Smart Meters and the Benefits from Electricity Quality Improvements*

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Abstract

Poor service quality is a challenge common to the electricity sector in many developing countries. Smart meters provide additional information to both consumers and utilities, potentially mitigating this challenge. In a randomized experiment in Kyrgyzstan, smart meters replaced houses' old meters. Post-intervention electricity service quality was significantly better among the treatment group relative to the control group. High frequency data provided by the smart meters directed the utility to the most problematic locations within the electricity distribution system. Consumers' benefits from electricity quality improvements were substantial. Treated households' peak electricity consumption increased, along with investments in energy efficiency and expenditures on electric appliances.

Keywords: electricity, infrastructure, service quality,
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1 Introduction

Poor service quality is well 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). Infrastructure sectors, including those delivering water and electricity services, need not suffer from these challenges; tariffs designed such that consumers pay for infrastructure maintenance, repairs, and upgrades can ensure standard quality of services delivered. Yet, low-quality electricity services remain common in many developing countries (Trimble et al., 2016; Zhang, 2018).

Contracting between an electricity utility and its customers should mitigate poor 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. This agreement, however, often breaks down in practice, likely because of insufficient information to enforce these contracts on both sides. Consumers lack data on the actual quality of electricity services delivered, and utilities lack information on the locations of poorest service quality.

We report results from a randomized experiment implemented in the Kyrgyz Republic, a lower-middle-income country in Central Asia, to test whether smart meters can mitigate electricity quality challenges and, if so, whether it results in greater electricity consumption and increased appliance ownership. These are first order questions in understanding the impacts of electricity in developing countries. Although electricity access has increased during the 21st century, hundreds of millions of households still depend on grid connections that provide low-quality and unreliable electricity services (Day, 2020). Low-quality and irregular electricity services may attenuate the economic benefits from grid connections (Pargal and Ghosh Banerjee, 2014; Samad and Zhang, 2016), constrain consumption of electricity services (Zhang, 2018), damage appliances, and influence the portfolio of appliances that households own and use (McRae, 2010; Jacome et al., 2019).

Utilities increasingly install smart meters, which provide high-frequency energy readings (i.e., readings occur often) and two-way communication between the meter and the utility, to address electricity sector challenges.[1] In both high- and low-income countries, utilities argue that smart meters can improve service quality and grid reliability.[2] Although the returns to smart meters could be substantial, their installation can be controversial and their benefits disputed.[3] Until now, these benefits have largely remained untested.

This paper provides causal evidence on the impact of smart meters on electricity quality and the returns to those electricity quality improvements for residential consumers.[4] We selected 20 neighborhoods within one city, each with electricity access via its own 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 permit direct communication between the utility and the consumers or high-frequency energy readings. The control houses, 846 in total, retained their old meters. Electricity prices remained the same across groups.

Smart meters themselves cannot directly improve electricity service quality; however, they provide information to facilitate improvements. To improve electricity service quality, smart meters provide high-frequency information to both customers and utilities

[1]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).

[2]For examples of these claims, see industry news (e.g., Sprinz (2018)), North American electricity utility websites (e.g., Duke Energy Progress (2020) and BC Hydro (2016)), and multi-lateral development bank reports (ESMAP, 2019).

[3]For news coverage of the debate over benefits and costs, see, for example, Smith (2009).

[4]Prior economics research 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. For examples, see Wolak (2011), Jessoe and Rapson (2014), and Ito et al. (2018).

[5]Transformers on the electrical grid convert high-voltage electricity to usable, low-voltage electricity for household consumption (Glover et al., 2011).

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 response to the necessary locations. Additionally, smart meters automatically disconnect houses from the electricity supply when the voltage substantially spikes or drops. Automatic disconnections both protect consumers' appliances from damage and provide consumers with a record of substandard service quality.

As in other sectors, estimating changes in and benefits from quality improvements in the electricity sector is challenging for multiple reasons. First, electricity quality is typically endogenous to and mutually determined by local characteristics. Second, measuring changes in outages and voltage fluctuations is rare because of a lack of data and incentives for utilities to report these measures (Carranza and Meeks, forthcoming). Our analysis overcomes the former challenge by employing the exogenous variation introduced by the household-level smart meter installation. To overcome the latter challenge, we measure electricity service quality using data obtained at frequent intervals from 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.

We find that residential consumers significantly benefit from the smart meters. Electricity service quality after the installation of smart meters was better for treated houses relative to control houses. Voltage fluctuation events were significantly less frequent among the treated group, an effect that persisted into the second year. Transformer repairs and replacements appear to be the channel through which electricity service quality improved, supporting the claim that smart meters alert utilities of problematic locations. Consumers benefit from these quality improvements; with electricity available and within the standard voltage range for more hours per day, households can increase their electricity consumption. Consistent with unmet demand prior to the intervention and improved electricity service quality thereafter, the treated houses' billed electricity consumption increased in peak months following the smart meter installation. Consumers' returns to the electricity quality improvements are 28 USD per house per year, approximately one-half to one-third the cost of a smart meter. These quality improvements come with greater investment in electrical appliances: treated households' quarterly expenditures on home appliances increased by 14 USD.

Development organizations increasingly underscore the need to move beyond the historical focus on electricity access and emphasize service quality more,[6] yet there is a dearth of evidence on the returns to electricity service quality improvements. In filling this gap, this paper complements existing work estimating the economic impacts of electricity shortages on firms (Fisher-Vanden et al., 2015; Allcott et al., 2016; Cole et al., 2018; Hardy and Mccasland, 2019). Given the low returns to electrification found in some settings (Lee et al., 2020; Burlig and Preonas, 2016) but not others (Dinkelman, 2011; Lipscomb et al., 2013; Rud, 2012; Van de Walle et al., 2013; Usmani and Fetter, 2019), this is an important line of inquiry. Low-quality and unreliable electricity service provide potential explanations for heterogeneous findings across settings. Pro-poor growth in the developing countries is expected to result in greater household appliance ownership and, thus, increased residential electricity demand (Wolfram et al., 2012); however, such increases in appliance ownership likely depend on the quality of electricity services delivered.

In addition, this paper contributes to a growing body of experimental research designed to improve public service delivery (Duflo et al., 2012; Dhaliwal and Hanna, 2017; Das et al., 2016; Callen et al., 2016; Banerjee et al., 2018; Muralidharan et al., 2018), as well as demonstrate the impact of information on product quality in the private sector (e.g., Jin and Leslie, 2003; Bai, 2018). Ex ante, however, the extent to which an infrastructure sector would respond to a smart technology (and the information it provides) was not obvious. Infrastructure sectors, even when privatized, are typically characterized by less competi-

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

tion than the private sector more broadly.[7] Yet, these utilities also differ from many other public sector institutions.

The paper proceeds as follows. Section 2 explains poor electricity quality, losses, and smart meters' potential to alleviate these challenges. Section 3 describes the study setting, the experimental design, and data sources. Section 4 presents the impacts of smart meters on electricity service quality and the benefits to consumers. Section 5 concludes.

2 Electricity Quality, Demand for Electricity Services, and Smart Meters

A household's demand for electricity services is determined by the demand for services from each of the household's electrical devices (McRae, 2010). Here, we consider how electricity quality affects the demand for those services. First, we describe two scenarios in which electricity quality is poor: unreliable service due to outages and low service quality due to voltage fluctuations.[8] We next illustrate the role of smart meters to improve service quality.

2.1 Two Scenarios of Poor Electricity Service Quality

Unreliable Service Due to Outages. An outage is a complete stoppage in electricity distribution. Unplanned outages are typically due to infrastructure breakage, malfunction, and overloads.[9] Outages can be lengthy in duration, lasting until replacement parts are purchased and repairs are complete. Such unplanned outages differ from planned outages that occur for regular repairs and maintenance, which are typically of limited dura-

[7] The prevalence of natural monopolies in the water and electricity sectors is well documented.
[8] Our discussion is informed by Klytchnikova and Lokshin (2009) and McRae (2015b).
[9] 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).

tion and scheduled for off-peak seasons.[10] Given that electrical appliances cannot function during outages, outages typically result in a lower quantity of electricity services demanded.

We depict the relationship between an outage and the quantity of electricity services demanded in Scenario 1 of Figure 1. To do so, we first illustrate the quantity of electricity services demanded under standard (full) 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.[11]

Poor service quality can result in a quantity of electricity services consumed that is less than q_S. In the figure, the demand curve during an outage, when 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 is again D_S. This means that the consumption observed on the electricity bill will include both periods of standard (full) supply and periods of outages. Therefore, the electricity bill will represent an average of the two, as illustrated by q_{Avg}. The extent to which q_{Avg} is less than q_S will depend on the duration of outages during the billing period (Klytchnikova and Lokshin, 2009) and the consumer response to those outages.

If the 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 the figure.

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 sources, including faulty and old distribution infrastructure, insufficient maintenance

[10]Our setting did not have outages for electricity rationing (also known as "load shedding") during the study period, so we do not address those here.

[11]This is a simplification. We note that in many contexts, including our study setting, consumers face a non-linear tariff. The overall intuition, however, remains the same.

and repairs, or demand that exceeds the infrastructure's capacity. Voltage fluctuations can affect the quantity of electricity services demanded via multiple channels. First, low voltage can mean that power is insufficient to run certain appliances. Second, voltage spikes may damage appliances, rendering them useless. Consumers may be particularly concerned about damage to expensive appliances (e.g., a refrigerator). Third, some appliances may function at lower voltages but provide 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. Finally, if electricity service quality impacts households' appliance use, then it will also impact their purchase decisions and the portfolio of appliances owned (McRae, 2010). Each of these channels results in a lower quantity of electricity services consumed than would be consumed under a standard voltage scenario.

when voltage fluctuations occur the voltage can either exceed the maximum or fall below the minimum of the standard voltage range. As a result, voltage fluctuations can affect demand via multiple channels: fewer appliances may be used or purchased within the household. For example, a household may not purchase a refrigerator if they think voltage fluctuations will damage it or render it unusable.[12]

Alternatively, when certain appliances are run at low voltage, they consume fewer kWh per minute of appliance 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 lower quantity than standard (full) supply, is represented by D_L in the figure. This illustrates how the quantity of electricity services consumed when there are voltage fluctuations, q_L, will be less than the quantity demanded under standard quality, q_S.

If the 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

[12] 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 in our data.

shift is illustrated by the arrow in the figure.

2.2 Can Smart Meters Improve Electricity Service Quality?

Smart meters can improve electricity service quality by increasing information available 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 faster with repairs, maintenance, and overhauls. Second, smart meters 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 step increases 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.

Both outages and voltage fluctuations result in unsatiated demand for electricity services, negatively affecting consumption. If service quality improves after smart meter installation, then consumption of electricity services should increase. When prices are constant, as in our study location, such increased consumption represents an improvement in consumer welfare.

3 Randomized Experiment with Smart Meters

3.1 Electricity Services in the Kyrgyz Republic

3.1.1 Electricity Sector Challenges

Nearly 100% of Kyrgyzstan's population is connected to the electrical grid, the result of large-scale infrastructure construction when the country was part of the former Soviet Union. Much of the existing electricity infrastructure dates back to that time (Zozulinsky, 2007). Since 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. The country's low electricity tariff has contributed to the growth in electricity consumption.[13] 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.

Unreliable and low-quality electricity services are pervasive, caused by the poor condition of the energy sector assets, intensive electricity use, and large seasonal variations in demand. Between 2009 and 2012, distribution companies reported an average of two outages per hour within their areas of coverage (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).

[13]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.

3.1.2 Contracting in the Electricity Sector

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.

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.

3.2 Randomized Experiment

In collaboration with an electricity distribution company, the experiment was implemented in one city in the Kyrgyz Republic. Prior to the experiment, a substantial number of smart meters were installed in the country, but none had been installed in this city.

The randomized design focused on the last two steps in the electricity distribution system: neighborhood transformers and residential electricity consumers (Appendix Figure A1).[14]

The experiment was designed as follows. 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 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.

3.3 Data

To estimate the intervention's impact, we employ data from several sources, including baseline and follow-up survey data, utility transformer and billing records, and data from

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

smart meters installed at transformers. Appendix Figure A4 depicts the timing of the intervention relative to the different datasets.

3.3.1 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 "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.[15]

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 alarm 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 in houses and therefore cannot provide sufficient pre-intervention

[15]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.

data.

3.3.2 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 households within the treatment and control transformer groups. Survey respondents totaled 1,143 in the baseline survey and 1,125 in the follow-up survey. When we include only the households that responded to both survey rounds, the 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 that period. 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.

3.3.3 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, data on customer debts to the utility and consumers' history of disconnection for bill non-payment; and, third, 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.

3.4 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.

In the response rates for the treatment and control groups in the baseline and follow-up surveys, we 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).

3.5 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.

4 Effects on Electricity Quality and Consumer Benefits

In this section, we estimate the effects of smart meters on the two measures of electricity quality: voltage fluctuations and outages. We perform additional analyses for insights on the mechanisms through which these effects occur and then estimate the returns to changes in electricity service quality. Lastly, we assess the effect of the smart meters on household expenditures and appliances.

4.1 Effects on Electricity Quality

To estimate the intervention's effect on indicators of electricity quality, we employ the data on alarms from the transformer-level smart meters during the post-intervention period. The two outcome measures are transformer-level alarms per day indicating one of two types of events: 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.[16]

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

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

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.

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 indeed that transformer smart meter events indicating electricity quality problems are 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. Theft events, which we do not expect to be similarly associated, 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 the household smart meter events. 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).

4.2 Mechanism for Electricity Quality Improvements

How did smart meters lead to electricity quality improvements? Discussions with consumers inform our hypothesis. During the smart meter installation in summer 2018, consumers reported previous 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.[17]

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

$$y_{gt} = \alpha \text{Treat}_g \times \text{Post}_t + \beta \text{Post}_t + \lambda_g + \epsilon_{gt}, \quad (2)$$

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 Table 3, are informative in several respects. First, trans-

[17] Prior research has highlighted transformers as a critical component in determining electricity service quality (Carranza and Meeks, forthcoming).

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

Is the utility responding to information from the household smart meters or just to knowledge of an ongoing study? To shed light on this question, we test whether greater frequency of household-level smart meter alarms per day, which indicate more electricity quality problems, are associated with a greater probability of a transformer being replaced or overhauled.[18] Indeed, treated transformers that were replaced did have significantly more household-level alarms per day prior to the replacement (Appendix Table A8), 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 A9). 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 A10); however, we are cautious not to interpret this as a causal relationship, given that replacements and repairs are determined by electricity service quality.

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

4.3 Effects on Billed Electricity Consumption

As detailed in Section 2, the smart meters could impact billed electricity consumption in multiple ways, particularly given the electricity quality improvements just presented. The intervention's effects on billed electricity consumption are important to understand, given the large role they play in the extent to which consumers and the utility benefit from the intervention.

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

$$\text{Bill}_{igt} = \beta_1 \text{Treat}_g \times \text{Post1}_t + \beta_2 \text{Treat}_g \times \text{Post2}_t + \lambda_i + \delta_t + \epsilon_{igt}, \tag{3}$$

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 4. 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 4.1. The increased consumption is also consistent with less meter malfunctioning (i.e., better capturing of consumption that occurs at a low voltage). We can neither confirm nor reject this additional channel; however, that does not negate the solid evidence of electricity quality improvements. The fact that the increase does not persist into the second year suggests that households adapt 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). In contrast, the billed electricity consumption in the non-heating season decreases (Column 2), which is also consistent with these same adaptations following the smart meter installation, suggesting that at least some of the household adaptations affect consumption in the non-heating season. We further illustrate these heterogeneous impacts in monthly billed electricity consumption across seasons and over time with a basic graph of monthly billed electricity consumption (Appendix Figure A5).

One potential concern is that households with different consumption patterns during the heating or non-heating season will respond differently to the installation of smart meters. To address this concern, we controls for monthly billed electricity consumption in 2017. The corresponding results, reported in Appendix Table A11 are still robust.

4.4 Returns to Electricity Quality Improvements

To estimate the returns to these electricity service quality improvements, we must isolate the changes in billed electricity consumption resulting from the voltage fluctuation and outage improvements induced by the smart meters. Focusing on the household billed electricity consumption over the winter heating season (i.e., from November to March of the next year), we calculate the total billed electricity consumption during this period both before and after the intervention for each household. We also 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.[19]

[19]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 nega-

Using this panel data of both electricity quality and billed electricity consumption, we estimate the consumer welfare effects of smart meter installation 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

tively correlated with smart meter alarms indicating electricity quality problems (Appendix Table A6), as expected.

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.

The results of these calculations are in Table 5. 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 months of peak electricity consumption (28.35 USD per year). This calculation includes the returns to reliability improvements during the five-month heating period but is silent on the non-heating months.

4.5 Household Adaptation to Quality Improvements

Thus far, we have shown that electricity quality improves after the intervention, and households benefit from these quality improvements. Additionally, the analysis of the billed electricity consumption data indicates that households are responding to these 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.[20] Both the baseline and follow-up surveys asked about these expenditures for the previous months, providing a panel dataset of these variables. The follow-up survey was implemented in May 2019. This timing is important for understanding household changes, as it is after the households experienced the first winter heating season, but before the second.

We estimate the impact of treatment on household expenditures as follows:

$$\text{Expenditure}_{igt} = \beta_1 \text{Treat}_g \times \text{Post}_t + \beta_2 \text{Post}_t + \lambda_i + \epsilon_{igt}, \tag{6}$$

where Expenditure_{igt} is household expenditure (KGS) on certain items. The indicator variables, Treat_g and Post_t, as well as household fixed effects, are defined as before.

Table 6 presents the corresponding results. Consistent with the returns to quality improvements, we document a statistically significant increase in household electrical appliance expenditures of 13.58 USD over a three-month period (4.53 USD per month; Column 11). This is only marginally statistically significant; however, for the regressions including household fixed effects, the study is likely underpowered given the relatively limited sample size and clustered standard errors. None of the other expenditure categories change significantly between baseline and follow-up.

These increased electrical appliance expenditures could indicate either additional benefits in the form of new services or increased efficiency in services previously consumed. 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 time of the intervention. Treated households were more likely to report making energy efficiency improvements since the intervention. Specifically, treated households are significantly more likely to report having re-

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

placed the windows on their homes (Appendix Table A12). Window replacement – an energy-efficiency investment promoted for these old homes – would explain why the billed electricity consumption increases do not persist into the second year. We also test whether the treated households made smaller-scale improvements to increase their energy efficiency (i.e., energy-efficient light bulbs). The coefficient is positive but is not statistically significant (Appendix Table A13) and likely also underpowered. 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 A14), nor do we find any effect on the total number of appliances owned (results not shown). Electricity-related device ownership is also not affected (Appendix Table A15).

5 Conclusions

Results from this randomized experiment provide evidence on the effects of and returns to smart meters. 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. 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 benefits that accrue to consumers are substantial; focusing on only the returns from meters to utilities would underestimate the full benefits of the technology. On the other hand, we note that although information from smart meters appears important for inducing quality improvements, there might be other cost-effective ways to improve service quality without installing smart meters on individual houses.

Further, a handful of factors could affect the impact of smart meters and, therefore, the generalizability of results. Two of the most prominent are the study setting and the functionalities of the smart meters installed in this intervention. First, the Kyrgyz Republic is a lower-middle-income country with relatively low labor costs and extremely low electricity tariff prices.[21] We anticipate that point estimates of utility benefits in high-income countries, which likely have both higher labor costs and higher electricity tariffs, will differ. Also, the setting's electrification status and history may be important in determining benefits. 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. Additionally, 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 is beyond the scope of this study.

[21]Based on the World Bank country lending groups, lower-middle-income economies are those with a gross national income (GNI) per capita between 1,026 and 3,995 USD, whereas upper-middle-income economies are those with a GNI per capita between 3,996 and 12,375 USD.

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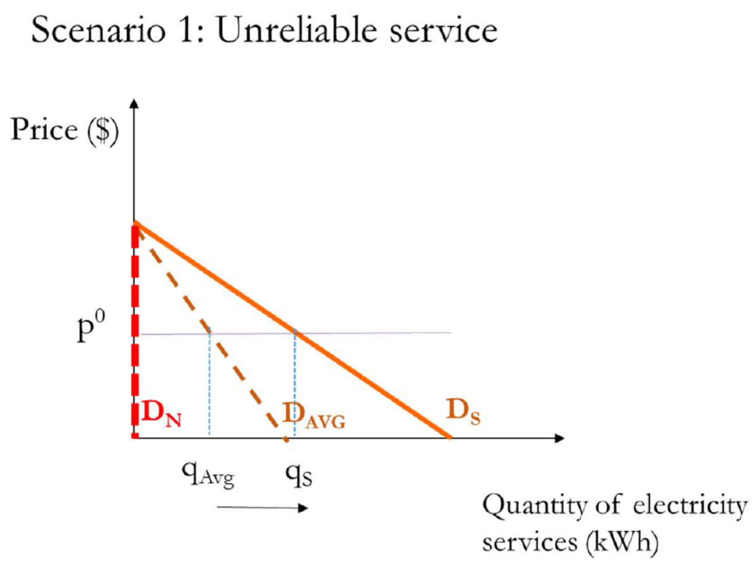
Figures and Tables



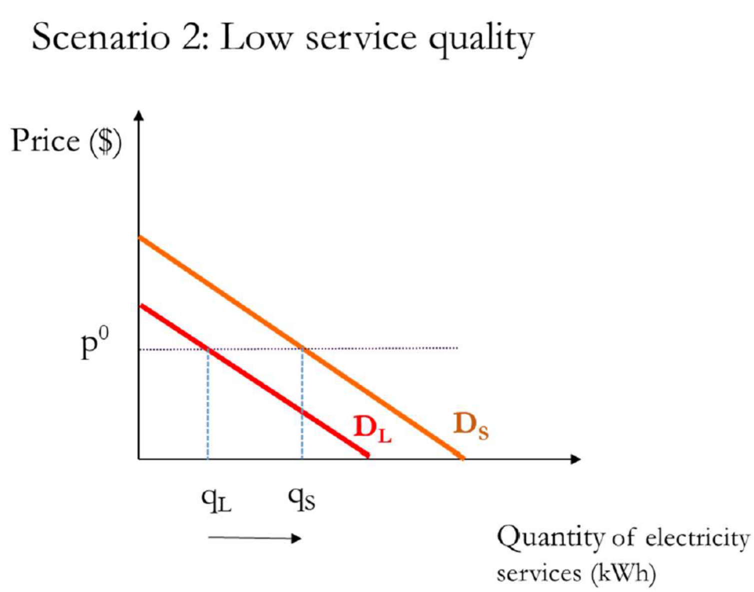


Figure 1: Framework for Impacts of Service Quality on Electricity Services Consumed

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.

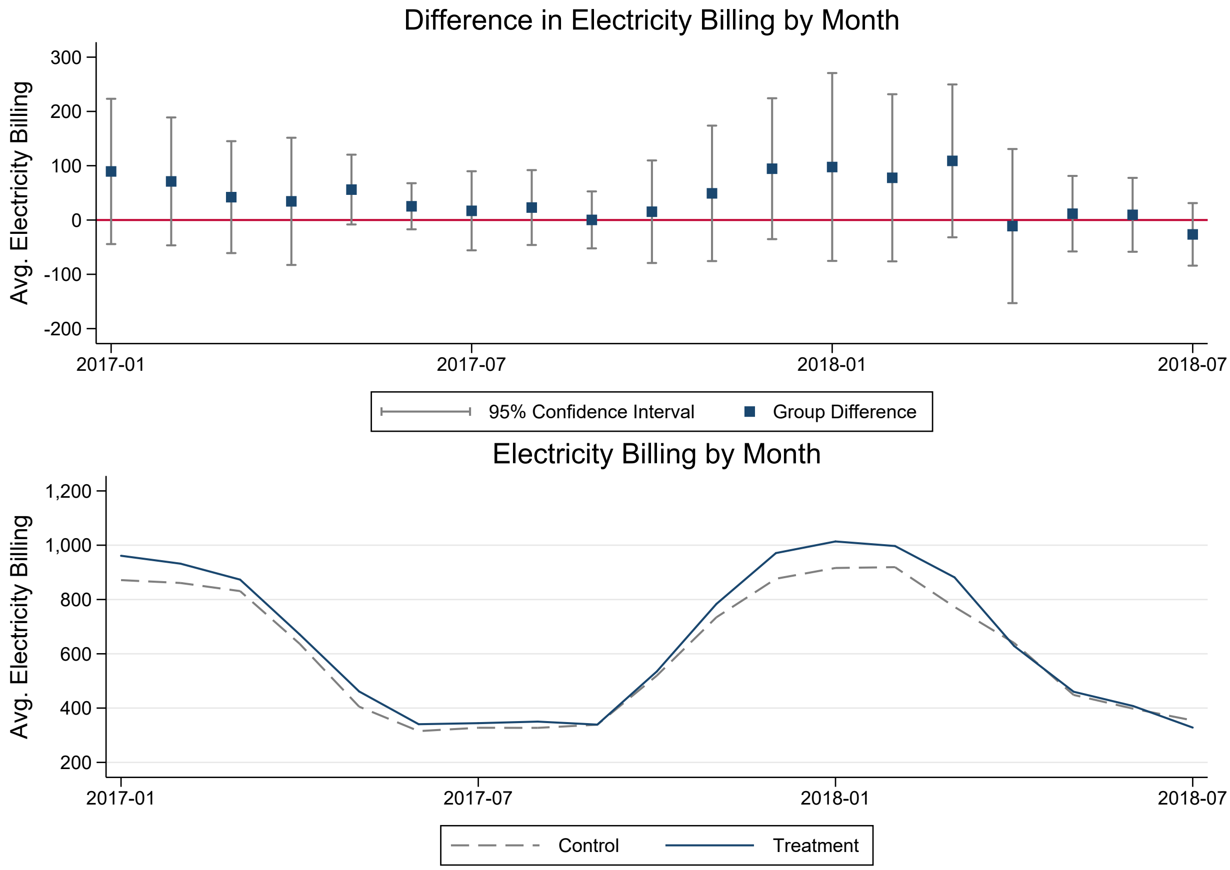


Figure 2: Billed Electricity Consumption before Smart Meter Installation

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 basic comparison, and no other variables are controlled. The standard errors are clustered at the transformer level.

Table 1: Balance Test on Transformer and 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)
Observations	10	10	20
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

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.

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.

Table 3: 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 4: 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 5: 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.

Table 6: 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	✓	✓	✓	✓	✓	✓

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.

APPENDIX: FOR ONLINE PUBLICATION

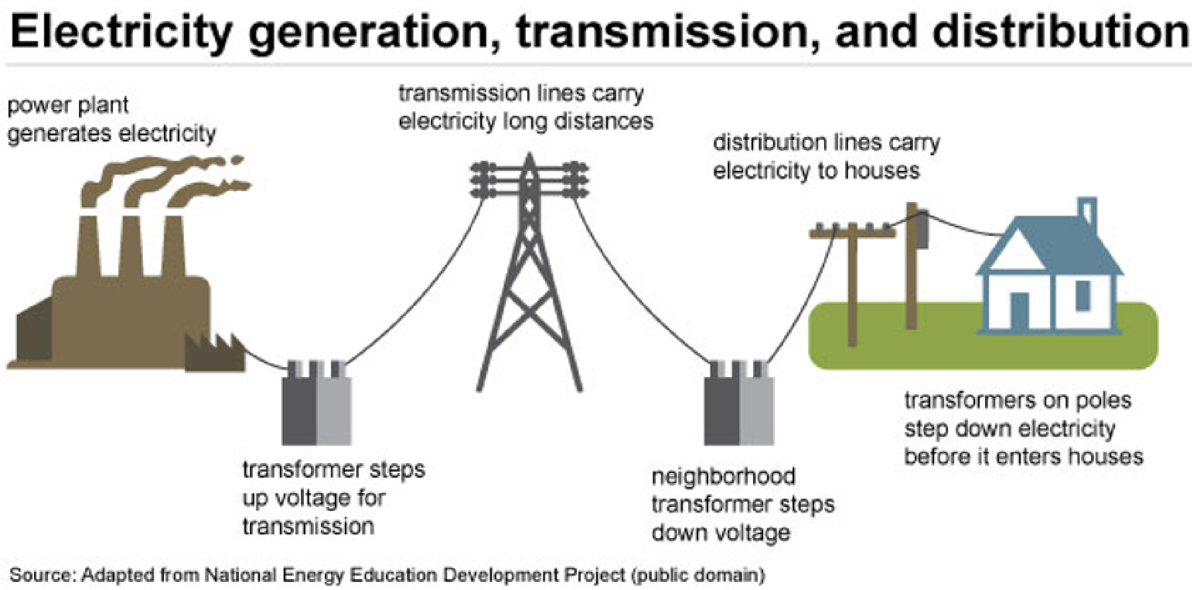


Figure A1: Intervention within the distribution system

Notes: Figure from U.S. Energy Information Administration's website (U.S. Energy Information Administration, 2019a) explaining electricity delivery. 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.

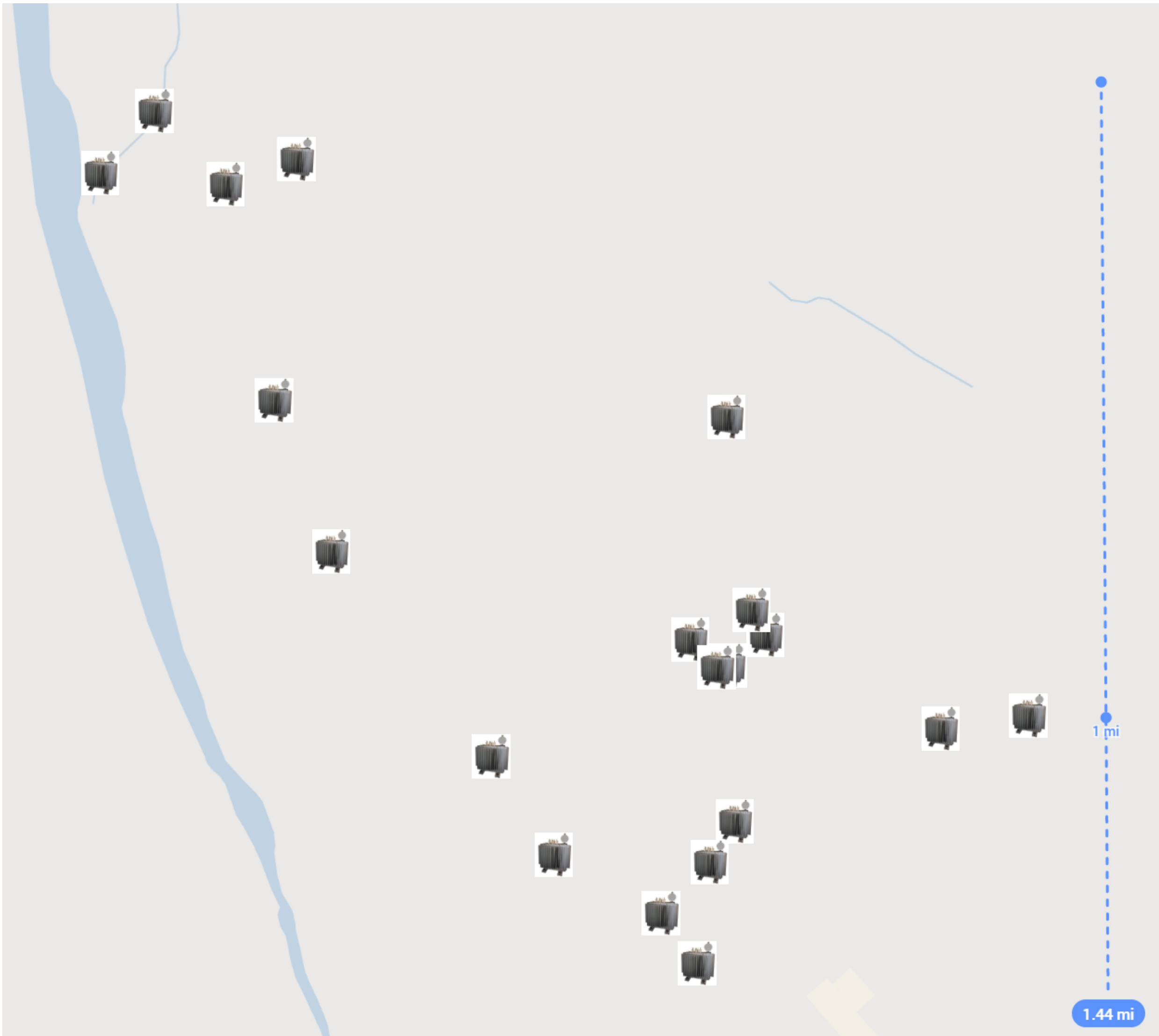


Figure A2: Transformer Locations

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.

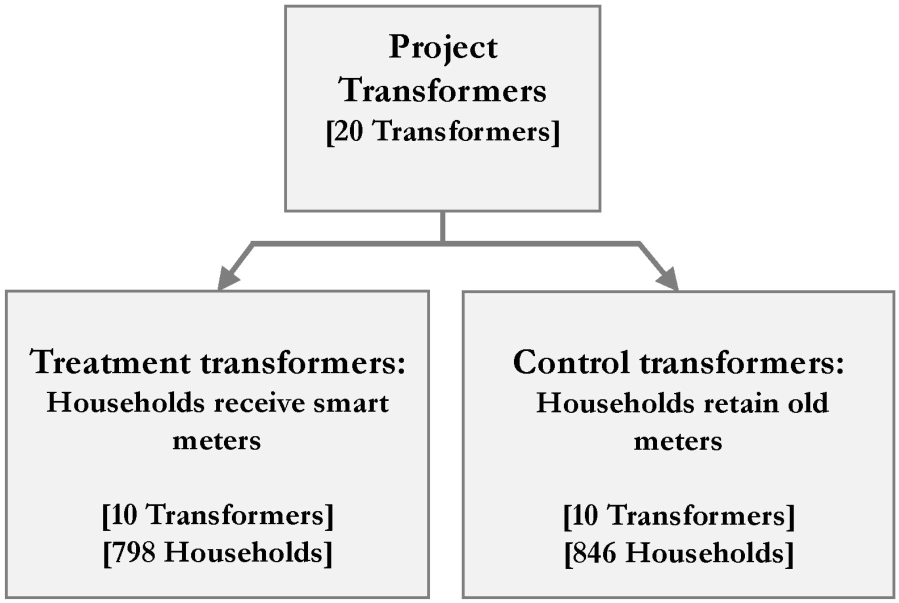


Figure A3: Randomized Design

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.

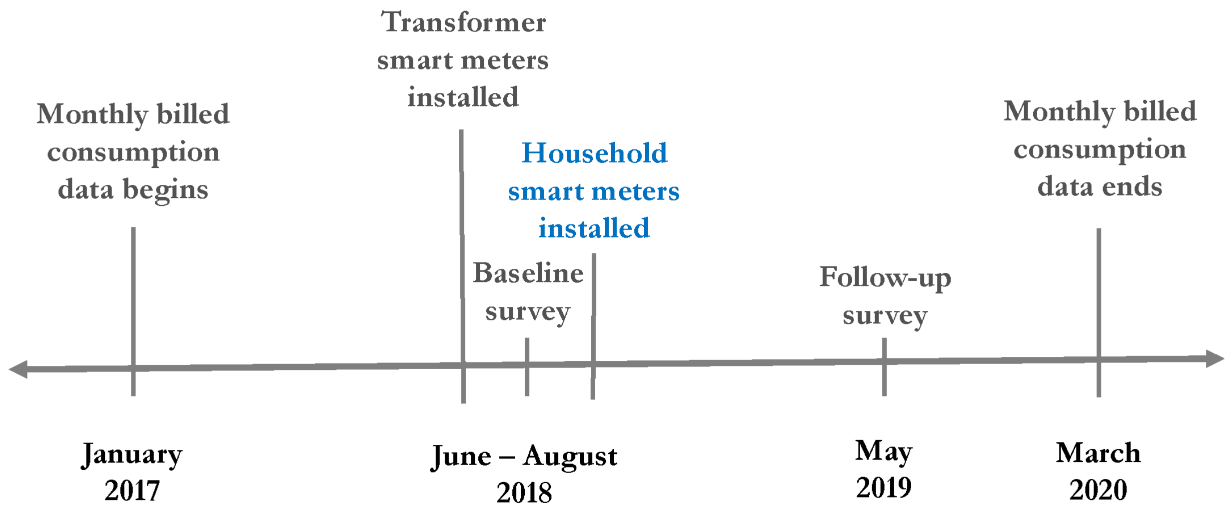


Figure A4: Timeline of Meter Installation and Data Collection

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. 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 b 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: 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 A9: 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 A10: 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 (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A11: 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.

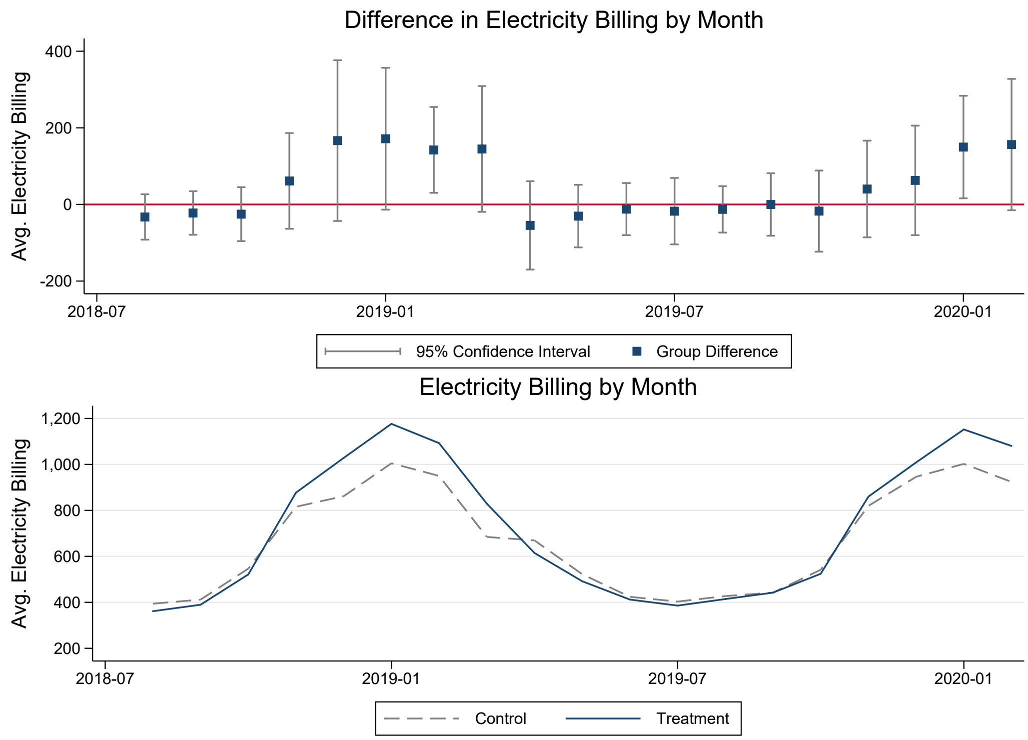


Figure A5: Billed Electricity Consumption (kWh/month) after Smart Meter Installation

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 A12: 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" and equaling 1 if the household made the corresponding change. 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 A13: 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 A14: 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 A15: 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. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

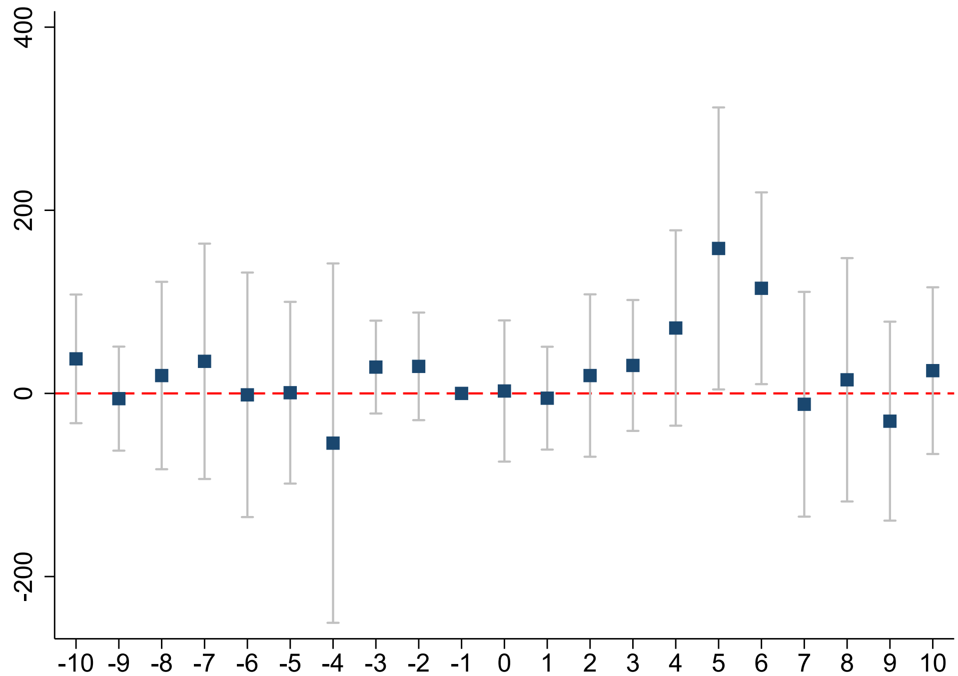


Figure A6: Event Study of Smart Meter Installation on Billed Electricity Consumption

Notes: This figure plots the event-study estimates and the corresponding 95% confidence intervals for households belonging to the Autobazar feeder line. The time indicator for one month prior to the smart meter installation (i.e., July 2018) is considered as the reference group and hence omitted from the regression. In period 5 and 6 when the replacement of transformers happened (i.e., January and February of 2019, we see significant differences in billed electricity consumption between the treatment group and control group.