Smart Meters and the Benefits from Electricity Quality Improvements*

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Abstract

With hundreds of millions of households depending on grid connections that provide low quality and unreliable electricity services, this poor quality is considered a barrier to development. In the Kyrgyz Republic, we investigate the impacts of and residential consumer response to electricity quality improvements through a randomized installation of smart meters – a technology that utilities can install to improve electricity service quality. Service quality improvements led to increased billed electricity consumption during peak months. Residential consumers responded by increasing expenditures on household appliances and investing in energy efficiency.

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1 Introduction

Poor service quality is documented in a number of public sectors, including education, health care, and social assistance (Duflo et al., 2012; Dhaliwal and Hanna, 2017; Das et al., 2016; Callen et al., 2016; Banerjee et al., 2018; Muralidharan et al., 2018). Service quality is similarly problematic for infrastructure sectors, including those delivering water and electricity services. 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) with hundreds of millions of households depending on grid connections that provide low-quality and unreliable electricity services (Day, 2020). Low-quality and irregular electricity services limit consumption of electricity services (Zhang, 2018) and likely attenuate the economic benefits from grid connections (Pargal and Ghosh Banerjee, 2014; Samad and Zhang, 2016; Timilsina et al., 2018).

With low returns to electrification found in some contexts (Lee et al., 2020b; 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), differences in electricity service quality provide a potential explanation for electrification's heterogeneous impacts across settings (Lee et al., 2020a). With this in mind, development organizations and governments increasingly emphasize not only expanding the number of electricity connections, but also improving electricity service quality for existing connections.[1] Although recent evidence suggests substantial willingness-to-pay for improved electricity service quality (Alberini et al., 2020; Deutschmann et al., 2021), little causal evidence exists on the benefits from – and consumer response to – electricity quality improvements.

This paper reports results from a randomized installation of smart meters in the Kyrgyz Republic, a lower-middle-income country in Central Asia. Utilities increasingly in-

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

stall smart meters to address electricity sector challenges,[2] and many entities argue that smart meters can improve service quality and grid reliability.[3] Although these returns to smart meters could be substantial, their installation can be controversial (e.g., Smith (2009)). In this paper, we first document the electricity service quality improvement that followed the smart meter installation and then estimate consumers' responses to these electricity quality improvements through their billed electricity consumption, household expenditures, and energy efficiency investments.[4]

Smart meters themselves cannot directly improve electricity service quality; however, through high-frequency energy readings (i.e., readings occur often), they can facilitate improvements. The smart meters provide two-way communication between the meter and the utility, providing information on outages and other service quality problems (e.g., voltage fluctuations) within the distribution system. Alarms from the meters alert the utility to problems, allowing for faster, more targeted responses to the necessary locations. Additionally, smart meters automatically disconnect houses from the electricity supply when the voltage spikes or drops, both protecting consumers' appliances from damage and providing consumers with evidence of substandard service quality.

Contracting between an electricity utility and its customers should mitigate poor service quality; however, this often breaks down in practice, likely because of insufficient information to enforce these contracts on both sides. 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

[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]For examples, see industry news (e.g., Sprinz (2018)), North American electricity utility websites (e.g., Duke Energy Progress (2020) and BC Hydro (2016)), United States Government investment assessments (U.S. Department of Energy, 2014), and multi-lateral development bank reports (ESMAP, 2019).

[4]This focus on smart meters to improve electricity quality differs from prior economics research that has used smart meters primarily 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. For examples, see Wolak (2011), Jessoe and Rapson (2014), and Ito et al. (2018). In our study setting, there are no in-home displays to provide information on prices, etc.

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.

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.[5] These transformers, and the approximately 1,600 households that they serve, were randomly assigned to treatment or control status. In 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, high-frequency energy readings, or alerts of poor service quality events, nor did the old meters automatically shutoff connections when voltage spikes and drops occur. 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 (Carranza and Meeks, forthcoming). As a result, most prior economics research on electricity quality has employed electricity shortages as a proxy for service quality. In this paper, 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' experienced electricity service quality, as well as data on household expenditures, appliances,

[5] 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).

and energy efficiency investments. These datasets are complemented by utility data on household billed electricity consumption over time, as well as details on the electricity distribution system's characteristics.

Results confirm that the smart meters led to improvements in service quality. We find that incidences of voltage fluctuations (spikes and drops) were significantly less frequent among the treated group, relative to the control, post-intervention. This effect persisted into the second year following the smart meter installation.

Building upon this, our analyses provide evidence on the consumer response to the smart meters and the electricity quality improvements that followed. First, we find that treated houses' monthly billed electricity consumption increased during months of peak demand (November to March) and decreased during off-peak months (April to October). The increase in peak months is consistent with unmet demand prior to the intervention and improved electricity service quality and greater consumption thereafter. Prior to the intervention, electricity service quality was most problematic during these peak demand months, when outages and voltage fluctuations occurred frequently. As a result, these months are the time when quality improvements could occur. 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. In our setting, smoothing electricity consumption during the winter is important for household safety and health, as the peak demand is driven by electric heating.

We investigate potential explanations for these effects on billed electricity consumption. 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: treated households' quarterly expenditures on home appliances increased by 14 USD. We cannot, however, rule out the former explanation.

The impacts on off-peak billed electricity consumption likely occur through a different channel than the on-peak impacts, given service quality was not problematic during these months. Instead, the decrease in off-peak billed electricity consumption could result from increased investment in energy efficiency or energy saving behaviors, more broadly. Having experienced increased billed electricity consumption in the first months post-intervention, treated households may have invested in energy efficiency and household improvements. We find evidence that treated households were more likely to invest in upgrading their windows - a weatherization improvement that increases a building's retention of heat in the winter and cool air in the summer. This impact on house weatherization, in conjunction with the common residential use of electric heating, implies that the increase in on-peak billed electricity consumption would have been even larger in the absence of these energy efficiency gains. Without meters on individual appliances, we cannot rule out electricity-saving behavioral changes that might have occurred in addition to these energy efficiency investments.

To conclude, we assess consumer returns to the electricity quality improvements during peak months. We estimate that these returns are approximately 28 USD per house per year, which is between one-half to one-third the cost of a smart meter. This finding, in addition to the positive impacts on household appliance investments, is indicative of consumer benefits from these electricity service quality improvements.

Broadly, this paper contributes to experimental research on methods to – and impacts of – improving 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). More specifically, we contribute to literature on the role of service quality in electrification and development. Providing evidence of consumer gains – with respect to increased electricity consumption and appliance investments – following electricity service quality improvements, adds important insights to the existing research on the economic impacts of electrification in developing countries (Dinkelman, 2011; Lipscomb et al., 2013; Rud, 2012; Van de Walle et al., 2013; Usmani and Fetter, 2019; Lee et al., 2020b; Burlig and Preonas, 2016; Meeks et al., 2021). Further, 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.

Understanding residential consumers' responses to changes in electricity quality is important for development planning. Pro-poor growth in developing countries is expected to result in greater household appliance ownership and increased residential electricity demand (Wolfram et al., 2012). Residential electricity consumers, however, may not adapt to low service quality through the same mechanisms as firms, such as self-generation (Steinbuks and Foster, 2010), and their appliance ownership and use and demand for electricity services likely depend on the quality of services delivered (McRae, 2010). Yet, little empirical evidence exists on such responses.

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

2 Electricity Quality, Demand, and Smart Meters

In this section, we first describe types of poor electricity quality and discuss the potential role of smart meters in service quality improvements. We then illustrate how consumers may benefit from and respond to electricity quality improvements through a conceptual framework.

2.1 Forms of Poor Electricity Service Quality

There are mainly two types of poor electricity service to consider: unreliable service due to outages and low service quality due to voltage fluctuations.

Unreliable Service Due to Outages. An outage is a complete stoppage within the distribution system that prevents the delivery of electricity. 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.[6] Unplanned outages are typically due to infrastructure breakage, malfunction, and overloads.[7] These unplanned outages can be lengthy in duration, lasting until replacement parts are purchased and repairs are completed. Absent back-up generation, electrical appliances cannot be powered during a grid outage.

Low Service Quality Due to Voltage Fluctuations. Voltage fluctuations – a spike above or a drop below the standard acceptable voltage range – result from a number of reasons, including faulty and old distribution infrastructure, insufficient maintenance and repairs, or demand that exceeds the infrastructure's capacity.

2.2 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. If the utility monitors this information, it can respond quickly with repairs, maintenance, and overhauls. Second, smart meters can detect voltage fluctuations and automatically disconnect 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 extra step increases

[6] Rationing, which is commonly referred to as "load shedding," did not occur during our study period and therefore not further discussed in this section.

[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).

the salience of voltage fluctuations for consumers and provides evidence of unsafe voltage fluctuations. With this information, consumers may argue for better maintenance, upgrades, and repair. Without it, their complaints of voltage problems are typically unverified. If standard voltage does not resume, the smart meter prevents electricity flow until the utility performs the necessary repairs. Thus, the meters help the utility target efforts to the neediest locations within the distribution system, thereby potentially improving electricity service quality.

2.3 Conceptual Framework: Electricity Service Quality and Demand

In this subsection, we provide a conceptual framework as to how electricity quality changes affect demand for electricity services, including the role of smart meters. This framework is informed by existing literature (see e.g., Klytchnikova and Lokshin (2009), McRae (2010), and McRae (2015b).) A household's demand for electricity services is determined by the demand for services from each of the household's electrical devices. Changes in electricity service quality will also impact the demand for services from individual electrical devices. This 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.

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. Each of these service quality problems result in demand for electricity services that is not fully satiated, thereby negatively affecting billed electricity consumption.

Unreliable Service Due to Outages. We depict the relationship between an outage and the quantity of electricity services demanded in Scenario 1 of Figure 1. We first illustrate the quantity of electricity services demanded under standard (full) service quality (i.e., no outages and no voltage fluctuations). In this graph, the electricity service demand curve under standard (full) electricity service is depicted as D_S. Assuming a linear electricity price, p^0, the quantity of electricity services demanded will be q_S.[8]

Poor service quality can result in a quantity of electricity services consumed that is less than q_S. The demand curve during an outage, when no electricity is distributed and therefore no electricity services are consumed, is represented by D_N. However, when standard (full) electricity service (i.e., with no outage) resumes, the demand curve returns to D_S. As a result, if the billing cycle (e.g., one month) includes both periods of standard (full) supply, as well as periods of outages, the electricity bill will represent an average of the two. This quantity demanded, as observed on the electricity bill, is depicted as q_{Avg} in the figure. The extent to which q_{Avg} is less than q_S will depend on the frequency and duration of outages during the billing period (Klytchnikova and Lokshin, 2009) and the consumer response to those outages.

Consumers may have various responses to outages. They may opt to not purchase a certain appliance, particularly expensive appliances (e.g., an electric cooker). If this occurs, then the quantity of electricity services consumed will be lower than q_S. Alternatively, the consumer may not plug in an appliance already owned to consume its services if the appliance may be damaged by an outage.

If service quality improves after smart meter installation, then consumption of electricity services should increase due to greater consumption of the services provided by electrical devices in the home. If smart meters can reduce outages, then we may observe a shift in the quantity consumed, as observed on the electricity bill, from q_{Avg} to q_S. This potential shift is illustrated by the arrow in Scenario 1.

It is possible that consumer behavioral responses to changes in electricity quality and their electricity bills may push consumers away from q_S following the smart meter intervention. First, if consumers respond to the electricity quality improvements by purchasing additional electrical devices, then electricity consumption increases could be even greater than q_S. Alternatively, if consumers experience a higher electricity bill (than

[8]This is a simplification. In many contexts, including our study setting, consumers face a non-linear tariff. The overall intuition, however, remains the same.

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 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, the electricity bills may actually decline.

Low Service Quality Due to Voltage Fluctuations. Voltage fluctuations can affect the quantity of electricity services demanded via multiple channels, some of which occur through the same mechanisms as outages. First, low voltage can mean that power is insufficient to run certain appliances, in which case the service 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 can damage it or render it unusable.[9] 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. We illustrate these forms of low-quality electricity service in Scenario 2 of Figure 1. The demand curve during periods of low-quality service, when electricity services may be consumed but at a

[9] 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 within the study setting.

lower quantity than standard (full) supply, is represented by D_L. As shown in the figure, the quantity of electricity services consumed when there are voltage fluctuations, q_L, will be less than the quantity consumed under standard quality, q_S.

If smart meters can reduce voltage fluctuations, then we may observe a shift in the quantity consumed, as observed on the electricity bill, from q_L to q_S. This potential shift is illustrated by the arrow in Scenario 2.

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 information on the drivers of electricity consumption within the country. We 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. After reporting to the government oversight body, the consumer may recover from the supplier damages that result from a service interruption or voltage fluctuation. 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 survey respondents reported voltage problems, and approximately one-fifth of survey respondents reported damage to electrical appliances from poor electricity quality (World Bank, 2017a).

Electricity consumption has been changing 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.[10] Currently, consumption in the winter is approximately three to four times that of summer, a pattern that is indicative of the use of electric heating in the winter and the absence of air conditioning in the summer.

3.2 Randomized Experiment

In collaboration with one of the electricity distribution companies, the experiment was implemented in one city in the Kyrgyz Republic. 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).[11] Twenty transformers, which each serve a neighborhood of households, were selected for the project. A map of the 20 transformers shows that they are all located within a two-square-mile area (Appendix Figure A2). Transformers were randomly assigned to treatment or control status, with 10 transformers in each group. Houses served by the transformers in the treatment group (798 houses) received smart meters, and houses served by the control group of transformers (846 houses) retained their old meters (Appendix Figure A3). The utility replaced the old meters with smart meters at all houses in the treatment group in July and August 2018.

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

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

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

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 A4).

4.1.1 Transformer Smart Meter Data

During summer 2018, 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 and are for data collection purposes. These smart meters record "event alarms" indicating problematic events within the neighborhood covered by the transformer. Alarms can be activated for a number of reasons, including signs of electricity theft and indicators of poor service quality.[12]

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

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.

Transformer-level smart meter data are critical for the study. 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. Transformer smart meters were installed approximately two months before the intervention smart meters were installed at houses and therefore do not provide much pre-intervention data.

4.1.2 Baseline and Follow-up Survey Data

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

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

4.1.3 Utility Data

The electricity utility provided several datasets: first, transformer-level data including cross-sectional information on transformer characteristics (age of transformer, capacity, etc.) as well as monthly panel data starting in January 2017 and continuing for 33 months, including dates of overhaul maintenance, repairs, and replacements for all project transformers; second, 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 COVID-19.

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).

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. 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). Additionally, no significant baseline differences exist between the treatment and control households for 12 categories of household expenditures, including electricity and household appliances (Appendix Table A3). 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 and Appendix Table A5).

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 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 Confirming 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 two outcome measures are the number of transformer-level events per day indicating either voltage fluctuations or power outages. We estimate the following equation:

$$E_{gt} = \alpha \text{Treat}_g + \beta \text{Treat}_g \times \text{Post2}_t + \delta' \mathbf{X}_g + \gamma_t + \epsilon_{gt}, \tag{1}$$

where E_{gt} is the number of either voltage fluctuations or outage events recorded by the transformer smart meter per day for transformer g in time period t. Treat_g is an indicator of transformer treatment status equaling 1 for those randomly assigned to the treatment status. Post2 is a binary indicator that equals 0 in the first year after the intervention and 1 in the second, $\mathbf{X}_g$ 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.[13]

Results are presented in Table 2. Columns 1 and 2 present results from regressions in which voltage fluctuation events are the outcome variable. We find significantly fewer voltage fluctuation events per day in the treatment group than in the control group during the first year after the intervention (Column 1). 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. The coefficient on the interaction term, β, shows that this difference between the treatment and control groups persists into the second year. To account for any differences in electricity quality that might be driven by feeder line differences, we additionally include feeder line fixed effects in a second specification. Column 2 shows that the results are robust to their inclusion. Columns 3 and 4 display results from regressions in which power outage events are the outcome. Notably, the control group mean of 0.518 outage events per day is much less frequent than the voltage event mean. Column 3 shows a small and marginally significant increase in these events in the first year after the intervention. This positive coefficient could be due to outages from the increased transformer repairs. The coefficient on the interaction term indicates a change in the direction of the effect in the second year. These results, however, provide no evidence of a significant negative effect on power outage events relative to the control (as we saw with the voltage events). Lastly, as a robustness check, we run these regressions again, this time using the "other" events as the outcome measure. This is the category of alarms for which we anticipated no impacts, ex ante. The results in Columns 5 and 6 indeed show no significant differences between the treatment and control groups.

Transformer repairs and replacements appear to be the channel through which electricity service quality improved. Appendix A2 presents evidence on the mechanisms for electricity quality improvements, showing that the treated transformers were more likely to be overhauled or replaced (Appendix Table A12) and the event alarms from the house-

[13] Given the limited number of clusters, we report the wild-bootstrap p-values with main results.

hold smart meters directed utility attention to the transformers in greatest need of repairs (Appendix Table A13). Those transformer repairs result in improved electricity service quality, as measured by both event alarms (Appendix Table A14) and consumers' perceived quality improvements (Appendix Table A15).

To check that the voltage fluctuation and outage events 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. 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).

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 determining the extent to which consumers benefit from smart meter installation.

5.2.1 Billed Electricity Consumption

To motivate further analysis, we first present an event study analysis that illustrates the impacts on monthly billed electricity consumption across seasons and over time. Figure 3 shows a statistically significantly higher billed electricity consumption in treatment households, relative to control households, during the post-intervention peak months.

Building upon the event study, we estimate the impact of smart meters on household billed electricity consumption as follows:

$$\text{Bill}_{igt} = \beta_1 \text{Treat}_g \times \text{Post1}_t + \beta_2 \text{Treat}_g \times \text{Post2}_t + \lambda_i + \delta_t + \epsilon_{igt}, \tag{2}$$

where Bill_{igt} is the monthly billed electricity consumption by household i in transformer g in month 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 variables, Post1_t and Post2_t, are indicators equaling 1 for months within the first and second years after the intervention, respectively. This allows the estimated effects to change over time. 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.

The results are presented in Table 3. We find that household billed consumption significantly increased during the heating season in the first year after the intervention, but this increase does not persist into the second year (Column 1). The increase in year

1 is consistent with better service quality (i.e., fewer voltage fluctuations), as we found in Section 5.1. That the increase does not remain of a similar magnitude or statistically significant into the second year, suggests that households 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 subsections that follow. The billed electricity consumption in the non-heating season decreases (Column 2). This is also consistent with these same adaptations following the smart meter installation, suggesting that the household adaptations affect billed electricity consumption across seasons.

One potential concern is 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 addressing this concern, we rerun 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 A8).

5.2.2 Household Expenditures

Thus far, we have shown that electricity quality improves after the intervention and that household billed electricity consumption data indicates that household response changes over time.

To better understand households' responses to the improvements in electricity quality, in terms of technological adaptations and expenditures, we utilize household survey data.[14] Both the baseline and follow-up surveys asked about expenditures for the previous months, providing a panel dataset of these variables. The follow-up survey was implemented in May 2019. The survey timing is important for understanding household

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

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 expenditures as follows:

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

where Expenditure_{igt} is household expenditure (KGS) on categories of goods and services. 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.

Table 4 presents the corresponding results. We document a statistically significant increase in household electrical appliance expenditures of 13.58 USD over a three-month period (Column 11). This is consistent with households investing in more electrical appliances in response to the electricity quality improvements. None of the other expenditure categories change significantly between baseline and follow-up.

5.2.3 Energy Efficiency Investments

These increased electrical appliance expenditures could indicate either additional benefits in the form of new services, increased efficiency in services previously consumed, or both. 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).

We estimate the impacts of the smart meter intervention on households' investments in energy efficiency. Results are presented in Table 5. 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. Window replacement – an energy-efficiency investment promoted for these old homes – would explain why the peak billed electricity consumption increases do not persist into the second year.

We also test for patterns in specific appliance purchases and 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 A9). Households could also increase or decrease the number of appliances that they use; however, we find no significant effect on any of the large commonly used appliances (Appendix Table A10), nor do we find any effect on the total number of appliances owned (results not shown). Electricity-related device ownership is also not affected, although it was also low within the control group (Appendix Table A11).

6 Returns to Electricity Quality Improvements

In an effort to value the benefits to consumers from the smart meter intervention, we estimate the returns to these electricity service quality improvements. To do so, we isolate the changes in billed electricity consumption resulting from the voltage fluctuation and outage 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 reliability measure from household reported electricity service quality (the total number of outages and number of voltage fluctuations within a week), using household data from both the baseline and follow-up surveys.[15] As a final outcome measure, we focus on the household billed electricity consumption dur-

[15]We use the household reported quality measure because this variable exists for both the pre- and post-intervention periods, in contrast to the alarm data, for which we do not have baseline data. We consider this analysis to be sufficient because we previously showed that the measure is significantly and negatively correlated with smart meter alarms indicating electricity quality problems (Appendix Table A6), as expected.

ing the peak season (i.e., from November to March of the next year), as that was the period of greatest electricity demand and worst service quality pre-intervention. We calculate the total billed electricity consumption during this period both before and after the intervention for each household.

Using this panel data of both electricity quality and billed electricity consumption, we estimate the returns to the smart meter installation and the resulting electricity quality improvements employing a two-stage least squares approach. In the first stage, we estimate the effect of the smart meter intervention on electricity service quality as follows:

$$\text{Reliability}_{igt} = \beta_1 \text{Treat}_g \times \text{Post}_t + \beta_2 \text{Replace}_g \times \text{Post}_t + \beta_3 \text{Post}_t + \lambda_i + \epsilon_{igt}, \tag{4}$$

where Reliability_{igt} is the negative of the total number of outage and voltage fluctuation events within a week, self-reported by household i in transformer g during time period t. Treat_{ig} is an indicator of transformer treatment status, and Replace_{ig} is an indicator of transformer replacement status equaling 1 if the transformer has been replaced and 0 otherwise. The indicator variable, Post_t, equals 1 for the post-intervention heating season and 0 for the pre-intervention heating season. We include household fixed effects, λ_i, to control for time-invariant unobserved household characteristics.

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

$$q_{igt} = \beta_1 \widehat{\text{Reliability}}_{igt} + \lambda_i + \epsilon_{igt}, \tag{5}$$

where q_{igt} is the total monetized billed electricity consumption during the heating season from November to March (kWh) for household i in transformer g in time period t. $\widehat{\text{Reliability}}_{igt}$ is the estimated outcome from the first-stage regression, and λ_i represents household fixed effects.

The estimation requires that the exclusion restriction holds: the interaction of $\text{Replace}_g \times \text{Post}_t$ must not affect the monetized billed consumption except through changes in reliability. We argue this assumption is reasonable given the bounds set on the meter voltage fluctuations. 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, the meters automatically shutdown if voltage drops too outside of the safe range. This feature of the smart meters rules out this channel through which the smart meters might affect electricity consumption.

Results are in Table 6. Column 1 contains the results from the first-stage regression: the impact of transformer treatment assignment and replacement on electricity quality. Column 2 provides the second-stage results: the impact of estimated electricity quality on electricity consumption. The coefficients can be interpreted as the marginal increase in monetized electricity consumption with respect to the decrease in the weekly average outage or voltage fluctuation. The result in Column 2 indicates that reducing the number of electricity quality incidents (either voltage fluctuation or outage) by one per week on average results in 1,833 KGS more in billed electricity consumption over the five-month heating period. This is a welfare improvement of approximately 5.67 USD per month during the five months of peak electricity consumption (28.35 USD per year).

7 Conclusions

Results from this randomized experiment provide evidence on the effects of and returns to smart meters and the electricity quality improvements that followed. Utilities in both developed and developing countries are installing smart meters for a variety of purposes, such as reducing non-technical losses and increasing electricity service quality. These basic drivers play an important role in utility adoption of such smart technologies, yet to date they have received little attention in economics.

We find that consumers experienced improvements in electricity service quality following smart meter installation. These improvements include not only more stable voltage (i.e., fewer voltage fluctuations), but also the automatic shutoff that protects appliances against damage from voltage fluctuations. The returns to electricity quality improvements for consumers are substantial in magnitude. Better electricity service quality permitted greater electricity service consumption, and with those improvements, households invested more in electrical appliances.

These are important findings with 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 efforts to maximize the benefits from electrification, attention must be paid to the quality of electrical service, not merely access to electrical connections. The substantial benefits that accrue to consumers also imply that only focusing on the returns from meters to utilities would underestimate the full benefits of the technology.

To conclude, we note a handful of factors could affect the impact of smart meters and, which provide interesting topics for future research. First, in our study, information from smart meters was important for inducing quality improvements. There might, however, be other cost-effective ways to improve service quality without installing smart meters on individual houses and these alternatives are worth investigating. Additionally, the setting's electrification status and history may be important in determining benefits from the smart meters. For example, new electricity consumers (those without prior electricity access) might respond differently to smart meters than households that previously had low-tech meters and were shifted to smart meters. Given the high electrification rates in this setting, the study provides evidence on the latter, not the former. Lastly, benefits will also depend on the functionalities of the new metering technology employed and the extent to which these functionalities provide additional benefits beyond the status quo. Comparing the functionalities of different metering technologies could also be a fruitful area for further research.

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Figures and Tables

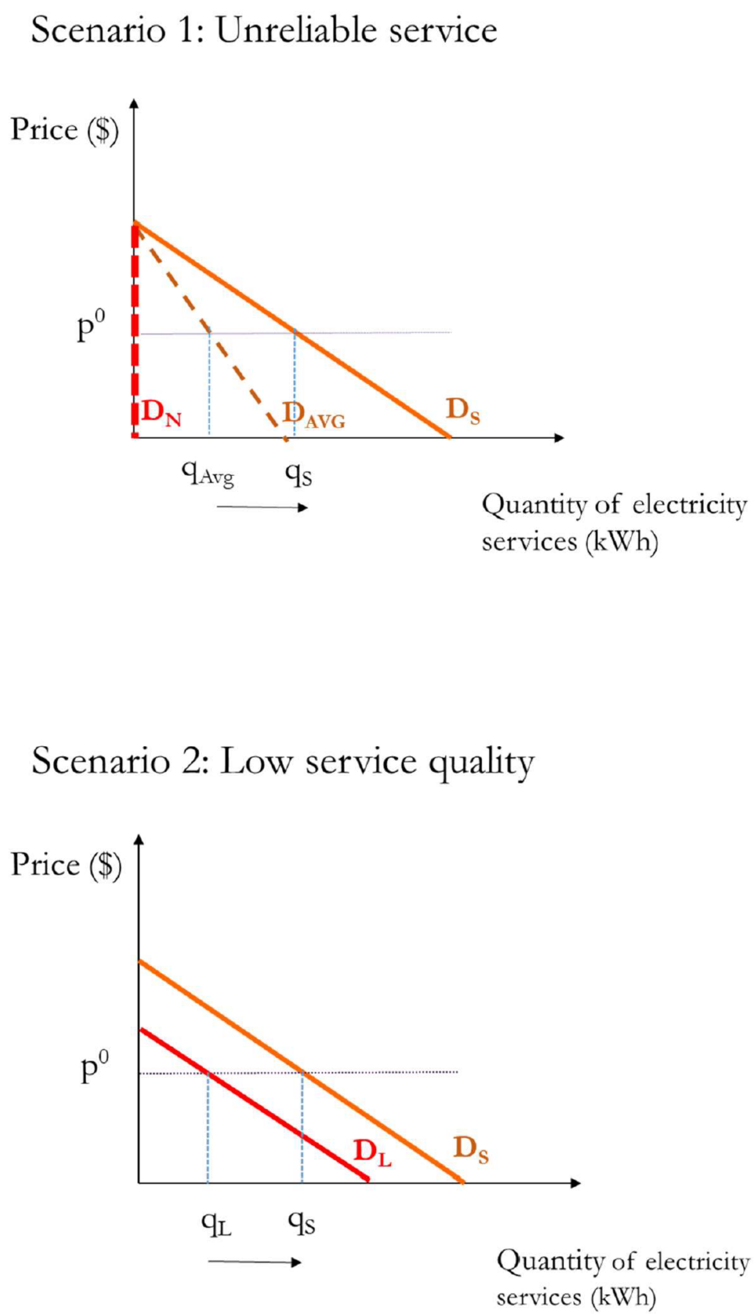

Figure 1: Framework for Impacts of Service Quality on Electricity Services Consumed

Notes: Graphs based on insights from Klytchnikova and Lokshin (2009) and McRae (2015b). In both scenarios the demand curve with standard quantity is denoted by D_S, and when facing the tariff price, p^0, households will consume quantity q_S. In Scenario 1, in which there is an outage, the demand curve during the outage will be D_N. The quantity that the utility reports on a monthly electricity bill is q_{Avg}, which results from an average of demand during periods with standard electricity service (D_S) and periods with outages (D_N). In Scenario 2, in which there are voltage fluctuations (e.g., low voltage), the demand curve is represented by D_L and the quantity observed on the electricity bill is q_L. The arrows denote the direction of the impact that smart meters would have on the quantity.

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)
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.

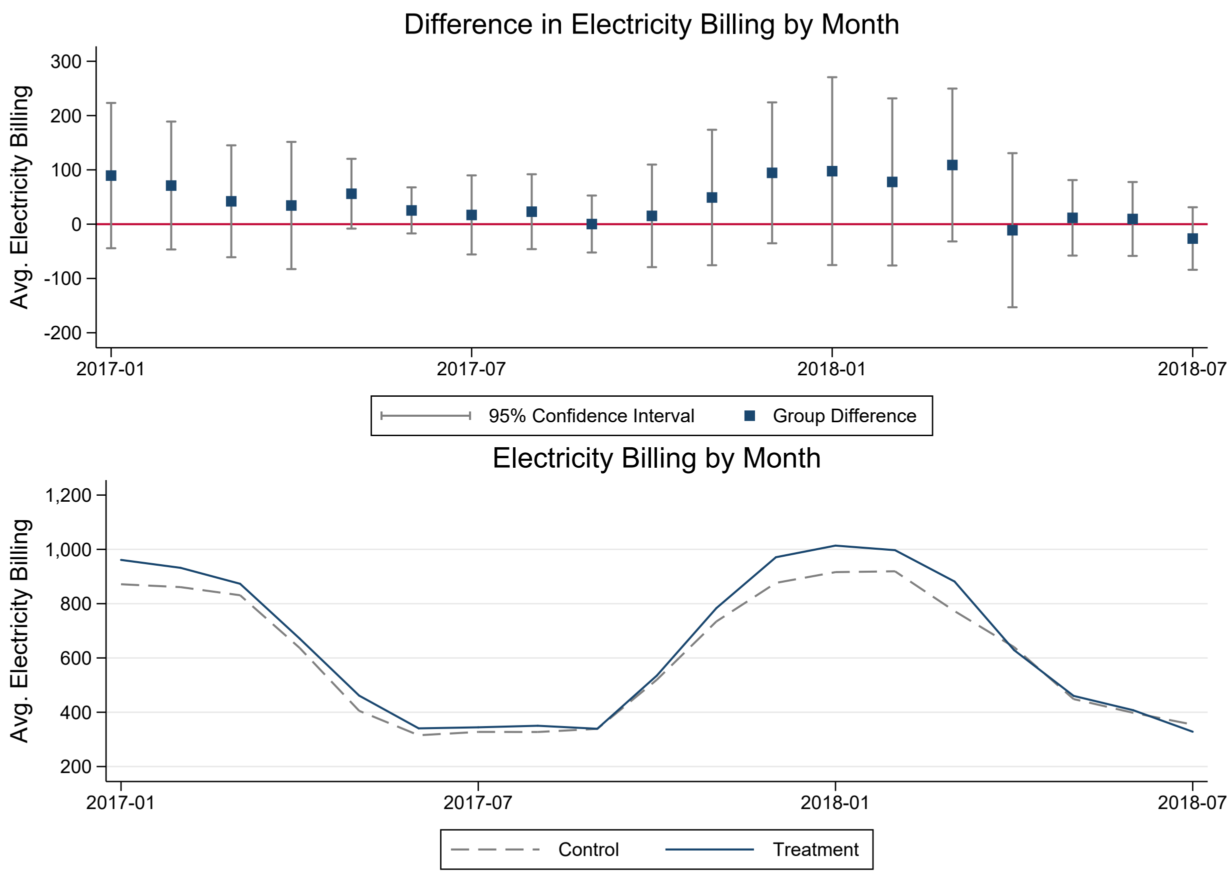

Figure 2: Billed Electricity Consumption before Smart Meter Installation

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

Events per day indicating:	Voltage problems		Power outage		Other types	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−2.339***	−2.336***	0.098*	0.087	0.702	0.636
	(0.655)	(0.728)	(0.056)	(0.058)	(0.634)	(0.576)
	[0.001]	[0.001]	[0.097]	[0.160]	[0.341]	[1.103]
Treat × Post2	0.106	0.105	−0.120	−0.118	0.493	0.503
	(1.249)	(1.233)	(0.076)	(0.076)	(0.532)	(0.539)
	[0.924]	[0.913]	[0.147]	[0.159]	[0.568]	[0.563]
Mean of Control Group	2.374	2.371	0.518	0.532	0.214	0.297
Observations	8,355	8,355	8,355	8,355	8,355	8,355
R-squared	0.104	0.104	0.052	0.053	0.043	0.045
Transformer Characteristics	✓	✓	✓	✓	✓	✓
Month-by-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Feeder Line Fixed Effects		✓		✓		✓

Notes: Event data are provided by the electricity utility covering the period from September 2018 to March 2020. The outcome variable is the number of events recorded by the transformer smart meter in one 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.

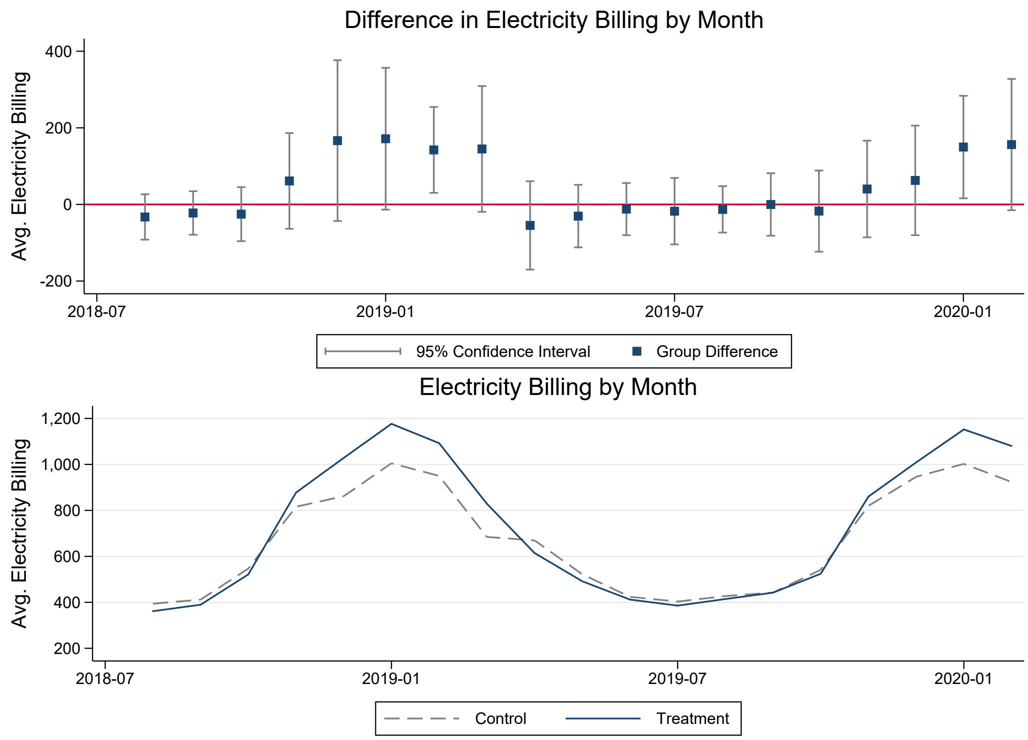

Figure 3: Billed Electricity Consumption (kWh/month) after Smart Meter Installation

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.

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

	(1) Heating Season	(2) Non-heating Season
Treat × Post1	59.292**	−37.749**
	(23.991)	(15.044)
	[0.041]	[0.016]
Treat × Post2	13.667	−21.666
	(18.469)	(27.262)
	[0.464]	[0.476]
Mean of Control Group	851.071	432.379
Observations	13,836	17,250
Number of Households	871	871
Adjusted R-squared	0.047	0.148
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. 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 4: Household Expenditures (in KGS)

	(1) food	(2) school	(3) electricity	(4) heat	(5) other utilities	(6) communication
Treat × Post	−406.227	−1,385.340	43.007	−31.678	−16.996	−40.338
	(317.531)	(2,430.723)	(99.299)	(63.439)	(35.757)	(58.840)
	[0.345]	[0.792]	[0.698]	[0.786]	[0.657]	[0.517]
Control Group Mean	2079.244	3991.788	338.849	2.067	236.284	403.260

	(7) transportation	(8) medical	(9) clothing	(10) house expenses	(11) house appliance	(12) discretionary expenses
Treat × Post	−114.256	263.149	−1,001.215	−2,156.205	930.803*	−9,950.487
	(332.172)	(350.966)	(785.362)	(3,398.171)	(467.199)	(20,259.367)
	[0.742]	[0.475]	[0.352]	[0.571]	[0.127]	[0.651]
Control Group Mean	1161.502	1587.556	3010.333	4919.822	1328.899	38750.120

Observations	1,760	1,760	1,760	1,760	1,760	1,760
Number of Households	880	880	880	880	880	880
Household Fixed Effects	✓	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓	✓

Notes: Data collected via household baseline and follow-up surveys. We restrict analysis to the balanced panel of households in both surveys. The outcome variables measure households' expenses on the corresponding items over the past week (food), past year (school), past month (electricity, heat, other utility, communication, transportation, medical), and past three months (clothing, house expenses, house appliance, discretionary). The reference time period for certain reported expenditures differs between the baseline and follow-up surveys. In these cases, we adjust the data to make it compatible across surveys. The exchange rate at time of the baseline survey was 1 USD to 68.5 KGS. 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 5: Changes in Home Energy Efficiency

VARIABLES	(1) made any change	(2) install insulation	(3) replace windows	(4) insulate windows	(5) change to energy-efficient appliances	(6) install energy-efficient light bulbs	(7) replace heating system
Treat	0.075*	−0.009	0.087***	−0.000	0.001	0.015	0.003
	(0.041)	(0.045)	(0.030)	(0.003)	(0.002)	(0.012)	(0.004)
Mean of Control Group	0.205	0.109	0.080	0.004	0.002	0.019	0.002
Observations	1,125	1,125	1,125	1,125	1,125	1,125	1,125
R-squared	0.024	0.021	0.020	0.001	0.002	0.003	0.002
Basic Characteristics	✓	✓	✓	✓	✓	✓	✓

Notes: Data collected through the household follow-up survey in May 2019. The outcome variables are binary variables 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. The outcome variable in column 1 equals 1 if the household reported making any of the changes reported in columns 2 through 7, and zero otherwise. 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 and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 6: Returns to Electricity Service Quality Improvements

	(1) Reliability	(2) Monetized Bill
Reliability		1,833.833***
		(551.304)
		[0.000]
Treat × Post	−0.796	
	(0.870)	
	[0.440]	
Treat × Replace × Post	2.222***	
	(0.632)	
	[0.178]	
Post	−0.991	
	(0.599)	
	[0.252]	
Observations	1,742	1,742
K-P F-statistics	84.46	
R-squared	0.039	
Number of Households	871	871
Household Fixed Effects	✓	✓
Estimate	IV Stage 1	IV Stage 2

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 May 2018 and May 2019, respectively. Billed electricity data are from the electricity utility. We calculated the total monetized electricity consumption in the winter for both the pre-intervention period and the post-intervention period and then merged it with household self-reported electricity service quality. *Reliability* is measured by the negative of the total number of outage and voltage fluctuation events within a week, self-reported by the households. *Monetized Bill* is the total monetized billed electricity consumption in the heating season from November to March. *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. 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.

APPENDIX: FOR ONLINE PUBLICATION

A1 Additional Figures and Tables

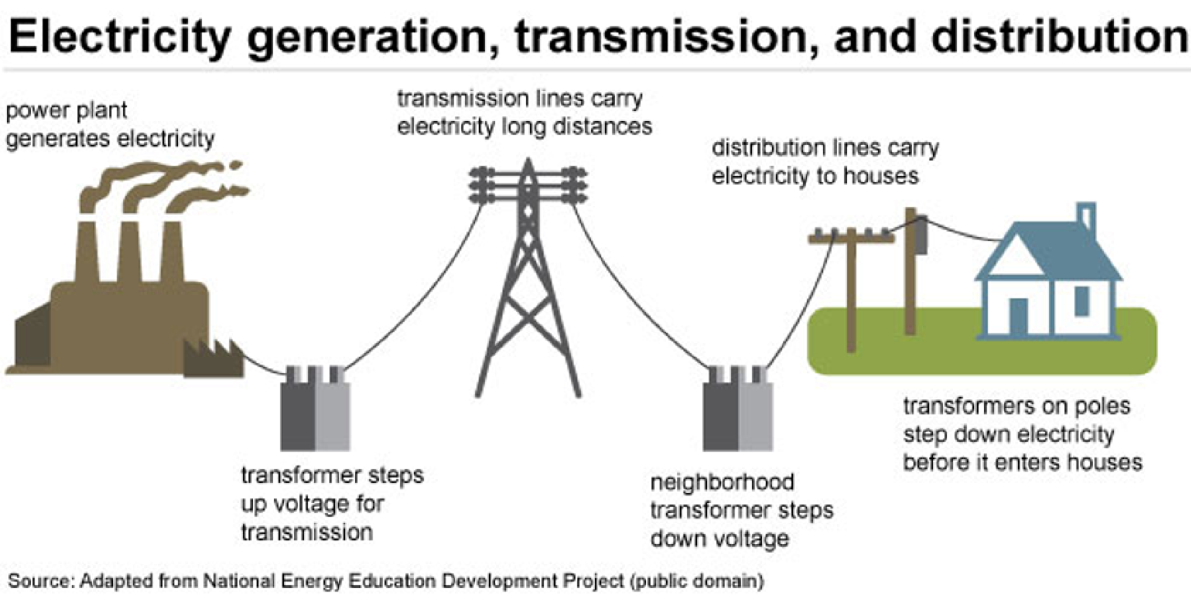

Figure A1: Intervention within the distribution system

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.

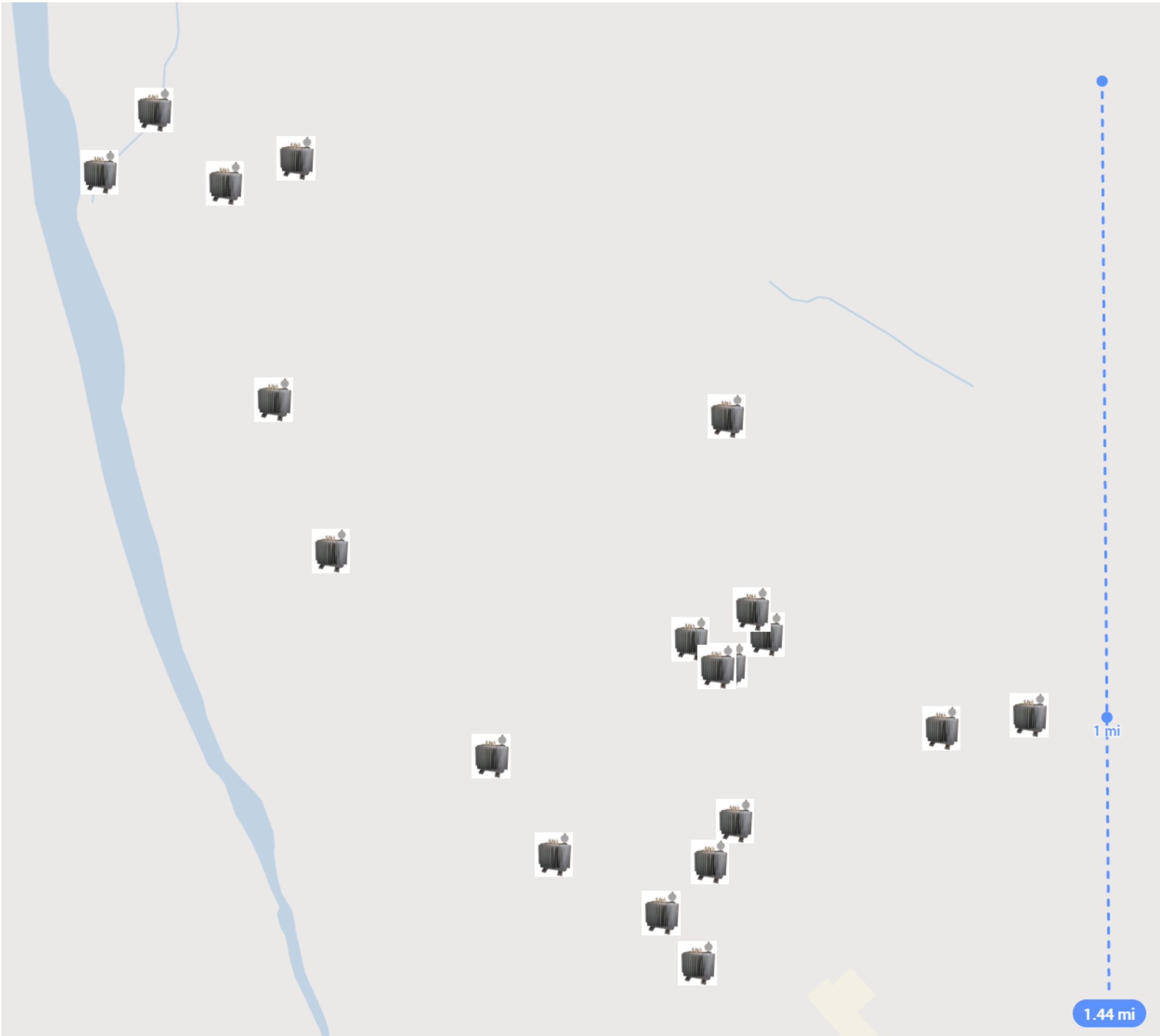

Figure A2: Transformer Locations

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.

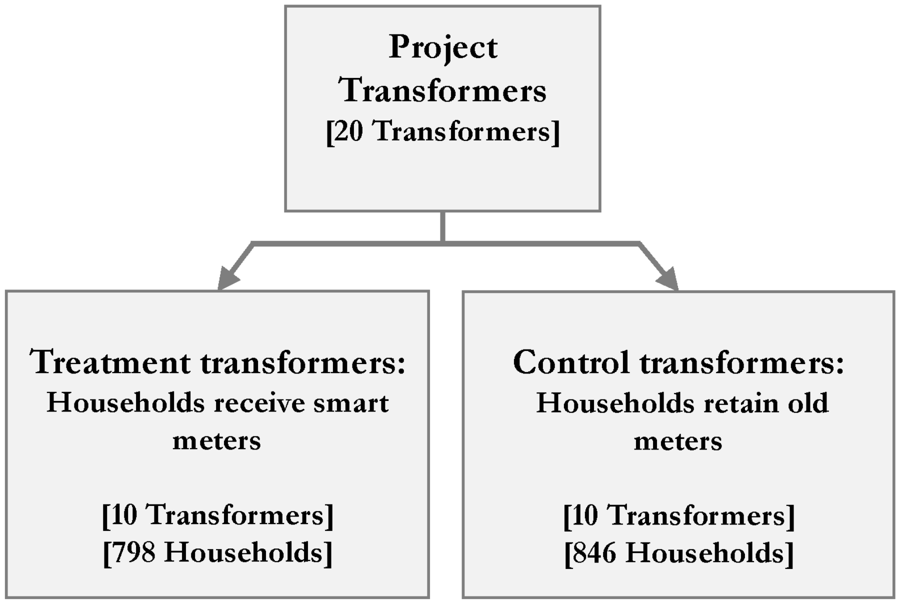

Figure A3: Randomized Design

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.

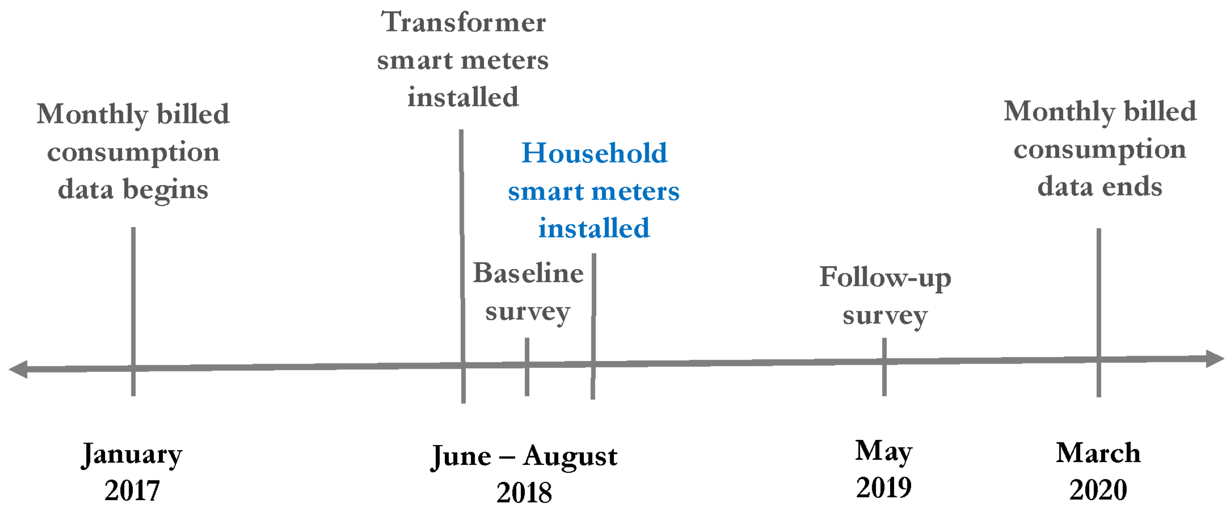

Figure A4: Timeline of Meter Installation and Data Collection

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	Baseline Responses	Follow-Up Responses	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: Balance Test on Household Expenses

VARIABLES	Control	Treat	Difference
Food	2,079.244	2,389.872	310.628
	(1,399.762)	(1,632.380)	(338.498)
School	3,991.778	5,087.907	1,096.129
	(11,603.503)	(10,668.910)	(2,003.874)
Electricity	338.849	338.921	0.072
	(315.986)	(484.812)	(48.476)
Heat	2.067	14.233	12.166
	(19.331)	(175.460)	(13.820)
Other Utilities	236.284	243.795	7.511
	(302.296)	(325.704)	(33.712)
Communication	403.260	486.288	83.028
	(479.078)	(446.747)	(62.361)
Transportation	1,161.502	1,194.423	32.921
	(2,766.942)	(1,910.585)	(291.953)
Medical	1,587.556	1,178.563	−408.993
	(4,541.160)	(3,525.414)	(340.282)
Clothing	3,010.333	3,671.802	661.469
	(4,822.782)	(5,027.772)	(759.205)
House Expenses	4,919.822	8,247.441	3,327.620
	(18,670.148)	(37,312.887)	(2,782.833)
House Appliances	1,328.889	1,325.442	−3.447
	(4,189.350)	(4,671.530)	(637.148)
Discretionary Expenses	38,750.121	47,989.176	9,239.052
	(74,871.656)	(100,905.539)	(20,550.715)
Observations	450	430	880

Notes: Data collected through the household baseline survey. We restrict this analysis to the households that appear in both the baseline and follow-up surveys. The outcome variables measure households' expenses on the corresponding items. *Control* represents the mean value for the control group, while *Treat* represents the mean value for the treatment group. *Difference* is the difference between the mean value of the treatment group and the mean value of the control group. Robust standard errors are clustered at the transformer level.

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: Balance Test on Household Expenses Based on All Households

VARIABLES	Control	Treat	Difference
Food	2,056.565	2,459.921	403.356
	(1,380.428)	(1,699.949)	(336.971)
School	3,864.957	5,099.296	1,234.339
	(10,885.922)	(12,669.304)	(1,808.371)
Electricity	335.310	352.352	17.043
	(298.500)	(467.313)	(48.077)
Heating	1.617	11.866	10.249
	(17.118)	(154.182)	(11.342)
Other Utilities	231.663	238.722	7.059
	(298.501)	(315.631)	(29.501)
Communication	416.162	518.889	102.727
	(479.406)	(509.067)	(65.633)
Transportation	1,325.628	1,320.215	-5.413
	(3,679.287)	(2,800.123)	(297.625)
Medical	1,537.965	1,172.292	-365.673
	(4,501.009)	(3,372.664)	(303.175)
Clothing	2,881.478	3,896.083	1,014.604
	(4,430.101)	(5,465.106)	(787.867)
House Expenses	5,401.600	8,576.937	3,175.337
	(20,515.947)	(46,904.070)	(3,009.059)
House Appliances	1,475.478	1,383.081	-92.397
	(4,955.584)	(4,962.081)	(588.709)
Discretionary Expenses	39,352.930	47,553.195	8,200.265
	(75,666.883)	(102,625.523)	(18,718.855)
Observations	575	568	1,143

Notes: Data collected through the household baseline survey. The outcome variables measure households' expenses on the corresponding items. *Control* represents the mean value for the control group, while *Treat* represents the mean value for the treatment group. *Difference* is the difference between the mean value of the treatment group and the mean value of the control group. Robust standard errors are clustered at the transformer level.

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: Robustness Check: Billed Electricity Consumption by Season (Heating vs. Non-heating)

	(1) Heating Season	(2) Non-Heating Season
Treat × Post1	57.025**	-37.490**
	(23.086)	(14.640)
Treat × Post2	4.122	-15.475
	(19.133)	(23.853)
Mean of Control Group	851.071	432.379
Observations	13,438	16,745
Number of Households	867	862
Adjusted R-squared	0.122	0.284
Household Fixed Effect	Y	Y
Month-by-Year Fixed Effect	Y	Y

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. 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 A9: Use of Energy-Efficient Light Bulbs

VARIABLES	(1) EElight	(2) EElight
Treat×Post	0.056	0.056
	(0.099)	(0.041)
Post	0.282***	0.282***
	(0.073)	(0.029)
Mean of Control Group	0.193	0.193
Observations	1,759	1,759
R-squared	0.206	0.206
Clustered Standard Errors	Transformer	Household
Household Fixed Effects	✓	✓

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 or at the household level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A10: Electrical Appliance Ownership

VARIABLES	(1) Refrigerator	(2) Clothes Washer	(3) Color TV	(4) Sound Equipment	(5) Computer/ Laptop	(6) Water Heater	(7) Cell Phone Charger	(8) Electric Heater
Treat	0.031	0.004	0.020	−0.042	−0.033	0.079	0.002	−0.013
	(0.029)	(0.028)	(0.025)	(0.039)	(0.032)	(0.063)	(0.032)	(0.059)
Mean of Control Group	0.827	0.836	0.862	0.142	0.184	0.433	0.702	0.722
Observations	1,125	1,125	1,125	1,125	1,125	1,125	1,125	1,125
R-squared	0.018	0.008	0.007	0.036	0.027	0.015	0.001	0.003
Basic Characteristics	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Data collected through household follow-up survey in May 2019. The outcome variables are dummy variables indicating whether the household owned certain electric appliances. 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.

Table A11: 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. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

A2 Mechanisms for Electricity Quality Improvements

How did smart meters lead to electricity quality improvements? 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.[16]

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.

The results, presented in Appendix Table A12, 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.

[16]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, forthcoming).

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.[17] Indeed, treated transformers that were replaced did have significantly more household-level alarms per day prior to the replacement (Appendix Table A13), 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 A14). 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 A15); however, we are cautious not to interpret this as a causal relationship, given that replacements and repairs are determined by electricity service quality.

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

Table A12: 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 A13: 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 A14: The Effect of Transformer Replacement on Household-Level Events

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

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

Table A15: 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 (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).