase in treated household electric heater ownership. This is consistent with households investing in more electrical appliances in response to the electricity quality improvements, specifically an appliance that is solely used in the peak consumption season, when the electricity quality improvements occur. None of the other appliance categories change significantly between baseline and follow-up.

Panel B, which presents the interaction effects, shows that the increase in the electric heater ownership is significantly larger among the treated renters than the treated home owners. This is consistent with the billed electricity consumption results, in which we found greater increases in the heating season billed electricity consumption among the renters than the homeowners.

Additional checks with randomization inference and wild-bootstrap p-values are in

[15] Without devices monitoring consumption by each individual appliance, we are unable to test specific behavioral adaptations.

Appendix Table A10.

5.2.3 Energy Efficiency Investments

After witnessing their electricity bills increase during the first heating season, treated households could increase the efficiency of their homes. Considering this possibility, the follow-up survey asked respondents whether they made any energy efficiency improvements to their house since the end of 2018 (i.e., the time of the meter installation).

We estimate the impacts of the smart meter intervention on households' investments in energy efficiency. Results are presented in Table 5, including Westfall-Young step-down adjusted p-values for multiple hypothesis testing. Treated households were more likely to report making energy efficiency improvements since the intervention. Specifically, treated households tend to replace their houses' windows. We also use wild-bootstrapping and randomization inference to compute p-values for the coefficients (Appendix Table A11).

Although thermal improvements may not lead to great gains in some contexts (Davis et al., 2020), they are in demand in cold weather settings such as ours. Given much of the housing stock was constructed during the former Soviet Union, original windows are often a substantial source of heat leakage. Households will at a minimum respond by placing cellophane (thin plastic sheets) over the windows during the winter (for example, see photo in Appendix Figure A4). Studies done prior to ours indicated that heating comfort was a substantial concern (Bergström and Johannessen, 2014) and the dominant planned home upgrades in the Kyrgyz Republic were replacement of heating systems and windows, in an effort to increase comfort and save money during the cold weather months (Bakteeva and van der Straeten, 2015).

We also test as to whether the treated households made smaller-scale improvements to increase their energy efficiency, specifically energy-efficient light bulbs; however, due to our limited panel dataset, these analyses are likely under-powered. The coefficient is positive but is not statistically significant (Appendix Table A12). Ownership of electricity-related protective devices and back-up generation is also not affected, although it was also low within the control group (Appendix Table A13).

6 Discussion of Results

We discuss our interpretation of the results versus alternative explanations, followed by a discussion of the generalizability of the findings.

6.1 Interpretation

We have interpreted the results as showing that electricity quality improved following the smart meter introduction, and the better electricity service quality permitted greater electricity service consumption. With those improvements, households invested more in electrical appliances, specifically those providing heating services.

Here we discuss reasons as to why we rule out three alternative explanations for these findings. First, we might be concerned that the smart meters are able to "read" electricity consumed at the low voltage and therefore could impact the electricity consumption through a channel other than changes in reliability. However, these meters automatically shutdown if voltage drops or spikes outside of preset voltage bounds set on the meter. This feature of the smart meters therefore minimizes the potential for this channel to affect electricity bills and, even if it did, it could not explain the improvements in both subjective and objective measures of electricity quality. Second, it is possible that households value these voltage bounds set on the smart meters and the protection (i.e., protecting appliances from damage) that the automatic shutdown function provides. This expectation of protection against voltage spikes and drops may encourage households to invest in new appliances. If so, we may expect to see either evidence of households' pre-intervention investments in equipment protecting appliances or post-intervention less of such investment among the treated households. We saw no evidence of the former in our baseline summary statistics (i.e., Table 1 showed almost no baseline use of stabilizers, the primary form of appliance protection available). We tested for the latter (Appendix Table A13) and found adoption of such equipment is low in both groups and the difference between the two is not statistically significant. Third, the increase in billed electricity consumption could be mechanical, due to a reduction in electricity theft within the treatment group rather than an improvement in electricity quality. If households steal less electricity as a result of the smart meters, then their electricity bill could increase. Nevertheless, this would not explain the quality improvements found. We use data from the transformer-level smart meters to check whether the treated and control groups differed in the frequency of theft events post-intervention. We find no evidence that the intervention impacted theft (Appendix Table A14). This is not surprising, as the utility was not using the meters' functionalities that could potentially reduce theft.

6.2 Generalizing the Results

To put our results into context, we discuss the experiment setting and consider how the results may generalize to other settings.

Our analyses focus on the increased billed electricity consumption and appliance ownership and therefore do not capture the potentially larger benefits acquired from those additional electricity services consumed. For example, there is increasing evidence on the association between temperature and mortality. Exposures to both extreme hot and cold temperatures are linked with premature death; a recent study of the global mortality burden attributed to non-optimal temperatures estimated 9.43% of all deaths to be cold-related (Zhao et al., 2021). In our setting, the improved electricity service quality led to increased electric heating. If these heating changes translate into avoided cold-related deaths, then our estimated returns to electricity quality improvements alone would be much lower than the full consumer welfare gains. This link between electricity service quality and avoided cold-related deaths is relevant beyond the Kyrgyz Republic. Of all the individuals inhabiting locations with a mean winter temperature below 8°C – the threshold at which negative health effects of cold temperatures start to occur (Bone et al., 2014) – we estimate that more than 200 million people live in low or lower-middle income countries.[16]

The link between electricity service quality, appliance use, and avoided temperature related deaths is relevant in warm climates as well. Estimated heat-related premature deaths increased substantially between 2000 and 2019, with greater future increases expected due to climate change (Zhao et al., 2021). As average temperatures increase, adoption of air conditioning also increases (Biardeau et al., 2020). Electricity service quality is often worst during a location's season of peak consumption (i.e., winter in colder climates and summer in hotter climates) due to the excess demand for electricity services. Together, these points suggest that reliability and electricity quality will also play a role in a population's ability to adapt to rising temperatures via consumption of cooling services.

A full welfare analysis should also consider the costs (e.g., environmental costs due to releasing harmful pollutants such as SO_2, NOx, and particulate matter) from the additional electricity generation required to meet the increased consumption of electricity services. In the Kyrgyz Republic, these costs are minimal because the heating increases occur via electric heating and the country's electricity generation is predominantly (90%) via hydropower. Other countries, in which the generation is predominately fossil fuel based, could experience marked pollution increases (and therefore implications for the environment and climate change) should electricity service consumption increase.

[16]This figure was calculated based on a spatial analysis of population distribution (Gridded Population Data of the World, http://sedac.ciesin.columbia.edu/data/collection/gpw-v3/sets/browse) and gridded WorldClim mean monthly temperatures. Winter temperature was defined as the mean of the three coldest months in the year at each location. The country income classification is from the World Bank.

7 Conclusions

The United Nations Sustainable Development Goal 7.1 calls for "affordable, *reliable* and modern energy services" (United Nations, 2020), thereby incorporating electricity service quality into development goals. Yet, little is known about the impacts of such advances on the environment and development. We provide evidence on the effects of and returns to electricity quality improvements. We find that consumers experienced improved electricity service quality in the form of more stable voltage (i.e., fewer voltage fluctuations) following the smart meter installation. Billed electricity consumption increased during the peak season, when service quality is historically the worst. Better electricity service quality permitted greater electricity service consumption, and with those improvements, households invested more in electrical appliances, specifically those providing heating.

These findings have important implications for international development and energy policy. Although development organizations and national governments have long focused on electrification as a key ingredient to promote development, academic research on the returns to electrification remains mixed. Our findings lend credence to the claim that in order to maximize the benefits from electrification, attention must be paid to the quality of electricity services, not merely access to electrical connections. Additionally, the heterogeneous effects across households by ownership types is surprisingly consistent with documented gaps between renters and homeowners in developed countries such as the United States. We find that renters' ownership of electric heating devices in the treated group increased significantly more than the homeowners, which explains the greater increase in winter billed electricity consumption among this same group. To the extent that heterogeneity in responses is driven by differences in those who pay the marginal cost of additional units of electricity consumed (i.e., home owners) versus those that do not (i.e., renters), these results also provide potentially useful information as to how consumers facing different electricity tariffs (e.g., increasing block price versus a fixed monthly price) may respond to improved electricity quality.

Our findings also provide important implications for the pathway to a net-zero economy. Over the past few years, an increasing number of national governments have embraced the idea of transitioning to an economy with net-zero carbon emissions. One area of particular challenge is the emissions from direct combustion of fossil fuels in residential buildings mostly for heating purposes. To achieve the net-zero target, all the buildings will ultimately need to be electrified by zero-carbon electricity. Our analysis shows that improved electricity quality can lead to higher adoption of electric appliances, especially space heaters. This result is important in a setting where the alternative heating fuel is the burning of coal; it adds to the discussions on building electrification (Davis, 2021b) and sheds light on the factors that influence heating electrification in a developing country setting.

To conclude, we note several areas for potential future research. First, due to the onset of the COVID-19 pandemic, our data collection period ends in March 2020. With our post-intervention period limited to 1.5 years (September 2018 to March 2020), there is room for future work on the long-term effects of and responses to electricity quality. Second, this paper is silent on the electricity utility's benefits from the smart meter installation. With lower cost methods of detecting electricity quality anomalies under development (see, e.g., Klugman et al., 2019), understanding the relative cost effectiveness of different service quality monitoring systems remain an area for future studies. Third, further research integrating smart meter systems with utility billing systems would negate the need for meter readers, thereby potentially reducing non-technical losses. Understanding the potential impacts of smart meters on non-technical electricity losses would be beneficial for the sector. Lastly, in settings in which electricity generation is dominated by fossil fuels, the additional consumption of electricity services could result in greater costs in the form of environmental damages (i.e., increased pollution). Understanding the relationship between electricity quality and pollution generation in developing countries is an important area for future study.

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Figures and Tables

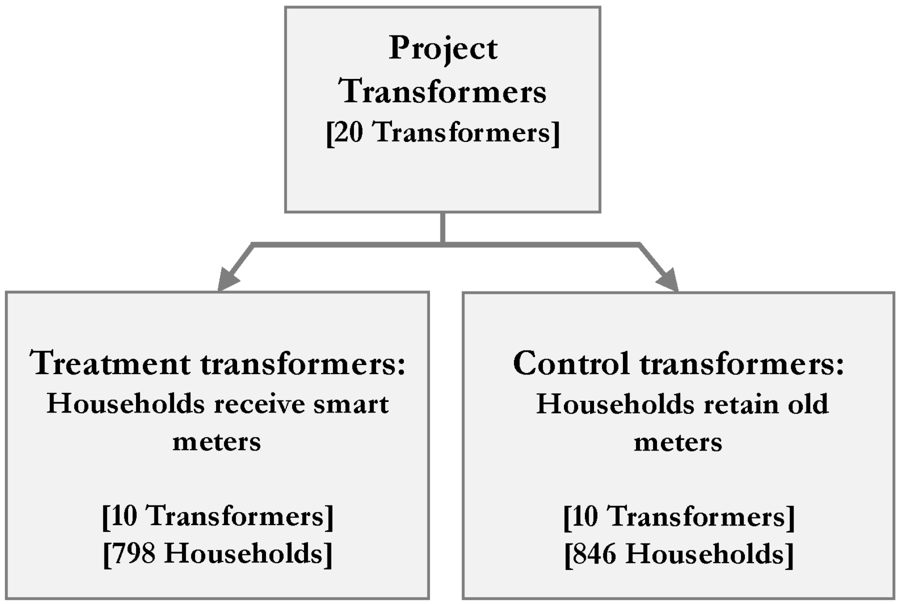

Figure 1: Randomized Design

Notes: Randomization occurred at the transformer level, with 20 transformers randomly assigned to either treatment or control status. Households in the treatment transformer group (798) had smart meters installed. Households in the control transformer group (846) retained their old meters.

Table 1: Balance Test: Household Characteristics

	Control	Treatment	Difference
Panel A: Transformer Characteristics			
Number of Households	84.600	79.600	−5.000
	(44.560)	(54.726)	(22.317)
Capacity (kVA)	381.000	406.000	25.000
	(263.963)	(181.365)	(101.277)
Age (Years)	33.400	27.900	−5.500
	(17.475)	(20.328)	(8.477)
Panel B: Household Characteristics			
Number of Rooms in the House	2.996	2.919	0.077
	(1.284)	(1.130)	(0.222)
Homes Owned	0.831	0.781	0.050
	(0.375)	(0.414)	(0.044)
Homes with Insulation	0.160	0.267	−0.107
	(0.367)	(0.443)	(0.075)
Houses Using Energy-Efficient Light Bulbs	0.193	0.200	−0.007
	(0.395)	(0.401)	(0.056)
Houses Using Central Heating	0.038	0.084	−0.046
	(0.191)	(0.277)	(0.053)
Houses Using Electric Heating	0.616	0.700	−0.084
	(0.487)	(0.459)	(0.064)
Reporting 1+ Outages Per Week (Jan.–Feb. 2018)	0.445	0.450	−0.005
	(0.498)	(0.498)	(0.118)
Reporting 1+ Voltage Fluctuations Per Week	0.703	0.702	0.001
	(0.457)	(0.458)	(0.109)
Houses with Electric Generators	0.002	0.007	−0.005
	(0.047)	(0.083)	(0.003)
Houses with Stabilizers	0.004	0.005	−0.000
	(0.067)	(0.068)	(0.004)
Houses with Appliance Damage	0.187	0.252	−0.066
	(0.390)	(0.435)	(0.100)
Household Observations	450	430	880
Transformers	10	10	20

Notes: We report the mean values of transformer and household characteristic variables. Transformer data in Panel A are provided by the electricity utility. Household data in Panel B are from the baseline household survey conducted in spring 2018. Robust standard errors are clustered at the transformer level. These results are for the households represented in the balanced panel (i.e., they are surveyed in both the baseline and follow-up surveys). Robustness checks using the unbalanced sample are in the Appendix.

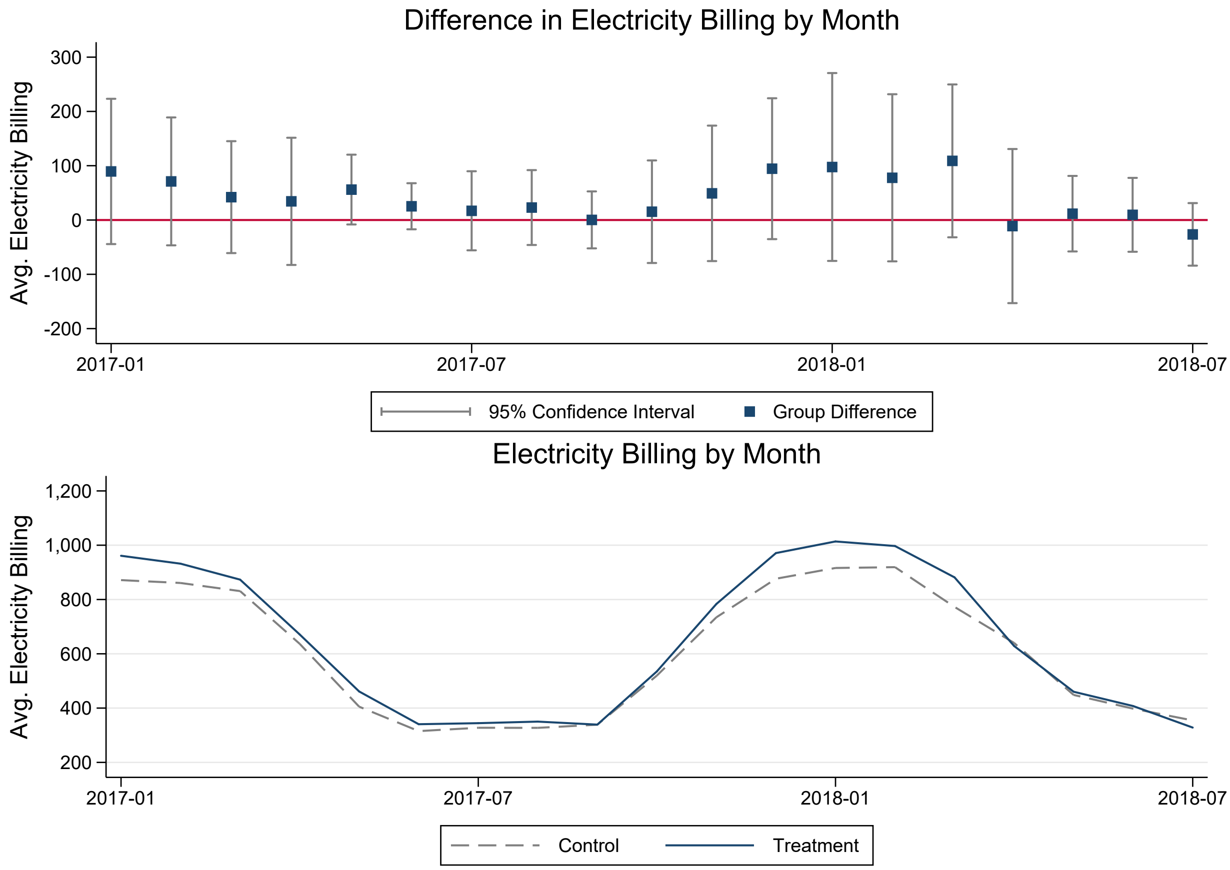

Figure 2: Billed Electricity Consumption before Smart Meter Installation

Notes: Billing data are provided by the electricity utility. The vertical axis is the average electricity billing measured in KGS. The analysis here is a simple comparison between treatment and control households. The standard errors are clustered at the transformer level.

Table 2: Transformer-Level Smart Meter Events: Electricity Quality

Alarms (in one day) indicating:	(1) Voltage events	(2) Outage events
Treat	-2.283**	0.035
	(0.988)	(0.029)
Mean of Control Group	2.324	0.525
Observations	8,355	8,355
R-squared	0.104	0.052
Transformer Characteristics	✓	✓
Month-by-Year FE	✓	✓

Notes: Event data are provided by the electricity utility covering the period from September 2018 to March 2020. The outcome variables are the number of these events recorded by the transformer smart meter per day. Regressions control for transformer characteristics including the number of households served by the transformer and its capacity. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). We calculate wild-bootstrap and randomization inference p-values and present them in supporting tables within the Appendix.

Table 3: Billed Electricity Consumption by Season (Heating vs. Non-heating)

Monthly electricity bill in:	(1) Heating Season	(2) Non-heating Season	(3) Heating Season	(4) Non-heating Season
Treat × Post	50.698***	−15.077	145.316***	-22.783
	(15.518)	(13.132)	(48.847)	(18.353)
Treat × Post × Owner			-114.524*	10.061
			(59.951)	(19.247)
Mean of Control Group	806.223	415.017	806.223	415.017
Observations	13,021	17,245	13,021	17,245
Number of Households	871	871	871	871
Adjusted R-squared	0.091	0.271	0.091	0.271
Household Fixed Effects	✓	✓	✓	✓
Month-by-Year Fixed Effects	✓	✓	✓	✓

Notes: Billing data are provided by the electricity utility covering the period between January 2017 and March 2020. Control group means are for the baseline (pre-intervention) period. The outcome variable is the monthly billed electricity consumption (kWh/month) for a household forward by one month (t+1), which accounts for delay between consumption and bill. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). We calculate wild-bootstrap and randomization inference p-values and present them in supporting tables within the Appendix.

Table 4: Electrical Appliance Ownership

	(1) Clothes Washer	(2) Color TV	(3) Computer/ Laptop	(4) Water Heater	(5) Cell Phone Charger	(6) Electric Heater
Panel A: Overall effect						
Treat × Post	0.010	0.007	-0.026	0.001	0.109	0.094*
	(0.033)	(0.027)	(0.022)	(0.017)	(0.102)	(0.050)
	[0.942]	[0.942]	[0.270]	[0.942]	[0.270]	[0.036]
Panel B: Heterogeneous effect						
Treat × Post	0.018	0.023	-0.031	-0.018	0.184	0.171**
	(0.055)	(0.034)	(0.028)	(0.033)	(0.115)	(0.064)
	[0.916]	[0.894]	[0.670]	[0.916]	[0.240]	[0.018]
Treat × Post × Owner	-0.011	-0.019	0.007	0.024	-0.094	-0.099**
	(0.046)	(0.036)	(0.036)	(0.034)	(0.097)	(0.043)
	[0.924]	[0.916]	[0.924]	[0.886]	[0.770]	[0.084]
Mean of Control Group	0.836	0.862	0.184	0.433	0.702	0.722
Observations	1,760	1,760	1,760	1,760	1,760	1,760
R-squared	0.861	0.843	0.946	0.971	0.734	0.883
Control Household FE	✓	✓	✓	✓	✓	✓

Notes: Data collected through household survey. The outcome variables are dummy variables indicating whether the household owned certain electric appliances. Standard errors in parentheses are clustered at the transformer level. Westfall-Young stepdown adjusted p-values for multiple hypothesis testing are reported in brackets. We calculate wild-bootstrap and randomization inference p-values and present them in supporting tables within the Appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Changes in Home Energy Efficiency

Energy efficiency changes:	made any changes		installed insulation		replaced windows	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.063	0.007	-0.011	-0.041	0.090***	0.021
	(0.049)	(0.065)	(0.054)	(0.047)	(0.031)	(0.044)
	[0.060]	[0.898]	[0.664]	[0.672]	[0.001]	[0.756]
Treat × Post × Owner		0.073		0.039		0.084
		(0.087)		(0.060)		(0.069)
		[0.672]		[0.756]		[0.460]
Mean of Control Group	0.205		0.109		0.080	
Observations	1,760	1,760	1,760	1,760	1,760	1,760
R-squared	0.572	0.574	0.529	0.530	0.541	0.542
Control Household FE	✓	✓	✓	✓	✓	✓

Notes: Data collected through the household survey. The outcome variables are binary variables created using survey responses indicating whether the household made certain changes to the house "since last summer" (when the smart meters were installed) and equaling 1 if the household made the corresponding change. Standard errors are clustered at the transformer level and included in parentheses. Westfall-Young stepdown adjusted p-values for multiple hypothesis testing are reported in brackets. We calculate wild-bootstrap and randomization inference p-values and present them in supporting tables within the Appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX: FOR ONLINE PUBLICATION

A1 Additional Figures and Tables

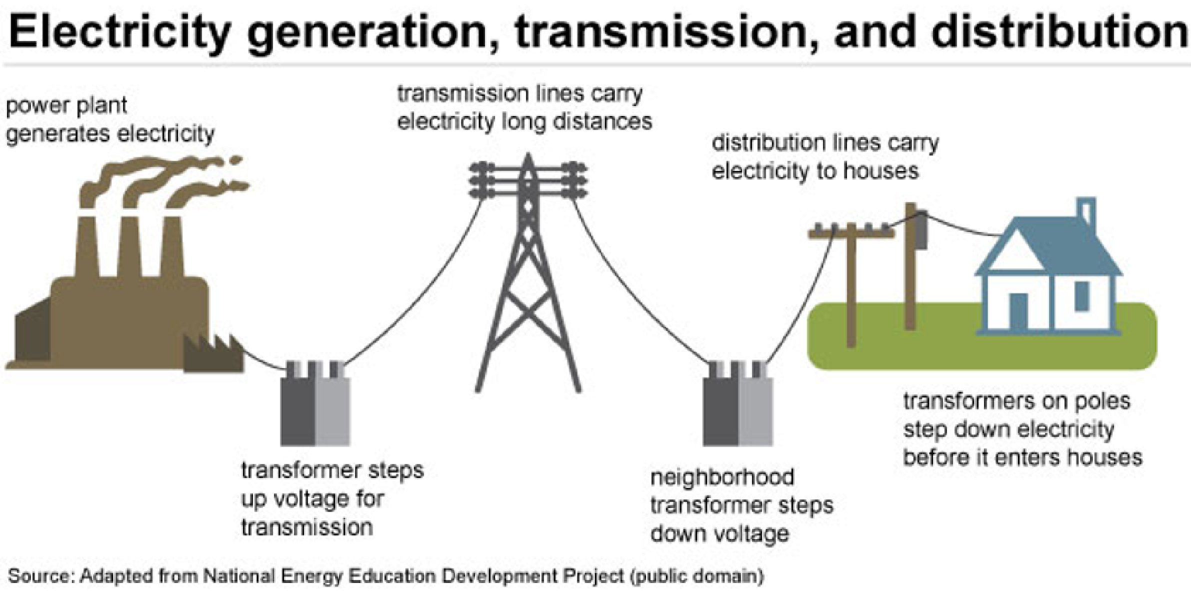

Figure A1: Intervention within the distribution system

Notes: Figure from U.S. Energy Information Administration's website (U.S. Energy Information Administration, 2019a) explaining electricity delivery. Our project operated and collected data at these last stages of the distribution system: the neighborhood transformer and the houses. The intervention in this study consists of smart meters installed at households in the treatment group but not in the control group. In addition to the intervention, smart meters are installed at all 20 neighborhood transformers for measuring outcomes.

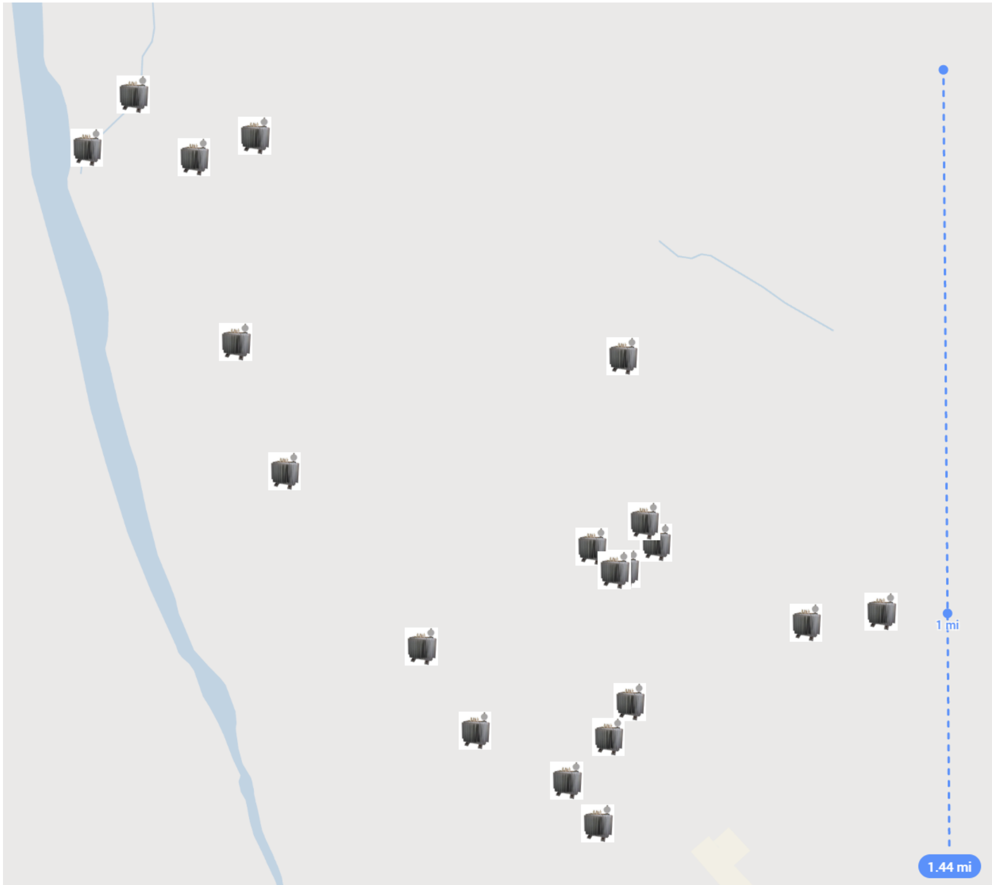

Figure A2: Transformer Locations

Notes: This map shows the study transformer locations, which are located within one city in the Kyrgyz Republic. The transformers are all located within an approximately two-square-mile area. Each transformer serves a neighborhood of electricity consumers. We hide the identifying information.

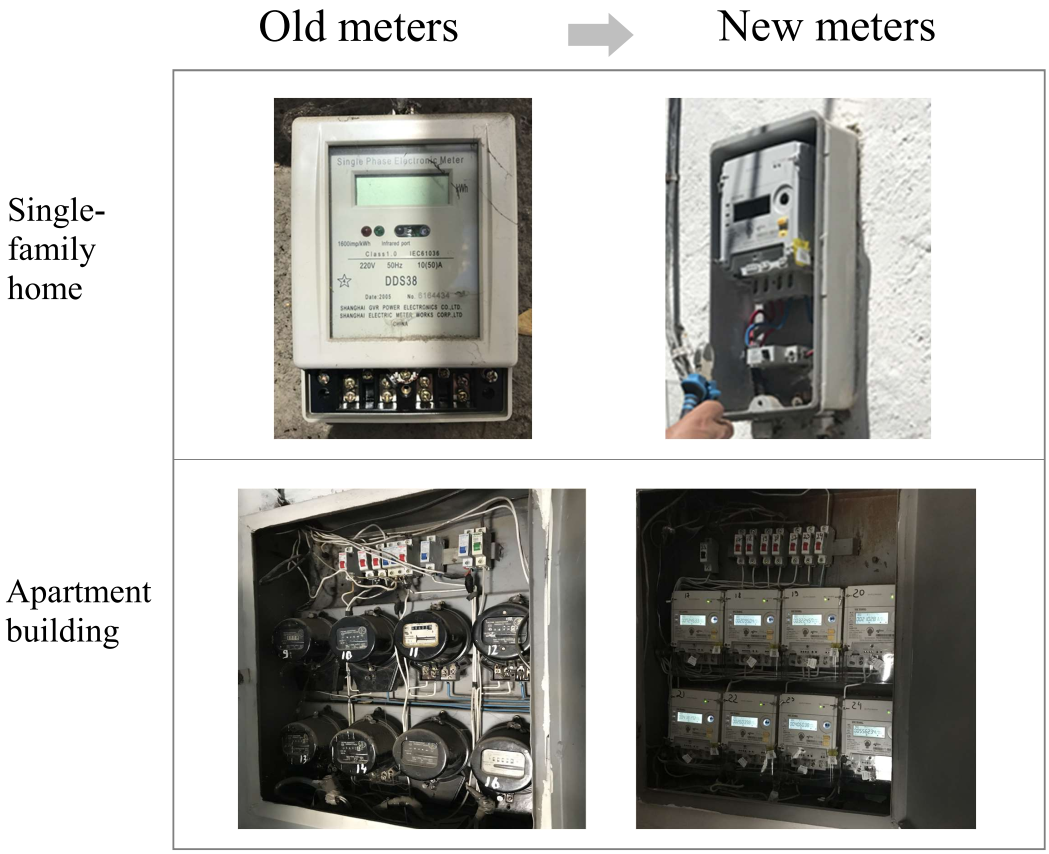

Figure A3: Photo Examples of Old Meters and Newly-installed Smart Meters

Notes: Photos show examples of the old meters (left) and the smart meters (right) that replaced them. Meters installed for single-family homes are attached to the house outside (top row). The meters for homes in apartment buildings are installed in a shared stairway within the building (bottom row).

Figure A4: Example Showing Smart Meters Installed on Outside of House

Notes: Photo provides an example of a smart meter installed for a single-family home, attached to the outside of the house. Photo also shows the plastic film commonly affixed outside windows to reduce heat loss in the winter.

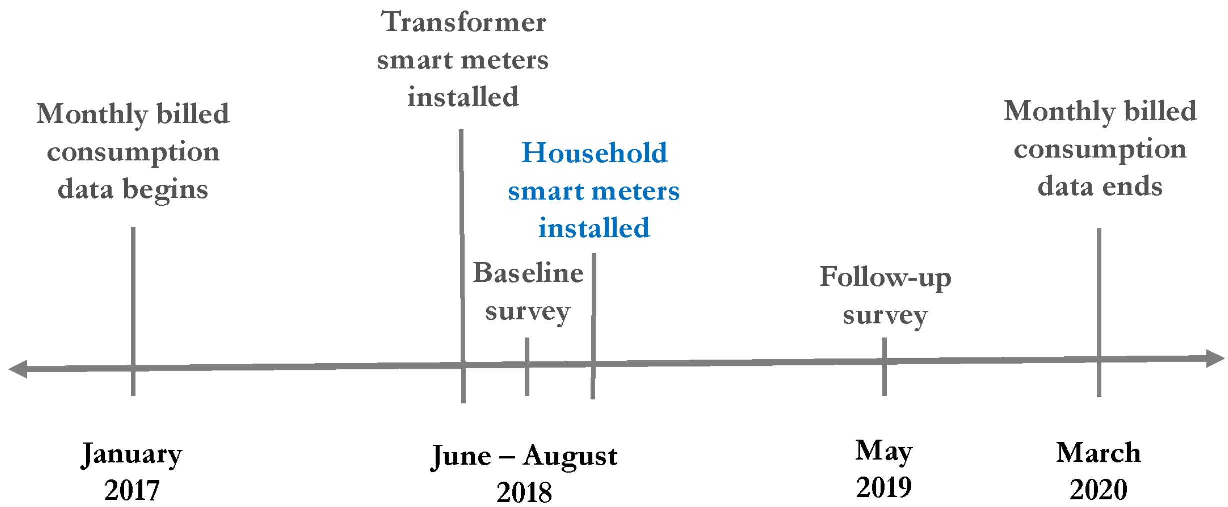

Figure A5: Timeline of Meter Installation and Data Collection

Notes: Monthly billed electricity consumption data are provided by the electricity utility. The transformer smart meters were installed just before the intervention to ensure outcome measures were collected by the time of the intervention. The installation of the household smart meters was the intervention. Once the transformer and household smart meters were installed, the technology sends the data directly to the utility. We receive those data from the utility's server.

Table A1: Categorization of events: transformer smart meters

Event Category	Event Type	Count	Percentage
Voltage Quality	Over voltage L1 start	13,484	27.71%
	Over voltage L2 start	9,096	18.69%
	Over voltage L3 start	6,592	13.55%
Power Outage	Disconnect relay	53	0.11%
	Limiter threshold exceeded	4,683	9.62%
	Manual connection	45	0.09%
	Power down (long power failure)	2,300	4.73%
	Power down (short power failure)	552	1.13%
	Power up (long power failure)	2,365	4.86%
	Power up (short power failure)	555	1.14%
Other	Association authentication failure	58	0.12%
	Clock adjusted (new date/time)	1	0.00%
	Clock adjusted (old date/time)	1	0.00%
	Current reverse generation in any phase	3,305	6.79%
	Module power down	2,490	5.12%
Total		48,664	100.0%

Notes: Event data are provided by the smart meters installed at the transformers. Categorization is based on the technical manual from the manufacturer of the smart meters. “Other” events are all those that do not fit into the first categories (voltage quality, and power outages).

Table A2: Check for Differential Attrition

Group	(1) Baseline Responses	(2) Follow-Up Responses	(3) Response Change
Control	575	450	78.6%
Treatment	568	430	75.5%

Notes: This table reports the number of responses by treatment group in the baseline and follow-up surveys. Column 3 reports the number of responses in the follow-up survey (Column 2) divided by the number of responses in the baseline survey (Column 1).

Table A3: Balancing Test for Attrition

VARIABLES	(1) Attritors	(2) Non-Attritors	(3) Diff.
Number of Rooms in the House	3.000	2.958	-0.042
	(1.409)	(1.211)	(0.097)
Homes Owned	0.787	0.807	0.020
	(0.410)	(0.395)	(0.024)
Homes with Insulation	0.213	0.213	-0.000
	(0.410)	(0.409)	(0.023)
Houses Using Energy-Efficient Light Bulbs	0.209	0.197	-0.012
	(0.407)	(0.398)	(0.027)
Houses Using Central Heating	0.046	0.060	0.015
	(0.209)	(0.238)	(0.013)
Houses Using Electric Heating	0.631	0.657	0.026
	(0.483)	(0.475)	(0.026)
Reporting 1+ Outages Per Week	0.531	0.448	-0.084
	(0.500)	(0.498)	(0.050)
Reporting 1+ Voltage Fluctuations Per Week	0.717	0.702	-0.015
	(0.451)	(0.458)	(0.032)
Houses with Electric Generators	0.004	0.005	0.001
	(0.062)	(0.067)	(0.004)
Houses with Stabilizers	0.008	0.005	-0.003
	(0.087)	(0.067)	(0.006)
Houses with Appliance Damage	0.183	0.219	0.036
	(0.387)	(0.414)	(0.037)
Observations	263	880	1,143

Notes: Column 1 presents baseline means for the attritors (i.e., those households in the baseline survey but not the follow-up survey). Column 2 presents means for the non-attritors (i.e., those households in both the baseline and the follow-up surveys). Standard errors in parenthesis are clustered at the transformer level. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

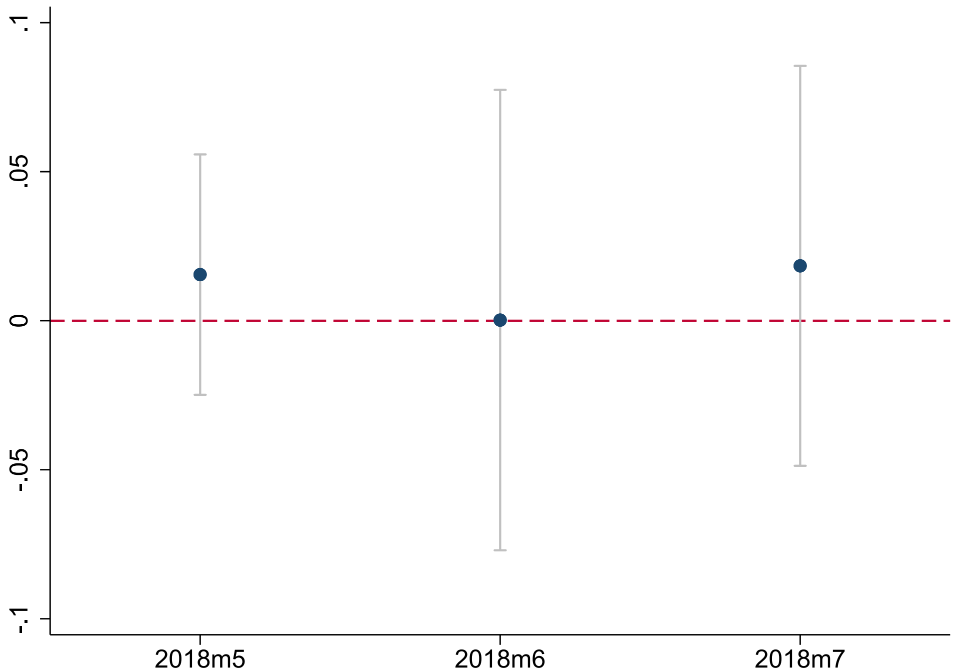

Figure A6: Difference in Total Number of Transformer Alarms before the Intervention

Notes: This figure plots the difference in total number of transformer alarms prior to the installation of household smart meters. The outcome variable is the total number of transformer alarms within a day. We estimate the difference by month using an event study framework, where we control for month-by-year fixed effects, the number of households served by each transformer, and the transformer's technical capacity. Standard errors are clustered at the transformer level. The data for transformer-level alarms are only available pre-intervention for these three months.

Table A4: Balance Test on Household Characteristics Based on All Households

VARIABLES	Control	Treatment	Difference
Number of Rooms in the House	2.977	2.958	0.020
	(1.268)	(1.251)	(0.231)
Homes Owned	0.826	0.778	0.048
	(0.379)	(0.416)	(0.043)
Homes with Insulation	0.162	0.264	−0.102
	(0.369)	(0.441)	(0.071)
Houses Using Energy-Efficient Light Bulbs	0.191	0.208	−0.017
	(0.394)	(0.406)	(0.052)
Houses Using Central Heating	0.035	0.079	−0.044
	(0.183)	(0.270)	(0.050)
Houses Using Electric Heating	0.614	0.688	−0.074
	(0.487)	(0.464)	(0.070)
Reporting 1+ Outages Per Week (Jan.–Feb. 2018)	0.482	0.452	0.030
	(0.500)	(0.498)	(0.114)
Reporting 1+ Voltage Fluctuations Per Week	0.717	0.695	0.022
	(0.451)	(0.461)	(0.104)
Houses with Electric Generators	0.003	0.005	−0.002
	(0.059)	(0.073)	(0.003)
Houses with Stabilizers	0.005	0.005	−0.000
	(0.072)	(0.073)	(0.004)
Houses with Appliance Damage	0.183	0.239	−0.056
	(0.387)	(0.427)	(0.092)
Observations	575	568	1,143

Notes: We report the mean values of household characteristic variables. Household data were collected via the baseline household survey, conducted in spring 2018. Robust standard errors are clustered at the transformer level.

Table A5: Transformer-Level Smart Meter Events: Electricity Quality (Supplemental p-values)

Alarms (in one day) indicating:	(1) Voltage events	(2) Outage events
Treat	-2.283**	0.035
	(0.004)	(0.324)
	[0.004]	[0.258]
Mean of Control Group	2.324	0.525
Observations	8,355	8,355
R-squared	0.104	0.052
Transformer Characteristics	✓	✓
Month-by-Year FE	✓	✓

Notes: We use wild bootstrapping and randomization inference approach to compute the p-values for the coefficient estimates. We first replicate the baseline estimates using standard errors clustered at the transformer level. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). P-values calculated from randomization inference with 500 permutations of the treatment status are reported in parentheses. Wild-bootstrap p-values are reported in brackets.

Table A6: Correlation between Reported Electricity Quality and Events Recorded by Smart Meters

VARIABLES	Reliability Reported by Household		
	(1)	(2)	(3)
Quality Events	−0.200***		
	(0.069)		
Power Events		−0.181*	
		(0.095)	
Theft Events			−0.712
			(0.835)
Observations	871	871	871

Notes: Event data are from the household smart meters. The household self-reported reliability data are from the follow-up survey, conducted in May 2019. Reliability is measured as the negative of the total number of outage and voltage fluctuation events within a week, self-reported by the households during the previous winter. Standard errors are clustered at the transformer level and displayed in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A7: Correlation between Events Measured by Transformer and Household Smart Meters

VARIABLES	Household Events: Voltage		Household Events: Outage	
	(1)	(2)	(3)	(4)
Transformer Events: Voltage	0.038***	0.039***		
	(0.003)	(0.004)		
Transformer Events: Outage			0.098***	0.099***
			(0.017)	(0.017)
Observations	70,497	70,497	70,497	70,497
R-squared	0.016	0.016	0.023	0.025
Transformer Fixed Effects		✓		✓

Notes: Event data are from either the transformer smart meters (the independent variable) or the household smart meters (the dependent variable). Robust standard errors are clustered at the transformer level and displayed in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A8: Billed Electricity Consumption by Season, with Supplemental p-values

Monthly electricity bill (kWh):	(1) Heating Season	(2) Non-heating Season	(3) Heating Season	(4) Non-heating Season
Treat × Post	50.698***	−15.077	145.316***	-22.783
	(0.008)	(0.348)	(0.024)	(0.256)
	[0.006]	[0.304]	[0.017]	[0.225]
Treat × Post × Owner			-114.524*	10.061
			(0.122)	(0.664)
			[0.106]	[0.622]
Mean of Control Group	806.223	415.017	806.223	415.017
Observations	13,021	17,245	13,021	17,245
Number of Households	871	871	871	871
Adjusted R-squared	0.091	0.271	0.091	0.271
Household Fixed Effects	✓	✓	✓	✓
Month-by-Year Fixed Effects	✓	✓	✓	✓

Notes: We use wild bootstrapping and randomization inference approach to compute the p-values for the coefficient estimates. We first replicate the baseline estimates using standard errors clustered at the transformer level. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). P-values calculated from randomization inference with 500 permutations of the treatment status are reported in parentheses. Wild-bootstrap p-values are reported in brackets.

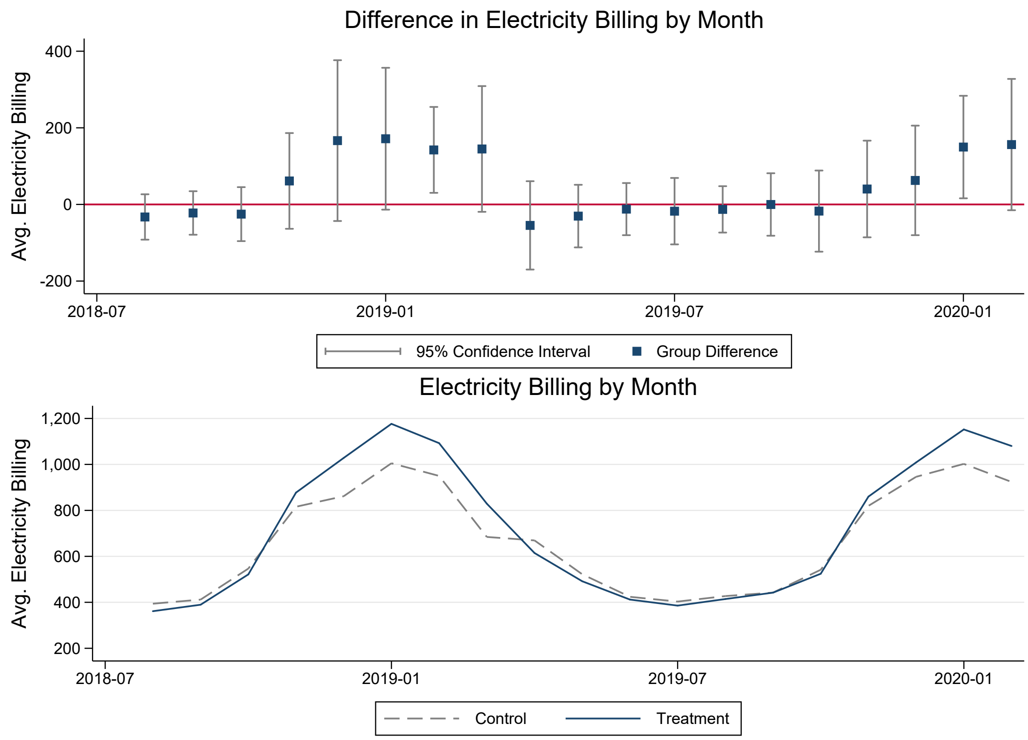

Figure A7: Billed Electricity Consumption (kWh/month) after Smart Meter Installation

Notes: Billing data are provided by the electricity utility. The analysis here is a basic comparison, and no other control variables are included. Addresses that have businesses at the location are dropped. The standard errors are clustered at the transformer level.

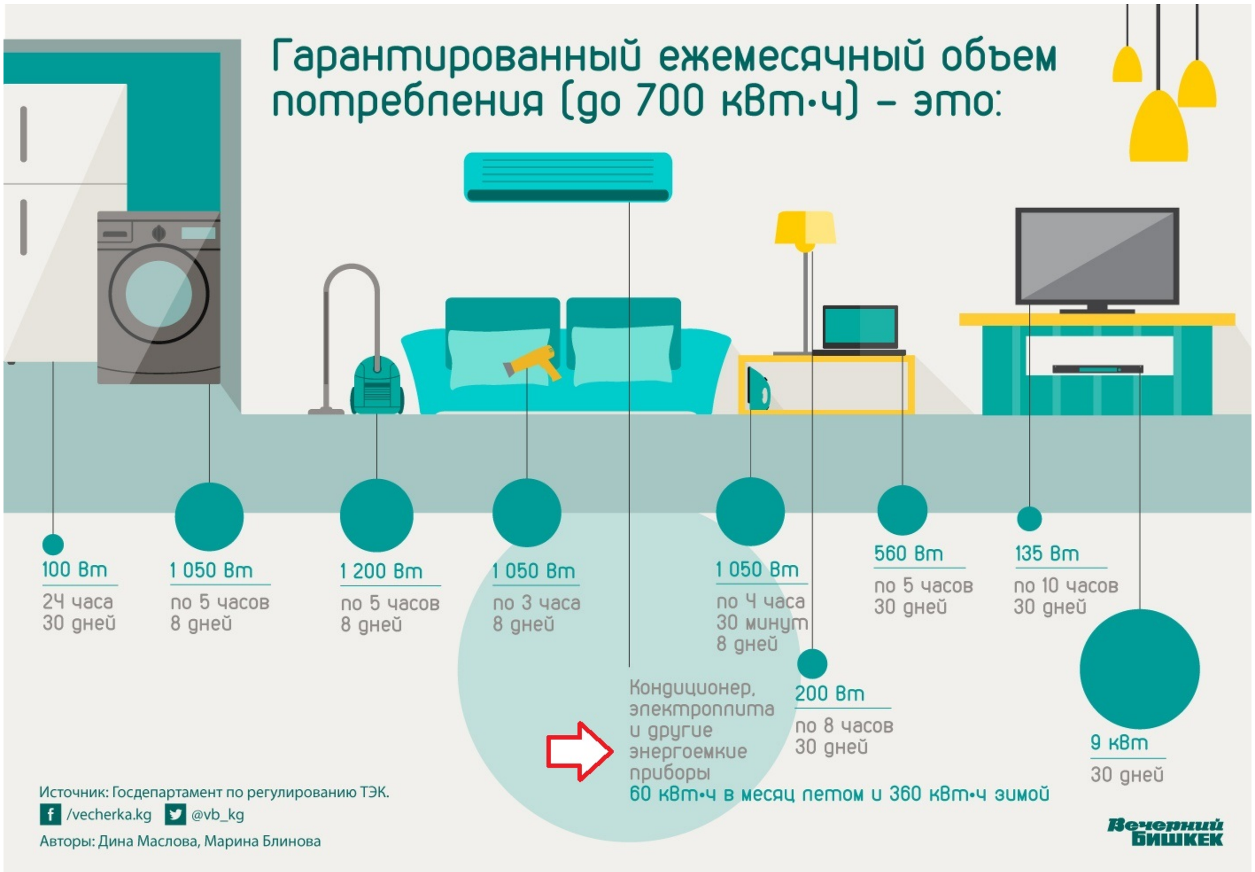

Figure A8: Information Campaign to Inform Residents as to How Appliances Contribute to Electricity Bills

Notes: Graphic (in Russian) was created by the regulator and circulated in the newspaper "Evening Bishkek" during winter 2014. The increasing block tariff was introduced on December 11, 2014. Below 700kWh the tariff for 1kWh was 0.70 KGS. Billed consumption over 700 kWh in a month was charged at 2.05 KGS per kWh. The goal of this graphic was to inform consumers how their appliances could contribute to a monthly electricity bill of 700kWh, which is the quantity at which the price increased to the higher price tier. The graphic is titled "Guaranteed monthly consumption (to 700 kWh) is." We have added the red arrow to point to the information about cooling and heating, which states "AC, electric range, or other energy intensive appliances - 60 kWh during summer months, 360 kWh during winter time."

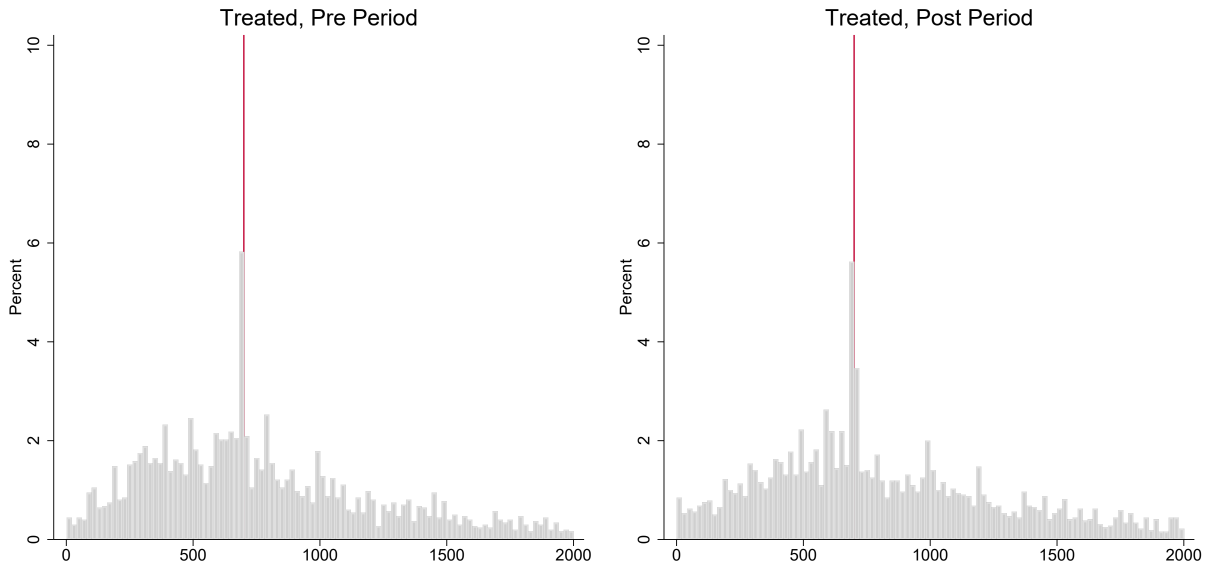

Figure A9: Distribution of Billed Electricity Consumption During the Heating Season

Notes: Monthly billed electricity consumption data are provided by the electricity utility. This figure plots the distribution of monthly billed electricity consumption (in kW) by the treated households and for pre- and post- intervention period. The vertical red line marks 700 kW, which is the threshold of the higher tariff.

Table A9: Robustness Check: Billed Electricity Consumption by Season, Controlling for Baseline Consumption

Monthly electricity bill (kWh):	(1) Heating Season	(2) Non-heating Season	(3) Heating Season	(4) Non-heating Season
Treat $\times$ Post	49.574**	10.598	161.337***	-0.572
	(22.279)	(17.360)	(46.658)	(17.766)
Treat $\times$ Post $\times$ Owner			-133.175*	14.598
			(62.027)	(22.655)
Mean of Control Group	847.541	428.688	847.541	428.688
Observations	8,504	10,963	8,504	10,962
Number of Households	864	860	864	860
Adjusted R-squared	0.102	0.287	0.103	0.287
Household Fixed Effects	✓	✓	✓	✓
Month-by-Year Fixed Effects	✓	✓	✓	✓

Notes: In this analysis, we add household's 2017 billed consumption as a control. Billing data are provided by the electricity utility covering the period between January 2017 and March 2020. Control group means are for the baseline (pre-intervention) period. The outcome variable is the monthly billed electricity consumption (kWh/month) for a household forward by one month. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A10: Electrical Appliance Ownership (Supplemental p-values)

	(1) Clothes Washer	(2) Color TV	(3) Computer/ Laptop	(4) Water Heater	(5) Cell Phone Charger	(6) Electric Heater
Panel A: Overall effect						
Treat × Post	0.010	0.007	-0.026	0.001	0.109	0.094*
	(0.764)	(0.782)	(0.308)	(0.942)	(0.340)	(0.076)
	[0.781]	[0.808]	[0.257]	[0.942]	[0.314]	[0.125]
Panel B: Heterogeneous effect						
Treat × Post	0.018	0.023	-0.031	-0.018	0.184	0.171**
	(0.762)	(0.594)	(0.268)	(0.608)	(0.148)	(0.064)
	[0.787]	[0.587]	[0.358]	[0.662]	[0.140]	[0.062]
Treat × Post × Owner	-0.011	-0.019	0.007	0.024	-0.094	-0.099**
	(0.858)	(0.692)	(0.812)	(0.552)	(0.366)	(0.200)
	[0.833]	[0.64]	[0.899]	[0.505]	[0.378]	[0.061]
Mean of Control Group	0.836	0.862	0.184	0.433	0.702	0.722
Observations	1,760	1,760	1,760	1,760	1,760	1,760
R-squared	0.861	0.843	0.946	0.971	0.734	0.883
Control Household FE	✓	✓	✓	✓	✓	✓

Notes: We use wild bootstrapping and randomization inference approach to compute the p-values for the coefficient estimates. We first replicate the baseline estimates using standard errors clustered at the transformer level. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). P-values calculated from randomization inference with 500 permutations of the treatment status are reported in parentheses. Wild-bootstrap p-values are reported in brackets.

Table A11: Changes in Home Energy Efficiency (Supplemental p-values)

Energy efficiency changes:	made any changes		installed insulation		replaced windows	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.063	0.007	-0.011	-0.041	0.090***	0.021
	(0.204)	(0.932)	(0.850)	(0.394)	(0.010)	(0.752)
	[0.191]	[0.918]	[0.843]	[0.411]	[0.006]	[0.698]
Treat × Post × Owner		0.073		0.039		0.084
		(0.370)		(0.514)		(0.218)
		[0.470]		[0.573]		[0.300]
Mean of Control Group	0.205		0.109		0.080	
Observations	1,760	1,760	1,760	1,760	1,760	1,760
R-squared	0.572	0.574	0.529	0.530	0.541	0.542
Control Household FE	✓	✓	✓	✓	✓	✓

Notes: We use wild bootstrapping and randomization inference approach to compute the p-values for the coefficient estimates. We first replicate the baseline estimates using standard errors clustered at the transformer level. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). P-values calculated from randomization inference with 500 permutations of the treatment status are reported in parentheses. Wild-bootstrap p-values are reported in brackets.

Table A12: Use of Energy-Efficient Light Bulbs

	(1) EE lighting	(2) EE lighting
Treat × Post	0.056	0.014
	(0.099)	(0.134)
Treat × Post × Owner		0.054
		(0.090)
Mean of Control Group	0.193	0.193
Observations	1,758	1,758
R-squared	0.594	0.595
Control Household FE	✓	✓

Notes: Data collected through baseline and follow-up surveys. *EElighting* is a binary variable that equals 1 if the household uses energy-efficient light bulbs in the home. We use a balanced panel restricted to households in both the baseline and follow-up surveys. Robust standard errors are clustered either at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A13: Electricity-Related Device Ownership

VARIABLES	(1) Electricity Generator	(2) Stabilizer	(3) Battery with Inverter	(4) Uninterruptible Power Supply	(5) Solar Panel	(6) Solar Water Heater	(7) Other Solar Device
Treat	0.003	−0.002	0.000	−0.002	0.000	−0.002	0.000
	(0.008)	(0.005)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
Mean of Control Group	0.009	0.011	0.000	0.002	0.000	0.002	0.000
Observations	1,125	1,125	1,125	1,125	1,125	1,125	1,125
R-squared	0.005	0.002	0.000	0.001	0.000	0.001	0.000
Basic Characteristics	✓	✓	✓	✓	✓	✓	✓

Notes: Data collected through the household follow-up survey in May 2019. The outcome variables are dummy variables indicating whether the household owned certain electricity-related devices. We control for household basic characteristics, including the number of rooms in a house and whether the house is owner occupied. Robust standard errors are clustered at the transformer level. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A14: Theft Alarms

Alarms in one day indicating:	(1) theft
Treat	0.787
	(0.902)
	[0.703]
Mean of Control Group	0.343
Observations	8,355
R-squared	0.037
Transformer Characteristics	✓
Year-Month FE	✓

Notes: Event data are provided by the electricity utility covering the period from September 2018 to March 2020. The outcome variables are the number of these events recorded by the transformer smart meter per day. Regressions control for transformer characteristics including the number of households served by the transformer and its capacity. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Wild-bootstrap p-values are reported in brackets.

A2 Potential Mechanisms for Electricity Quality Improvements

How did smart meters lead to electricity quality improvements? Due to the limited number of transformers included in the study, any analysis to this effect is limited in statistical power. For this reason, we can provide only suggestive evidence here. We show that the treated transformers were more likely to be overhauled or replaced (Appendix Table A15) and the event alarms from the household smart meters directed utility's attention to the transformers in greatest need of repairs (Appendix Table A16). Those transformer repairs result in improved electricity service quality, as measured by both event alarms (Appendix Table A17) and consumers' perceived quality improvements (Appendix Table A18).

A2.1 Smart Meters and Electricity Service Quality Improvements

Smart meters can improve electricity service quality by providing additional information to either consumers or the utility. First, smart meters can detect and directly alert the utility to outages and voltage fluctuations, allowing it to respond quickly with repairs, maintenance, and overhauls. If the utility analyzes this information on problematic events, the smart meter data can help them understand which locations suffer from the worst quality. Second, smart meters can detect voltage fluctuations and automatically disconnect households from the distribution system, protecting appliances from damage. If standard voltage resumes, the consumer must press a button on the smart meter to restart electricity flow. This required step increases the salience of voltage fluctuations for consumers and provides evidence of unsafe voltage fluctuations. If standard voltage does not resume, the smart meter prevents electricity flow until the utility performs the necessary repairs.

The smart meters are providing information – to both consumers and the utility – that can be used to improve electricity service quality. With the information, consumers may argue for better maintenance, upgrades, and repair. Without it, their complaints of voltage problems may remain unverified. The utility receives many complaints regarding service quality and it may be difficult to know which places have the greatest need for repairs. Thus, the meters help the utility target efforts to the neediest locations within the distribution system, thereby improving electricity service quality.

Typically, the connection of a house (or business) to the electrical grid involves a contract; the distribution company commits to providing reliable electricity services that meet voltage standards, and the customer commits to paying for the electricity consumed. Yet consumers lack data on the actual quality of electricity services delivered and utilities lack information on the locations of poorest service quality. The information smart meters provide could alleviate a contract failure between electricity utilities and their customers.

A2.2 Empirical Results

Smart meters provide information to the electricity utility via high frequency readings, allowing the utility to more rapidly identify problematic locations within the distribution network. We found support for these industry claims via discussions with consumers.[17]

We test whether the household smart meters induced transformer replacements and maintenance overhauls, using electricity utility panel data for the 20 transformers over a 33-month period covering both before and after the intervention. We estimate the following equation:

$$y_{gt} = \alpha \text{Treat}_g \times \text{Post}_t + \beta \text{Post}_t + \lambda_g + \epsilon_{gt}, \tag{A1}$$

in which the outcome variable is the number of times transformer g was replaced or overhauled within month t. Treat_g is an indicator for the treated transformers, while Post_t is an indicator for the post-intervention period. We include transformer fixed effects λ_g to control for transformer characteristics that are fixed over time.

[17]Prior to the smart meter installation, consumers reported of frequent complaints to the electricity utility about voltage fluctuations, appliance damage, and the inability to power certain electrical appliances. These consumers reported previously submitting requests to the utility for neighborhood transformer repairs that went without replacement or extensive overhaul. Prior research has highlighted transformers as a critical component in determining electricity service quality (Carranza and Meeks, 2021) .

The results, presented in Appendix Table A15, are informative in several respects. First, transformer replacements and overhauls are infrequent; the control group baseline mean shows that the monthly probability of replacement or overhaul was low. Second, the coefficient (Post) indicates a slight, albeit non-significant, increase in replacements and overhauls for all study transformers after the intervention. Lastly, the coefficient on the interaction term shows that treated transformers, serving the houses that received the smart meters, were almost 5% more likely to be overhauled or replaced after the intervention. This suggests that the household-level smart meters are drawing the utility to make improvements.

Is the utility responding to information from the household smart meters or just to knowledge of an ongoing study? To shed light on this question, we test whether greater frequency of household-level smart meter alarms per day, which indicate more electricity quality problems, are associated with a greater probability of a transformer being replaced or overhauled.[18] Indeed, treated transformers that were replaced did have significantly more household-level alarms per day prior to the replacement (Appendix Table A16), lending support to the suggestion that the household-level intervention directed utility attention to the places in greatest need.

We conduct two additional sets of analyses to understand whether transformer replacements and overhauls actually result in better electricity service quality. First, if alarms are indicative of electricity quality problems and the transformer replacements and overhauls fix those problems, then we should see a decline in alarms following transformer replacement. Indeed, a decline in the number of household-level smart meter alarms per day follows transformer replacement (Appendix Table A17). Second, we use the household reported voltage, outage, and overall quality measures from the baseline and follow-up surveys. We find that transformer replacement is a significant driver of respondents' perceived quality improvements (Appendix Table A18).

[18]We limit this analysis to the period before the first transformer was replaced.

Table A15: Transformer-Level Replacement and Overhauls

	Transformer Replaced or Overhauled
Treat × Post	0.048*
	(0.028)
	[0.116]
Post	0.026
	(0.021)
	[0.205]
Mean of Control Group	0.02
Observations	660
R-squared	0.026
Transformer Fixed Effects	✓

Notes: Transformer maintenance data are provided by the electricity utility covering the period from January 2017 to October 2019. The mean of the control group is calculated for the baseline period. The outcome variable is the transformer-level number of planned overhauls and replacements in a month. *Treat* is a binary variable that equals 1 if the transformer belongs to the treatment group. *Post* is a binary variable that equals 1 for the period after August 2018. We control for transformer fixed effects. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Wild-bootstrap p-values are reported in brackets.

Table A16: Comparing Household-Level Events across Transformer Groups

VARIABLES	Alarms	
	(1)	(2)
Replace	0.184**	0.220**
	(0.064)	(0.068)
Repair	0.113	0.088
	(0.095)	(0.059)
Observations	35,724	35,724
R-squared	0.006	0.008
Month-by-Year Fixed Effects	✓	✓
Feeder-Line Fixed Effects		✓

Notes: Event data are provided by the electricity utility. Here, we compare the number of Events for the two replaced transformers, the three transformers with unplanned repairs, and the other transformers in the treatment group. We focus our analysis before the date when the first transformer replacement happened (February 4, 2019). The outcome variable is the household-level number of events recorded by the smart meter in a day. *Replace* is a binary variable that equals 1 if the transformer was replaced. *Repair* is a binary variable that equals 1 if the transformer had unplanned repairs due to breakage. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A17: The Effect of Transformer Replacement on Household-Level Events

VARIABLES	(1) Total	(2) Quality	(3) Power	(4) Theft	(5) Other
Post Replace	0.023	-0.009	0.035	-0.001	-0.002
	(0.042)	(0.014)	(0.032)	(0.002)	(0.001)
Replace $\times$ Post Replace	-0.116**	-0.036	-0.090**	0.010	0.000
	(0.043)	(0.020)	(0.032)	(0.011)	(0.000)
Observations	128,011	128,011	128,011	128,011	128,011
R-squared	0.025	0.013	0.035	0.013	0.003
Household FE	✓	✓	✓	✓	✓
Month-by-Year FE	✓	✓	✓	✓	✓

Notes: Alarms data come from the household smart meters and cover the period from September 2018 to March 2020. The outcome variable is the number of events in one day. *Replace* is a binary variable that equals 1 if the transformer was replaced. *Post Replace* is an indicator for the post-replacement period. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A18: Intervention Impacts on Households' Self-Reported Electricity Service Quality

VARIABLES	Voltage		Outage		Reliability	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	−0.789	−0.627	−0.007	−0.007	−0.796	−0.634
	(0.694)	(0.686)	(0.381)	(0.377)	(0.870)	(0.862)
Treat × Replace × Post	2.229***		−0.007		2.222***	
	(0.663)		(0.319)		(0.632)	
Post	−0.747**	−0.747**	−0.244	−0.244	−0.991	−0.991
	(0.323)	(0.322)	(0.346)	(0.346)	(0.599)	(0.598)
Observations	1,742	1,742	1,742	1,742	1,742	1,742
R-squared	0.091	0.080	0.015	0.015	0.087	0.080
Number of Households	871	871	871	871	871	871
Household Fixed Effects	✓	✓	✓	✓	✓	✓

Notes: Regressions are restricted to the households for which we have a balanced panel. Reliability data are collected from the household baseline and follow-up surveys conducted in July 2018 and May 2019, respectively. *Reliability* is measured by the negative of the total number of outage and voltage fluctuation events within a week, self-reported by the households. *Voltage* is measured by the negative of the total number of voltage fluctuation events within a week, self-reported by the households. *Outage* is measured by the negative of the total number of outage fluctuation events within a week, self-reported by the households. *Treat* is a binary variable that equals 1 if the household belongs to the treatment group. *Post* is a binary variable that equals 1 for the post-intervention period. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).