Enforcement in Electricity Services: Evidence from a Randomized Smart Meter Experiment*

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Abstract

Unreliable electricity service and non-technical losses – including theft – are challenges common to the electricity sector in developing countries. This paper presents evidence on the role of smart meters technology in mitigating these problems. We partnered with an electricity utility operating within the Kyrgyz Republic to implement a randomized installation of smart meters at both households and transformers. Smart meters could increase the electricity utility's ability to enforce payment for electricity services consumed. Alternatively, smart meters could provide consumers' with new information on electricity service quality, enabling them to hold the utility accountable.

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Results support the latter channel but not the former. We find no evidence of reduced electricity theft following smart meter installation. Electricity service quality, however, substantially improved via significantly fewer outages and voltage spikes. Alarms from the smart meters increased the probability of transformers being repaired or replaced. These infrastructure investments are the channel through which electricity service quality improved. Billed electricity consumption increased during peak electricity consumption months, which is consistent with both unmet demand prior to the intervention and improved electricity quality thereafter. Consumer welfare increases by 6 USD per month, on average, from improvements in electricity quality. Increased average household expenditures on appliances by 4 USD per month provides further evidence that consumers benefit from smart meter installation.

Keywords: Electricity, infrastructure, reliability

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1 Introduction

In many sectors, including education, healthcare, and social programs, the quality of services delivered affects the impacts of those services. The electricity sector is no different. Poor quality electricity services – in the form of outages and voltage fluctuations – impact both households (Chakravorty, Pelli and Marchand, 2014) and firms (Allcott, Collard-Wexler and O'Connell, 2016), preventing them from consuming the full quantity of electricity services demanded and attenuating the economic benefits from electrical grid connections (Pargal and Banerjee (2014); Blimpo and Cosgrove-Davies (2019)).

The connection of a house (or firm) to an electrical grid typically comes with a contract between the electricity distribution company and the customer. The distribution company commits to providing reliable, quality electricity services meeting certain engineering standards. The customer commits to paying for the electricity services consumed. This agreement often breaks down in practice, due to incomplete information: consumers may lack data on the quality of electricity services delivered and/or distribution companies do not know who is not paying for electricity consumed.

This paper reports results from a field experiment in the Kyrgyz Republic that randomly installed smart meters to measure their impact on electricity service quality. Smart meters themselves do not improve electricity service quality; however, they can provide real-time information to both customers and utilities on problems (e.g., outages, voltage fluctuations) within the electricity distribution network. We study the impacts of smart meters on electricity quality in the Kyrgyz Republic for multiple reasons. Quality of electricity services and utility cost recovery may link in a downward cycle, "infrastructure trap." When the quality of electricity services delivered is poor or unreliable, consumers may feel justified in stealing electricity or not paying for the full quantity of electricity consumed. Such non-technical losses (NTL) cost electricity utilities an estimated $25 billion per year worldwide

(Depuru, Wang and Devabhaktuni, 2011). These losses mean lower levels of cost recovery and therefore insufficient funds to invest in infrastructure maintenance, modernization, and technical upgrades. Such "infrastructure traps" are persistent in less developed countries (McRae, 2015*b*).

Smart meter installations grew in the past decade in both developed and less developed countries.[1] They are installed by utilities in both developed and developing countries for a variety of purposes, including improving grid reliability and reducing non-technical losses;[2] Although the potential benefits from these meters include interrupting the infrastructure quality trap, there is a dearth of evidence.[3]

Collaborating with an electricity utility operating within a city in the Kyrgyz Republic,[4] we study the impact of smart meters on electricity service quality, bill electricity consumption and indicators of theft, as well as household expenditures. The experimental intervention proceeded as follows. Twenty transformers within the city were selected to be included in the study, covering more than 1500 utility customers. In spring 2018, smart meters were installed at all 20 project transformers to measure electricity consumption for the neighborhood.[5] Transformers were randomly assigned to treatment or control status, resulting in 10 transformers in each group. Smart meters were installed at all houses within the treatment transformers by September 2018. These smart meters replace old meters, which are susceptible to various sources of electricity loss and do not protect against voltage

[1]In the United States, approximately 79 million smart meters were installed by 2017 (EIA, 2018) accounting for roughly half of the meters serving electricity customers (FERC, 2018).

[2]Industry news accounts document use for grid reliability. See for example: www.smart-energy.com/magazine-article/global-trends-in-smart-metering. And Canadian utility, BCHydro, documents the installation of smart meter to deter theft on its website (www.bchydro.com).

[3]Prior economics research involving smart meters primarily uses the technology as a vehicle for other interventions, such as facilitating time-varying electricity prices or providing households with real-time information on electricity consumption. For examples, see: Wolak (2011); Jessoe and Rapson (2014); Ito, Ida and Tanaka (2018))

[4]The Kyrgyz Republic is a lower-middle income country located in Central Asia.

[5]Transformers on the electrical grid convert high-voltage electricity to usable, low-voltage electricity for household consumption. Each transformer can transfer a certain maximum electricity load at any given time and exceeding that load may cause breakage (Glover, 2011).

surges. Households in control transformers retained the old meters.

The study produces three main results. First, electricity service quality improved in the form of significantly fewer voltage spikes and drops. The smart meters provided information to the consumers, allowing them to enforce the utilitys commitment to quality electricity service provision. Higher numbers of smart meter alarms are associated with an increased probability of transformers being repaired or replaced, providing the channel through which electricity service quality improved.

Second, the smart meters heterogeneously impacted billed electricity consumption across seasons. In the non-peak electricity consumption months (summer, spring/fall) billed electricity consumption decreased amongst the treated houses on which smart meters were installed. This is consistent with households either investing in energy efficiency or making behavior changes resulting in energy savings. During peak electricity consumption months (i.e. winter when electricity is used for heating), billed electricity consumption increased, consistent with both unmet demand prior to the intervention and improved electricity quality thereafter. Consumer welfare increased by 6 USD per month, on average, from improvements in electricity quality and thereby increased electricity consumption.

How did the households respond to the smart meters and resulting improvements in electricity quality? Treated households increase expenditures on home appliances by approximately 14 USD over a 3 month period. There is evidence the treated households invest in energy efficiency, in the form of replacing windows. An increase in household expenditures on appliances by 4 USD per month is consistent with these increased consumer benefits from smart meter installation.

Third, although the meters reduced non-payment of billed electricity consumption, we find no measurable impact on overall electricity theft. Results indicate that the threat of remote disconnection due to non-payment seemed to deter consumers from paying late or not at all. However, there is no evidence of reduced electricity theft as measured by transformer level alarms following the installation of household smart meters. The electricity utility did not appear to use the meters data on electricity consumption and suspected theft to crack down on non-technical losses.

Understanding the feasibility of smart meters to improve electricity service quality and/or cost recovery is of first-order importance for development. Poor reliability may be one reason for the heterogeneous benefits document in studies measuring electrification's impacts.[6] The technology's other characteristics – such as the enforcement of payment, monitoring of electricity consumption, and the ability to balance electricity load and reduce voltage fluctuations – may themselves provide a solution to the infrastructure quality trap, rather than merely serving as the tool permitting tariff reform or providing information. In doing so, we contribute to a nascent experimental literature on electricity reliability[7] and provide the first of such evidence on ways to interrupt the infrastructure quality trap.

there is a growing body of research testing interventions to improve service delivery in the education (Duflo, Hanna, and Ryan, 2012), healthcare (Dhaliwal and Hanna, 2016; Das et al, 2016; Callen et al, 2016), and social services sectors (Banerjee et al, 2018; Muralidharan et al, 2019). Less evidence exists on the electricity sector.[8]

In addition, we contribute to a literature measuring the impacts of metering interventions on water and electricity consumption and their ability to increase utility cost recovery for those services.[9] McRae (2015*a*) measures the impact of moving from a zero to a positive marginal price, as facilitated by the introduction of electricity meters, on residential electricity consumption in Colombia. Jack and Smith (2018) assess the impacts of shifting

[6] Although electrification has improved indicators of development in some settings (Dinkelman (2011); Lipscomb, Mobarak and Barnham (2013); Rud (2012); Van de Walle et al. (2013)), it does not always (Lee, Miguel and Wolfram (2018); Burlig and Preonas (2016)).

[7] Carranza and Meeks (2019) study the role of energy efficiency investments in electricity reliability in a different location with a different electricity utility within the Kyrgyz Republic.

[8] Carranza and Meeks (2019) investigate the impact of energy efficiency on reliability.

[9] Szabo and Ujhelyi (2015) implement a randomized information intervention to measure its impact on water bill payment in South Africa.

from traditional post-pay to pre-pay meters in South Africa, which reduces the costs of bill enforcement to the utility. Both studies find that metering introduction led to reductions in consumption (albeit by varying magnitudes and subject to differing heterogeneities).

The paper proceeds as follows. In Section 2, we explain the problem with electricity losses, their contribution to the infrastructure quality trap, and how the functionality of smart meters might interrupt this cycle. Section 3 describes the experiment, the data, and balance tests. The empirical specifications and results are presented in Section 4. Section 5 wraps up with some conclusions.

2 Electricity quality, losses, and smart meters

In this section, we describe how these two challenges commonly faced by electricity utilities – poor electricity service quality and non-technical losses – impact household consumption of electricity services and the potential for smart meters to alleviate each of those challenges.

2.1 Poor quality electricity service

We consider two forms of poor quality electricity service: unplanned outages and voltage fluctuations.[10] During an outage, there is a complete stoppage in electricity service delivery. In contrast, during voltage fluctuations service delivery continues but is of impaired quality that is outside of the standard acceptable range. Voltage fluctuations can be either spikes above the maximum standard or drops below the voltage minimum standard. Such voltage variability can result in damage to electric appliances or in insufficient to power to run certain household appliances. Both unplanned outages and voltage fluctuations can result from a number of sources, including equipment failure, insufficient maintenance, and excess demand

[10]Our setting does not have planned outages for electricity rationing (i.e.. when electricity supply generated is insufficient to meet consumer demand), so we do not address those here.

given infrastructure constraints, such as overloaded transformers.[11]

2.1.1 What poor quality means for electricity service consumption

A household's demand for electricity services depends on the demand for services provided by all the household's electricity-using devices (McRae, 2010). We illustrate the potential difference in electricity services demanded under perfect electricity quality and poor electricity quality in Appendix Figure A1, which depicts two scenarios in which poor electricity service quality negatively impacts electricity consumption.[12] We assume a linear price p^0. [13] In these graphs, the electricity services demand curve under perfect electricity service (i.e. no outages and no voltage fluctuations) is depicted as D_S and the quantity of electricity demanded will be q_S.

Poor quality service likely results in the electricity consumed being less than q_S, depending on the source of service quality problem and the consumer response. In the following two paragraphs, we show how this occurs due to outages and voltage fluctuations.

First, there are unplanned and unpredictable service disruptions (outages) due to infrastructure malfunctions and breakages. We show this "unreliable service" (Scenario 1). An outage is a complete stoppage of electricity services. During an outage, no electricity services are consumed. The demand curve is depicted as D_N and consumption is zero. When there is electricity service (i.e. no outage), the demand curve is unconstrained, D_S. The consumption observed from the electricity bill, which includes periods of both reliable and unreliable supply, will look like an average of the two (service and no service), as represented by q_{Avg}. The extent to which q_{Avg} is less than q_S depends on the duration of outages during the billing period (Klytchnikova and Lokshin, 2009).

[11]Transformers convert high-voltage electricity to usable, low-voltage electricity for end-use consumption. Each transformer can transfer a certain maximum electricity load at any given time and exceeding that load may cause breakage (Glover, Sarma and Overbye, 2011).

[12]This discussion follows Klytchnikova and Lokshin (2009) and McRae (2015*b*).

[13]This is a simplification, as graphs show a linear electricity price. In many contexts, including ours, the consumer actually faces an non-linear tariff. The intuition, however, is the same.

Second, there are frequent voltage issues, either in the form of spikes or dips (Scenario 2). A voltage spike might damage an appliance rendering in unusable or it may not allow the appliance to function as designed. A voltage drop also interferes with proper appliance functioning. For example, a light bulb may shine when voltage is low, but not as brightly as intended. Or, if voltage drops low enough, it might be that certain appliances – such as an electric heater – are unable to function. Tied to this, the quality of electricity supplied will impact households' decisions to purchase appliances and therefore their appliance portfolio (McRae, 2010). A household might not purchase a refrigerator if they think voltage fluctuations will either damage their appliance or render it unusable. In this respect, we can think of the electricity services being consumed are less than that which would be demanded under perfect electricity service quality. And over the course of a billing cycle (e.g. one month) this will look like q_L.

2.1.2 Smart meters to improve electricity service quality?

Smart meters may improve service quality – as depicted in Model A of the figure – through several channels. First, the smart meters are directly in contact with the utility, detecting and reporting outages in real time. If the utility is monitoring this information, it can be more responsive when an outage occurs. Second, smart meters detect voltage anomalies outside of a "safe" range and automatically disconnect a house from the source when the voltage spikes, thereby protecting appliances from damage. When the voltage returns to a safe, normal range, the consumer can re-start the electricity flow by pressing a button on the smart meter. If the voltage does not return to a safe range, then utility must perform repairs. Importantly, this automatic disconnect serves as proof of unsafe voltage fluctuations, supporting consumers as they pressure the utility to take on maintenance and repair activities (without this, it is difficult for consumers to verify voltage problems).

Importantly, both of these mechanisms for smart meters to improve quality of electricity services operate by increasing information – either to the utility or to the consumers. This information may be acted upon to help the utility target maintenance, repair, and replacement of infrastructure within the distribution system. If the information leads to improvements in electricity quality, then consumption of electricity electricity services could increase, shifting to q_S.

If both outages and voltage fluctuations result in unsatiated demand for electricity services and smart meters improve the quality, then the meters could result in an increase of electricity services consumed, .

2.2 Low cost recovery and non-technical losses

The low cost recovery translates into constraints on funding for infrastructure maintenance and investments in expansion (Figure 1). The lack of investments lead to (or perpetuate existing) poor service quality in the form of frequent electricity outages and substantial voltage fluctuations with the capacity to damage or ruin expensive household appliances. This further contributes to low cost recovery, as customers do not feel compelled to pay for poor quality services. Such traps are common in developing countries and are not limited to electricity infrastructure; other basic services such as water provision, also fall prey.

A major source of low cost recovery is non-technical losses (NTL). These NTL come from a number of sources including: (1) meter malfunctioning (if the voltage is very low due then the meter might not register the household's electricity being consumed, albeit at a low voltage), (2) meter tampering (consumers have countless ways of "rolling back" or pausing the metering of their consumption), (3) by-passing the meter (this can involve running electrical wires from the house directly to the distribution wires to avoid the meter), (4) billing irregularities (consumers may pay off the meter reader – a human that comes to document the consumption logged on the meter, typically once per month – to log a lower consumption than the amount actually registered on the meter), and (5) non-payment of bills (depending on capacity and will to enforce payment, utilities may or may not disconnect consumers if a certain period of time passes without payment). Of these five sources of NTL, only the first is not theft-related. These fives sources of NTL, and examples of each, are summarized in Appendix Table A1.[14]

In the following sections, we consider how each type of NTL might cause electricity bills to deviate from actual electricity services consumed and how the functionalities of smart meters might lessen those deviations.

2.2.1 Impacts on electricity service consumption

Non-technical losses are an implicit subsidy if households are not paying the full cost of the electricity services consumed (Appendix Figure A3). With NTL, the consumer faces a price (p^N) that is lower than the official electricity tariff p^0, resulting in the over-consumption of electricity services (q_N). If non-technical losses decrease – for example, through the installation of smart meters – such that the price per kWh that households face is p^0, then quantity consumed will be at q_0.

The electricity utility (and researchers, in this case) observes the measured electricity consumption, not the electricity services actually consumed. So in the presence of NTL, consumers will be consuming at q_N, whereas the quantity observed by the utility (and the amount for which the consumer will be billed) will be less than that. In all types of NTL, except bill non-payment, we expect that the billed electricity consumption will be less than the true electricity services consumed (Column 3 of Appendix Table A1).

2.2.2 To increase cost recovery

We document how the smart meters installed via the intervention studied here could reduce the NTL in our setting (Column 4 of Appendix Table A1). Every 15 minutes, the smart

[14] The USAID online Toolkit (USAID, 2009) provides more general information on the capabilities of different meter types.

meters relay information directly to the utility on both the electricity consumption measured by the meter and any alarms indicating problems (outages, voltage fluctuations, indicators of theft, etc). We anticipate that the smart meters installed in the study site could potentially reduce meter malfunction (a), meter tampering (b), by-passing of the meter (c), and bill non-payment. In our setting, we do not expect that billing irregularities to be reduced given the smart meters were not integrated with the billing system and therefore the human meter reader is still required.[15]

By way of technological advancement, the new smart meters should have a lower rate of meter malfunctioning, in comparison to the older, more basic meters. These meters will read consumption more accurately even in the presence of voltage dips and spikes, but they will also shut down the connection when severe voltage fluctuations occur.

The smart meters have the potential to reduce both meter tampering and by-passing through two channels: deterrence or detection. First, the smart meters could serve to deter theft, if the seal technology, etc makes it more difficult for tampering to occur. But realistically, households that want to steal, will find a way to do so and so we do not expect much deterrence. Second, the smart meters provide frequent information (via alarms) on potentially suspicious activity. If the utility monitors consumption patterns, it can quickly identify theft and other losses and take action to rectify them.

Lastly, the smart meters could reduce bill non-payment, as it provides the utility with the ability to remotely disconnect non-paying consumers, providing a low-cost mechanism to enforce on-time bill payment. Without the ability to remotely disconnect, the utility previously would send a team of employees to manually disconnect the non-paying household. Upon bill payment, the same employee team would return to reconnect the household. This is process is labor intensive and costly.

[15] In contexts in which the two systems are integrated and human meter readers are no longer required, then billing irregularities could be reduced.

3 Randomized experiment with smart meters

3.1 Electricity services in the Kyrgyz Republic

Kyrgyzstan is a lower-middle income country in Central Asia. Nearly 100% of the country's population is connected to the electrical grid, the result of infrastructure construction during the former Soviet Union. Since the country's independence in 1992, its electricity sector has been restructured. Kyrgyzenergo was incorporated as a joint stock company, with the Kyrgyz Government owning approximately 95 of the shares. An unbundling of the sector by functionality – generation, transmission, and distribution – was completed by 2000. This process resulted in one national generation company, one national transmission company, and four distribution companies that cover non-overlapping territories within the country (World Bank, 2017*b*). The distribution companies are responsible for purchasing electricity from the national transmission company and delivering it to residential, commercial, and industrial consumers. A standard natural monopoly, the distribution company is the only entity supplying electricity for residential consumers.

Even with the country's near universal electricity access, the sector has substantial challenges. First, both transmission and distribution losses are high in the country. Electric power transmission and distribution losses include both (i) losses in transmission between electricity generation sources and points of distribution and (ii) losses in the process of distribution to consumers, which include both technical and non-technical losses (e.g. theft and pilferage). At 23.7% in 2014, the Kyrgyz Republic had the world's 16th highest electric power transmission and distribution losses, as a percentage of total electricity output (OECD/IEA, 2018).[16] Distribution losses alone are more difficult to isolate and precisley measure. Estimates of distribution losses in the Kyrgyz Republic are between 15 and 18%

[16] Low income country transmission and distribution losses are on average 18.4%. Calculations made using OECD/IEA data (2018). Source: http://www.iea.org/stats/index.asp

(World Bank, 2017*a*). Not all non-technical losses are theft-related, but many are. Common sources of non-technical losses include: meter malfunction, meter tampering, by-passing the meter, billing irregularities, and non-payment of bills. These high losses result in low cost recovery for the sector.

Second, unreliable and poor quality electricity services are pervasive. Between 2009 and 2012, distribution companies reported an average of 2 outages/hour within their areas of coverage. When electricity is being delivered, the system has regular voltage and frequency fluctuations. Per a 2013 survey, more than 50% survey respondents reported problems with voltage (including low voltage and voltage fluctuations). If voltage is too low, some appliances may not function. If voltage spikes too high, appliances can be damaged. Approximately one fifth of survey respondents reported damage to electrical appliances because of poor electricity quality (World Bank, 2017*a*).

Unreliable and poor quality service are caused by the poor condition of the energy sector assets, intensive electricity use, and seasonal variations in demand. Much of the existing electricity infrastructure dates back to the former Soviet Union (Zozulinsky, 2007). Technically, the capacity of both generation and transmission infrastructure could constrain household electricity services and result in unreliable electricity services (frequent electricity outages); however, during the study period, distribution constraints, old and poorly maintained infrastructure are the primary sources of unreliable service. Consumers are metered and typically individually metered (i.e. not sharing a meter with another consumer), but the meters are old.

The Kyrgyz Government, by Decree 576, provides the regulations on the use of electric energy. By contract between the distribution company ("the supplier"), the Supplier ensure uninterrupted, reliable, high-quality and safe supply of electricity to the consumer, which is defined as a consistent voltage of 220/280 volts delivered to the consumer. The consumer has the right to contact the government bodies and public organization regarding fulfillment by supplier and to record any deviations from the quality indicators and any material damages that result. The consumer may recover from the supplier damages causes as a result of interruption in electricity supply or quality that does not meet the voltage specification. The consumer is required to pay for electricity consumed in accordance to the invoice, calculated based on monthly meter readings. Timely payment is required. In the case of non-payment, the supplier can charge the consumer a penalty for each day of delay in payment and disconnect the consumer from the power supply if the payment is delayed beyond what is specified in the payment document (Government of the Kyrgyz Republic, 2012).

Additionally, residential electricity demand has increased since the country's independence in 1992. Over the past two decades, the proportion of total electricity consumption comprised by the residential sector steadily increased, with 63% of the country's current electricity supply consumed by the residential sector (Obozov et al., 2013). The intensity of electricity consumption is consistent with pro-poor growth and increasing ownership of appliances. The country's low electricity tariff exacerbates the growth in electricity consumption.[17] Electricity consumption in the winter – when many households heat with electricity – is approximately 3 to 4 times that of summer, resulting in heterogeneity in demand across seasons.

3.2 Randomized experiment

We collaborate with one electricity distribution company to implement the experiment in a small city within the Kyrgyz Republic.[18] Electricity losses and poor service quality are concerns for this utility. The experimental intervention and randomized design are cen-

[17] Residential consumers face a two-tiered increasing block price with a non-linearity in the price is at 700 kWh per month. Below the cutoff consumers pay .77 Kyrgyz soms per kWh. Above the cutoff, consumers pay 2.16 Kyrgyz soms per kWh. The exchange rate was 69 KSG = 1 USD as of September 1, 2018. Residential consumers rarely exceed the threshold between the first and second tiers in the warm summer months.

[18] Although private operators are permitted to provide competition within the country, the private operators work in and around the countries capital, not near the small city in which our experiment is implemented.

tered around the last two steps in electricity distribution: the transformers and electricity consumers. This particular experiment focuses on residential electricity consumers.

The experiment was designed a follows (depicted in Figure 2). Twenty transformers were selected for the project. Smart meters were installed at all 20 project transformers in May 2018. Transformers were assigned to treatment or control status, resulting in 10 transformers in each group. Transformers serve a neighborhood of households. In our study transformers, there is a mean (median) of 68 (67) residential electricity consumers per transformer.[19] By September 2018, smart meters replaced the old meters at all households located in the treatment transformers. Households located in the control transformers retained their old meters. This resulted in 798 households having smart meters installed (the "Treatment Group") and XXX households retaining their old meters (the "Control Group").

Residential electricity consumers may reside in either multi-story apartment buildings or single family dwellings. The average home in our sample has 3 rooms. Eighty percent of the homes are owner occupied. The majority of households (sixty-five percent) use electricity for winter heating. Residences have only modest investments in energy efficiency at the experiment's outset, with 20 percent and 21 percent of households using energy efficient lightbulbs and insulation, respectively. Households do report electricity quality issues, with 47 percent reporting one or more outage per week during winter 2018 and 71 percent reporting one or more voltage fluctuation per week during the same time period. Twenty-one percent of households report prior appliance damage due to the poor electricity quality. However, there is little investment in durables to protect against poor electricity quality, such as electricity generators or stabilizers. We provide more detailed information on the baseline average ownership of various electric appliances and devices in Appendix Table A2.

[19]We identify these as the residential consumers based on the tariff rate the entity pays for electricity consumption. The residential tariff is lower than that paid by commercial and industrial consumers.

3.3 Data

We employ data from several sources for the analysis, including baseline and follow-up survey data, utility transformer and consumer billing records, and the data from the smart meters. Appendix Figure A4 depicts the timing of meter installation in relation to different data sets used in analyses.

Survey data: We implemented baseline and follow-up survey data in the spring of 2018 and 2019, respectively. Both surveys ask questions on characteristics of the home, quality of electricity services, the set of home appliances, overall household expenditures, amongst others. The baseline was a streamlined survey, meant to be a limited touch at the household level. The follow-up survey was more extensive, resulting in greater data available for the follow-up period. We sought to survey all households within the treated and control transformers. Survey respondents totalled 1143 in the baseline and 1125 in the follow-up survey. When we limit the dataset to the balanced panel of respondents in both the baseline and follow-up surveys, the dataset includes 880 households.

Utility data: The electricity utility provides data pertaining to project transformers and the residential consumers located in areas served by the transformers. The transformer-level data includes transformer characteristics and dates of maintenance, repair, and last replacement. The consumer data includes monthly billed electricity consumption. Records start in January 2017, providing approximately 1.5 years of pre-intervention data. Data also include information on the customer debts to the utility and whether and when a consumer's electricity connection was cutoff (disconnected) for failure to pay its bill.

Smart meter data: Data from transformer-level smart meters provide measurements at the level of treatment-assignment. Transformer-level smart meter data start in summer 2018, which is approximately 4 - 5 months prior to the installation of the household-level meters within the treatment group. These transformer-level data provide records in 15-minutes increments of "alarms." Smart meter alarms can be activated for a number of reasons, such as if a connection is disconnected but power is detected (an indicator of theft), if an over voltage is detected (an indicator of poor electricity quality), or if a power failure is detected (an indicator of an outage). For the analysis we create transformer-level outcomes by grouping the alarms into bins of similar alarms indicating the same type of problem (theft, poor quality, and outages). The types of alarms and how we group them are shown in Appendix Table A7. Of the alarms recorded after the start of the intervention, approximately 21% indicated theft, 46.3% indicated electricity voltage problems, and 22.4% were related to power outages. We use the alarms data post-intervention, as the alarm types are different in nature than the alarms data following the intervention.[20]

3.4 Baseline balance tests

We provide evidence of baseline balance between treatment and control groups using billed monthly electricity consumption data and the baseline survey data.

Figure 3 graphs pre-treatment billed electricity consumption between January 2017 and July 2018. The bottom panel plots billed electricity consumption for both Treatment and Control households during each month, without controlling for any other variables. For both groups, the average monthly electricity consumption in the winter is approximately three times consumption in the summer. This seasonal electricity consumption pattern is indicative of some households – but not all – using electric heating during winter. We note the treatment households' consumption is slightly higher than the control households on average in the winter months.

The top panel plots the differences between Treatment and Control households each month, with the lines indicating the 90% confidence intervals. This serves as balance test between the two group with respect to baseline monthly billed electricity consumption. The graph shows no significant differences in electricity consumption between the treatment and

[20]This is due to a change in the transformer-level smart meters at that time.

the control households in any month during the pre-intervention period.

Additional evidence in support of balance is in the Appendix. Using data from the baseline survey, we find no significant differences between the two groups on all of the variables tested, including the size of the house, use of insulation and energy efficient lightbulbs, fuel used for heating, various measures of electricity quality (outages and voltage fluctuations), and use of technologies to protect against poor electricity quality (e.g. generators and stabilizers) (Appendix Table A3). There are also no significant baseline differences between the two groups in 12 categories of household expenditures, including electricity and household appliances (Appendix Table A4).

3.5 Non-compliance and attrition

Non-compliance is not an issue in this setting. By law, all electrical installation are required to be metered to monitor and control electricity consumption. Legally, the meters (whether smart or traditional) are the property of the electricity distribution company. Consumer consent is not required for the utility to change the meters (Government of the Kyrgyz Republic, 2012). Treatment was assigned at the transformer level and all residential electricity consumers within the treated transformers had smart meters installed by the electricity utility.

We check response rates for both treatment and control groups in baseline and follow-up surveys and find no evidence of differential attrition across groups. Attrition rates between the baseline and follow-up surveys are 24.3% and 21.7% in the treatment and control, respectively (Appendix Table A5). When we limit our analysis of the survey data to the households for which we have a balanced panel, we have 880 households.

4 Impacts of smart meters

4.1 On electricity consumption

We plot the raw monthly billed electricity consumption for treatment and control groups during the months following the smart meter installation (Figure A5). The differences in average electricity consumption between the treatment and control groups post-intervention are more pronounced than in the pre-intervention months. However, the direction of these differences is heterogeneous across seasons. During "peak" consumption months, which are the winter months during which electric heating services are consumed, billed electricity consumption is higher on average in the treatment group than the control. During one month, the two groups are statistically significant different from one another. In the "off-peak" consumption months – the warmer, non-heating months – the billed electricity consumption for the control households is, on average, higher than that of the treatment households. There are statistically significant differences between the treatment and control groups in this post-intervention figure in both "peak" and "off-peak" months, which were not present in the pre-intervention period (Figure 3). This figure is generated without any additional control variables, so we interpret it with caution. However, it motivates the regression analysis that follows.

We employ a standard difference-in-differences regression model using the panel nature of the monthly billed electricity consumption data. To measure the impacts of smart meters on household billed electricity consumption, we estimate the following:

$$q_{igt} = \beta_1 Treat_{ig} \times Post_t + \beta_2 Post_t + \beta_3 Treat_{ig} + \gamma_t + \lambda_i + \epsilon_{igt} \tag{1}$$

where q_{igt} is quantity of billed electricity consumption (kWh) for household i in transformer g during time t (a month), $Treat_{ig}$ is an indicator of transformer treatment status for household

i in transformer g that equals 1 if treated and 0 if not treated, γ_t are month-by-year fixed effects, and λ_i are household fixed effects. Standard errors are clustered at the transformer level to account for the transformer level treatment assignment. The household fixed effects control for any household characteristics that are fixed over time (such as the location of the house, the transformer by which the household is served, etc.). Time fixed effects control for any shocks – including weather – that impact all households in a given month.

Results are reported in Table 1. Given the heterogeneities in billed electricity consumption across the "peak" and "off-peak" months in Figure A5, we perform the regressions separately for these periods. Column 1 shows the results for the "peak" months. Electricity consumption increases for the treated households by 32 kWh per month following the installation of smart meters, albeit insignificantly. Column 2 presents the results from the off-peak months. During off-peak months, electricity consumption decreased post-meter installation by 30.5 kWh per month. As a robustness check, we perform this analysis but drop the top 1% of observations. Coefficients asre smaller in magnitude, but the results overall are consistent with this analysis (Appendix Table A6).

As discussed in Section **??**, we could see increases and decreases in billed electricity consumption for a number of reasons. XXXX PLACEHOLDER FOR MORE INTERPRETATION OF RESULTS. XXX We investigate the channel of impacts in the sections that follow.

4.2 Impacts on non-technical losses, including theft

We want to measure the impacts of the smart meters installed at the household-level on non-technical losses, including: meter malfunction, meter tampering, bypassing the meter, billing irregularities, and non-payment of bills.

4.2.1 Indicators of theft

Our measurement of alarms is from transformer-level smart meters, which allow us to test for impacts on the following indicators of theft: meter malfunction, meter tampering, bypassing the meter. We limit our analysis to the post-intervention period, estimating the following equation:

$$A_{gt} = \beta_1 Treat_g + \beta_2 X_g + \gamma_t + \epsilon_g \tag{2}$$

where A_{gt} is the number of (theft-related) alarms recorded by the transformer smart meter in one day for transformer g in time period t, $Treat_{gt}$ is an indicator of transformer treatment status, X_g is a vector of transformer characteristics (the number of households served by the transformer and the transformer's technical capacity), and γ_t are month-by-year fixed effects. Standard errors are clustered at the transformer level.

Results are in Table 2, with columns 1 and 2 displaying results from OLS and poisson regression models, respectively. The control group mean tells us that, on average, the control transformers are picking up a theft-related alarm almost every other day (0.395 theft-related alarms per day per control transformer). The treated transformers are not statistically different from the control transformers with respect to the number of alarms reported per day.

4.2.2 Evidence of unpaid bills

Another main source of non-technical losses are unpaid bills. In these cases the electricity consumed is billed by the electricity utility, but the consumer substantially delays payment, potentially resulting in disconnection. We use two sources of data on payment and disconnection: utility records (debts to the utility and cutoff for non-payment) and the household survey (whether the household reports that they arranged for late payment of their electricity bill or whether they paid their bill late). We estimate a similar equation to the one in the section above, but it is at the household level with household controls. We estimate the following equation:

$$U_{ig} = \beta_1 Treat_{ig} + \beta_2 X_{ig} + \epsilon_g \tag{3}$$

where U_{ig} is one of our outcome measures related to unpaid bills, $Treat_g$ is an indicator of transformer treatment status, and X_{ig} is a vector of household characteristics (the number of rooms in the house and whether the house is owner occupied). Standard errors are clustered at the transformer level.

Results are in Table 3. Using utility records, we see households in treated transformers do not have significantly different amount of debt owed to the utility (Column 1); however, they are less likely to be cutoff for not paying their bills (Column 2). Using the household survey data, we see that households in treated transformer are less likely than those in control to arrange for a delayed or late bill payment, however the difference is not statistically significant. Households in treated transformers are significantly less likely to report paying their electricity bill late. This is indicative of households' awareness of the smart meters' remote disconnection functionality and an increased probability of disconnection for late/non-payment of bills. It suggests the smart meters act as a deterrent to late- or non-payment; however, it does not indicate decreases in overall electricity theft as result of the smart meter intervention. Shows households are being more serious about paying bills.

4.3 Impacts on electricity quality

Our measures of electricity quality are overall transformer-level alarms per day, electricity quality-specific alarms (voltage spikes, outages), and household quality reports. To estimate the impacts of the smart meters on indicators of electricity quality, we again estimate Equation 2, but use the quality related alarms from the transformer smart meters as our outcome measures.

In Table 4, we test the impact of the treatment on alarms specific to electricity quality. We find that alarms indicating voltage spikes and power outages are significantly lower in the treatment transformers that the control (Column 1). However, there is no significant difference in alarms related to outages or other sources (Columns 2 and 3, respectively).

5 Mechanism for electricity quality improvements?

The smart meters themselves do not have the functionality to improve electricity quality. We want to understand the mechanism by which they might do so. Discussions with some consumers and the electricity inform our hypothesis. During the summer 2018, when smart meters were being installed at the transformers, we heard reports from household consumers that they had previously complained to the electricity utility about voltage problems, damage to appliances, and the inability to use certain appliances. These individuals reported that the utility had not responded to their concerns or done any repairs. their complaints did nothing.

The smart meters alarms provided the consumers with proof of the poor quality electricity service. When the voltage spiked or dropped outside of the standard range (as required by contract), the smart shuts down the connection. This protects the households' appliances from damage, but in and of itself does not improve electricity quality. But it is a verified report of poor electricity service quality that the utility cannot dispute or ignore. We hypothesize that the smart meter alarms led to improvements at the transformers (performed by the electricity utility). These repairs and replacements led to improved electricity service in the areas covered by those transformers. We discuss the testing of this hypothesis in the paragraphs that follow.

We test whether the transformer-level treatment assignment led the utility to increase its effort [or cost expended] on electricity infrastructure. Using electricity utility panel data on transformer maintenance and repairs starting in January 2017, we measure the impact of treatment on unplanned repairs (response due to breakage) ans planned improvements (transformer overhauls or replacements). Results are presented in Table 5. In Column 1, the coefficient on Post indicates that overall unplanned repairs increased following treatment. However, the coefficient on TreatXPost tells us that the unplanned repairs were not significantly different for the treatment and control transformers. They appeared to not respond any differently to breakages between the two groups. This is good. We would be concerned if they were responding differently. We learn several important things from the result in Column 2. First, planned improvements are relatively infrequent. However, treated transformers are significantly more likely to have planned improvements after the onset of the intervention. We interpret these results with caution as the analysis is limited to monthly data over a 33 month period for the 20 transformers.

We want to know if it was indeed the smart meters and information provided by the alarms that led to the increased in planned transformer improvements. Next we check that the utility was not just trying to demonstrate something else, and performing improvements to all the transformers that received smart meters. We use the transformer alarms data in the period between meter installation and Feb 14, 2019, which was the time when the first transformer replacement occurred. By using this period we are able to test whether alarms were associated with a higher probability of replacement or repairs before the replacement.[21] Results are in Table 6. This provides evidence that a deferentially greater number of alarms did precede the transformer work and supports the claim that the alarms were indicating to the utility the transformers with the greatest need for work.

[21] "Replace" indicates the transformers that have bene completely replaces, whereas "Repair" indicates the transformers that have had unplanned repairs due to breakage.

6 Effects of improved electricity quality on consumer welfare

In this section, we estimate the impacts of smart meters on consumer welfare and provide additional evidence supporting the interpretation of these calculations.

6.1 Welfare calculations

We calculate the welfare impacts of the improved reliability. Klytchnikova and Lokshin (2009) provides support for using the increased electricity consumption, in the case of voltage and outage improvements, as an estimate of the welfare impacts.

To carry our this estimate, we aggregate the household billed consumption and calculated the total pre-winter consumption and total post-winter consumption for each household. We merge the data with household surveys (both baseline and follow-up) to get the self-reported electricity service quality, which is the total # of outages and # of voltage fluctuations within a week. We use the panel data to run IV regression, both controlling for household fixed effects.

We estimate the welfare impacts using two-stage least squares with the panel data. In the first equation we estimate the impact of treatment on electricity quality events in a week. In the second equation, we estimate the impact of electricity quality events in a week on billed electricity consumption.

First stage:

$$\text{Reliability}_{igt} = Treat_{ig} \times Post_t + Replace_{ig} \times Post_t + \lambda_i + \epsilon_{igt} \tag{4}$$

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 survey s. $Treat_{ig}$

is an indicator of transformer treatment status. $Replace_{ig}$ is an indicator of transformer replacement status. $Post_t$ is an indicator variable and equals 1 for the following-up survey conducted in 2019 spring. λ_i are household fixed effects.

Second stage:

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

where q_{ig} is the total monetized billed electricity consumption in the winter period covering from November to March (kWh) for household i in transformer g in time t. $\widehat{\text{Reliability}}_{igt}$ is the estimates from the first stage. λ_i are household fixed effects.

The result of these welfare calculations are in Table 8. Column 1 contains the results from the first stage regression (the impact of treatment assignment 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. We interpret the result in Column 2 to mean 1 fewer electricity quality incident (either voltage fluctuation or outage) per week on average results in 2251 KGS more in billed electricity over the five month winter period. This equals approximately a welfare improvement of approximately 6.50 USD per month during the months of peak electricity consumption.

7 Conclusions

Pro-poor growth in the developing world is expected to result in greater household appliance ownership and, thus, increased residential electricity demand (Wolfram, Gertler and Shelef, 2012). Pressure on the existing infrastructure, therefore, will continue to build and such quality traps will exacerbate constraints on growth, acting as a barrier to future development. With this in mind, there is tremendous need for evidence-based mechanisms to disrupt this cycle and break free from the infrastructure quality trap. Yet, very limited evidence exists to date.

Through a randomized experiment in collaboration with an electricity utility in the Kyrgyz Republic, we provide evidence on the impact of smart meters on the infrastructure quality trap. Utilities in both developed and developing countries install smart meters for the purpose of reducing such losses; yet the existing economics research does not address these potential benefits. Through this study, we contribute to a literature on methods to improve electricity reliability and provide the first of such evidence on ways to interrupt infrastructure quality trap.

These findings, which provide evidence on the short-run impacts of the meters, indicate that the smart meters assist in improving electricity quality. Results suggest that smart technologies alone are insufficient to eliminate non-technical losses (electricity theft). The technological improvements likely must be paired with monitoring of the information provided by the technology and enforcement against theft. Electrical utilities installing smart meters to reduce theft ought to budget not only for purchasing technological improvements, but also for labor costs required to monitor the technology.

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Figure 1: Example of infrastructure quality trap

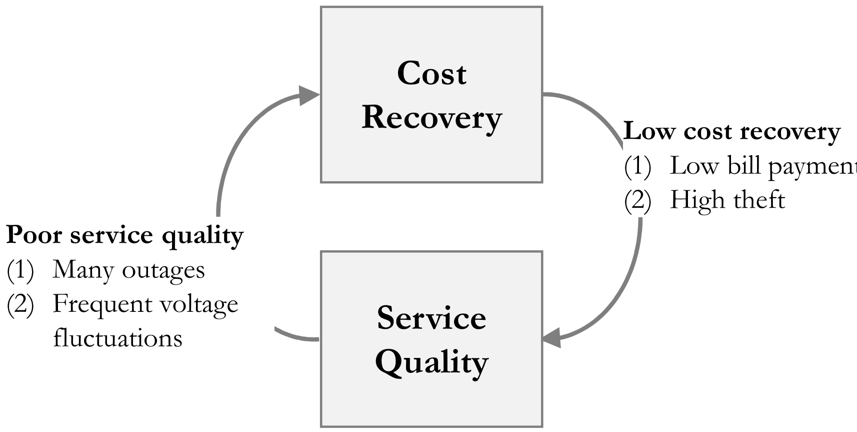
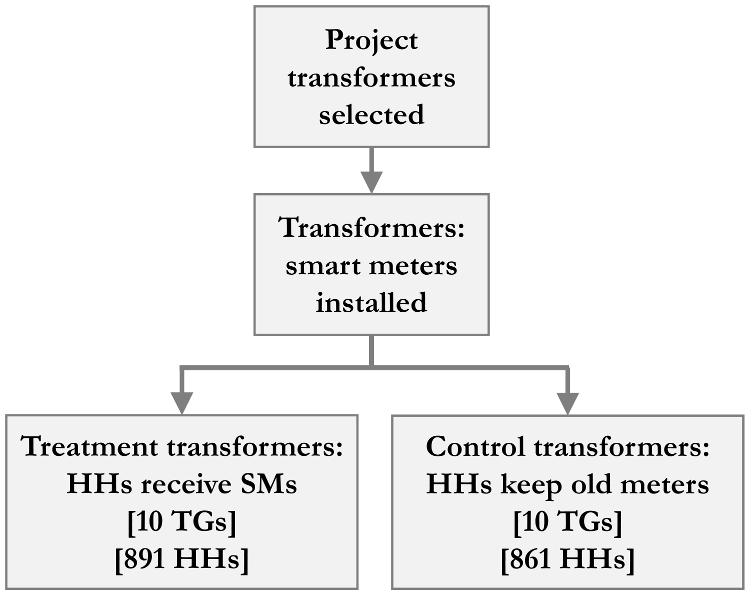


Figure 2: Randomized design



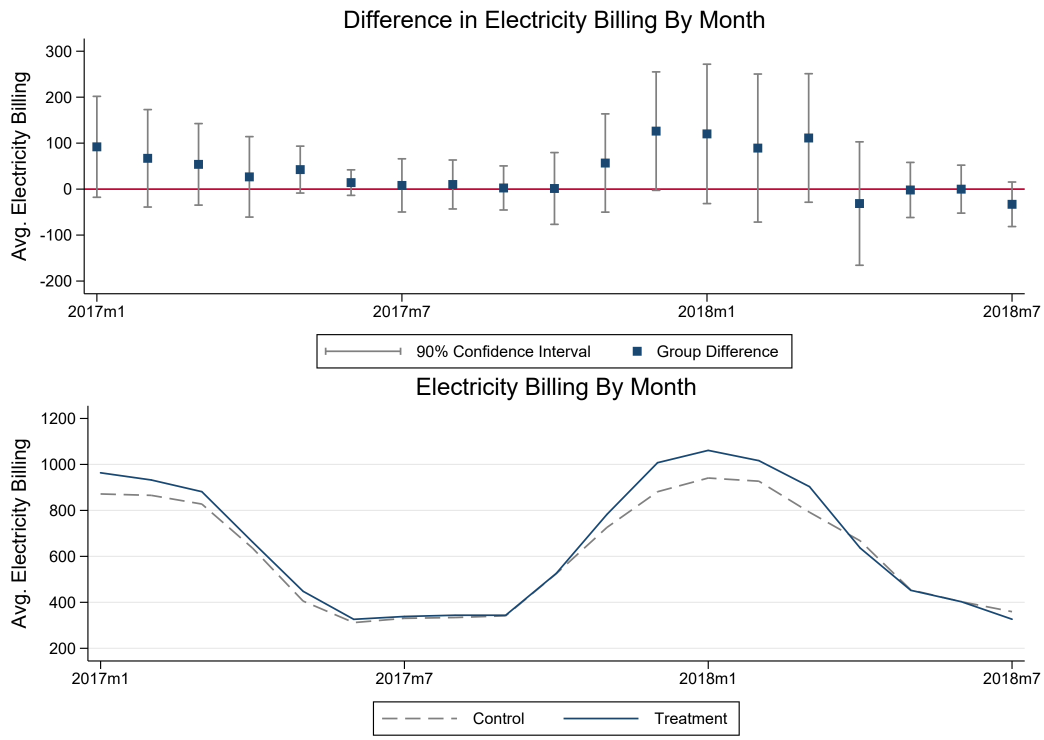


Figure 3: Pre-treatment Billed Electricity Consumption

Notes: Billing data are provided by the electricity utility. The analysis here is basic comparison and no other variables are controlled. Addresses that are non-residential are dropped. The standard errors are clustered at the transformer level. The grey lines in the upper figure indicate the 90% confidence interval.

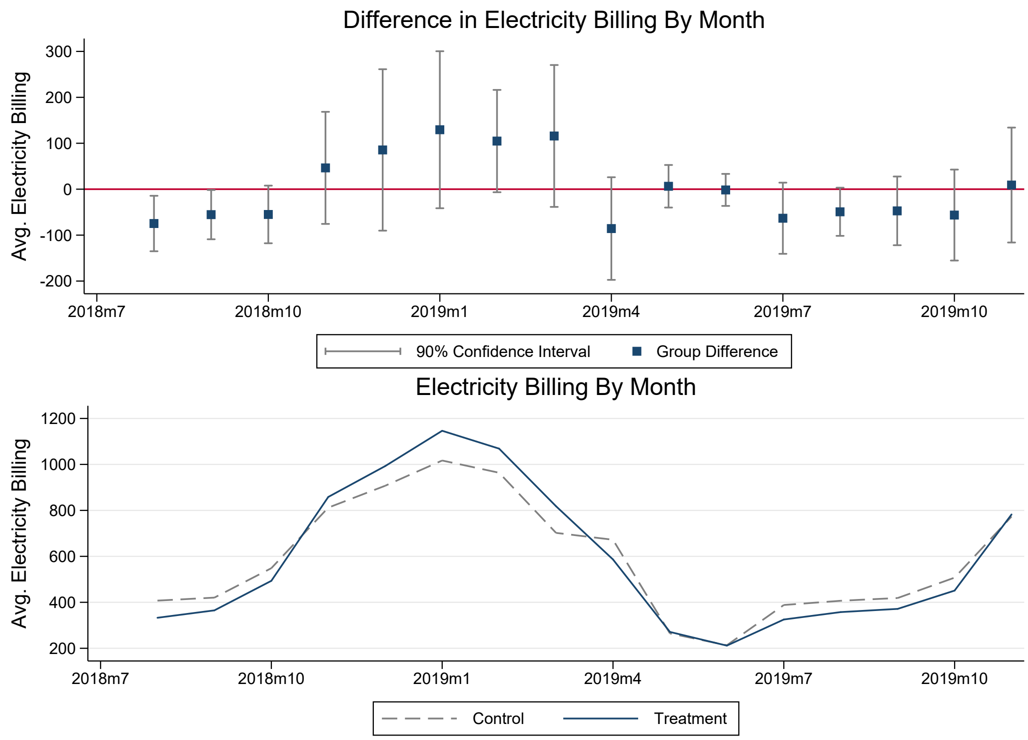


Figure 4: Post-treatment Billed Electricity Consumption (kWh/month)

Notes: Billing data are provided by the electricity utility. The analysis here is basic comparison and no other control variables are included. The standard errors are clustered at the transformer level. The grey lines in the upper figure indicate the 90% confidence interval.

Table 1: Billed Electricity Consumption, By Season

VARIABLES	(1) bill	(2) bill
Treat × Post	18.276	-29.837**
	(22.703)	(12.138)
Post	-166.874***	-226.044***
	(33.690)	(16.731)
Constant	914.487***	631.385***
	(16.710)	(14.701)
Mean of Control Group	851.071	432.379
Observations	19,408	29,073
Number of Household	1,453	1,453
Adjusted R-squared	0.043	0.162
Household Fixed Effect	Y	Y
Month-by-Year Fixed Effect	Y	Y
Cluster SE	Transformer	Transformer
Season	Peak (Heating)	Off-peak (Non-Heating)

Notes: Billing data are provided by the electricity utility covering the period between January 2017 and November 2019. Control group means are for the baseline (pre-intervention) period. The outcome variable *bill* measures the monthly billed electricity consumption (kWh/month) for a household. *lag bill* is the one-period lagged monthly billed electricity consumption. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

Table 2: Transformer-Level Smart Meter Alarms - Potential Theft

Alarms (in one day) indicating:	Potential theft	
	(1)	(2)
Treat	0.558	1.098
	(0.755)	(1.207)
Constant	0.556	0.167
	(0.342)	(0.443)
Mean of Control Group	0.393	0.393
Observations	6,277	6,277
R-squared	0.007	0.051
Month-by-Year Fixed Effect		Y
Feeder-line Fixed Effect		Y
Cluster SE	Transformer	Transformer

Notes: Alarms data are the smart meters installed on the transformers and cover the period from April 2018 to November 2019. The outcome variable is the number of alarms indicating potential theft recorded by the transformer smart meter in one day. Regressions control for transformer characteristics including number households served by the transformer and its capacity. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

Table 3: Household Electricity Bill Payment

	Debts to utility (1)	Cutoff for non-payment (2)	Arranged delayed payment (3)	Paid bill late (4)
Treat	23.041	-0.012***	-0.112	-0.061**
	(49.357)	(0.004)	(0.142)	(0.024)
Constant	143.921	0.026***	0.171	0.131***
	(97.301)	(0.006)	(0.122)	(0.036)
Mean of Control Group	54.129	0.015	0.398	0.105
Observations	1,576	1,576	1,125	1,125
R-squared	0.001	0.005	0.034	0.016
Basic Characteristics	Y	Y	Y	Y
Cluster SE	Transformer	Transformer	Transformer	Transformer
Data source	Utility records	Utility records	Household survey	Household survey

Notes: Utility records were as of September 2019. Household survey data were collected in Spring 2019. The outcome variables are binary indicators and equal 1 if the household reports the corresponding behavior in the past year. Control variables for basic household characteristics include the number of rooms in a house and whether the house is owned by the household. Robust standard errors are clustered either at the transformer level or the household level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

Table 4: Transformer-Level Smart Meter Alarms - Electricity Quality Alarms

Alarms (in one day) indicating:	Voltage problems		Power outage		Other alarms	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-2.442**	-2.620**	-0.007	0.076*	0.001	0.022
	(1.038)	(1.074)	(0.040)	(0.042)	(0.022)	(0.022)
Constant	2.310**	2.339**	0.570***	0.515***	0.256***	0.241***
	(1.034)	(1.076)	(0.049)	(0.049)	(0.027)	(0.027)
Mean of Control Group	2.596	2.596	0.589	0.589	0.26	0.26
Observations	6,277	6,277	6,277	6,277	6,277	6,277
Month-by-Year Fixed Effect		Y		Y		Y
Feeder-line Fixed Effect		Y		Y		Y
R-squared	0.069	0.119	0.000	0.058	0.000	0.060
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer

Notes: Alarms data are provided by the electricity utility covering the period from September 2018 to October 2019. The outcome variable is the number of alarms recorded by the transformer smart meter in one day. Regressions control for transformer characteristics including number households served by the transformer and its capacity. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table 5: Transformer-Level Maintenance

VARIABLES	Unplanned Repair		Planned Improvement	
	(1)	(2)	(3)	(4)
Treat × Post	-0.033	-1.386	0.048*	1.299
	(0.032)	(1.144)	(0.028)	(1.065)
Post	0.052*	1.817*	0.026	0.836
	(0.026)	(1.061)	(0.021)	(0.756)
Constant	0.023***	-2.987***	0.015**	-4.211***
	(0.006)	(0.375)	(0.006)	(0.409)
Mean of Control Group	0.01	0.01	0.02	0.02
Observations	660	297	660	627
R-squared	0.045		0.026	
Transformer FE	Y	Y	Y	Y
Cluster SE	Transformer	Transformer	Transformer	Transformer
Model	OLS	Poisson	OLS	Poisson

Notes: Transformer maintenance data are provided by the electricity utility covering the period from January 2017 to October 2019. The mean of control group is calculated for the baseline period. Unplanned Repair is the transformer-level number of repair in a month. Planned Improvement is the transformer-level number of planned maintenance and replacement in a month. *Treat* is a binary variable and equals 1 if the transformer belongs to the treatment group. *Post* is a binary variable and equals 1 for the periods after August 2018. We control transformer fixed effects. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

Table 6: Compare the Number of Alarms among Three Transformer Groups

VARIABLES	(1) alarms	(2) alarms
Treat	0.816***	1.543***
	(0.160)	(0.189)
Treat × Replace	0.368**	0.375**
	(0.161)	(0.184)
Treat × Repair	0.322	0.259
	(0.332)	(0.236)
Constant	0.192***	-1.533***
	(0.061)	(0.094)
Observations	2,709	2,709
R-squared	0.033	
Cluster SE	Transformer	Transformer
Model	OLS	Poisson

Notes: Alarms data are provided by the electricity utility. Here, we compare the number of alarms for the two replaced transformers (114 and 591), three transformers with unplanned repairs (33, 100, and 408), and other treated transformers, and the control transformers. We focus our analysis before the time when the first replace of transformer happens (Feb 04, 2019). The outcome variable is the transformer-level number of alarms recorded by the smart meter in a day. *Treat* is a binary variable and equals 1 if the transformer belongs to the treatment group. *Replace* is a binary variable and equals 1 if the transformer was replaced. *Repair* is a binary variable and equals 1 if the transformer had unplanned repairs due to breakage. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table 7: Transformer-Level Smart Meter Alarms - After Transformer Replacement

Alarms (in one day):	Total Alarm Count	
	(1)	(2)
Changed x Postchange	-1.292**	-1.473**
	(0.615)	(0.647)
Unchanged x Postchange		-0.331
		(1.169)
Postchange	1.480**	1.662**
	(0.613)	(0.646)
Constant	1.562***	1.542***
	(0.301)	(0.273)
Observations	7,748	7,748
R-squared	0.150	0.150
Transformer Fixed Effect	Y	Y
Cluster SE	Transformer	Transformer

Notes: Alarms data are the smart meters installed on the transformers and cover the period from April 2018 to November 2019. The outcome variable is the number of alarms indicating potential theft recorded by the transformer smart meter in one day. Regressions control for transformer characteristics including number households served by the transformer and its capacity. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$). ZW: What is the time period for these data?

Table 8: Welfare Impact of Electricity Service Quality Improvements

VARIABLES	(1) reliability	(2) monetized bill
reliability		1,857.761***
		(292.518)
Treat × Post	-1.237***	
	(0.284)	
Replace × Post	2.243***	
	(0.810)	
Post	-0.267	
	(0.202)	
Constant	-4.071***	15,587.463***
	(0.099)	(1,314.117)
Observations	2,906	2,906
F-statistics	19.86	
R-squared	0.039	
Number of id	1,453	1,453
Household FE	Y	Y
Estimate	IV Stage 1	IV Stage 2

Notes: Reliability data are collected from the household baseline and follow-up survey conducted in May of 2018 and 2019, respectively. Billed electricity data comes from the electricity utility. We calculated the total monetized electricity consumption in the winter for both pre-experiment period and post-experiment 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 winter period covering from November to March. *Treat* is a binary variable and equals 1 if the household belongs to the treatment group. *Post* is a binary variable and equals 1 for the post-experiment period. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

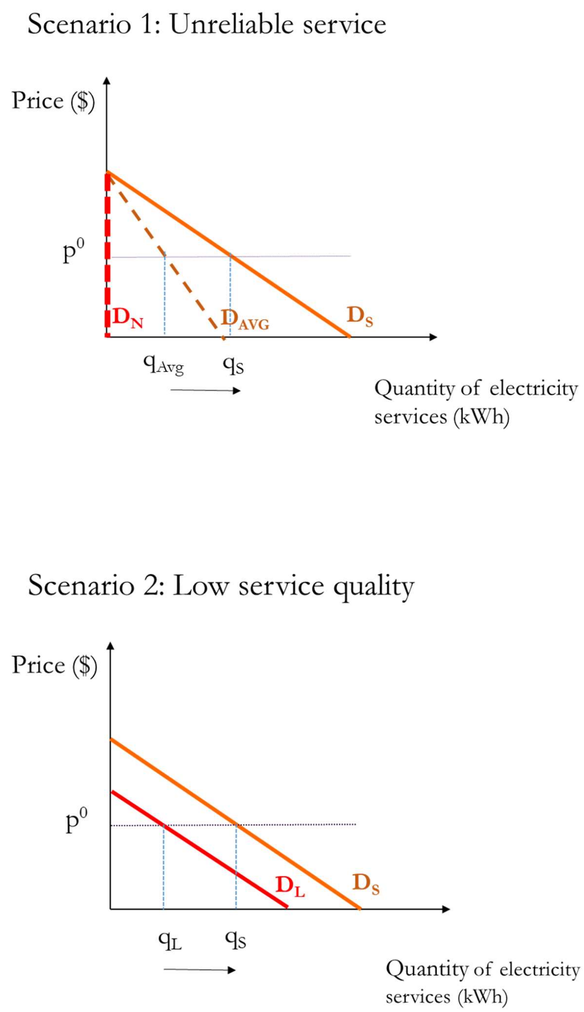
Table 9: Household Expenditures (in KGS)

VARIABLES	(1) food	(2) school	(3) electricity	(4) heat	(5) other utilities	(6) communication
Treat × Post	-405.360	-1,370.930	42.235	-31.577	-16.915	-42.354
	(318.015)	(2,428.577)	(99.037)	(63.354)	(35.725)	(58.857)
Treat	325.162	1,122.246	10.460	9.648	12.179	87.322
	(350.981)	(1,992.095)	(49.588)	(11.998)	(31.823)	(66.843)
Post	72.182	1,992.837**	796.880***	57.224	24.062	71.056**
	(136.038)	(933.554)	(71.442)	(59.525)	(30.690)	(27.609)
Constant	1,702.943***	3,173.740***	-11.988	68.976	121.135***	268.552***
	(197.337)	(1,217.277)	(69.489)	(44.668)	(33.946)	(43.533)
Control Group Mean	2079.244	3991.788	338.849	2.067	236.284	403.260
Observations	1,760	1,760	1,760	1,760	1,760	1,760
Number of id	880	880	880	880	880	880
Basic Characterstics	Y	Y	Y	Y	Y	Y
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer
VARIABLES	(7) transportation	(8) medical	(9) clothing	(10) house repairs	(11) house appliance	(12) discretionary expenses
Treat × Post	-111.895	262.024	-1,010.192	-2,185.022	912.637**	-10,081.081
	(330.734)	(350.155)	(781.090)	(3,391.429)	(464.975)	(20,259.433)
Treat	50.534	-401.516	661.354	3,376.204	6.873	9,305.921
	(301.547)	(338.622)	(779.583)	(2,806.444)	(635.113)	(20,459.956)
Post	-116.059	-999.452***	645.538*	901.688	414.410*	-27,538.243**
	(179.535)	(225.318)	(380.000)	(1,833.053)	(232.972)	(12,705.953)
Constant	676.919***	1,442.204***	2,573.377***	3,560.180	959.313*	37,696.130***
	(262.678)	(315.924)	(590.554)	(2,284.247)	(528.743)	(13,426.979)
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 HHs	880	880	880	880	880	880
Basic Characterstics	Y	Y	Y	Y	Y	Y
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer

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 one month (electricity, heat, other utility, communication, transportation, medical), and past 3 months (clothing, house expenses, house appliance, discretionary). The exchange rate at time of the baseline survey was 1 USD to 68.5 KGS. Control variables for basic household characteristics include the number of rooms in a house and whether the house is owned by the household. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

APPENDIX: FOR ON-LINE PUBLICATION

Figure A1: Framework for impacts of service quality on electricity services consumed



Notes: Graphs based on insights provided by Klytchnikova and Lokshin (2009) and McRae (2015b).

Figure A2: Smart meters: potential channels to increase (i) enforcement of payment for services consumed, and (ii) accountability to deliver quality services

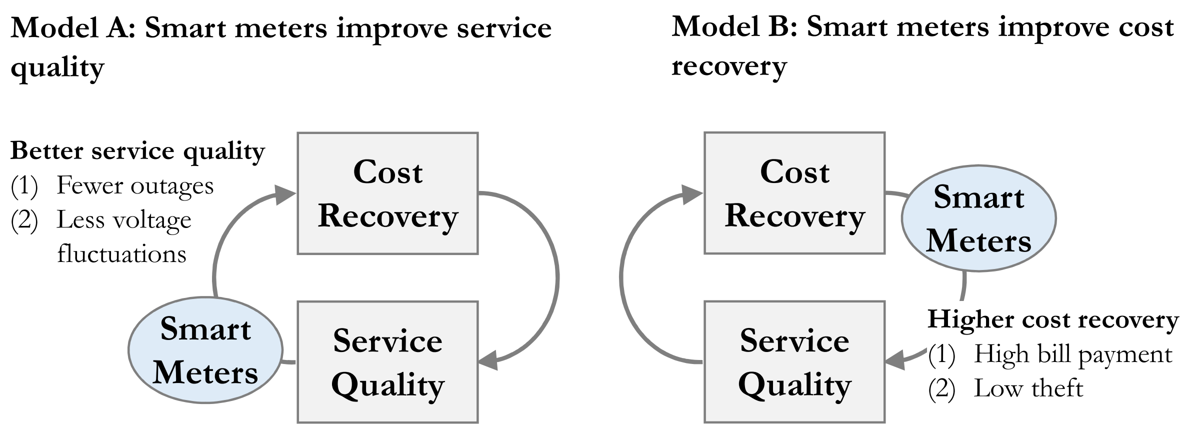


Table A1: Types of non-technical losses, impacts on billing and role of smart meters

	(1) NTL Type	(2) Examples of NTL	(3) Impact on Billing	(4) Role of Smart Meters
(a)	Meter malfunction	mechanical, meter inaccurately registers quantity, common with low voltage	bill $<$ actual consumption	consumption more accurately recorded, even low voltage
(b)	Meter tampering	meter paused with physical impediment, "rolled back", altered with magnets, etc	bill $<$ actual consumption	detects some tampering and provides utility info
(c)	By-passing meter	wiring circumvents meter through illegal tapping, etc.	bill $<$ actual consumption	detects some by-passing and provides utility info
(d)	Billing irregularity	utility employee documents quantity consumed $<$ meter reads	bill $<$ actual consumption	human meter reader unnecessary if billing system is integrated
(e)	Bill non-payment	customer receives bill, but does not pay and non-payment is unpunished	bill $\leq$ actual consumption but bill not paid	utility can remotely disconnect non-payers

Notes: Table created based on information specific to the particular smart meters installed in this setting. More general information on capabilities of different types of meters is available in USAID (2009) Online Toolkit for for Optimal Feeder Level Connection.

Figure A3: Framework for impacts of NTL on electricity services consumed

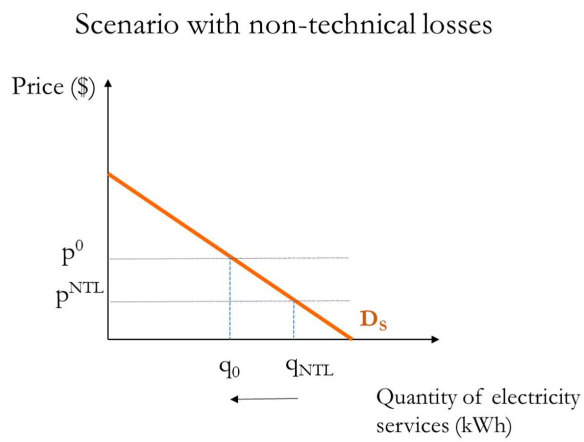
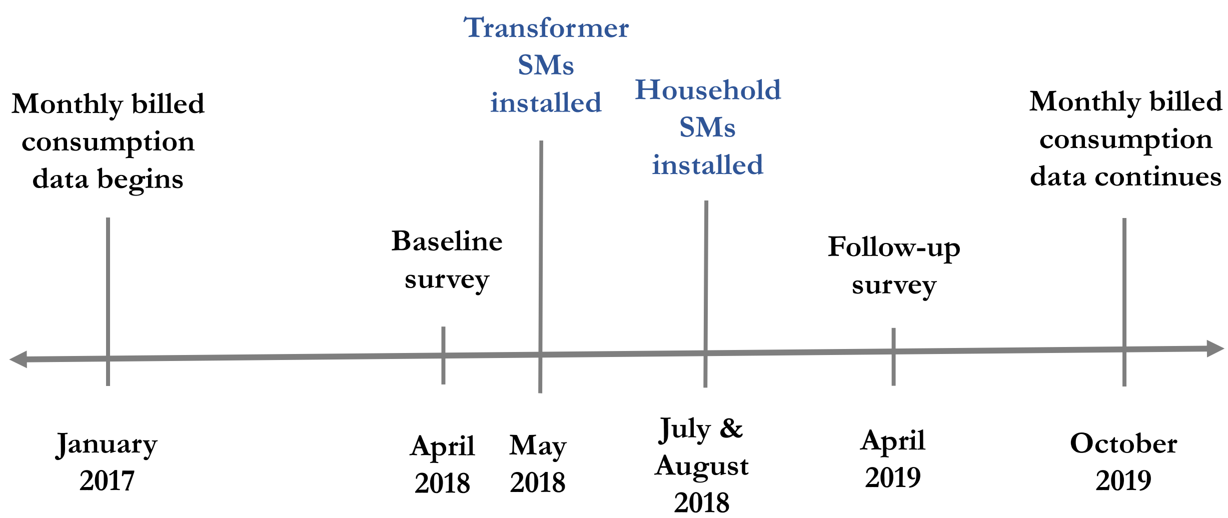


Table A2: Mean baseline values: electric appliances and other devices

Variables		Control	Treat
electric appliance ownership	refrigerator	0.827	0.888
	clothes washer	0.836	0.828
	color TV	0.862	0.872
	sound equipment	0.142	0.093
	computer/laptop	0.184	0.184
	water heater	0.433	0.507
	cellphone charger	0.702	0.602
	electric heater	0.722	0.609
electricity-related device ownership	electricity generator	0.009	0.016
	stabilizer	0.011	0.005
	battery with inverter	0.000	0.000
	uninterruptable power supply	0.002	0.000
	solar panel	0.000	0.000
	solar water heater	0.002	0.000
	other solar device	0.000	0.000
energy efficient lightbulb	usage	0.191	0.208
	EE lightbulb share	0.229	0.271

Notes: Data collected via baseline household survey, conducted in spring 2018. We calculate the mean values of the outcome variables for both the control and treatment group. *Electric appliance ownership* and *Electricity-related device ownership* are binary variables indicating whether the household have certain electric appliances or devices. *Energy efficient lightbulb usage* is a binary variable indicating whether the household use energy efficient lightbulb at home.

Figure A4: Timeline of meter installation and data collection



Notes: Monthly billed electricity consumption data are provided by the electricity utility. After 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 A3: Balance at Baseline: Treated and Control Household Characteristics

	Mean	Treatment Mean	Control Mean	Difference	P-value
Average # of rooms in the house	2.968	2.958	2.977	-0.020	0.942
Proportion of homes owned	0.802	0.778	0.826	-0.048	0.383
Proportion of homes with insulation	0.213	0.264	0.162	0.102	0.352
Proportion of houses using EE lightbulbs	0.200	0.208	0.191	0.017	0.798
Proportion of houses using central heating	0.057	0.079	0.035	0.044	0.485
Proportion of houses using electric heating	0.651	0.688	0.614	0.075	0.393
Proportion reporting 1+ outages per week (Jan - Feb 2018)	0.467	0.451	0.482	-0.030	0.817
Proportion reporting 1+ voltage fluctuations per week (Jan - Feb 2018)	0.705	0.695	0.717	-0.022	0.854
Proportion of houses with electric generators	0.004	0.005	0.004	0.002	0.715
Proportion of houses with stabilizers	0.005	0.005	0.005	0.000	0.991
Proportion of houses with appliances that have been damaged	0.210	0.239	0.183	0.056	0.595
Observations	1143	568	575		

Notes: Data collected via baseline household survey, conducted in spring 2018. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

Table A4: Balance Table - Household Expenses

	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)
heat	1.617	11.866	10.249
	(17.118)	(154.182)	(11.342)
other utility	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 appliance	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)	(102625.523)	(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 of the mean value between the treatment group and control group. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table A5: Check for differential attrition

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

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

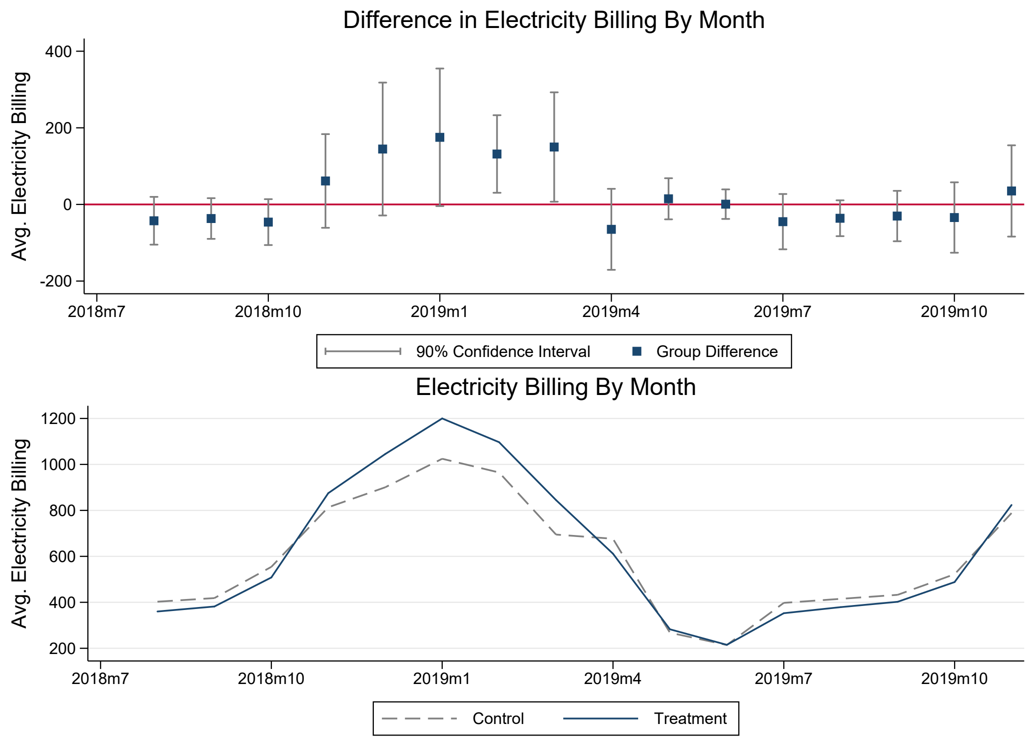


Figure A5: Post-treatment Billed Electricity Consumption (kWh/month), Robustness

Notes: Billing data are provided by the electricity utility. The analysis here is basic comparison and no other control variables are included. Addresses which have businesses are dropped. The standard errors are clustered at the transformer level. The grey lines in the upper figure indicate the 90% confidence interval.

Table A6: Billed Electricity Consumption, By Season (Exclude Non-residential Consumers)

VARIABLES	(1) bill	(2) bill
Treat × Post	23.463	-33.114**
	(17.623)	(12.921)
Post	-167.004***	-419.958***
	(33.665)	(26.603)
Constant	915.320***	648.411***
	(15.656)	(15.884)
Mean of Control Group	853.644	433.837
Observations	15,126	22,703
Number of Household	1,123	1,123
Adjusted R-squared	0.046	0.168
Household Fixed Effect	Y	Y
Month-by-Year Fixed Effect	Y	Y
Cluster SE	Transformer	Transformer
Season	Peak (Heating)	Off-peak (Non-Heating)

Notes: Billing data are provided by the electricity utility covering the period between January 2017 and November 2019. Regressions drop the non-residential consumers. The outcome variable *bill* measures the monthly billed electricity consumption (kWh/month) for a household. *lag bill* is the one-period lagged monthly billed electricity consumption. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

Table A7: Alarms types at the transformer smart meters

Category	Alarm Type	Count	Percentage
Theft	Current reverse generation in any phase of three phase	1,828	10.7%
	Recover from disconencted but power is detected	838	4.9%
	Disconencted but power is detected	935	5.5%
Quality	Over voltage L1 start	2,991	17.6%
	Over voltage L2 start	2,603	15.3%
	Over voltage L3 start	2,278	13.4%
Power	Power down (long power failure)	1,501	8.8%
	Power down (short power failure)	376	2.2%
	Power up (long power failure)	1,559	9.2%
	Power up (short power failure)	379	2.2%
Other	Association authentication failure	13	0.1%
	Disconnect relay	40	0.2%
	Limiter threshold exceeded	27	0.2%
	Manual connection	30	0.2%
	Module cover closed	7	0.0%
	Module cover removed	9	0.1%
	Module power down	1,616	9.5%
Sum		17,030	100.0%

Notes: Alarms data are provided by the electricity utility.

Table A8: Use of Energy Efficient Lightbulbs

VARIABLES	(1) EElight	(2) EElight	(3) EElight	(4) EElight	(5) EEbulbshare	(6) EEbulbshare
Treat×Post	0.048	0.048	0.056	0.056		
	(0.098)	(0.037)	(0.099)	(0.041)		
Treat	0.021	0.021			0.049	0.049***
	(0.054)	(0.023)			(0.048)	(0.018)
Post	0.291***	0.291***	0.282***	0.282***		
	(0.081)	(0.026)	(0.073)	(0.029)		
Constant	0.003	0.003	0.197***	0.197***	0.137**	0.137***
	(0.048)	(0.031)	(0.025)	(0.010)	(0.064)	(0.028)
Mean of Control Group	0.191	0.191	0.193	0.193	0.229	0.229
Observations	2,267	2,267	1,759	1,759	1,125	1,125
R-squared	0.128	0.128	0.206	0.206	0.017	0.017
Cluster SE	Transformer	Household	Transformer	Household	Transformer	Household
Basic Characteristics	Y	Y			Y	Y
Household FE			Y	Y		

Notes: Data collected through baseline and follow-up surveys. *EElight* is a binary variable and equals 1 if the household use energy efficient lightbulbs in their home. *EEbulbshare* is the share of energy efficient lightbulbs among all lightbulbs used by the household. In column (3) and (4), we use a balanced panel restricted to households in both baseline and endline survey. Due to more in-responses in the endline survey, we have fewer observations. Control variables for household basic characteristics include the number of rooms in a house, and whether the house is owned by the household. Robust standard errors are clustered either at the transformer level or at the household level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)