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, which is a barrier to development. We investigate the impacts of and residential consumer response to electricity quality improvements in Kyrgyzstan through the randomized installation of smart meters, which utilities can install to improve service quality. Voltage fluctuations were nearly eliminated among the treated households. Billed electricity consumption increased during peak months post-intervention. Consistent with this, treated households, particularly renters, significantly increased electric heating. Treated households made significantly more energy efficiency investments, potentially mitigating their electricity increases post-intervention. Consumer welfare gains were approximately 8 USD per household per year.

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1 Introduction

Although the number of people with electricity access has increased during the 21st century, poor electricity service quality remains a persistent problem in many developing countries (Trimble et al., 2016; Zhang, 2018). Hundreds of millions of households depend on grid connections that provide low-quality and unreliable electricity services (Day, 2020). This is problematic for development, as low-quality and irregular electricity services may limit consumption of electricity services and attenuate the economic benefits from grid connections (Pargal and Ghosh Banerjee, 2014; Samad and Zhang, 2016; Timilsina et al., 2018; Zhang, 2018). With this in mind, international and development organizations increasingly emphasize improving electricity service quality.[1]

Understanding residential consumers' responses to changes in electricity quality is 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); however, appliance ownership and use – and therefore the demand for electricity services – are also correlated with electricity quality (McRae, 2010; Jacome et al., 2019). Recent evidence suggests a substantial willingness-to-pay for improved electricity service quality (Alberini et al., 2020; Deutschmann et al., 2021; Meles et al., 2021). If improvements in electricity quality result in greater consumption of electricity services, then there are implications not only for household welfare, but for the environment and climate change as well (Jayachandran, 2021).

This paper reports results from a randomized experiment that was implemented in the Kyrgyz Republic and designed to provide causal evidence on the benefits from – and consumer response to – electricity quality improvements. The setting is a lower-middle-income country in Central Asia that suffers from electricity quality issues common to many developing countries. The randomized treatment was an infrastructure upgrade

[1] For example, Sustainable Development Goal 7.1 of the United Nations calls for "affordable, *reliable* and modern energy services" (United Nations, 2020).

within the local electricity distribution system: smart meters installed at residential locations.

Utilities increasingly install smart meters to address a number of electricity sector challenges and in an effort to transition to a smart grid.[2] Sector experts (Sprinz, 2018), electricity utilities (see, e.g., Duke Energy Progress, 2020; BC Hydro, 2016), governments (U.S. Department of Energy, 2014), and multi-lateral development banks (ESMAP, 2019) argue that such investments can improve reliability as well as power quality.

Smart meters, through high-frequency energy readings (i.e., readings occur often) and alarms indicating the location and timing of outages and poor service quality events (i.e., voltage fluctuations), can facilitate service quality improvements, eradicating "disruptions in voltage or frequency" (Joskow, 2012). How the smart technology is used and its potential to improve service quality will depend on the context. A survey of employees across 3 electricity utilities in the Kyrgyz Republic – all with smart meters installed within a portion of their distribution network – revealed that the majority of respondents believed smart meters mitigate appliance breakage due to voltage problems and reduce consumer complaints (Isaev et al., 2022).[3]

In this paper, we first document an electricity service quality improvement following smart meter installation and then estimate consumers' responses to these electricity quality improvements in terms of their billed electricity consumption, household appliance ownership, and energy efficiency investments. Given we expect that renters may not incur the full cost of changes in electricity bills (if, for example, they pay a fixed monthly sum to their landlords that covers utility bills), we test for heterogeneous impacts by home ownership status. We conclude by estimating the consumer welfare gains from the electricity quality improvements.

[2]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).

[3]In contrast, the roll-out of smart meters in Texas significantly reduced duration of outages within the state (Meeks et al., 2022).

The randomized experiment was designed to overcome endogenous electricity quality that is often mutually determined by local neighborhood characteristics. In collaboration with an electricity utility, 20 neighborhoods were selected within one city. Each neighborhood receives electricity services via a transformer.[4] These 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.

A unique combination of datasets permit us to overcome typical challenges in researching electricity service quality. Limited data and utilities' lack of incentive to report on electricity quality measures makes measuring changes in outages and voltage fluctuations difficult. 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 service quality. Here, we measure electricity service quality using data obtained 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.

After confirming that the smart meters led to service quality improvements – in the form of fewer voltage fluctuations – we estimate the household response with respect to

[4]Transformers are a crucial component of the electrical grid, converting high-voltage electricity to usable, low-voltage electricity for household consumption (Glover et al., 2011).

consumption of electricity services. We find that 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 the off-peak months (April to October). The increase in billed electricity consumption of treated renters is almost 5 times that of treated homeowners.

These increases in peak months are consistent with unmet demand prior to the intervention, followed by improved electricity service quality and greater consumption thereafter. Prior to the intervention, electricity service quality was most problematic during these peak demand months, when voltage fluctuations occurred frequently. As a result, these months are the time when there is more room for quality improvements. Post-intervention during peak demand months, households consume a greater quantity of electricity services due to electricity being available for more hours per day within the standard voltage range. The extent to which improved electricity quality results in changed residential consumption of those services depends on additional factors, such as the appliances owned and used, as well as the house's energy efficiency.

We investigate potential explanations for these effects on billed electricity consumption, including the heterogeneous response of renters and homeowners. 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.[5] 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, we find treated households were also more likely

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

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.

To conclude, we estimate consumers' welfare gains from electricity quality improvements. During the five peak months of the first year, the gains from electricity quality improvements among treated households is 7.64 USD. We provide further support for these results by ruling out alternative channels for billed electricity consumption increases.

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 technological interventions in local electricity distribution systems, such as metering (McRae, 2015a; Jack and Smith, 2020) and aerial bundled cables (Ahmad et al., 2022), on utility finances and consumer bill payment. 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) like the 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 of this intervention ex ante were expected to be via electricity quality improvements.

Broadly, this paper contributes to experimental research on the impacts of improving both delivery of public services (Duflo et al., 2012; Dhaliwal and Hanna, 2017; Das et al., 2016; Callen et al., 2016; Banerjee et al., 2018; Muralidharan et al., 2018) and infrastructure

(Gonzalez-Navarro and Quintana-Domeque, 2016). More specifically, this research adds to our understanding of the role of service quality in electrification and development. By focusing on residential consumers, this paper complements existing research estimating the economic impacts of electricity shortages (Fisher-Vanden et al., 2015; Allcott et al., 2016; Cole et al., 2018; Hardy and Mccasland, 2019) and reliability (Mahadevan, 2021) on firms. Although firms can adapt to low service quality through investments in self-generation (Steinbuks and Foster, 2010), households' responses likely differ from firms given the high cost of self-generation.

Providing evidence of consumer gains and responses – with respect to increased electricity consumption, appliance investments, and energy efficiency upgrades – following electricity service quality improvements, our study underscores two important sources of heterogeneity in understanding the role of electricity services in development: heterogeneous electricity service quality and differential responses to these services by home ownership.[6] These sources of heterogeneous impacts and responses to electricity services are important given the low returns to electrification previously 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; Usmani and Fetter, 2019; Lee et al., 2020; Burlig and Preonas, 2016; Kassem, 2021; Meeks et al., 2021). Further, by investigating energy efficiency as a channel for household response, we complement research on the impacts of residential energy efficiency (see, e.g., Davis et al., 2014, 2020; Carranza and Meeks, 2021) and contribute to research on the drivers of energy efficiency investments in developing countries (Fowlie and Meeks, 2021; Beattie et al., 2021).

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

[6] A homeowner-renter gap in electric appliance ownership and energy efficiency investments has been well-documented in developed countries (see, e.g., Davis, 2012, 2021).

quality and the consumer response. Section 6 presents estimates of the consumer welfare gains from the electricity service quality improvements and discusses generalizing results to other settings. Section 7 concludes.

2 Conceptual Framework: Electricity Quality and Demand

In this section, we provide a conceptual framework, which is informed by existing literature (see, e.g., Klytchnikova and Lokshin, 2009; McRae, 2010, 2015b), as to how electricity quality changes affect demand for electricity services. A household's demand for electricity services is determined by the demand for services from each of the household's electrical devices; however, changes in electricity service quality impact the demand for services from those individual electrical devices. Both outages and voltage fluctuations can affect the appliances owned, the extent to which the appliances are used, and the quantity of electricity services consumed. This relationship between electricity service quality and demand for electricity services is particularly problematic for development, given service quality is typically worst during times of peak demand, when electricity generation and distribution systems are insufficient to meet the quantity of electricity services demanded. We describe these relationships in further detail here.

We consider two main types of poor electricity service: unreliable service due to outages and low service quality due to voltage fluctuations. Rationing, which typically occurs when generation is insufficient to meet demand and commonly referred to as "load shedding," did not occur during our study period and therefore is not further discussed in this section.

2.1 Unreliable Service Due to Outages

An outage is a complete stoppage within the electricity distribution system that prevents 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. Unplanned outages are typically due to infrastructure breakage, malfunction, and overloaded distribution systems.[7] 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 a grid outage.

Beyond the stoppage itself, consumers may respond to outages in ways that further suppress the quantity of electricity services consumed. They may avoid purchasing certain appliances (e.g., an electric cooker), if they believe that they cannot often use them due to frequent outages. Alternatively, consumers may unplug appliances that they own (e.g., refrigerators) due to concerns that the appliance may be damaged. If service quality improves, then consumption of electricity services can increase due to greater consumption of the services provided by these household electrical devices.

Consumers may respond behaviorally to changes in electricity quality. First, if consumers respond to the electricity quality improvements by purchasing additional electrical devices, then billed electricity consumption can increase. Alternatively, if consumers experience a higher electricity bill (i.e., greater than expected or than previously experienced), then they may respond by replacing devices with more efficient models, investing in other forms of energy efficiency such as weatherization, or changing use behaviors. In such scenarios, and depending on the magnitude of the energy-saving behaviors relative to the electricity service consumption increases due to quality improvements, electricity bills may increase or decrease.

[7] 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).

2.2 Low Service Quality Due to Voltage Fluctuations

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 affect the quantity of electricity services demanded via multiple channels, some of which operate through the same mechanisms as outages. First, low voltage means that power is insufficient to run certain appliances, in which case the services provided by that appliance cannot be consumed. Second, voltage spikes may damage appliances, rendering them unusable. Consumers may be particularly concerned about potential damage to expensive appliances (e.g., a refrigerator), and hence fewer appliances may be used or purchased within a household. For example, a household may not purchase a refrigerator if they think voltage fluctuations will likely damage it or render it unusable.[8] Finally, as with outages, if electricity service quality impacts households' ability to consume an appliance's services, then it will also impact their purchase decisions and the portfolio of appliances owned. These channels all result in a lower quantity of electricity services consumed than under a standard voltage scenario.

There is at least one mechanism through which voltage fluctuations may impact electricity service consumption differently than in the outage scenario. Some appliances may function at lower voltages, while providing lower service quality (while using less electricity). For example, a light bulb may provide lighting services when voltage is low, but the lighting is less bright than it would be with standard voltage. When certain appliances run at low voltage, they consume fewer kWh per minute of use. If smart meters result in fewer voltage fluctuations, then we may observe an increase in the quantity of electricity services consumed.

[8] 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, as discussed later.

3 Randomized Experiment with Smart Meters

With a history of poor quality electricity services and recent efforts to improve services with smart meter installations, 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 on the country's electricity sector and then 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 cover distinct territories, purchasing electricity from the national transmission company and delivering it to residential, commercial, and industrial consumers.

Government regulations dictate the relationship between the distribution companies and the electricity customers. Per the government's Decree 576 (”Regulations on the Use of Electric Energy”), when a new customer connects to the electrical grid, the consumer and the distribution company ("the supplier") sign a contract with requirements regarding service quality and payment. The supplier commits to deliver reliable electricity service at a consistent voltage (220/280 volts). The supplier installs and retains ownership of a meter at the customer's location to track consumption. Consumers can record deviations from the electricity quality standards and any resulting material damages. By reporting to the government oversight body, the consumer may recover from the supplier damages that result from a service interruption or voltage fluctuation; however, these historically were difficult to prove. The consumer commits to pay for the electricity services consumed – as calculated based on monthly meter readings – by a specified date. If payment is not made, the supplier can charge a daily penalty and eventually disconnect the consumer from the power supply.

In recent decades, unreliable and low-quality electricity services have been pervasive, caused by the poor condition of the energy sector assets, intensive electricity use, and large seasonal variations in demand. 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 Bank, 2017a).

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 increasing appliance ownership. Low electricity prices have also contributed to the growth in residential electricity consumption.[9] Currently, consumption in the winter is approximately three to four times that of summer. This seasonality in consumption is indicative of the use of electric heating in the winter and the absence of air conditioning in the summer. As a result of peak demand occurring during the winter, electricity service quality is typically worst during those months.

[9]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.

3.2 Randomized Experiment

The experiment was implemented in one city, in collaboration with the electricity distribution company serving it. In this city, the mean temperature during the winter is between negative 10 and 15 degrees Celsius. Prior to the experiment, a substantial number of smart meters had been installed in other cities within the country, but not in this particular city.

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).[10] 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 houses served by the control transformers (846 houses) retained their old meters. The utility replaced the old meters with smart meters during July and August 2018. Pictures show old meters in comparison to smart meters (Appendix Figure A3) and a meter installed on the outside of a home (Appendix Figure A4). Smart meters were affixed where the old meters were previously installed.

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

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

The study's residential electricity consumers reside 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 winter 2018 (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 (as depicted by 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 strictly for data collection purposes and they provide high-frequency objective indicators of electricity theft and 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.[11]

We create transformer-level variables measuring the incidence of alarms indicating certain types of problems (i.e., theft, poor quality, and outages). Our categorization of alarm types is based on documentation provided by the meter manufacturer. 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 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,

[11]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.

and overall household expenditures, among others. Importantly, both survey rounds collected data on perceived electricity quality during the previous 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 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 (84.6 versus 79.6 households), their average capacity (an average of 381 versus 406 kVA), and their age (33.4 versus 27.9 years). Differences between treatment and control transformers are not statistically significant. The age of the transformers is reflective of the country's overall aging infrastructure. We complement the transformer-level comparisons displayed in Panel A with an even study analysis checking for differences in 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).

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).

Finally, 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. The graph shows no significant differences in monthly electricity bills before the intervention. Treatment households have slightly lower average electricity bills in July 2018, which is likely the result of outages required to install the intervention smart meters at these houses. The bottom panel plots the month-by-month average electricity bills for the treatment and control households. 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.

5 Effects on Electricity Quality and Consumer Response

In this section, we first confirm that the smart meter installation had the intended effect of improving electricity service quality. We 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

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, presented in Table 2, show significant improvements in electricity service quality. Column 1 presents results in which the number of voltage fluctuations per day is the outcome variable. We find significantly fewer voltage fluctuations events per day in the treatment group than in the control group after the intervention. 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. To put this in perspective and understand the seasonality of the voltage fluctuations in the absence of the treatment, we calculate the mean voltage events for the control group by season and find that there are 2.8 and 2.0 voltage events per day in the heating and non-heating seasons, respectively. This confirms our understanding that electricity service quality, in the absence of the treatment, was worst in the peak season.

Column 2 displays results from regressions in which power outages are the outcome variable. As indicated by the control group mean of 0.518 outages per day, outages were less problematic than voltage events and therefore had less room to improve. We find no impact on outages. This lack of a reduction in outages may be tied to the post-intervention increase in billed electricity consumption, which we discuss in the section on consumer responses.

To demonstrate that these results hold up to alternative inference methods, we present p-values from randomization inference with 500 permutations of the treatment status and wild-bootstrapped standard errors (Appendix Table A5).

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 experienced by the households, 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. We find that transformer smart meter events indicating electricity quality problems are indeed negatively and significantly correlated with better household-reported electricity reliability (Appendix Table A6), showing that households' perceived electricity quality and the transformer-level electricity quality measures are aligned. As expected, theft events are not correlated with households' reported electricity quality.

Our second robustness check tests the correlation between the transformer smart meter events (our outcome measures in Table 2) and events captured by the household smart meters. This can be done for only the treated households, where the intervention smart meters are installed. These two measures should not be perfectly correlated, for multiple reasons. First, household meters do not pick up exactly the same things as the transformer smart meters. Second, heterogeneity in electricity quality across households within a transformer's service area is expected. For example, households located closer to or farther from the transformer might experience voltage fluctuations differently: 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. Alternatively, an outage may impact one house served by a transformer or all the houses within that neighborhood. These two levels of smart meter alarms, however, should be positively correlated, and they are (Appendix Table A7).

Due to the limited number of transformers included in the study, we can provide only suggestive evidence on the mechanisms through which electricity quality improvements occurred (Appendix A2). We note that the difference between the treatment and control groups is that the households in the treatment transformers had smart meters installed. The results in Appendix A2 suggest that 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). 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.

We address potential SUTVA concerns. Some might worry that the intervention in the treatment transformers could direct all utility effort away from the control transformers to the treatment transformers. There were only 10 treated transformers. 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 not likely to impact the untreated transformers (essentially the remaining 690 transformers) in that city.

5.2 Consumer Responses to Electricity Quality Changes

As detailed in Section 2, the smart meters and the resulting electricity quality improvements could impact billed electricity consumption in multiple ways. These effects play a role in determining the extent to which consumers benefit from smart meter installation.

5.2.1 Billed Electricity Consumption

Building upon the electricity quality results, 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) seasons, given the heterogeneity in both consumption and service quality across seasons. November to March is the period of peak electricity consumption and also the time when electricity quality problems are worst.

We then build upon this analysis to assess whether the treatment has differential impacts depending on home ownership status. 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).

The results are presented in Table 3. We find that 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 we found in Section 5.1. There is no significant impact on billed electricity consumption in the non-heating season (Column 2). This is consistent with pre-intervention peak season electricity quality being quite poor, but less room for improvement off-peak. We also use wild-bootstrapping and randomization inference to compute p-values for the coefficients (Appendix Table A8). Further, an event study analysis (Appendix Figure A7) also illustrates the impacts on monthly billed electricity consumption across seasons and over time and shows a statistically significantly higher billed electricity consumption in treatment households, relative to control households, during the post-intervention peak months.

These findings support the claim that the increase in billed consumption is due to improvements in service quality. To exclude the possibility that the smart meters were just making consumers more attentive to their electricity bills and thereby affecting consumption, we check for differential bunching around the tariff discontinuity at 700kWh. When the increasing block price was introduced in Kyrgyzstan several years before our intervention, the regulator implemented information campaigns to inform residential consumers how their various appliances contributed to their bills and reaching the 700 kWh cutoff (see example in Appendix Figure A8) and prior research has shown that households were well aware of the tariff discontinuity (McRae and Meeks, 2016). If the smart meters were inducing consumers to more closely watch their consumption, then we could expect to see greater bunching among the treated households just below the 700kWh cutoff; however, we find no evidence of this behavior (Appendix Figure A9).

We address one potential concern with this estimation: that households with different consumption patterns pre-intervention (e.g., during the heating or non-heating season) will respond differently to the installation of smart meters. As a robustness check to address this concern, we re-run the regressions controlling for monthly billed electricity consumption in 2017 (well before the smart meter installation). The corresponding results are robust to including these controls (Appendix Table 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

Thus far, we have shown that electricity quality improves after the intervention and that household billed electricity consumption data indicates that households are impacted by the electricity quality improvements.

To better understand households' responses to the improvements in electricity quality, in terms of technological adaptations and expenditures, we utilize household survey data,[12] which asked about electrical appliance ownership and purchase timing, providing a panel dataset of these variables. The survey timing 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. Additional checks with randomization inference and wild-bootstrap p-values are in Appendix Table A10. 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.

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

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. With this possibility in mind, we asked follow-up survey respondents if they made any energy efficiency improvements to their house since the end of 2018 (i.e., the time of the meter installation).

Using the same estimation equation as we did with appliances, 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. We also use wild-bootstrapping and randomization inference to compute p-values for the coefficients (Appendix Table A11). Treated households were more likely to report making energy efficiency improvements since the intervention. Specifically, treated households are significantly more likely to report having replaced the windows on their homes.

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 A14).

6 Consumer Welfare and Electricity Quality Improvements

In this section, we estimate the consumer welfare gains from the electricity service quality improvements. We then discuss the broader implications of our findings and how they generalize to other contexts.

6.1 Welfare Estimates

To perform these estimates, we isolate the changes in billed electricity consumption resulting from the voltage fluctuation improvements induced by the household smart meter installation and the transformer repairs that followed.

This analysis requires the creation of several additional variables not employed in the earlier analyses. We create an aggregate electricity quality measure using data on transformer-level alarms and match it with the corresponding households served by each transformer. As a final outcome measure, we focus on the value of the household billed electricity consumption during the peak season (i.e., from November to March), as that was the period of greatest electricity demand and worst service quality pre-intervention. We calculate the total or monthly average billed electricity consumption during this period after the intervention for each household.

Using this post-period data on both electricity quality and electricity bill value, we estimate the gains from the smart meter installation and the resulting electricity quality improvements employing an instrumental variable approach. In the first stage, we estimate the effect of the smart meter intervention on electricity service quality as follows:

$$\text{Quality}_{ig} = \alpha \text{Treat}_g + X_i + \epsilon_{igt}, \tag{4}$$

where Quality_{ig} is the monthly average number of voltage fluctuation events during the heating season experienced by household i served by transformer g. Treat_g is an indicator of transformer treatment status. X_i is a vector of control variables, including household characteristics (e.g., number of rooms, home ownership indicator), transformer characteristics (e.g., number of household served by the transformer, capacity), and baseline billed electricity consumption and service quality measures.

In the second stage, we use the predicted change in electricity quality from the first stage to estimate the impact of improvement in electricity service quality on the household electricity bill value. We do so as follows:

$$q_{ig} = \beta \widehat{\text{Quality}}_{ig} + X_i + \epsilon_{igt}, \tag{5}$$

where q_{ig} is the total or average monetized billed electricity consumption during the heating season from November 2018 to March 2019 (kWh) for household i in transformer g. $\widehat{\text{Quality}}_{ig}$ is the estimated outcome from the first-stage regression. X_i is the same vector of control variables as above.

Results are in Table 6. Column 1 contains the results from the first-stage regression: the impact of transformer treatment assignment on electricity quality. Column 2 provides the second-stage results: the impact of estimated electricity quality on billed electricity consumption. The coefficients can be interpreted as the marginal increase in monetized electricity consumption with respect to the decrease in the monthly average outage or voltage fluctuation. Based on the regressions in Columns 1 and 2, we estimate that for the treated households, their returns to electricity quality improvements are 523.4 KGS (13.085 $\times$ 40) over the 5 months period, which is approximately 7.64 USD per household. Columns 3 and 4 of the table provide a slightly different estimation, resulting in estimated returns to electricity quality improvements of approximately 9.23 USD per household over the five month period. We also use wild-bootstrapping to compute p-values for the coefficients (Appendix Table A13).

The estimation requires that the exclusion restriction holds, which means that the intervention impacts electricity bill value only through the electricity quality improvements. We argue that this assumption is reasonable. We discuss three potential concerns regarding the exclusion and provide supporting evidence as to why the exclusion restriction holds. First, we might be concerned that the smart meters are able to "read" electricity consumed at the low voltage and therefore can 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. 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 this were the case, then we would expect that either households ex ante would have invested in equipment that protects appliances or we should see that treated households invest less in such protective equipment than control households post-intervention. We saw no evidence of the former in our baseline summary statistics (i.e., Table 1 showed almost no baseline use of stabilizers, one of the primary available forms of appliance protection). We tested for the latter (Appendix Table A14) and found that 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. We use data from the transformer-level smart meters, which also alert the utility of suspected theft events to check whether the treated and control groups had differences in the frequency of theft events post-intervention. We find no evidence that the intervention impacted theft-related measures (Appendix Table A15).

6.2 Discussion of Estimates and Generalizability

To put the estimated consumer welfare gains from electricity quality service improvements into context, we discuss the experiment setting and compare the gains to the costs of infrastructure improvements. Lastly, we consider how the results may generalize to other settings.

First, we aggregate the consumer welfare gains at the transformer level to put these results in context. Assuming 79.6 households per transformer (based on the treatment transformer baseline statistics), we calculate the aggregate consumer welfare gains to be between 608 to 735 USD per transformer in the first year post-intervention. Comparing these gains to the cost of substantial transformer maintenance (approximately 2,190 USD) or a complete transformer overhaul (approximately 4,670 USD), provides some context for these gains. However, we are careful in this comparison, given this paper is not attempting a utility-perspective cost-benefit analysis of smart meters.

These gains are based solely on the additional electricity consumed and therefore do not account for the potentially larger benefits acquired from the 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 estimates based on electricity consumption gains alone provide an underestimate of the true 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.[13]

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.

Further, a complete welfare analysis should also consider the costs (e.g., environmental costs due to releasing harmful pollutants such as SO2, 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.

7 Conclusions

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 installa-

[13] 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.

tion. Billed electricity consumption increased during the peak season, which is when electricity quality was worst pre-intervention. 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, our evidence on the heterogeneous treatment impacts across household 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 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

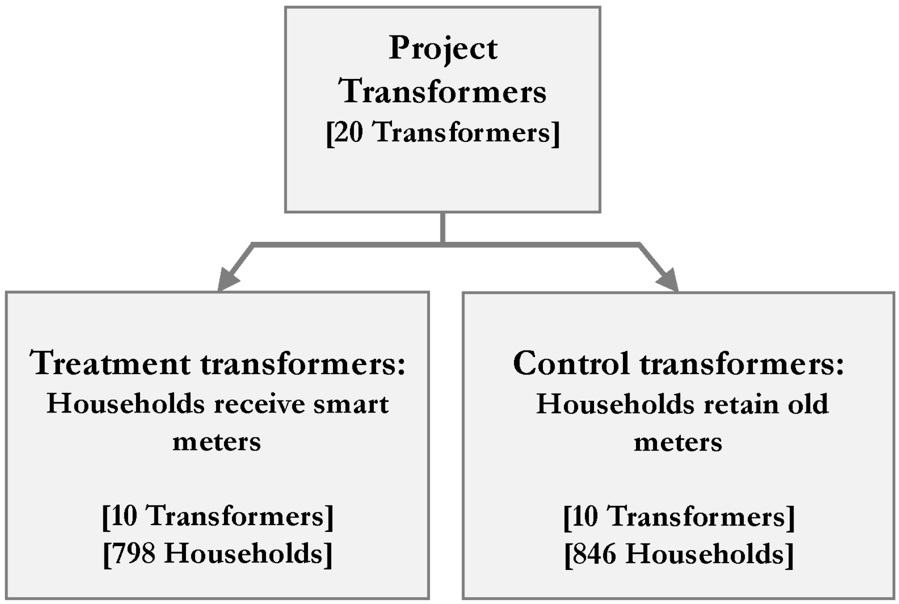

Figure 1: Randomized Design

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.

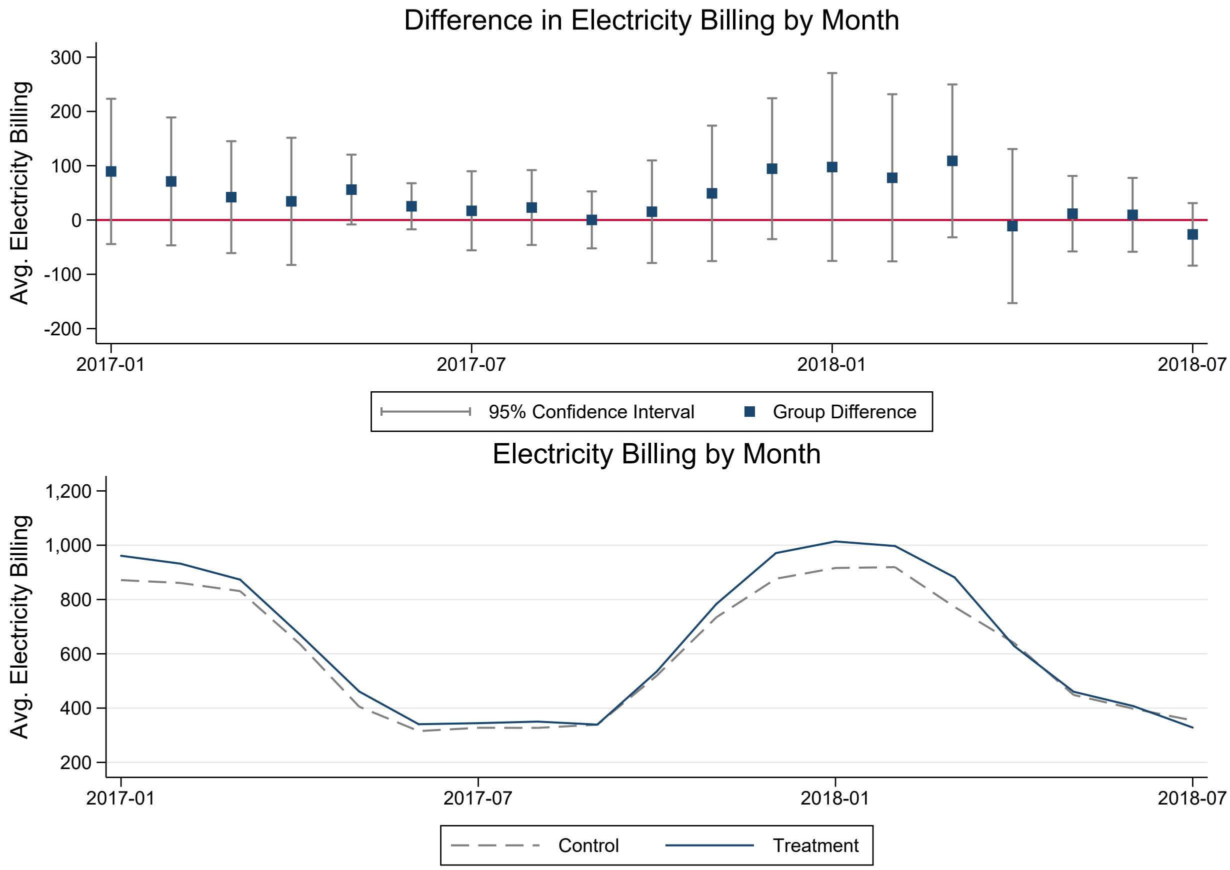

Figure 2: Billed Electricity Consumption before Smart Meter Installation

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

Table 6: Returns to Electricity Service Quality Improvements

	(1) Quality alarms	(2) Bill sum: all heating months	(3) Quality alarms	(4) Bill mean: per heating month
Treat	-40.284***		-40.284***	
	(11.331)		(11.337)	
Quality alarms		-13.085**		-3.140**
		(5.678)		(1.305)
Observations	871	871	871	864
R-squared	0.445	0.711	0.445	0.713
Baseline Controls	✓	✓	✓	✓
Estimate	IV Stage 1	IV Stage 2	IV Stage 1	IV Stage 2
K-P F-statistics		12.64		12.66

Notes: Regressions are restricted to the households for which we have a balanced panel. The ”Quality alarms” variable is the transformer-level monthly average alarms indicating problems during the heating season. “Bill sum” is the total monetized electricity consumption for all fiver winter heating months from November to March. “Bill mean” is the average monthly monetized electricity bill per month during the winter heating season. All regressions control for both households (number of rooms, whether the home is owned or rented) and transformer characteristics (number of households served by the transformer and the transformer capacity (kW)). Additionally, regressions control for the baseline electricity quality, using household self-reported reliability from the baseline survey conducted in May 2018. Columns 1 and 2 control for the baseline bill sum. Columns 3 and 4 control for baseline bill mean. Standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

APPENDIX: FOR ONLINE PUBLICATION

A1 Additional Figures and Tables

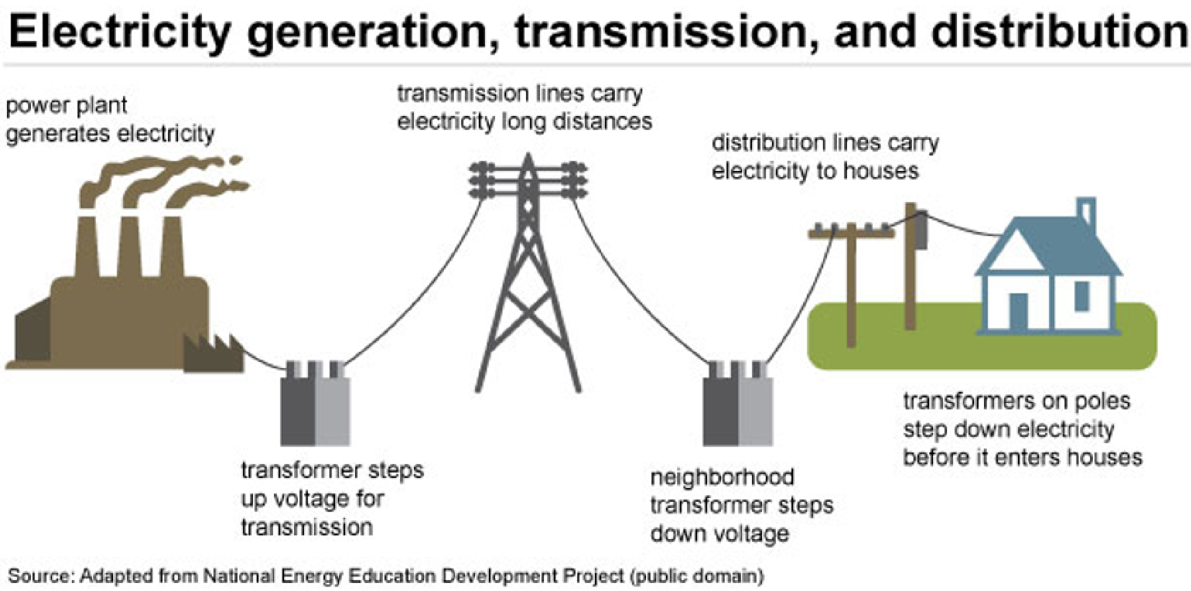

Figure A1: Intervention within the distribution system

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.

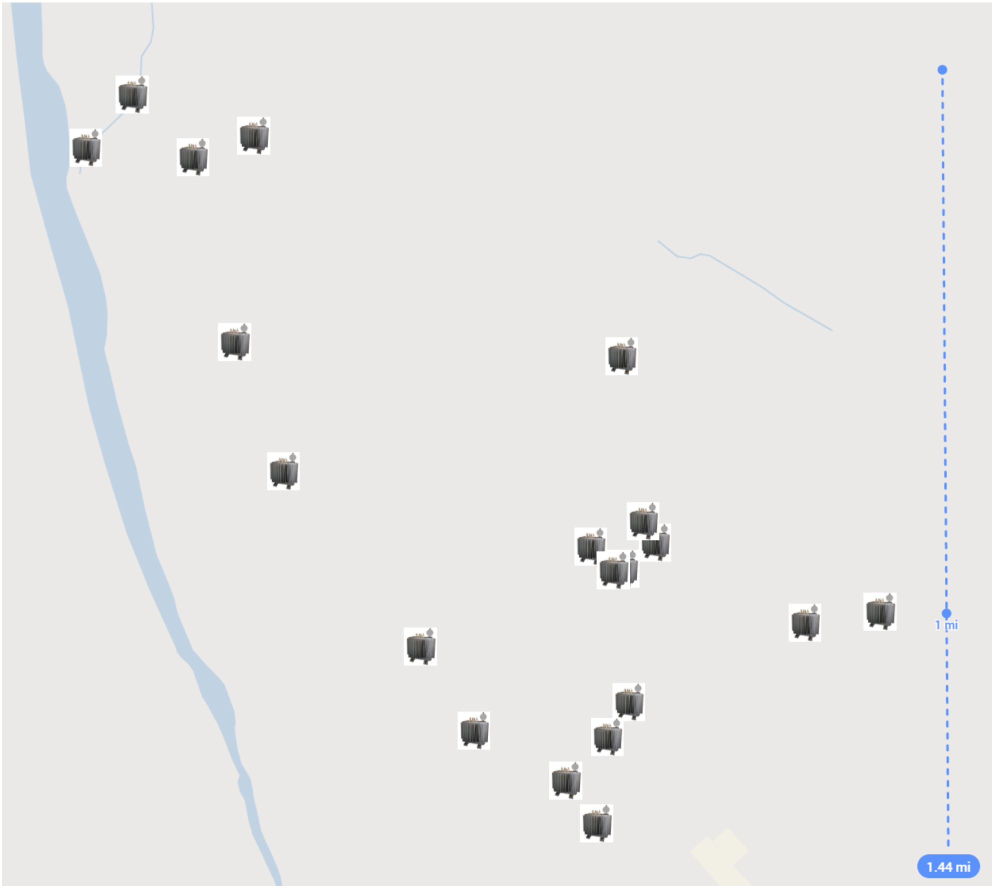

Figure A2: Transformer Locations

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.

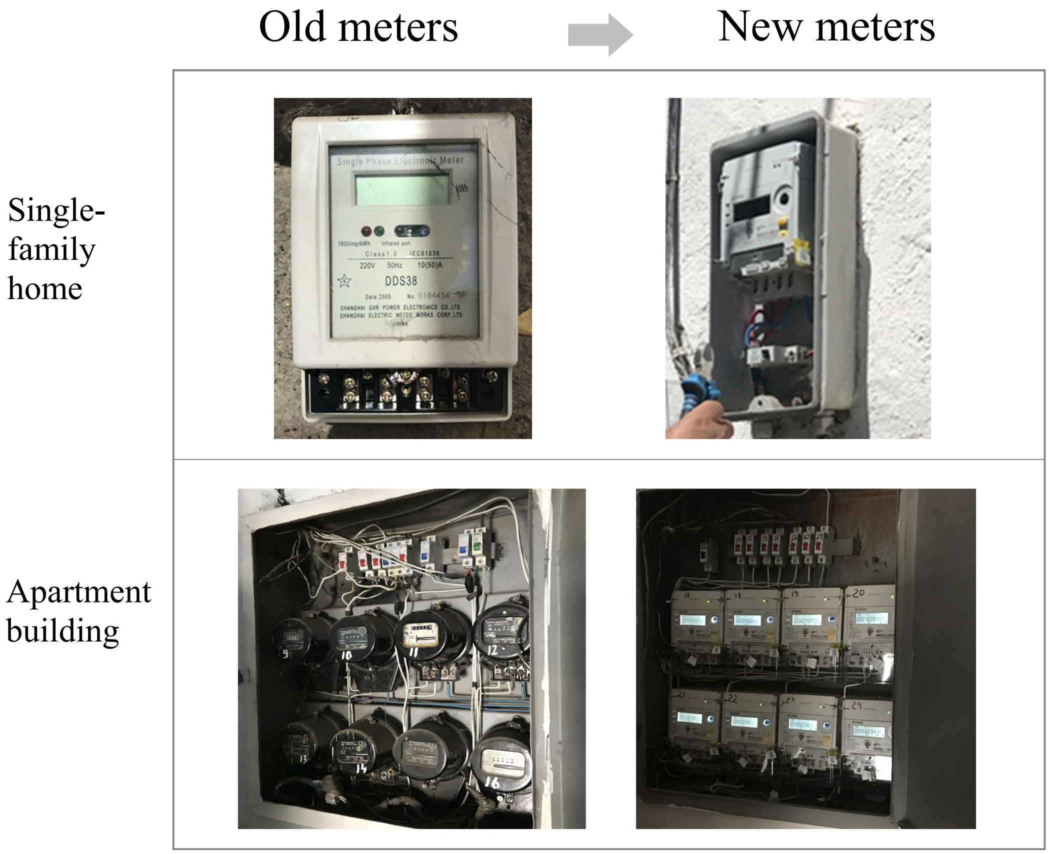

Figure A3: Photo Examples of Old Meters and Newly-installed Smart Meters

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.

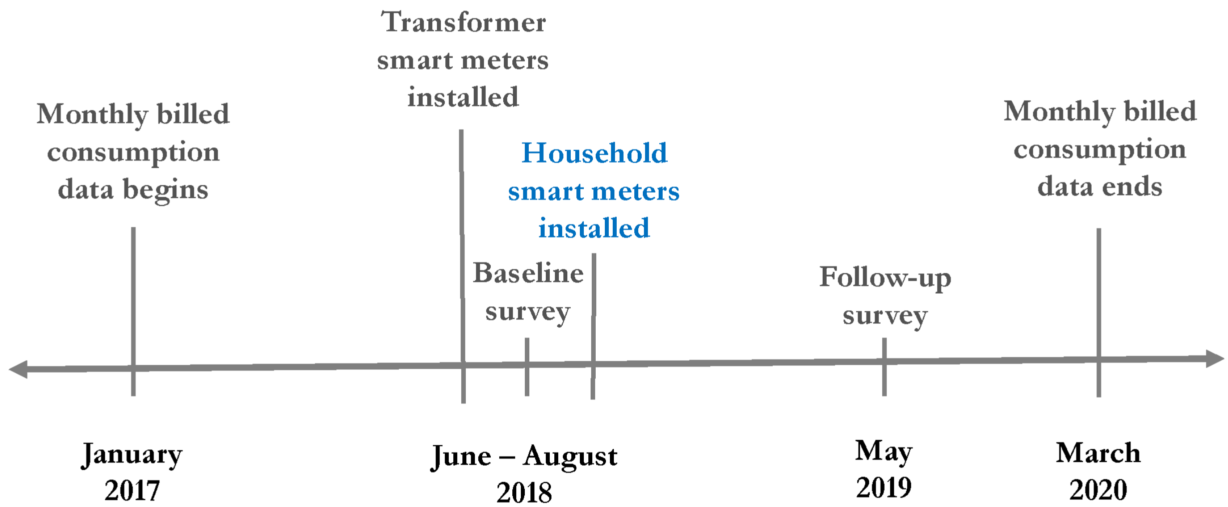

Figure A5: Timeline of Meter Installation and Data Collection

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

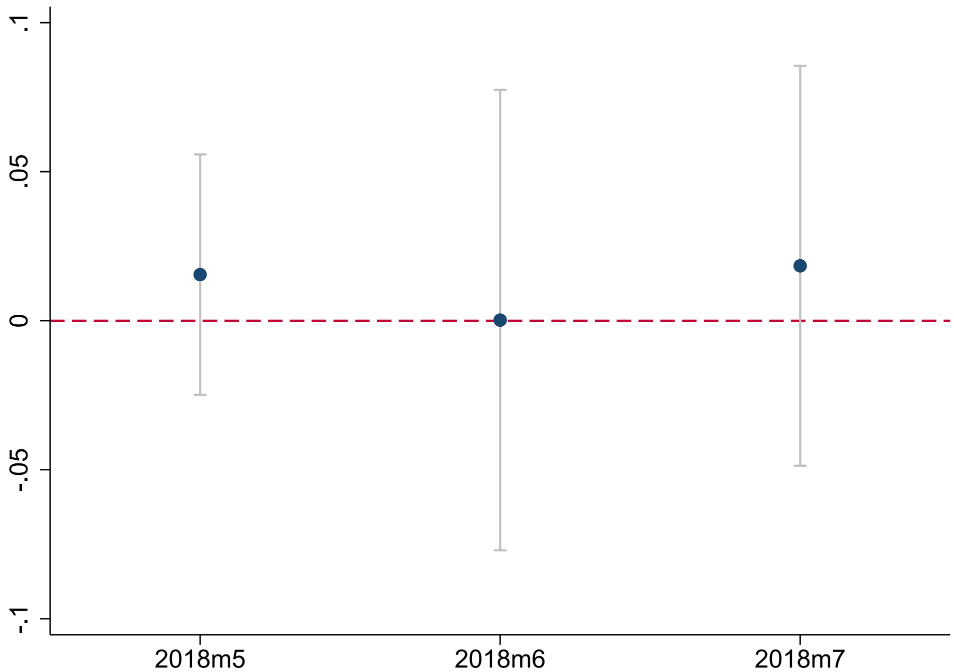

Figure A6: Difference in Total Number of Transformer Alarms before the Intervention

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 (Heating vs. Non-heating) (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.

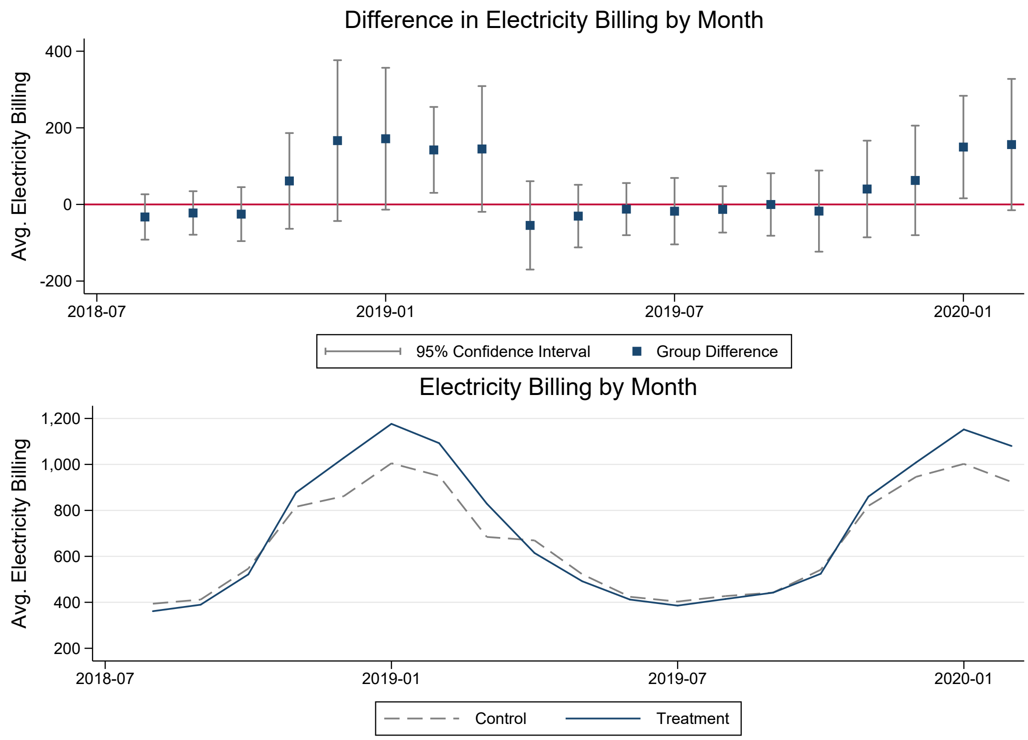

Figure A7: Billed Electricity Consumption (kWh/month) after Smart Meter Installation

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.

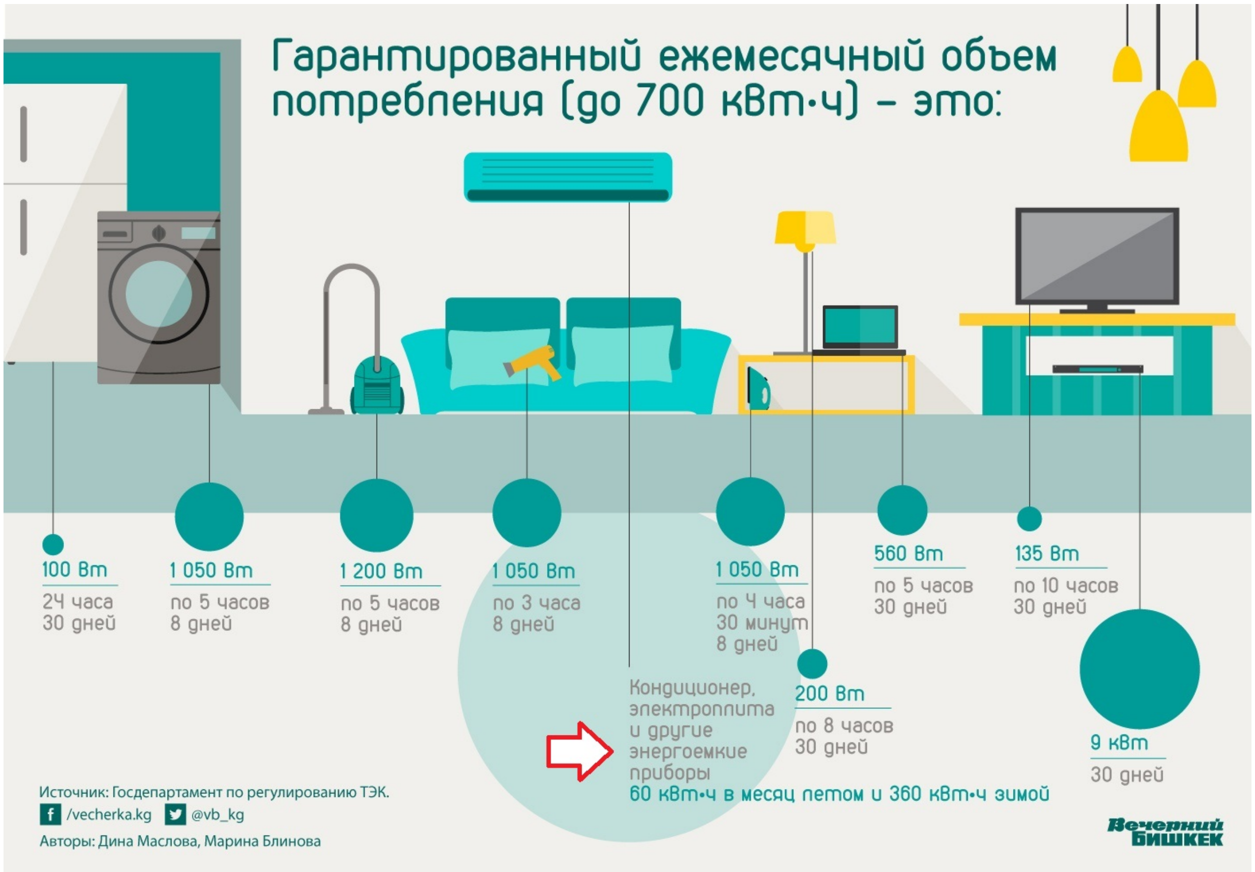

Figure A8: Information Campaign to Inform Residents as to How Appliances Contribute to Electricity Bills

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."

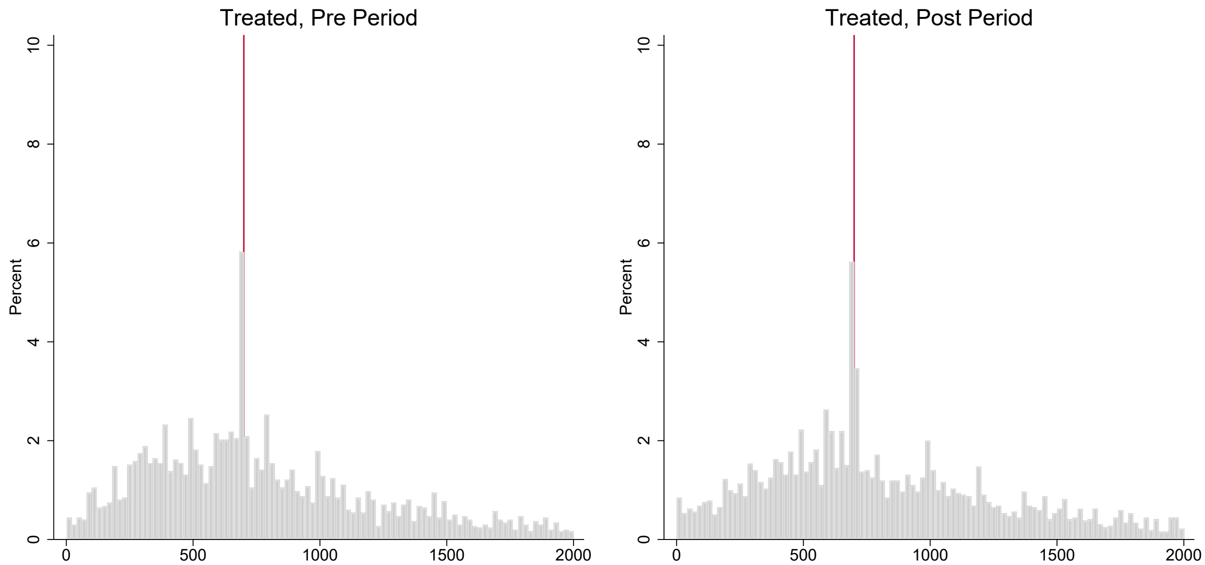

Figure A9: Distribution of Billed Electricity Consumption During the Heating Season

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 (Heating vs. Non-heating)

Monthly electricity bill (kWh):	(1) Heating Season	(2) Non-heating Season	(3) Heating Season	(4) Non-heating Season
Treat × Post	49.574**	10.598	161.337***	-0.572
	(22.279)	(17.360)	(46.658)	(17.766)
Treat × Post × 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 $\times$ 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 $\times$ Post $\times$ 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. *EElight* 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: Returns to Electricity Service Quality Improvements (with wild-bootstrapped p-values)

	(1) Quality alarms	(2) Bill sum: all heating months	(3) Quality alarms	(4) Bill mean: per heating month
Treat	-40.284***		-40.284***	
	[0.008]		[0.008]	
Quality alarms		-13.085**		-3.140**
		[0.065]		[0.055]
Observations	871	871	871	864
R-squared	0.445	0.711	0.445	0.713
Baseline Controls	✓	✓	✓	✓
Estimate	IV Stage 1	IV Stage 2	IV Stage 1	IV Stage 2
K-P F-statistics		12.64		12.66

Notes: Regressions are restricted to the households for which we have a balanced panel. The "Quality alarms" variable is the transformer-level monthly average alarms indicating problems during the heating season. "Bill sum" is the total monetized electricity consumption for all fiver winter heating months from November to March. "Bill mean" is the average monthly monetized electricity bill per month during the winter heating season. All regressions control for both households (number of rooms, whether the home is owned or rented) and transformer characteristics (number of households served by the transformer and the transformer capacity (kW)). Additionally, regressions control for the baseline electricity quality, using household self-reported reliability from the baseline survey conducted in May 2018. Columns 1 and 2 control for the baseline bill sum. Columns 3 and 4 control for baseline bill mean. 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 A14: 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 A15: Theft Alarms

	(1)
Alarms in one day indicating:	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 A16) and the event alarms from the household smart meters directed utility's attention to the transformers in greatest need of repairs (Appendix Table A17). Those transformer repairs result in improved electricity service quality, as measured by both event alarms (Appendix Table A18) and consumers' perceived quality improvements (Appendix Table A19).

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.[14]

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.

[14] 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 A16, 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.[15] Indeed, treated transformers that were replaced did have significantly more household-level alarms per day prior to the replacement (Appendix Table A17), 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 A18). 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 A19); however, we are

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

cautious not to interpret this as a causal relationship, given that replacements and repairs are determined by electricity service quality.

Table A16: 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 A17: 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 A18: 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 × 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 A19: 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 (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).