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

Robyn Meeks† Arstan Omuraliev‡ Ruslan Isaev§ Zhenxuan Wang¶

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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 from a randomized experiment in the Kyrgyz Republic testing the impact of smart meters in mitigating these problems. Smart meters provide additional information to both electricity consumers and utilities. This information could increase payment for electricity services consumed or improve the quality of electricity services delivered. We find evidence of reduced electricity theft in the first year following smart meter installation; however, this dissipates in the second year post-intervention.

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†Duke University, Sanford School of Public Policy. Email: robyn.meeks@duke.edu (corresponding author)

‡Scientific Research Institute for Energy and Economics, Kyrgyz Republic

§Scientific Research Institute for Energy and Economics, Kyrgyz Republic

¶Duke University, Sanford School of Public Policy.

Electricity service quality substantially improved via significantly fewer voltage fluctuations. 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. In peak consumption months, consumer welfare increases by 5.40 USD per month, on average, from improvements in electricity quality. Treated households' expenditures on appliances increased by 4 USD per month, providing further evidence that consumers benefit from smart meter installation. Billed electricity consumption increased during peak electricity consumption months, which is a benefit to utilities and consistent with both unmet demand prior to the intervention and improved electricity quality thereafter.

Keywords: Electricity, infrastructure, reliability, losses

JEL: D01, D62, O13

# 1 Introduction

Challenges with improving the quality of public services are well-documented in a number of sectors, including education, healthcare, and social services (Duflo, Hanna, and Ryan, 2012; Dhaliwal and Hanna, 2016; Das et al., 2016; Callen et al., 2016; Banerjee et al., 2018; and Muralidharan et al., 2019). Infrastructure sectors – delivering water and electricity services – need not similarly suffer from these challenges; tariffs can be designed such that consumers pay for infrastructure maintenance, repairs, and upgrades to ensure standard quality of services delivered. However, low quality electricity services remain common in many developing countries (McRae, 2015b; Jacome et al., 2019). When the quality of services delivered is poor, consumers may resist paying for those services. Low bill payment and high theft mean lower cost recovery and less money to invest in infrastructure maintenance, modernization, and technical upgrades. Insufficient infrastructure investment perpetuates poor quality service. This downward cycle of poor quality services and low cost recovery – an infrastructure quality trap as depicted in Figure 1 – can be quite persistent.[1]

Contracting between a service delivery company and its customers should mitigate this downward cycle. In the electricity sector, the connection of a house (or firm) to the electrical grid typically comes with a contract between the electricity distribution company and the customer. The distribution company commits to providing reliable electricity services that meet certain voltage standards. The customer commits to paying for electricity services consumed. This agreement, however, often breaks down in practice, likely due to insufficient information to enforce these contracts. Consumers lack data on the actual quality of electricity services delivered. Distribution companies lack information on the sources of losses and/or the locations of poorest service quality.

We report results from a randomized experiment, which was implemented in the Kyr-

[1] McRae (2015*b*) documents one form of this trap, the infrastructure quality subsidy trap, in the Colombian electricity sector.

gyz Republic and designed to test whether smart meters can interrupt this infrastructure quality trap.[2] We study the impacts of smart meters on electricity quality and cost recovery for multiple reasons. First, poor quality or irregular electricity services attenuates the economic benefits from grid connections (Pargal and Banerjee, 2014; Zhang, 2019), by limiting the appliances that can be powered, damaging appliances used, and impacting the set of appliances purchased (McRae, 2010). Second, non-technical losses (NTL) – including theft and bill non-payment – cost electricity utilities an estimated $25 billion per year worldwide (Depuru, Wang and Devabhaktuni, 2011). Losses are particularly a concern in developing countries: in 2014, electric power transmission an distribution losses were an estimated 18 and 16% of total electric output in low income and lower middle income, respectively. This is approximately 3 times higher than the losses reported for high income countries (OECD/IEA, 2018).[3]

With these challenges in mind, smart meter installations grew in the past decade in both developed and less developed countries.[4] 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.[5] Although the potential benefits from these meters include interrupting the infrastructure quality trap, there is a dearth of evidence on their impacts.[6]

In conjunction with an electricity utility operating within the Kyrgyz Republic, we study the impact of smart meters on electricity service quality, bill electricity consumption

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

[3]Calculations made using OECD/IEA (2018) data on losses. According to the data documentation, electric power transmission and distribution losses include losses in transmission between sources of supply and points of distribution and in the distribution to consumers, including pilferage.

[4]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).

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

[6]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 electricity consumption. For examples, see: Wolak (2011); Jessoe and Rapson (2014); Ito, Ida and Tanaka (2018))

and indicators of theft, as well as household expenditures. The experimental intervention, which is illustrated in Figure 2, proceeded as follows. Twenty transformers within one city, covering more than 1500 utility customers, were selected for the study.[7] Transformers were randomly assigned to treatment or control status, resulting in 10 transformers in each group. Within the treatment transformers, smart meters were installed at all houses, 798 residential consumers in total, by September 2018. These smart meters replaced old meters, which are susceptible to various sources of electricity loss and do not protect against voltage surges. Residential consumers served by control transformers, 846 houses in total, retained the old meters at their houses.

Smart meters themselves do not directly improve electricity service quality or increase cost recovery; however, they provide data, increasing information and potentially facilitating either of these improvements. In this study, there are three potential mechanisms through which smart meters may improve cost recovery. The first is mechanical: smart meters better capture consumption of electricity at low voltages. In contrast, old meters often cannot register electricity consumed when the voltage is low. Second, alarms sent from the smart meters to the utility can alert of potential electricity theft, allowing the service provider to identify losses more quickly. Third, and finally, the smart meters enable the utility to remotely disconnect (and re-connect) consumers, reducing the cost of sanctioning bill non-payment.

Regarding service quality, smart meters provide real-time information to both customers and utilities on outages and other service quality problems (e.g., voltage fluctuations) within the electricity distribution system. Alarms sent from the meters alert the utility of outages and voltage fluctuations, allowing for faster, more targeted utility response to distribution locations with the greatest need. Additionally, the smart meters automatically

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

disconnect consumers when the voltage spikes or drops. Such disconnections serve two purposes: protecting consumers' appliances from damage and providing consumers with data and proof of substandard service quality.

The study produces three main results. First, we found evidence of improvements associated with some elements of non-technical losses, but not all. Electricity bill payment was more likely to be on-time in treatment households than controls, indicating that the smart meters' functionality to remotely disconnect encouraged bill payment (i.e., payment for consumption that was billed). However, that functionality does not prevent other forms of electricity losses (i.e., electricity consumption that is not billed due to various forms of theft, such as meter manipulation or illegal connections to the distribution lines). We find that treatment areas have statistically fewer alarms indicating theft in the first year post-intervention; however, this difference does not persist into the second year.

Second, electricity service quality improved in the form of significantly fewer voltage fluctuations (spikes and drops). Transformer repairs and replacements are the channel through which electricity service quality improved. Higher numbers of smart meter alarms are associated with a greater probability of transformers being repaired or replaced, indicating that alarms alerted the utility of locations requiring improvements.

Third, the electricity consumers clearly benefit from the smart meters. Consumer welfare increased by approximately 5 to 6 USD per month, on average, from improvements in electricity quality and the resulting increased electricity consumption. 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. 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. This is consistent with increased electricity service quality.

Whether the benefits of smart meters exceed the costs from the electricity utility's standpoint is less clear. The utility benefits from additional peak season billed electricity consumption, which is likely the result of less meter malfunctioning (i.e., the smart meters can "read" electricity consumed at low voltages) and improvements in electricity quality supplied. This additional billed consumption is beneficial for the utility's cost recovery as it is charged at the higher tiered tariff price. However, these benefits from changes in billed electricity consumption are less than half the cost of the smart meters.

Understanding the feasibility of smart meters to improve electricity service quality and/or cost recovery is of first-order importance for development. Poor reliability is one explanation for the heterogeneous benefits documented in studies measuring electrification's impacts.[8] 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[9] and provide the first of such evidence on ways to interrupt the infrastructure quality trap.

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.[10] 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 from traditional post-pay to pre-pay meters in South Africa, which reduces the costs of bill

[8] 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)).

[9] 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.

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

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 challenge of electricity losses, their contribution to the infrastructure quality trap, and how the functionality of smart meters might interrupt this cycle. Section 3 describes the study setting, the experimental design, the various data sources, and results from balance tests. The impacts of the smart meters on utility cost recovery and electricity service quality are presented in Section 4. Section 5 discusses benefits of the smart meters to both consumers and utilities. Section 6 concludes.

# 2 Electricity quality, cost recovery, and smart meters

In this section, for each of these electricity sector challenges – poor electricity service quality and non-technical losses – we explain their potential impacts on household consumption and itemize how information provided via smart meters may alleviate each of the challenges.

## 2.1 Poor quality electricity service

Here we consider two forms of poor quality electricity service: outages and voltage fluctuations.[11] An outage is a complete stoppage in electricity service delivery. Unplanned outages, due to breakage and infrastructure overloads, can be lengthy in duration, lasting until repairs are complete.[12] Alternately, outages may be purposefully scheduled to enable the utility to undertake repairs and maintenance. Typically, such outages are planned and limited in duration.

[11] 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.

[12] For example, transformers can overload. 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).

In contrast, electricity service delivery continues during voltage fluctuations, but is poor quality that is outside 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 either damage to electric appliances or insufficient power to run certain household appliances. Voltage fluctuations can result from a number of sources, including faulty or old equipment, insufficient maintenance or repairs, as well as demand that exceed the infrastructure's capacity, such as when transformers are overloaded.

### 2.1.1 What poor quality means for electricity service consumption

A household's demand for electricity services depends on the demand for individual services provided by all of 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 A2, which depicts two scenarios in which poor electricity service quality negatively impacts electricity consumption.[13] We assume a linear price $p^0$. [14] 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

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

[14] 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.

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).

Second, there are frequent voltage issues, either in the form of spikes or dips (Scenario 2). A voltage spike might damage an appliance rendering it unusable or may prevent the appliance from functioning 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. As a result, the quality of electricity supplied will impact households' decisions to purchase appliances and therefore the portfolio of appliances in their homes (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 Appendix Figure A1 – 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. This would represent a welfare improvement for the consumers.

## 2.2 Low cost recovery and non-technical losses

Low cost recovery translates into less funding for infrastructure maintenance, repairs, upgrades, and investments in expansion. But what leads to low cost recovery? Non-technical losses (NTL) are one major contributor to low utility cost recovery. As summarized in Appendix Table A1, there are two overarching types of NTL: first, there are electricity services consumed by households that are unbilled and, second, consumption may be billed, but the bill is not paid. NTL grouped in the former category typically originate from one of four different sources, including: (1) meter malfunction, meaning that the meter does not register the household's consumption, because it cannot log consumption at low voltages; (2) meter tampering, through which consumers "roll back" or pause the meter such that it does not register the complete quantity consumed; (3) by-passing the meter, which typically involves consumers running illegal wires directly from the house to the distribution wires to

circumvent the meter; (4) billing irregularities, when consumers pay the meter reader – an individual who visits typically once per month to document the consumption logged on the meter, – a bribe to report a lower consumption than the meter registered. Of these four sources of NTL, only meter malfunctions is not theft-related.

The second category, non-payment or late payment of bills depends on the utility's capacity and will to enforce payment. Manual disconnection of non-paying customers is costly, as it requires sending a team of utility employees to the house to remove the distribution system connection and then again to reconnect after payment. As a result, utilities may not always disconnect consumers even if payment is overdue.

### 2.2.1 What NTL mean for consumption of electricity services

Non-technical losses, by definition, mean that households are not paying the full cost of the electricity services consumed. We illustrate this in Appendix Figure A3. NTL are an implicit subsidy to the households, such that the consumer faces a price, $p^N$, which is lower than the official electricity tariff, $p^0$. This results in the over-consumption of electricity services at a higher quantity, $q_N$, than would occur if the consumer were paying $p^0$. 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 the quantity of electricity services consumed will be at $q_0$.

Electricity utilities face another challenge in this respect. The utility (and researchers, in this case) observes the consumption as reported by the meter readers, not the electricity services actually consumed. The existence of NTL means the quantity of electricity billed will deviate from actual electricity services consumed. When electricity consumption is not represented fully in the bill, 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.

### 2.2.2 Smart meters to increase cost recovery?

We consider how smart meter functionalities could decrease NTL (Appendix Table A1).

**Reducing the gap between quantity billed and quantity consumed:** The smart meters could reduce NTL due to meter malfunctioning. By way of technological advancement, the new smart meters will register electricity consumption more accurately, even in the presence of voltage dips and spikes. However, because the improvements in technology also permit the meters to shut down the connection when severe voltage fluctuations occur, the meters may result in lower electricity consumption in the presence of poor quality services.

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 technology makes tampering more difficult. However, consumers intent on stealing may find alternative methods. Second, the smart meters provide frequent information (via alarms) on potentially suspicious activity. Every 15 minutes, the smart meters relay information directly to the utility on both the metered electricity consumption measured by the and any alarms indicating problems (outages, voltage fluctuations, indicators of theft, etc). If the utility monitors consumption patterns to identify sources of theft, it could rectify them.

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

**Increasing payment of electricity bills:** Through the increased threat of disconnection, the smart meters could reduce bill non-payment. The ability to remotely disconnect non-paying consumers provides a low-cost mechanism to enforce on-time bill payment. With-

out 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.

# 3 Randomized experiment with smart meters

## 3.1 Electricity services in the Kyrgyz Republic

### 3.1.1 Electricity sector challenges

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. 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.[15] 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.

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 dis-

[15]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.

tribution 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). Distribution losses alone difficult to isolate and precisely measure. Estimates of distribution losses in the Kyrgyz Republic are between 15 and 18% (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.

### 3.1.2 Electricity sector legal structure

Following the country's independence in 1992, the country's electricity sector was 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.

The government of the Kyrgyz Republic, by Decree 576, regulates the use of electric energy. When a house connects to the electrical grid, this consumer signs a contract with the distribution company ("the supplier"). The contract includes requirements for both the supplier and the consumer.

The supplier agrees to deliver uninterrupted, reliable, high-quality and safe electricity services – defined as a consistent voltage of 220/280 volts – to the consumer. Consumers have the right to record any deviations from the electricity standards (and resulting material damages) and report them to the government bodies overseeing the sector. From the supplier, the consumer may recover material damages resulting from a service interruption or deviation in quality (i.e., incident when services provided do not meet the specified voltage requirements).

According to this contract, the consumer is required to pay – by a specified date – for electricity consumed, as calculated based on monthly meter readings. If payment is not made, the supplier can charge the consumer a penalty for each day of past the due date and disconnect the consumer from the power supply altogether if the delay is beyond what is

specified in the agreement (Government of the Kyrgyz Republic, 2012).

## 3.2 Randomized experiment

We implement the experiment in collaboration with an electricity distribution company operating in a city within the Kyrgyz Republic.[16] The intervention and randomized design are centered around the last two steps in the electricity distribution system: the neighborhood transformers, which step down the electricity voltage for delivery to consumers, and the residential electricity consumers.

The experiment was designed a follows (depicted in Figure 2). Twenty transformers, which each serve a neighborhood of households, were selected for the project. Transformers were assigned to treatment or control status, resulting in 10 transformers in each group. In August and 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.[17] This resulted in 798 households having smart meters installed (the "Treatment Group") and 846 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-

[16] 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.

[17] 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.

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.

## 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 smart meters installed at transformers. Appendix Figure A4 depicts the timing of meter installation in relation to different data sets used in analyses.

**Transformer smart meter data:** During Summer 2018, smart meters were installed at all 20 project transformers. These smart meters are distinct from the smart meters installed at the treatment residential and are not part of the intervention. Providing data in 15-minutes increments at the treatment-assignment level, these smart meters record of "alarms" that are indicators of problems within the transformer. These alarms can be activated for a number of reasons, including: if power is detected going from a distribution line to a consumer when there is no formal connection (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). These data have the advantage of providing high-frequency indicators of both electricity theft and electricity quality; however, these smart meters did not collect substantial data pre-intervention, and therefore cannot serve as a baseline data source.

We create transformer-level outcome variables by grouping the alarms into bins of similar alarms indicating the same type of problem (theft, poor quality, and outages). The categorization of alarm types, which is based on documentation provided by the meter manufacturer, is shown in Appendix Table A3. Of the alarms recorded post-intervention,

approximately 6% indicated theft, 60% indicated electricity voltage problems, and 22% were related to power outages. The remaining 12% of alarms are grouped as "other", indicating that they are not in one of the groupings that we anticipate to be impacted by the treatment. The proportions of voltage alarms highlights the extent to which electricity quality is a concern in this setting.

**Survey data:** Baseline and follow-up survey data were collected in the spring of 2018 and 2019, respectively. The baseline survey was streamlined to limit interaction with households. The follow-up survey was more extensive, resulting in greater data available for the follow-up period. Both surveys ask questions on characteristics of the home, quality of electricity services, the set of home appliances, overall household expenditures, amongst others. Importantly, both survey rounds collect data on perceived electricity quality (both outages and voltage fluctuations). This provides panel data on electricity quality that includes the pre-intervention 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 in total.

**Utility data:** The electricity utility provided data on project transformers and residential consumption within the areas served by those transformers. The transformer-level data includes transformer characteristics and dates of maintenance, repair, and last replacement. The consumer monthly billed electricity consumption data start in January 2017, providing approximately 1.5 years of pre-intervention data. Consumer data also include customer debts to the utility and whether and when a consumer's electricity connection was disconnected for failure to pay a bill.

## 3.4 Baseline balance tests

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

In Table 1 we compare the characteristics of control and treatment transformers. The transformers are not statistically significantly different with respect to the the number of households that they serve (84.6 versus 79.6 households), their capacity (an average of 381 versus 406 kVA), or their age (33.4 versus 27.9 years old). It is worth noting that in general, these transformers are relatively old and serving a substantial number of households given their size. This is consistent with the poor quality electricity services in this city.

Additionally, we use household level data to test for balance across groups at baseline. 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 of Figure 3 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 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 A4). There are also no significant baseline differences between the two groups in 12 categories of household expenditures, including electricity and household appliances (Appendix Table A5).

### 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 A6). 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 Impacts on non-technical losses

To measure the impacts of the intervention – installing smart meters at houses – on non-technical losses, we estimate the impacts on indicators of two types of NTL: electricity theft

and unpaid electricity bills.

### 4.1.1 Evidence of electricity theft

Our measurement of alarms is from transformer-level smart meters, which allow us to test for evidence of impacts on two types of theft: meter tampering and bypassing of the meter.[18] We limit our analysis to the post-intervention period, estimating the following equation:

$$A_{gt} = \beta_1 Treat_g + \beta_2 Treat_g * Year2 + \beta_3 X_g + \gamma_t + \epsilon_g \tag{1}$$

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, $Treat_g$*Year2 is the interaction of the treatment status indicator variable and a binary indicator that equals 0 in the first year following the intervention and equals 1 in the second year, $X_g$ is a vector of transformer characteristics (the number of households served by the transformer and the transformer's technical capacity), and $\gamma_t$ are month-by-year fixed effects. Standard errors are clustered at the transformer level.

Results are in Table 2. The control group mean tells us that, on average, the control transformers are recording a theft-related alarm approximately every third day (0.358 theft-related alarms per day per control transformer). Column 1 provides our main result. Treatment transformers have significantly fewer theft alarms per day in the first year following the intervention, approximately half that of the control transformers. However, the coefficient on the interaction term indicates that the difference ceases in the second year post-intervention. Results in column 2 show that the estimates are robust to including feeder line fixed effects.

[18] The smart meter alarms provide no indicators of meter malfunction.

### 4.1.2 Evidence of unpaid electricity bills

We estimate the impact of the intervention on electricity bill payment, another source of NTL. 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 the following equation, at the household level:

$$U_{ig} = \beta_1 Treat_g + \beta_2 X_{ig} + \epsilon_g \tag{2}$$

where $U_{ig}$ are the household-level outcome variables related to unpaid bills, $Treat_g$ is an indicator of transformer treatment status, and $X_{ig}$ is a vector of household characteristics included as controls (the number of rooms in the house and whether the house is owner occupied). Because the utility records on bill payment continue through September 2019 – one year post-intervention – there is no differentiation in the analysis between first and second years. Standard errors are clustered at the transformer level.

Results are in Table 3. Columns 1 and 2 report results from regressions using outcome variables from the utility records. Households in treated transformers do not have significantly different amount of debt owed to the utility (Column 1); however, they are less likely to have been cutoff (disconnected) for not paying their bills (Column 2). Columns 2 and 3 report analysis using the household data from the follow-up survey. Households in treated transformer are less likely than those in control to arrange for a delayed or late bill payment, although the difference is not statistically significant (Column 3). Households in treated transformers were significantly less likely to report paying their electricity bill late. Taken together, the results in Table 3 indicate that households were aware of the smart meters' functionality to remotely disconnect and perceived an increased threat of disconnection for late and/or unpaid bills. This suggests the smart meters act as a deterrent to late-payment.

## 4.2 Impacts on electricity quality

### 4.2.1 Estimated impacts

To estimate the impact of the intervention n electricity quality, we emplot the data from the transformer smart meters. Our measures of electricity quality are transformer-level alarms per day that are indicative of voltage fluctuations, power outages, and other potential problems. We again estimate Equation 1, but now use the quality-related alarms as our outcome measures.

Results are presented in Table 4. We find significantly fewer alarms per day that are indicative of voltage fluctuations in the treatment transformers than in the control during the first year following the intervention (Column 1). This difference does not persist into the second year. This result is robust to including feeder line fixed effects (Column 2). Regarding alarms indicative of power outages, there is a small and marginally significant increase in these alarms in the first year post-intervention (Column 3). Because the outcome measure is from the transformer smart meters, which were installed before the treatment – the installation of the household smart meters – this increase in power outage alarms in Year 1 might reflect the planned outages required to install smart meters at households. However, this result is not robust to including feeder line fixed effects (Column 4). Columns 5 and 6 contain the results of robustness checks. We estimate the impacts of the intervention on the "other" alarms, a category of alarms for which we anticipated no impacts, ex ante. The results show significant differences between the treatment and the control.

As an additional robustness check, we test whether alarms indicating voltage fluctuations and power outages are correlated with the household reported electricity quality measures from the follow-up survey implemented around the same time. Results are in Appendix Table A10. Fewer alarms indicting voltage fluctuations (Column 1) and power outages (Column 2) are significantly correlated with better household reported reliability.

As an additional check, we test whether household reported reliability is correlated with theft alarms. Ex ante, we do not expect the two measures to be correlated and, indeed, we find no significant relationship between them.

#### 4.2.2 Mechanism for electricity quality improvements?

The smart meters alone cannot improve electricity quality. We investigate the mechanism by which they might lead to quality improvements. Discussions with consumers inform our hypothesis. During the summer 2018, when smart meters were being installed at the transformers, some consumers reported that they had previously complained to the electricity utility about problems with voltage fluctuations within their transformer, appliance damage, and the inability to power certain electric appliances. These individuals reported that the utility had not previously conducted transformer repairs or replacement in response to their concerns.

We test whether the treatment led to an increase in replacement and trapirs of particular electricity infrastructure components (i.e., transformers). Using electricity utility panel data on transformer maintenance and repairs starting in January 2017, we measure the impact of treatment on transformer improvements, such as transformer overhauls or replacements. Results are presented in Table 5. Results are informative in several respects. First, planned improvements are relatively infrequent. Second, transformers in which the households are treated are significantly more likely to be overhauled or replaced after the onset of the intervention. We cautiously interpret these results, as the analysis is limited to monthly data from the 20 transformers over a 33 month period.

Supporting that the quality improvements occurred via transformer overhauls and that the overhauls were in response to information from the smart meters, we provide evidence in that these transformer repairs and overhauls were were preceded by increased alarms within those sites (Appendix Table A8). In addition, we show that the alarms decreased at the

same sites after the transformer overhaul is performed (Appendix Table A9).

# 5 Benefits from improved electricity quality

In this section, we quantify the benefits from installation of smart meters to consumers and the utilities.

## 5.1 Benefits to electricity consumers

We calculate the welfare impacts of the improved reliability on households. Following Klytchnikova and Lokshin (2009), we use the increased electricity consumption, which occurs through voltage and outage improvements, as an estimate of the impacts on consumer welfare.

To carry out this estimate, we focus on the household billed electricity consumption over the heating season (i.e. from November to March the next year) and calculate the total pre-intervention consumption and total post-intervention consumption for each household. We merge the data with household surveys (both baseline and follow-up) to create a panel of self-reported electricity service quality. This aggregate reliability measure is the total number of outages and number of voltage fluctuations within a week.

Using this panel data, we estimate the consumer welfare impacts of smart meter installation employing a two-stage least squares approach. In the first stage, we estimate the treatment effect on electricity service quality as follows:

$$\text{Reliability}_{igt} = Treat_{ig} \times Post_t + Replace_{ig} \times Post_t + Post_t + \lambda_i + \epsilon_{igt} \tag{3}$$

where $\text{Reliability}_{igt}$ 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

$t$. Define $Treat_{ig}$ as an indicator of transformer treatment status while $Replace_{ig}$ as an indicator of transformer replacement status. The indicator variable, $Post_t$, equals 1 for the post-intervention heating season. We include household fixed effects, $\lambda_i$, to control for time-invariant unobserved household characteristics.

In the second stage, we estimate the impact of improvement in electricity service quality on household billed electricity consumption:

$$q_{igt} = \widehat{\text{Reliability}}_{igt} + \lambda_i + \epsilon_{igt} \tag{4}$$

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

The results of these welfare calculations are in Table 7. 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. The result in Column 2 indicates that 1 fewer electricity quality incident (either voltage fluctuation or outage) per week on average results in 1,833 KGS more in billed electricity consumption over the five month winter period. This equals approximately a welfare improvement of approximately 5.67 USD per month during the months of peak electricity consumption.

To explore the underlying mechanism of increased electricity consumption induced by improved electricity service quality, we estimate the impact of treatment assignment on

household expenditures across different categories as follows:

$$Expenditure_{igt} = Treat_{ig} \times Post_t + Post_t + \lambda_i + \epsilon_{igt} \tag{5}$$

where $Expenditure_{igt}$ is household's expenditure (KGS) on certain items. The dummy variables, $Treat_{ig}$ and $Post_t$, are defined as before. Table 8 presents the corresponding results. Consistent with the welfare analysis, we document statistically significant expenditure increase only in the category of household electric appliances.

## 5.2 Benefits to electricity utilities

To calculate the benefits to electricity utilities of installing household smart meters, we first estimate the impact of smart meters on household billed electricity consumption as follows:

$$Bill_{igt} = Treat_{ig} \times Post1_t + Treat_{ig} \times Post2_t + \lambda_i + \delta_t + \epsilon_{igt} \tag{6}$$

where $Bill_{igt}$ is the monthly billed electricity consumption by household $i$ in transformer $g$ at time $t$. Let $Treat_{ig}$ be the indicator of transformer treatment status. The binary variables, $Post1_t$ and $Post2_t$, are indicators for the first and second year after the intervention, respectively. Regressions are run separately for the heating (November to March) and non-heating seasons (April to October).

The estimation results are presented in Table 9. We find that household billed consumption significantly increased during the heating season in the first year post-intervention (Column 1). This significant increase does not persist in the second year post-intervention. In contrast, the billed electricity consumption decreases in the non-heating season, although the impact is statistically significant only in the first year post-intervention (Column 2). These heterogeneous impacts across seasons and over time are supported by an event study

analysis of the monthly billed electricity consumption post-intervention (Appendix Figure A5).

We quantify the benefits from the smart meters to the utility as the change in electricity consumption billed. Because consumers face an increasing block price in this setting, the impact of electricity consumption changes will depend on the tier at which the consumption is charged. If the electricity consumed is billed at the higher tiered price, then the utility gains from selling those additional units (kWh) of electricity. If the electricity consumed is billed at the lower price tier, then the utility loses money on each additional kWh sold. Assume the marginal cost of providing electricity service is the average of the higher and the lower tiered price, i.e., 1.465 KGS/kWh[19]. Since the electricity consumed during the heating season is charged with the higher tiered price, the increase in consumption leads to 86.86 KGS (59.292×1.465) gains per month from each household. In contrast, the electricity consumed during the non-heating season is charged with the lower tiered price, and therefore the decrease in consumption avoids 55.30 KGS (37.749×1.465) losses per month from each household. The total gains for the electricity utilities are therefore 86.86×5 + 55.30×7 = 821.40 KGS per year from each household, which equivalent to 10.16 USD per year from each household.

These calculations only include the benefits to the utility related to billed electricity consumption. These calculations do not include other benefits to the utility, such as the reduced cost in disconnecting non-payers. Also, in settings in which the smart meters are integrated with the billing system, the utility would benefit from not having to send meter readers to the households to collect consumption data. Because this experiment only covered a small portion of the utility's service territory, the intervention did not include such an integration of systems.

[19]For electricity consumption less than 700 kWh, the tariff is 0.77 KGS/kWh. For electricity consumption more than 700 kWh, the tariff is 2.16 KGS/kWh for the exceeding part.

# 6 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

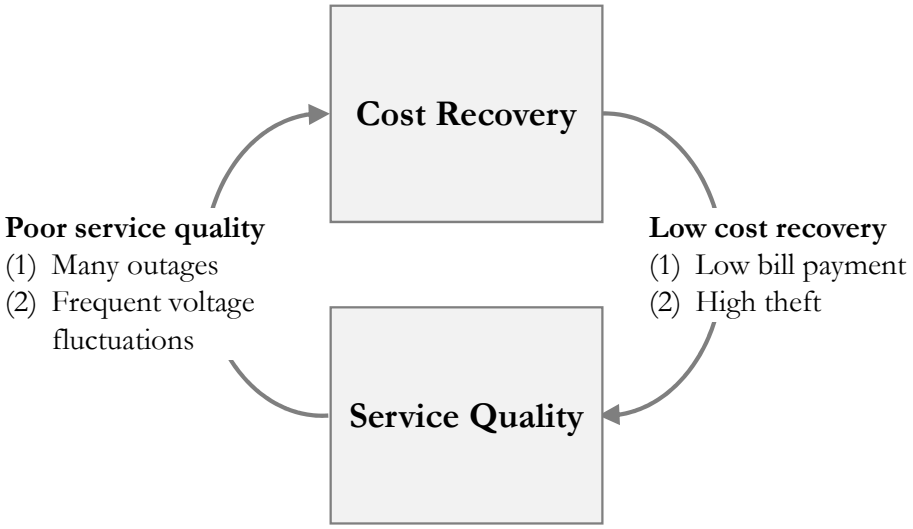
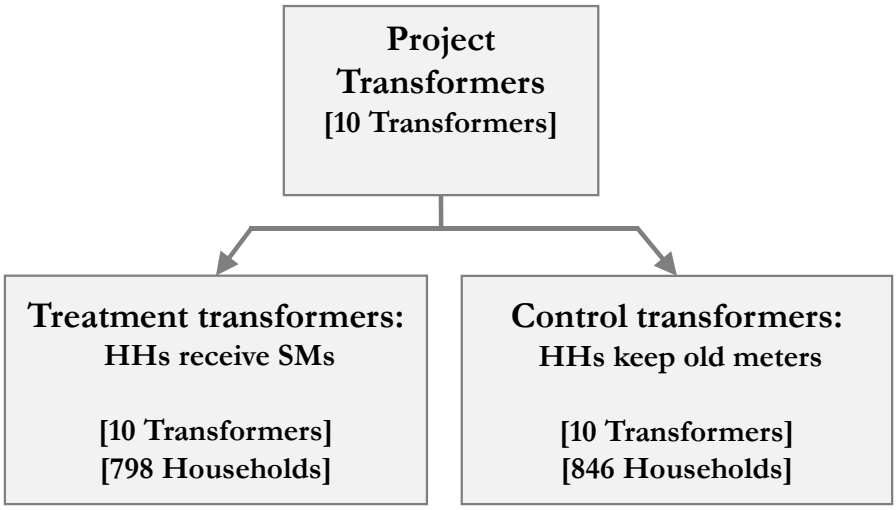


**Figure 2:** Randomized design




5

**Table 1:** Baseline Transformer Characteristics, Means

| VARIABLES | Control | Treatment | Difference |
|---|---|---|---|
| Number of households | 84.6 | 79.6 | -5.0 |
| | (44.6) | (54.7) | (22.3) |
| Capacity (kVA) | 381.0 | 406.0 | 25.0 |
| | (264.0) | (181.4) | (101.3) |
| Age (Years) | 33.4 | 27.9 | -5.5 |
| | (17.5) | (20.3) | (8.5) |
| Observations (transformers) | 10 | 10 | 20 |

*Notes:* Transformer data are provided by the electricity utility. Standard errors are in parentheses ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

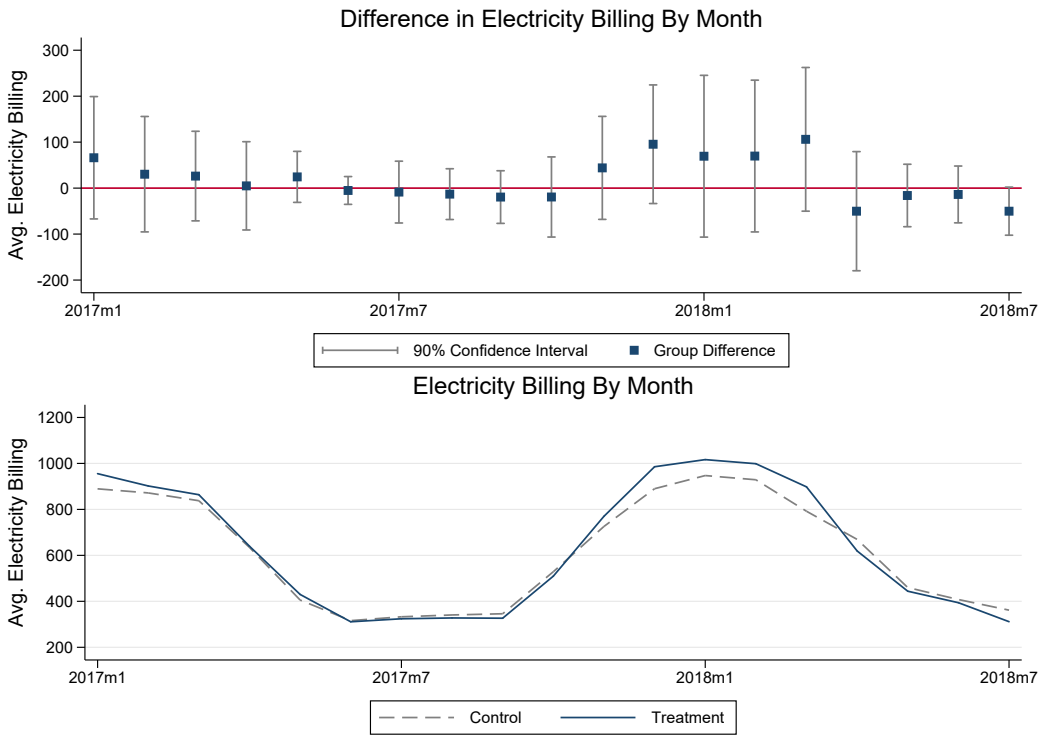



**Figure 3:** Pre-treatment Billed Electricity Consumption

*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.

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

| Alarms (in one day) indicating: | Potential theft | |
|---|---|---|
| | (1) | (2) |
| Treat | -0.175* | -0.168* |
| | (0.088) | (0.095) |
| Treat X Year2 | 0.027 | 0.026 |
| | (0.091) | (0.091) |
| Constant | 0.0.429*** | 0.422*** |
| | (0.088) | (0.094) |
| Mean of Control Group | 0.358 | 0.358 |
| Observations | 8,355 | 8,355 |
| R-squared | 0.035 | 0.036 |
| Month-by-Year Fixed Effect | Y | 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 February 2020. 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 the transformer capacity. Robust standard errors are clustered at the transformer level and included in parentheses ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

**Table 3:** Indicators of Household Electricity Bill Payment

| | From utility records: | | From household surveys: | |
|---|---|---|---|---|
| | Debts to utility (KGS) | Non-payment disconnection | Arranged late payment | Paid bill late |
| | (1) | (2) | (3) | (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 (households) | 1,576 | 1,576 | 1,125 | 1,125 |
| Basic Characteristics | Y | Y | Y | Y |
| Cluster SE | Transformer | Transformer | Transformer | Transformer |

*Notes:* Utility records were as of September 2019. Household survey data were collected in Spring 2019. The outcome in column 1 is in Kyrgyz soms. The exchange rate at time of the baseline survey was 1 USD to 68.5 KGS. The outcome variables in columns 2 - 4 are binary indicators and equal 1 if the household has 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

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

| Alarms (in one 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) |
| Treat X Year2 | 0.106 | 0.105 | -0.120 | -0.118 | 0.493 | 0.503 |
| | (1.249) | (1.233) | (0.076) | (0.076) | (0.532) | (0.539) |
| Constant | 2.374** | 2.371** | 0.518*** | 0.532*** | 0.214 | 0.297 |
| | (0.925) | (1.051) | (0.045) | (0.041) | (0.230) | (0.285) |
| Mean of Control Group | 2.156 | 2.156 | 0.539 | 0.539 | 0.231 | 0.231 |
| Observations | 8,355 | 8,355 | 8,355 | 8,355 | 8,355 | 8,355 |
| Month-by-Year Fixed Effect | Y | Y | Y | Y | Y | Y |
| Feeder-line Fixed Effect | | Y | | Y | | Y |
| R-squared | 0.104 | 0.104 | 0.052 | 0.053 | 0.043 | 0.045 |
| 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$)

**Table 5:** Transformer-Level Maintenance

| | Transformer Replaced or Overhauled (1) |
|---|---|
| Treat × Post | 0.048* |
| | (0.028) |
| Post | 0.026 |
| | (0.021) |
| Constant | 0.015** |
| | (0.006) |
| Mean of Control Group | 0.02 |
| Observations | 660 |
| R-squared | 0.026 |
| Transformer FE | Y |
| Cluster SE | Transformer |

*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. The outcome variable 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

**Table 6:** Intervention Impacts on Self-reported Electricity Service Quality

| | Voltage number | | Outage number | | Reliability sum | |
|---|---|---|---|---|---|---|
| | (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) |
| 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) |
| Constant | -4.325*** | -4.325*** | -1.024*** | -1.024*** | -5.350*** | -5.350*** |
| | (0.162) | (0.170) | (0.095) | (0.095) | (0.210) | (0.215) |
| 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 id | 871 | 871 | 871 | 871 | 871 | 871 |
| Household FE | Y | Y | Y | Y | Y | Y |

*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 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

**Table 7:** Welfare Impact of Electricity Service Quality Improvements

| VARIABLES | (1)<br>reliability | (2)<br>monetized bill |
|---|---|---|
| reliability | | 1,833.833*** |
| | | (551.304) |
| Treat × Post | -0.796 | |
| | (0.870) | |
| Replace × Post | 2.222*** | |
| | (0.632) | |
| Post | -0.991 | |
| | (0.599) | |
| Constant | -5.350*** | 18,156.777*** |
| | (0.210) | (3,308.138) |
| Observations | 1,742 | 1,742 |
| F-statistics | 84.46 | |
| R-squared | 0.039 | |
| Number of id | 871 | 871 |
| Household FE | Y | Y |
| 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 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

**Table 8:** Household Expenditures (in KGS)

| VARIABLES | (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) |
| Post | 69.176 | 2,004.454** | 796.584*** | 57.319 | 24.146 | 69.797** |
| | (135.668) | (928.052) | (71.659) | (59.598) | (30.704) | (27.724) |
| Constant | -3,483.450*** | 18,216.211*** | -235.337 | 198.246 | 238.708** | -1,102.483*** |
| | (400.740) | (2,809.292) | (197.512) | (161.548) | (83.628) | (80.429) |
| 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 |
| Household FE | 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 | -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) |
| Post | -113.806 | -1,002.765*** | 646.434 | 871.002 | 387.751 | -27,529.792** |
| | (181.039) | (224.597) | (381.202) | (1,833.899) | (232.485) | (12,735.251) |
| Constant | 3,664.207*** | -3,923.080*** | 7,514.544*** | -36,284.040*** | -37,470.537*** | 101,731.020*** |
| | (513.834) | (625.755) | (1,100.480) | (5,211.915) | (668.517) | (35,546.282) |
| 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 |
| Household FE | 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$)

**Table 9:** Billed Electricity Consumption, By Season (Heating versus Non-heating)

| | (1)<br>Heating season<br>bill | (2)<br>Non-Heating season<br>bill |
|---|---|---|
| Treat × Post1 | 59.292** | -37.749** |
| | (23.991) | (15.044) |
| Treat × Post2 | 13.667 | -21.666 |
| | (18.469) | (27.262) |
| Constant | 914.961*** | 653.689*** |
| | (14.651) | (18.054) |
| Mean of Control Group | 851.071 | 432.379 |
| Observations | 13,836 | 17,250 |
| Number of Household | 871 | 871 |
| Adjusted R-squared | 0.047 | 0.148 |
| Household Fixed Effect | Y | Y |
| Month-by-Year Fixed Effect | Y | Y |
| Cluster SE | Transformer | Transformer |

*Notes:* Billing data are provided by the electricity utility covering the period between January 2017 and February 2020. 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. Robust standard errors are clustered at the transformer level and included in parentheses ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

# APPENDIX: FOR ON-LINE PUBLICATION

**Figure A1:** Smart meters: potential channels to increase (i) enforcement of payment for services consumed, and (ii) accountability to deliver quality services

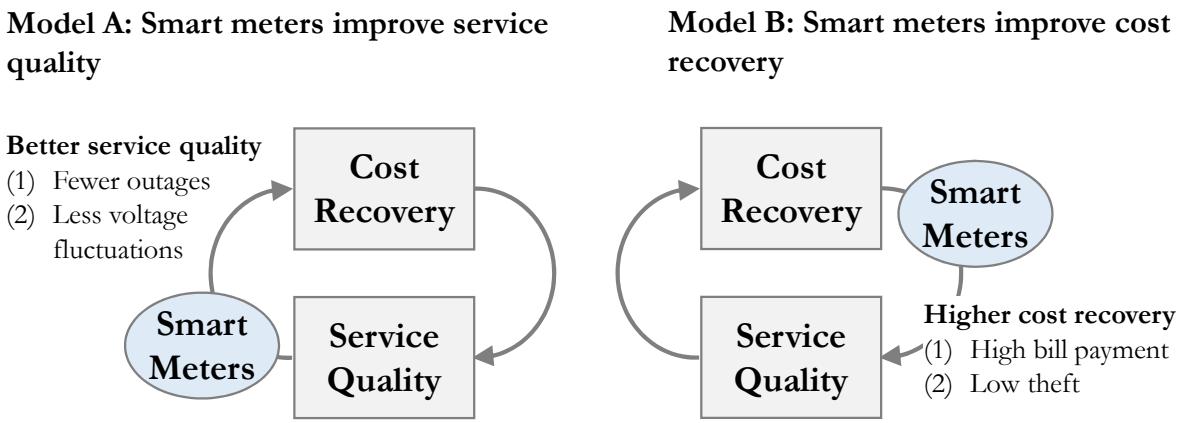
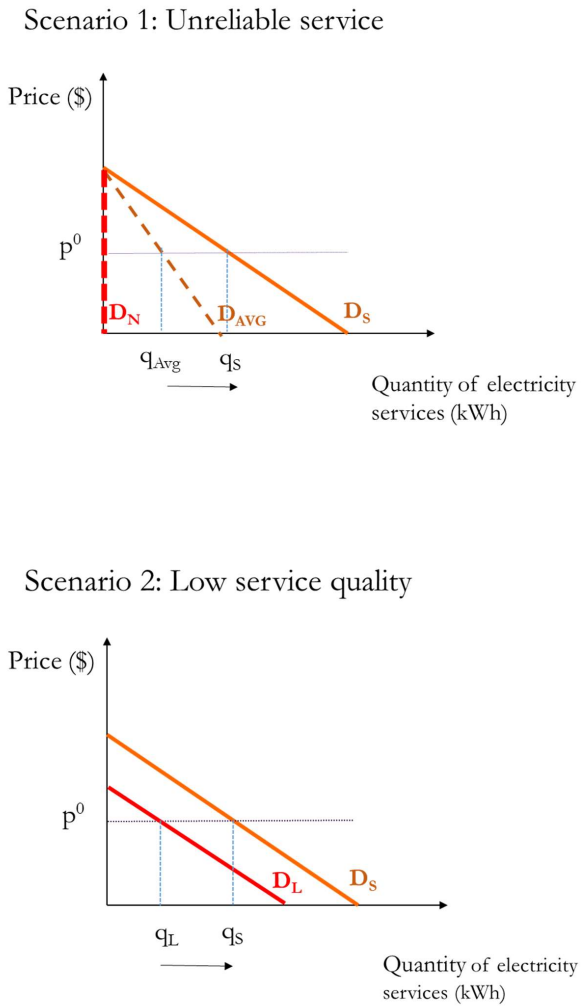


**Figure A2:** Framework for impacts of service quality on electricity services consumed




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

**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 |
|---|---|---|---|
| **I. Electricity is consumed, but not billed** | | | |
| (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 no longer needed if billing is integrated [Not applicable to our setting] |
| **II. Consumption is billed, but not paid** | | | |
| (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

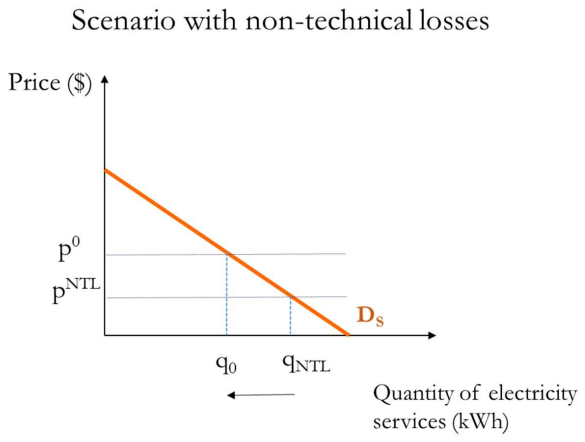
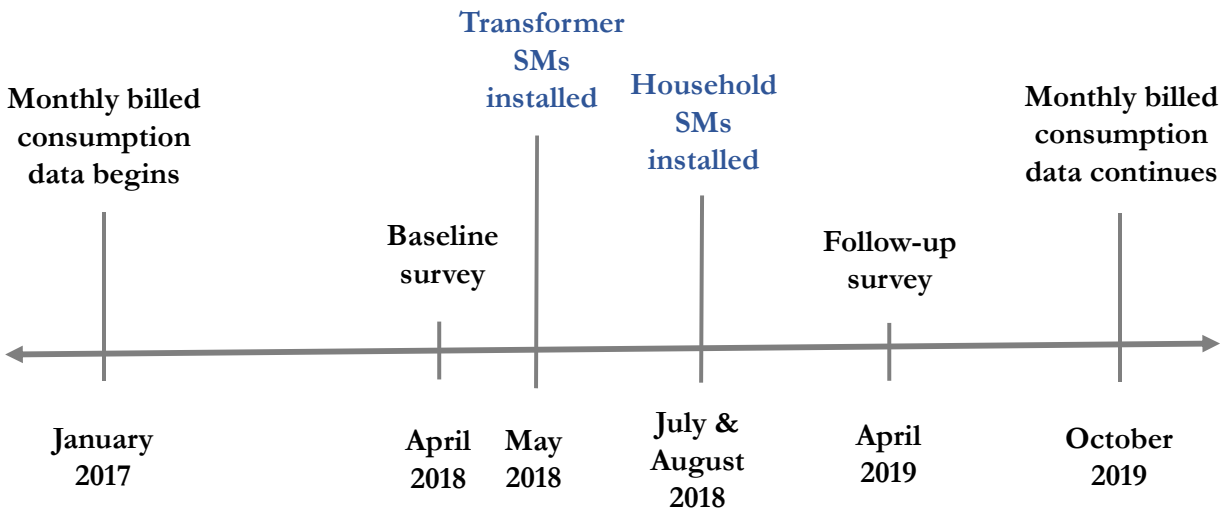


**Figure A4:** Timeline of meter installation and data collection




*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 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.

**Table A3:** Alarms: categorization of alarms from the transformer smart meters

| Category | Alarm Type | Count | Percentage |
|---|---|---|---|
| Theft | Disconnected but power is detected | 1587 | 3.26 % |
| | Module cover closed | 9 | 0.02 % |
| | Module cover removed | 11 | 0.02 % |
| | Recover from disconnected but power is detected | 1477 | 3.04 % |
| Quality | Over voltage L1 start | 13484 | 27.71 % |
| | Over voltage L2 start | 9096 | 18.69 % |
| | Over voltage L3 start | 6592 | 13.55 % |
| Power | Disconnect relay | 53 | 0.11 % |
| | Limiter threshold exceeded | 4683 | 9.62 % |
| | Manual connection | 45 | 0.09 % |
| | Power down (long power failure) | 2300 | 4.73 % |
| | Power down (short power failure) | 552 | 1.13 % |
| | Power up (long power failure) | 2365 | 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 of three phase | 3305 | 6.79 % |
| | Module power down | 2490 | 5.12 % |
| Sum | | 48,664 | 100.0% |

*Notes:* Alarms data are provided by the smart meters installed at the transformers. Categorization is based on technical manual from the maker of the smart meters. "Other" alarms are all those that do not fit into the other categories (theft, quality, and power outages).

**Table A4:** 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

**Table A5:** 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$)

**Table A6:** 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).

**Table A7:** Correlation between Transformer and Household Smart Meter Alarms

| | HH Alarms: Quality | | HH Alarms: Power Outage | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Transformer Alarms: quality | 0.038*** | 0.039*** | | |
| | (0.003) | (0.004) | | |
| Transformer Alarms: power | | | 0.098*** | 0.099*** |
| | | | (0.017) | (0.017) |
| Constant | 0.012** | 0.011*** | 0.079*** | 0.078*** |
| | (0.005) | (0.001) | (0.014) | (0.010) |
| Transformer FE | | Y | | Y |
| Observations | 70,497 | 70,497 | 70,497 | 70,497 |
| Transformer FE | | Y | | Y |

*Notes:* Alarms data are from either the transformer smart meters (the independent variable) or the households 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:** Compare the Number of Alarms among Three Transformer Groups

| VARIABLES | (1)<br>alarms |
|---|---|
| Treat | 0.816*** |
| | (0.160) |
| Treat × Replace | 0.368** |
| | (0.161) |
| Treat × Repair | 0.322 |
| | (0.332) |
| Constant | 0.192*** |
| | (0.061) |
| Observations | 2,709 |
| R-squared | 0.033 |
| Cluster SE | Transformer |
| Model | OLS |

*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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$)

**Table A9:** 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 ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

**Table A10:** Correlation between Survey-reported Electricity Quality and Smart Meter Alarms

| | Reliability: Reported by Household | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Alarms: quality | -0.200*** | | |
| | (0.069) | | |
| Alarms: power | | -0.181* | |
| | | (0.095) | |
| Alarms: theft | | | -0.712 |
| | | | (0.835) |
| Constant | -6.638*** | -6.638*** | -6.638*** |
| | (0.197) | (0.197) | (0.197) |
| Observations | 871 | 871 | 871 |

*Notes:* Alarms data are from the households smart meters. The household self-reported reliability data are from the follow-up survey, conducted in Spring 2019. Robust standard errors are clustered at the transformer level and displayed in parentheses ($^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$).

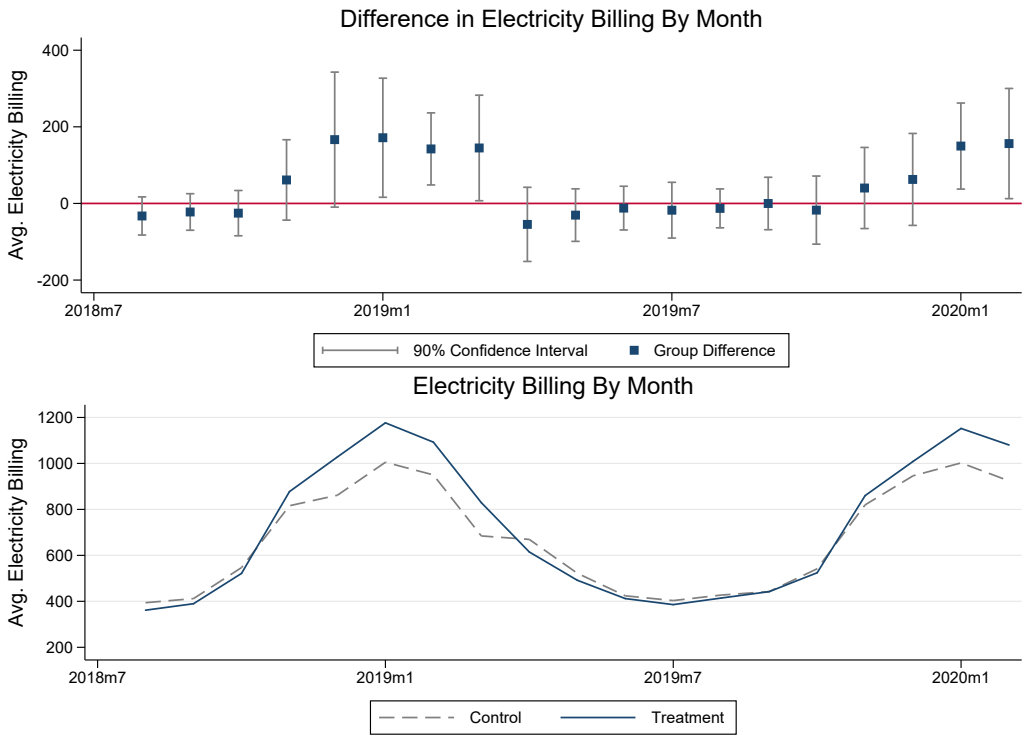



**Figure A5:** Post-treatment Billed Electricity Consumption (kWh/month)

*Notes:* Billing data are provided by the electricity utility. The analysis here is basic comparison and no other control variables are included. 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.