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Smart meters, electricity losses, and reliability*

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Abstract

Non-technical losses – including theft – and poor grid reliability are pervasive and costly problems for electricity utilities globally. To mitigate these challenges, some utilities have installed smart meters. Through a randomized experiment in the Kyrgyz Republic, we study the impact of smart meters on electricity bill payment and timing, electricity service quality, and household expenditures. Smart meters led to a significant reduction in outages and voltage fluctuations, an improvement in electricity service quality. Billed electricity consumption weakly increased during peak electricity consumption months following meter installation, likely the result of both improved electricity services and reductions in non-technical losses, but not theft per se. With improvements in electricity quality, consumers increase household expenditures on electrical appliances indicating demand for more reliable electricity service.

Keywords: Electricity, political economy, reliability

JEL: D01, D62, O13

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1 Introduction

Non-technical losses – including theft – are a pervasive problem for electricity utilities globally, totalling an estimated $25 billion per year (Depuru, Wang and Devabhaktuni, 2011). Electricity theft means consumers are not paying the full cost of the electricity services they consume, leading to over consumption of such services and, in locations where electricity generation uses "dirty" fuels, and excessive pollution. For electricity utilities, these losses translate into lower levels of cost recovery and thereby insufficient funds to invest in infrastructure maintenance, modernization, and technical upgrades.

Poor reliability and electricity service quality often result from insufficient gird investments, a first-order problem for economic development. Although electrification rates increased worldwide over the past decade,[1] reliability lags (Moss, 2019). Poor service quality is an impediment to achieving economic benefits from the electrical grid (Pargal and Banerjee (2014); Blimpo and Cosgrove-Davies (2019)), impacting both households (Chakravorty, Pelli and Marchand, 2014) and firms (Allcott, Collard-Wexler and O'Connell, 2016). Yet unreliable service perpetuates when consumers believe it warrants non-payment for their electricity consumption. This persistent cycle – an "infrastructure quality trap" (McRae, 2015*a*) – is illustrated in Figure 1.

Smart meter installations have skyrocketed in the past decade worldwide.[2] They are installed by utilities in both developed and developing countries for a variety of purposes, including improving grid reliability[3] and reducing non-technical losses;[4] Although the po-

[1]The Sustainable Development Goals (United Nation, 2016) stress the prominent role of energy in development. The United Nations state "Energy is crucial for achieving almost all of the Sustainable Development Goals, from its role in the eradication of poverty through advancements in health, education, water supply and industrialization, to combating climate change."

[2]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).

[3]Industry news accounts document these purposes. See for example: www.smart-energy.com/magazine-article/global-trends-in-smart-metering/

[4]For example, the Canadian utility, BCHydro, documents the installation of smart meter to deter theft on its website (www.bchydro.com).

tential benefits from these meters include interrupting the infrastructure quality trap, there is a dearth of evidence.[5]

We fill this gap through a randomized installation of smart meters, collaborating with an electricity utility operating within a small city in the Kyrgyz Republic.[6] Specifically, we study the impact of smart meters on electricity service quality, bill electricity consumption and indicators of theft, as well as household expenditures. 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.

The experimental intervention proceeded as follows. We collaborate with an electricity utility in a city within the Kyrgyz Republic. Twenty transformers within the city were selected to be included in the study, covering more than 1500 utility customers. In spring 2019, smart meters were installed at all 20 project transformers to measure electricity consumption for the neighborhood.[8] 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 surges. Households in control transformers retained the old meters. We collected baseline and follow-up survey data from households in the treatment and control transformers in the spring of 2018 and 2019, respectively. These complement other data, including monthly billing data from the electricity utility, as well as the electricity data from the smart meters

[5]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))

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

[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]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).

installed on all study transformers.

Results indicate the smart meter technology alone did not improve cost recovery or reduce non-technical losses. We find the smart meters did not significantly reduce indicators of theft, as measured by the transformer level smart meters. Billed electricity consumption – an indicator of reduced losses – increased during the peak electricity consumption months (winter), albeit insignificantly. During non-peak months, billed electricity consumption decreased. Conditional on paying their electricity bill,treated households are less likely to report paying their bill late.

In contrast, the smart meters led to improvements in electricity quality, including reductions in outages and voltage fluctuations, as measured by the transformer-level smart meters. There is suggestive evidence that service quality – in the form of voltage quality – may have initially worsened after the meter installation before improving. This, in conjunction with lower reported household appliance damage, demonstrates that the meter functionality protecting against voltage spikes may result in more service disruptions (in the short run) but then pressured the utility to make necessary repairs.

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.

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.[9] The technology's other characteristics – such as the enforcement of payment, monitoring of electricity consumption, and the ability to balance electricity load and reduce

[9]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)).

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 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*b*) 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 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 losses and smart meters

2.1 Electricity losses

Non-technical losses (NTL) come from a number of sources, some of which are theft-related but not all. Common sources of NTL include: meter malfunctioning (for example, if the voltage is very low due to grid quality issues the meter might not register the household's electricity being consumed), meter tampering (consumers have countless ways of "rolling back" or pausing the metering of their consumption), by-passing the meter (this involves

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

running the electrical wires from the house directly to the distribution wires, thereby avoiding the meter), 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 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). Only the first of this list is not theft-related.

These non-technical losses play a role in the infrastructure quality trap as portrayed in Figure 1. The utilitys low cost recovery is due to these NTL, including low bill payment, high levels of electricity theft, etc. The low cost recovery translates into constraints on funding for infrastructure maintenance and investments in expansion. 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.

2.2 Smart meters

The functionality of smart meters permits potential disruption of the infrastructure quality trap in two ways, as depicted in Figure 2.

First, 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).

Model B shows how smart meters could improve cost recovery. The meters measure electricity consumption every 15 minutes and relay this information to the utility. If the utility monitors consumption patterns, it can quickly identify theft and other losses and take action to rectify them. In addition, the utility can 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.

3 Randomized experiment and support

3.1 Electricity in Kyrgyzstan

Kyrgyzstan is a lower-middle income country in Central Asia and nearly 100% of its population has access to electricity. 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).

In the Kyrgyz Republic, much of the existing electricity infrastructure dates back to the Soviet Union including all 16 of its power plants (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 are the primary source of unreliable service.

The electricity's sector biggest problems are service quality and cost recovery, with reported distribution losses 15-18% (World Bank, 2017). In 2009-2012, distribution companies reported 2 outages/hour. In addition, the system has regular voltage and frequency fluctuations (World Bank, 2017). Per a 2013 survey > 50% survey respondents reported problems with voltage (including low voltage and voltage fluctuations) and 18.9% of respondents reported damage to electrical appliances because of poor electricity quality.

Residential consumers face a two-tiered increasing block price. The non-linearity in the price is at 700 kWh per month. Below the cutoff consumers pay .77 tyin per kWh. Above the cutoff, consumers pay 2.16 tyin per kWh. Residential consumers rarely exceed the threshold between the first and second tiers in the warm summer months; however, it is common in the winter, as many households heat with electricity.

Electric heating leads to large seasonal variations in electricity consumption, with average winter consumption approximately three times that of summer. The country's utilities face growing electricity consumption while constrained by a distribution system designed for substantially lower demand.

3.2 Randomized experiment

We collaborate with an electricity utility in a small city within the Kyrgyz Republic. Both electricity losses and service quality concerns for this utility. The experiment focuses on residential electricity consumers, which can reside in either multi-story apartment buildings or single family dwellings. Pre-intervention households were individually metered, but the meters were between old and susceptible to various forms of NTL.

The experimental intervention was designed around the last two steps in electricity distribution: the transformers and the households. 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, Sarma and Overbye, 2011).

The intervention proceed as depicted in Figure 3. Smart meters were installed at all 20 project transformers, which typically serve between 50 - 100 households, to measure electricity consumption for neighborhood. These transformer-level smart meters were installed in May 2018. Transformers were assigned to treatment or control status, resulting in 10 transformers in each group. Households in the treatment transformer had a smart meter installed to replace their old meters by September 2018. Households in the control transformers retained the old meters.

Installing smart meters at neighborhood transformers provides critical measurements at the level of treatment-assignment. First, the transformer-level smart meters collect information or "alarms" on indicators of both service quality issues (outages, voltage spikes, etc) and potential theft. Second, we can measure electricity losses as the differences between the transformer-level measurements of consumption and the aggregated household-level measurements of billed electricity consumption.

3.3 Data

We employ data from several sources for the analysis.

Survey data: We collected 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, and overall household expenditures.

We sought to survey all households within the treated and control transformers. Actual responding households numbered 1143 and 1125 in the baseline and follow-up surveys, respectively. When limited to the balanced panel of respondents in both the baseline and follow-up surveys, the dataset includes 880 households.

Smart meter data: Smart meters collect data at both the transformer and household level. Data are collected in 15-minute increments. These data are collected at an electronic aggregator installed at the transformer and then submitted to the electricity utility's server. Transformer smart meter data begin in April 2018, approximately 4 - 5 months prior to the installation of the household-level meters within the treatment group.

Utility billing data: We use monthly data on billed electricity consumption and timing of bill payment, as provided by the electricity utility. These monthly data start in January 2017, giving approximately 1.5 years of pre-intervention baseline data.

3.4 Baseline balance tests

We use both the billed electricity consumption and the baseline survey data to test for balance across the treatment and the control groups. Table 1 shows balance across the two groups on all of the household characteristics, including the size of the house, fuel used for heating and various measures of electricity quality.

Figure 4 depicts balance across groups with respect to electricity consumption. There is no significant difference in electricity consumption in any month during the pre-intervention period. In addition, the figure highlights that T and C households have the same seasonal electricity consumption pattern, which is indicative of electric heating in winter.

4 Analysis and results

4.1 Empirics

We employ a standard difference-in-differences model for most empirical specifications, with variations depending on whether the outcome data are at the transformer or household level.

For example, analysis of the impacts of the treatment on transformer alarms can be represented as:

$$a_{gt} = \tau Treat_g * Post + \beta Post_t + \delta Treat_g + \gamma_t + \tau_g + \epsilon_g \tag{1}$$

where a_{gt} is the number of alarms recorded by the transformer smart meter in one day for transformer g in time t, $Treat_g$ is an indicator of transformer treatment status, γ_t are month-by-year fixed effects, and τ_g are transformer fixed effects. Standard errors are clustered at the transformer level.

Alternatively, analysis of the impacts of smart meters on household billed electricity consumption can be represented by the following equation:

$$q_{igt} = \tau Treat_{ig} * Post + \beta Post_t + \delta Treat_{ig} + \gamma_t + \lambda_i + \epsilon_i \tag{2}$$

where q_{igt} is billed electricity consumption (kWh) for household i in transformer g in time t, $Treat_g$ is an indicator of transformer treatment status, γ_t are month-by-year fixed effects, and λ_i are household fixed effects. In our preferred specification, we cluster standard errors at the transformer level.

In regressions using the household survey data, we employ the baseline and follow-up survey data in a panel when the data allow.[11] Preferred specifications limit analysis to the balanced panel.

4.2 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.

In Table 2, we test the impact of the treatment on the total transformer alarms post in-

[11] 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.

stallation. We see alarms are significantly lower in the treated transformers post-treatment, indicating an overall difference. Appendix Table A1 confirms the treatment groups transformers were balanced at baseline.

Table 3 displays the estimated impacts on alarms specific to electricity quality. We see an that alarms indicating voltage spikes and power outages are significantly lower in the treatment transformers that the control.

Table 4 utilizes the panel data on reported outages, voltage spikes and appliance damages, as collected via the baseline and follow-up surveys. We show some signs that the treatment households experience increases in outages and voltage spikes, but a decrease in appliance damages post smart meter installation. These results are not statistically significant when standard errors are clustered at the transformer level, the preferred specification. Although speculative, these results suggest that the electricity service quality provided by the transformers may have been initially problematic post meter installation and thereby triggering the household smart meters' mechanism to disconnect upon a spike in voltage. This could have pressured the utility to make improvements and perform maintenance. This explanation is also consistent with the reported reduction in household appliances damaged by voltage spikes.

4.3 Impacts on billed consumption and theft

Table 6 shows that billed electricity consumption was not impacted by the smart meters. These results are not consistent with any reduction of non-technical losses. Table 7 breaks this analysis by season. Impacts are heterogeneous by season, with billed consumption increasing in peak electricity months (winter) and decreasing in off-peak electricity months. An event study graph in Figure 5 illustrates this heterogeneity across seasons.

We test the household self-reported bill response. Results are in Table 8. 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.

4.4 Other household responses

4.4.1 Household expenditures

Household expenditures were balanced across treatment groups at baseline, as shown in Appendix Table A2. In Table 9, we see a small – approximately 14 USD in value during a 3 month period – but statistically significant increase in house appliance expenditures post intervention. There are no statistically significant changes in any of the other expenditure categories, such as food, schooling, utilities, transportation, clothing or discretionary expenses.

4.4.2 Energy efficiency

If households are paying higher price (billed the full cost) for electricity services post-meter installation, then they may be incentivized to increase investment in energy efficiency or that may change the overall consumption patterns. Here we provide evidence on the household responses with respect to energy efficiency investments, investments in protection against poor reliability electricity service, and overall household consumption.

We first provide evidence on the changes in energy efficiency made following the installation of the smart meters. Treatment households are no more likely to install insulation (Table 12) or invest in energy efficient lighting (Table 10). They are, however, significantly more likely to to report having replaced their windows (Table 11). Window replacement is considered a a cost-effective energy efficient investment, given the cold winters and old housing stock.

Tests of additional types of appliance changes (Tables A3 and A4), differences in electric device ownership, such as generators, stabilizers, batteries, etc (Table A5),and differential use of electricity services show no evidence of impacts.

5 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.

References

Allcott, H., A. Collard-Wexler, and S. O'Connell. 2016. "How Do Electricity Shortages Affect Industry? Evidence from India." *American Economic Review*, 106(3).

Blimpo, M., and M. Cosgrove-Davies. 2019. *Electricity Access in Sub-Saharan Africa : Uptake, Reliability, and Complementary Factors for Economic Impact.* Washington, DC:World Bank.

Burlig, F., and L. Preonas. 2016. "Out of the Darkness and Into the Light? Development Effects of Rural Electrification." *Energy Institute Working Paper.*

Carranza, E., and R. Meeks. 2019. "Energy Efficiency and Electricity Reliability."

Chakravorty, U., M. Pelli, and B. Marchand. 2014. "Does the Quality of Electricity Matter? Evidence from Rural India." *Journal of Economic Behavior and Organization*, 107: 28–247.

Depuru, S., L. Wang, and V. Devabhaktuni. 2011. "Electricity theft: Overview, issues, prevention and a smart meter based approach to control theft." *Energy Policy*, 39.

Dinkelman, T. 2011. "The Effects of Rural Electrification on Employment: New Evidence from South Africa." *American Economic Review*, 101(7).

Glover, J.D., M.S. Sarma, and T. Overbye. 2011. *Power Systems Analysis and Design.* . 5th ed., Stamford, CT:Cengage Learning.

Ito, K., T. Ida, and M. Tanaka. 2018. "Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand." *American Economic Journal: Economic Policy*, 10.

Jack, K., and G. Smith. 2018. "Charging Ahead: Prepaid Metering, Electricity Use and Utility Revenue." *American Economic Journal: Applied Economics*, forthcoming.

Jessoe, K., and D. Rapson. 2014. "Knowledge is (less) power: Experimental evidence from residential energy use." *American Economic Review*, 104.

Lee, K., E. Miguel, and C. Wolfram. 2018. "Experimental Evidence on the Economics of Rural Electrification." *Energy Institute Working Paper.*

Lipscomb, M., A.M. Mobarak, and T. Barnham. 2013. "Development Effects of Electrification: Evidence from the Geological Placement of Hydropower Plants in Brazil." *American Economic Review: Applied Economics.*

McRae, S. 2015*a*. "Infrastructure Quality and the Subsidy Trap." *American Economic Review*, 105(1).

McRae, Shaun. 2015*b*. "Efficiency and Equity Effects of Electricity Metering: Evidence from Colombia."

Obozov, A., R. Isaev, V. Valiyev, Y. Hasanov, I. Mirzaliyev, and F. Imamverdiyev. 2013. "Prospects of Use of Renewable Energy Resources and energy-efficient Technologies in Azerbaijan and Kyrgyzstan." EcoMod Network Report, Baku, Azerbaijan.

Pargal, S., and S.G. Banerjee. 2014. "More Power to India: The Challenge of Electricity Distribution." World Bank, Washington, D.C.

Rud, J.P. 2012. "Electricity Provision and Industrial Development: Evidence from India." *Journal of Development Economics*, 97(2).

Szabo, A., and G. Ujhelyi. 2015. "Reducing nonpayment for public utilities: Experimental evidence from South Africa." *Journal of Development Economics*, 117.

Van de Walle, D, M Ravallion, V Mendiratta, and G Koolwal. 2013. "Long-term Impacts of Household Electrification in Rural India." *World Bank Working Paper*.

Wolak, K. 2011. "Do Residential Customers Respond to Hourly Prices? Evidence from a Dynamic Pricing Experiment." *American Economic Review*, 101.

Wolfram, C., P. Gertler, and O. Shelef. 2012. "How Will Energy Demand Develop in the Developing World?" *Journal of Economic Perspectives*, 26(Winter).

World Bank. 2017. "Analysis of the Kyrgyz Republic's Energy Sector."

Zozulinsky, A. 2007. "Kyrgyzstan: Power Generation and Transmission." BISNIS, Washington, D.C.

Figure 1: Example of infrastructure quality trap

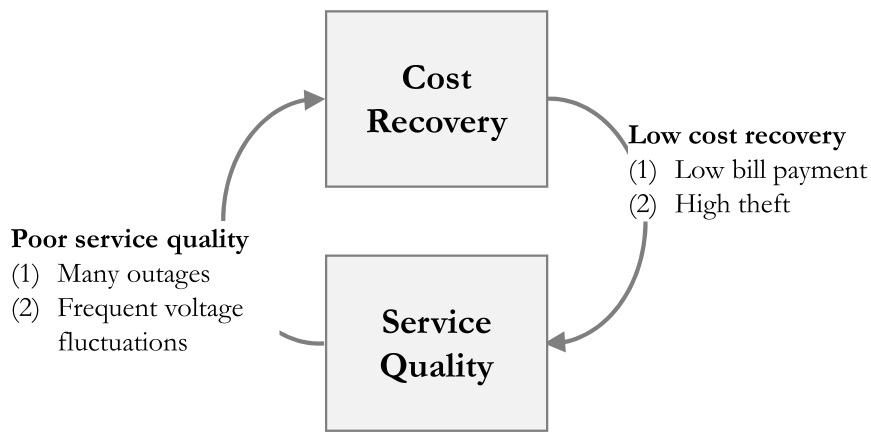

Figure 2: Smart meters potential to interrupt the infrastructure quality trap

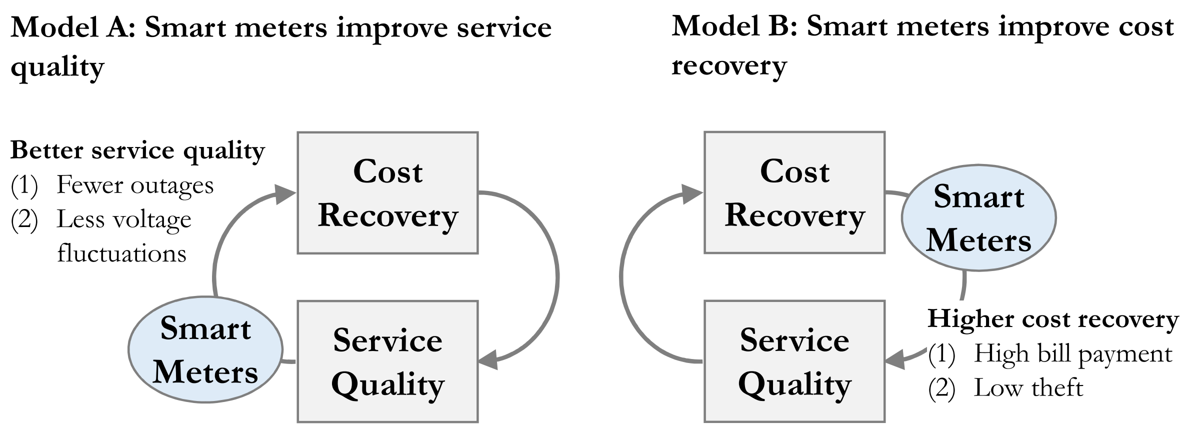

Figure 3: Randomized design

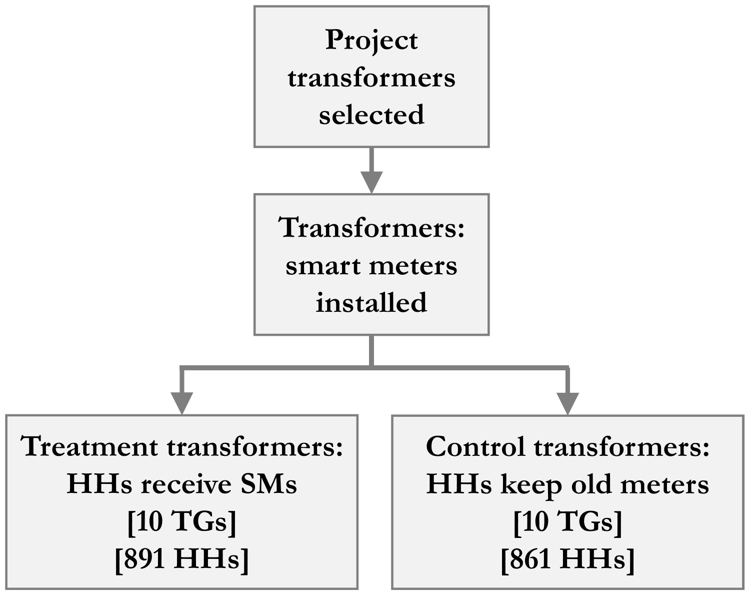

Table 1: Balance at Baseline: Treated and Control Household Characteristics

	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 (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$).

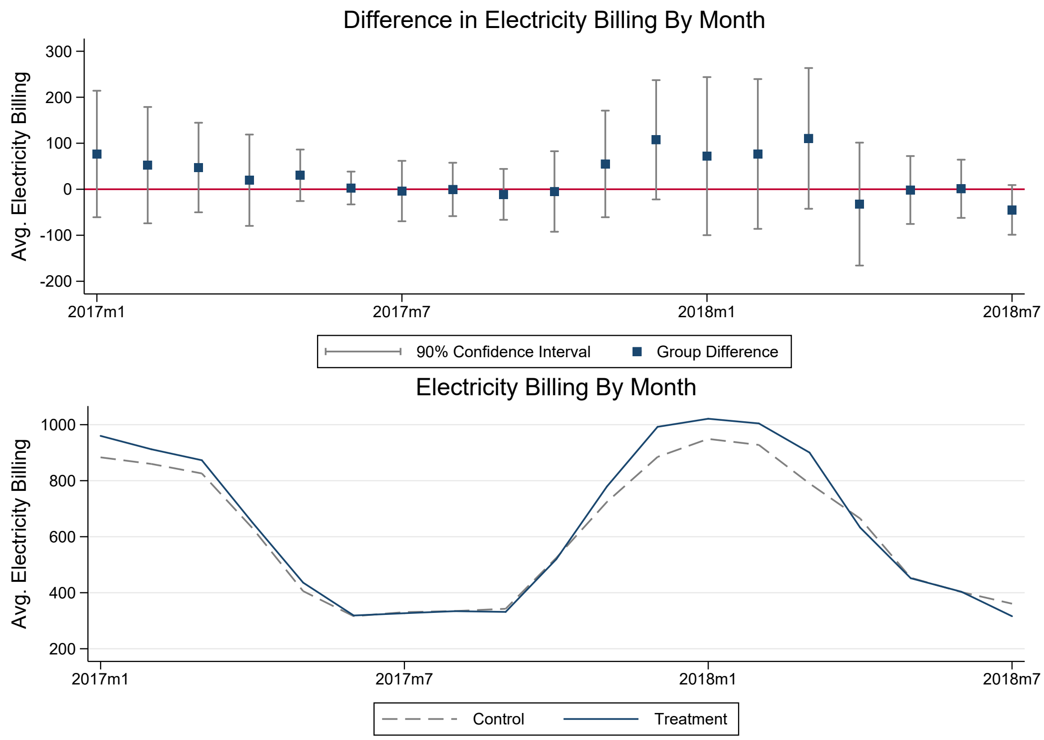

Figure 4: Pre-treatment Billed Electricity Consumption

Notes: Billing data are provided by the electricity utility. The analysis here is basic comparison and no other variables are controlled. 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 - Total

	(1)	(2)
VARIABLES	Total alarms in one day	
Treat × Post	-3.707**	-0.900*
	(1.727)	(0.480)
Post	6.314***	3.412***
	(1.347)	(0.258)
Constant	-0.276	-1.469***
	(0.615)	(0.237)
Mean of Control Group	0.246	0.246
Observations	4,647	4,647
R-squared	0.219	
Transformer FE	Y	Y
Cluster SE	Transformer	Transformer
Model	OLS	Poisson

Notes: Alarms data are the smart meters installed on the transformers and cover the period from April 2018 to June 2019. The outcome variable is the total number of alarms recorded by the transformer smart meter in one day. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table 3: Transformer-Level Smart Meter Alarms - Electricity Quality Alarm

VARIABLES	Voltage problems		Power outage		Other alarms	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-4.206***	-2.555***	-0.305***	-0.395***	-0.125***	-0.352***
	(1.200)	(0.715)	(0.056)	(0.067)	(0.028)	(0.069)
Constant	4.076***	1.435***	0.922***	-0.088	0.417***	-0.878***
	(1.114)	(0.415)	(0.068)	(0.084)	(0.031)	(0.078)
Mean of Control Group	4.486	4.486	0.936	0.936	0.422	0.422
Observations	3,176	3,176	3,176	3,176	3,176	3,176
R-squared	0.156		0.006		0.005	
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer
Model	OLS	Poisson	OLS	Poisson	OLS	Poisson

Notes: Alarms data are provided by the electricity utility covering the period from September 2018 to June 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 4: Electric Service Quality – Self-reported

VARIABLES	(1) At least 1 outage/week	(2)	(3) More than 1 voltage spike/week	(4)	(5) Appliance ever damaged	(6)
Treat × Post	0.067	0.067	0.080	0.080**	-0.096	-0.096***
	(0.190)	(0.048)	(0.103)	(0.037)	(0.103)	(0.033)
Treat	0.005	0.005	-0.003	-0.003	0.066	0.066**
	(0.119)	(0.034)	(0.107)	(0.031)	(0.098)	(0.028)
Post	-0.098	-0.098***	0.135**	0.135***	-0.086	-0.086***
	(0.155)	(0.033)	(0.068)	(0.027)	(0.061)	(0.023)
Constant	0.451***	0.451***	0.757***	0.757***	0.209***	0.209***
	(0.116)	(0.041)	(0.092)	(0.037)	(0.066)	(0.029)
Mean of Control Group	0.445	0.445	0.703	0.703	0.187	0.187
Observations	1,739	1,739	1,736	1,736	1,755	1,755
Number of id	880	880	879	879	880	880
Basic Characteristics	Y	Y	Y	Y	Y	Y
Cluster SE	Transformer	Household	Transformer	Household	Transformer	Household

Notes: Data collected through baseline and follow-up surveys. Analysis is restricted to the balanced panel. *outage* is a binary variable and equals 1 if the household experienced more than once electricity outage per week in the previous January and February. *voltage* is a binary variable and equals 1 if the household experienced more than once voltage fluctuations per week in the previous January and February. *appliance damage* is a binary variable and equals 1 if the household ever had an appliance damaged by electricity problems. 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 at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table 5: Transformer-Level Smart Meter Alarms - Potential Theft

VARIABLES	(1) Potential theft alarms in one day	(2) Potential theft alarms in one day
Treat	-0.035	-0.056
	(0.455)	(0.735)
Constant	0.776***	-0.225
	(0.257)	(0.407)
Mean of Control Group	0.654	0.654
Observations	3,176	3,176
R-squared	0.002	
Cluster SE	Transformer	Transformer
Model	OLS	Poisson

Notes: Alarms data are the smart meters installed on the transformers and cover the period from April 2018 to June 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 6: Billed Electricity Consumption

VARIABLES	(1) bill	(2) lag bill
Treat × Post	5.460	23.493
	(12.991)	(14.405)
Post	-653.245***	-683.679***
	(39.257)	(36.661)
Constant	923.106***	889.196***
	(21.520)	(19.590)
Mean of Control Group	611.827	586.899
Observations	40,128	38,789
Number of Households	1,383	1,383
Adjusted R-squared	0.274	0.276
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 April 2019. 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 7: Billed Electricity Consumption - By Season

VARIABLES	(1) bill	(2) bill	(3) lag bill	(4) lag bill
Treat × Post	37.475	-28.945*	26.571	6.395
	(25.615)	(15.723)	(25.062)	(17.521)
Post	91.082***	-409.210***	-269.278***	-152.771***
	(24.716)	(31.661)	(25.476)	(22.940)
Constant	922.223***	641.526***	889.069***	423.114***
	(17.882)	(15.979)	(19.427)	(6.102)
Mean of Control Group	855.462	433.885	816.285	419.017
Observations	17,445	22,683	17,428	21,361
Number of Household	1,383	1,383	1,383	1,383
Adjusted R-squared	0.044	0.174	0.089	0.259
Household FE	Y	Y	Y	Y
Month-by-Year FE	Y	Y	Y	Y
Cluster SE	Transformer	Transformer	Transformer	Transformer
Season	Heating	Non-Heating	Heating	Non-Heating

Notes: Billing data are provided by the electricity utility covering the period between January 2017 and June 2019. 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. Heating season covers from November to March. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

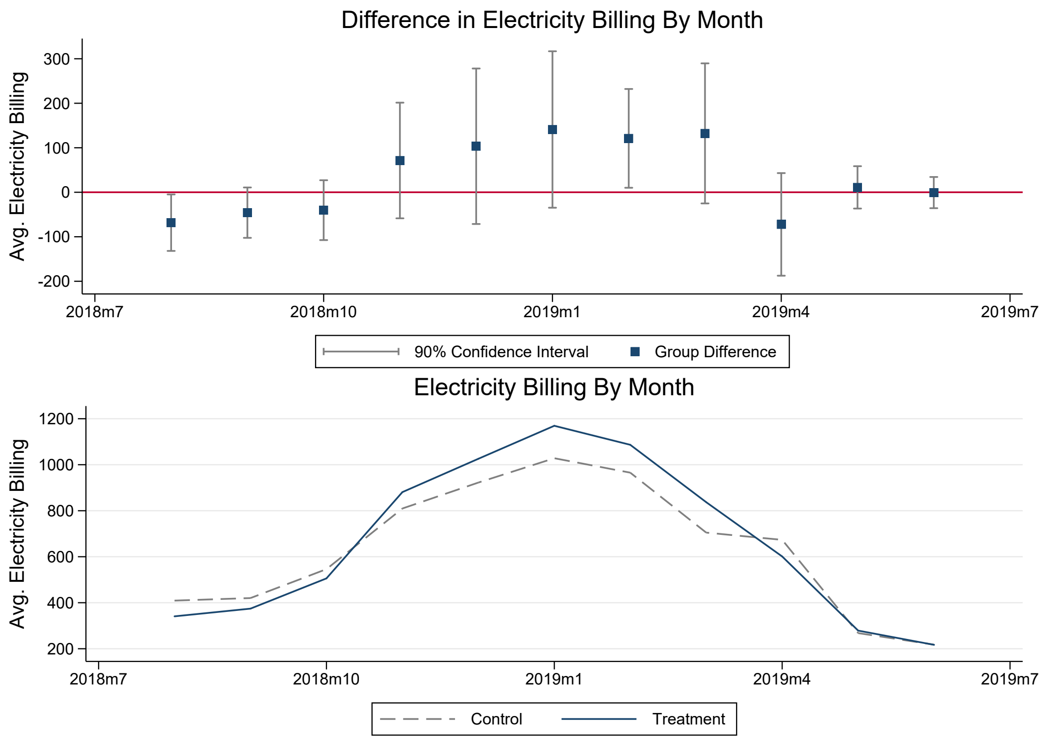

Figure 5: Post-treatment Billed Electricity Consumption (kWh/month)

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 8: Household Arrangements for Bill Payment

VARIABLES	Made arrangement for delayed payment		Paid electricity bill late		Paid other bill late	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.112	-0.112***	-0.061**	-0.061***	-0.027	-0.027
	(0.142)	(0.026)	(0.024)	(0.016)	(0.026)	(0.018)
Constant	0.171	0.171***	0.131***	0.131***	0.181***	0.181***
	(0.122)	(0.041)	(0.036)	(0.030)	(0.041)	(0.032)
Mean of Control Group	0.398	0.398	0.105	0.105	0.111	0.111
Observations	1,125	1,125	1,125	1,125	1,125	1,125
R-squared	0.034	0.034	0.016	0.016	0.009	0.009
Basic Characteristics	Y	Y	Y	Y	Y	Y
Cluster SE	Transformer	Household	Transformer	Household	Transformer	Household

VARIABLES	Reduced expenditure on essential items		Reduced expenditure on non-essential items	
	(7)	(8)	(9)	(10)
Treat	0.034	0.034	0.064	0.064**
	(0.078)	(0.029)	(0.061)	(0.030)
Constant	0.520***	0.520***	0.600***	0.600***
	(0.090)	(0.046)	(0.074)	(0.046)
Mean of Control Group	0.352	0.352	0.421	0.421
Observations	1,125	1,125	1,125	1,125
R-squared	0.018	0.018	0.023	0.023
Basic Characteristics	Y	Y	Y	Y
Cluster SE	Transformer	Household	Transformer	Household

Notes: Data collected through household follow-up survey. 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 9: Household Expenses (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 expenses	(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 id	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 (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table 10: 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 (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table 11: Changes in Home Energy Efficiency

VARIABLES	(1) made any change	(2) install insulation	(3) replace windows	(4) insulate window	(5) change energy efficient appliances	(6) install energy efficient lightbulbs	(7) replace heating system
Treat	0.075*	-0.009	0.087***	-0.000	0.001	0.015	0.003
	(0.041)	(0.045)	(0.030)	(0.003)	(0.002)	(0.012)	(0.004)
Constant	0.045	-0.008	0.052*	0.000	0.007	0.012	-0.002
	(0.042)	(0.047)	(0.027)	(0.005)	(0.004)	(0.014)	(0.004)
Mean of Control Group	0.205	0.109	0.080	0.004	0.002	0.019	0.002
Observations	1,125	1,125	1,125	1,125	1,125	1,125	1,125
R-squared	0.024	0.021	0.020	0.001	0.002	0.003	0.002
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer
Basic Characteristics	Y	Y	Y	Y	Y	Y	Y

Notes: Data collected through household follow-up survey in spring 2019. The outcome variables are binary variables indicating whether the household made certain changes to their house "since last summer" and equals 1 if they made the corresponding change. We control household basic characteristics, including 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 (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table 12: Home Insulation - Whether Installed in 2018?

VARIABLES	(1) external wall	(2) internal wall	(3) attic floor/celling	(4) floor	(5) foundation
Treat	0.002	-0.009	0.001	0.012	-0.133
	(0.045)	(0.019)	(0.014)	(0.025)	(0.107)
Constant	-0.016	-0.017	-0.003	0.004	0.155
	(0.048)	(0.021)	(0.013)	(0.021)	(0.101)
Mean of Control Group	0.530	0.417	0.261	0.347	0.929
Observations	1,125	1,125	1,125	1,125	1,125
R-squared	0.018	0.017	0.007	0.006	0.054
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer
Basic Characteristics	Y	Y	Y	Y	Y

Notes: Data collected through household follow-up survey. The outcome variables are binary indicators and equal 1 if the household installed insulation at the corresponding places in "the past year". 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 the household level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

APPENDIX: FOR ON-LINE PUBLICATION

Table A1: Balance Test for Transformer-Level Smart Meter Alarms

Month	Control	Treat	Difference
2018 04	0.767	0.727	-0.040
	(0.252)	(0.300)	(0.195)
2018 05	0.306	0.418	0.112
	(0.028)	(0.260)	(0.097)
2018 06	0.270	0.272	0.002
	(0.079)	(0.071)	(0.038)
2018 07	0.103	0.124	0.020
	(0.052)	(0.069)	(0.032)
Observations	10	10	20

Notes: Alarms data are provided by the electricity utility covering the period prior to the introduction of smart meters in the treatment households (from April to July 2018). The outcome variable is the number of alarms recorded by the transformer smart meter in one day.

Table A2: 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 questions on household expenditures in baseline survey. The outcome variables measure household's expenses on the corresponding items. 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. Robust standard errors are clustered at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table A3: Number of Total Electric Appliances

VARIABLES	(1) appliance num	(2) appliance num
Treat × Post	-0.001	-0.001
	(0.002)	(0.002)
Treat	-0.004	-0.004
	(0.343)	(0.187)
Post	-0.001	-0.001
	(0.000)	(0.001)
Constant	8.288***	8.288***
	(0.446)	(0.298)
Mean of Control Group	9.851	9.851
Observations	1,760	1,760
R-squared	0.037	0.037
Basic Characteristics	Y	Y
Cluster SE	Transformer	Household

Notes: Counts of total number of appliances created using data from the household baseline and follow-up surveys. Analysis is restricted to the balanced panel. The outcome variable is the total number of all the electric appliances owned by the household. 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 at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table A4: Electric Appliance Ownership

VARIABLES	(1) refrigerator	(2) clothes washer	(3) color TV	(4) sound equipment	(5) computers laptops	(6) water heater	(7) cellphone charger	(8) electric heater
Treat × Post	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treat	0.064*	-0.005	0.012	-0.045	0.004	0.079	-0.098	-0.112**
	(0.033)	(0.048)	(0.040)	(0.043)	(0.028)	(0.063)	(0.120)	(0.045)
Post	-0.000	-0.000	0.000	-0.000	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.774***	0.796***	0.838***	-0.008	0.059	0.302***	0.661***	0.707***
	(0.053)	(0.041)	(0.038)	(0.035)	(0.065)	(0.081)	(0.119)	(0.071)
Mean of Control Group	0.827	0.836	0.862	0.142	0.184	0.433	0.702	0.722
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared	0.011	0.003	0.002	0.036	0.013	0.014	0.012	0.014
Basic Characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer

Notes: Data collected household baseline and follow-up surveys. Analysis restricted to balanced panel. The outcome variables are binary indicators and equal 1 if the household have the corresponding electric appliance. Controls 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 at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table A5: Electric Device Ownership

VARIABLES	(1) electricity generator	(2) stabilizer	(3) battery with inverter	(4) uninterruptable power supply	(5) solar panel	(6) solar water heater	(7) other solar devices
Treat × Post	0.000	0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treat	0.008	-0.006	0.000	-0.002	0.000	-0.002	0.000
	(0.008)	(0.006)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
Post	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.014	-0.000	0.000	0.001	0.000	0.001	0.000
	(0.015)	(0.007)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)
Mean of Control Group	0.009	0.011	0.000	0.002	0.000	0.002	0.000
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared	0.011	0.004		0.001		0.001	
Basic Characteristics	Y	Y	Y	Y	Y	Y	Y
Cluster SE	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer	Transformer

Notes: Data collected household baseline and follow-up surveys. Analysis restricted to balanced panel. The outcome variables are binary indicators and equal 1 if the household has the corresponding electric device at home. Controls 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 at the transformer level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

Table A6: Services using electricity

VARIABLES	Cooking		Lighting		Appliances		Heating water		Heating house	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat	-0.005	-0.005	0.000	0.000	0.000	0.000	0.024	0.024*	0.027	0.027*
	(0.012)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.034)	(0.013)	(0.026)	(0.015)
Constant	0.987***	0.987***	1.000	1.000	1.000	1.000	0.917***	0.917***	0.974***	0.974***
	(0.014)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.045)	(0.022)	(0.027)	(0.021)
Mean of Control Group	0.983	0.983	1	1	1	1	0.943	0.943	0.922	0.922
Observations	1,125	1,125	1,125	1,125	1,125	1,125	1,125	1,125	1,125	1,125
R-squared	0.001	0.001					0.005	0.005	0.013	0.013
Basic Characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster SE	Transformer	Household	Transformer	Household	Transformer	Household	Transformer	Household	Transformer	Household

Notes: Data collected through household follow-up surveys. The outcome variables are binary indicators and equal 1 if the household use electricity for the corresponding activities. Controls 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 the household level and included in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$)

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