Energy Efficiency and Electricity Reliability*

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Abstract

Overloaded electrical systems are a major source of unreliable power. Using a randomized saturation design, we estimate the impact of compact fluorescent lamps (CFLs) on electricity reliability and household electricity consumption in the Kyrgyz Republic. Greater saturation of CFLs within a transformer leads to fewer outages, a technological externality benefitting all households, regardless of individual adoption. Spillovers in CFL adoption further reduce electricity consumption, contributing to increased reliability within a transformer. CFLs' impacts on household electricity consumption vary according to the effects on reliability. Receiving CFLs significantly reduces electricity consumption, but increased reliability permits greater consumption of electricity services.

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1 Introduction

Electricity reliability is a major concern in achieving economic benefits from grid connections (Pargal and Banerjee, 2014). When electrical grids are asked to deliver more power than system constraints allow – limited by either technical capacity or persistent power shortages – outages can result (Lawton et al., 2003; Sullivan et al., 2009; Singh and Singh, 2010; Samad and Zhang, 2016).

Energy efficient technologies are frequently deployed via government programs with the specific goals of reducing peak demand (Osborn and Kawann, 2001; Gillingham, Newell and Palmer, 2006) and increasing reliability of electricity supply (World Bank, 2006). These technologies are expected to deliver important electricity savings without requiring adopters to decrease their electricity services consumed (DOE, 2009). Moreover, as electricity savings reduce the stress on the distribution infrastructure, sufficient saturation of efficient technologies can induce more reliable electricity supply for *all* end-users served by the same infrastructure, regardless of their own adoption of the technologies (Trifunovic et al., 2009).

Whether impacts on electricity reliability are empirically possible is a first order question that speaks directly to the optimal scale of programs delivering efficient technologies and the extent to which these programs can accomplish the various goals they are set to deliver. An improvement in reliability resulting from energy efficiency distribution is a form of a technological externality.[1] Technological externalities are known to govern the take-up and impacts of other technologies (Miguel and Kremer, 2004; Cohen and Dupas, 2010).[2] Similarly, the

[1]Adoption of a particular technology generates a positive (negative) technological externality if an individual's returns to adoption increase (decrease) in the fraction of others adopting the technology (Foster and Rosenzweig, 2010).

[2]Cohen and Dupas (2010) identify the following factors that govern technology uptake and impacts: (1) the elasticity of demand with respect to price, (2) the elasticity of usage with respect to price, (3) the impact of price variation on the need of the marginal consumer, and (4) the presence of nonlinearities or externalities

adoption of energy efficient technologies and the benefits from their adoption are likely to hinge on such externalities.

To test for a technological externality in electricity reliability and assess how it contributes to electricity consumption and later technology adoption, we implemented an experimental distribution of compact fluorescent lamps (CFLs) in a district near Bishkek, the capital of the Kyrgyz Republic. CFLs are engineered to consume 75 percent less electricity per lumen relative to traditional incandescent bulbs (DOE, 2009). Efficient lighting technologies, such as CFLs, are a relatively accessible option for end-users and a popular choice of energy efficiency programs.[3] They are also particularly pertinent for reducing peak demand in developing countries, where lighting comprises up to 86 percent of electricity consumption (Mills, 2002) and consumption of lighting services typically occurs at peak times.

Designed to alleviate a constraint within the electricity distribution system that causes electricity outages – transformer overloads – we distribute CFLs to reduce peak loads and induce a technological externality. Transformers 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 transformer breakage, resulting in outage (Glover, Sarma and Overbye, 2011).[4] Local distribution transformers in the Kyrgyz Republic are regularly operating at a load factor that substantially

in the production function. Their experiment focused on factors 1 through 3, and assume three levels of externality in calculations of cost-effectiveness of a price subsidy. We directly test for the fourth factor.

[3]Between 1990 and the mid-2000s, the World Bank alone committed more than US$11 billion to energy efficiency in developing countries. Examples of projects distributing CFLs to reduce peak load and increase service reliability (amongst other goals) include: 800,000 CFLs in Uganda to reduce peak load by 30 MW; 400,000 CFLs in Rwanda to reduce peak load by 16 MW; 1 million CFLs in Vietnam to reduce peak load by 33 MW; 600,000 CFLs in Sri Lanka to reduce peak load by 34 MW; and 2.7 million CFLs in South Africa to reduce peak load by 90 MW (World Bank, 2006; Sarkar and Sadeque, 2010).

[4]This is not unique to our setting. For example, as peak electricity loads increase in India, utilities are reporting increasing numbers of transformer overloads and resulting outages (Parashar, 2017; Dabas, 2019).

exceeds the optimal, making them close to overload (Amankulova, 2006). Given transformer failure is a non-linear function of load, peak reductions of overloaded transformers can yield disproportionately large impacts on supply reliability (ANSI/IEEE, 1981).

In a novel application of a randomized saturation design (Baird et al., 2018) to the domain of energy efficiency, we randomly assign treatment status in two stages. First, we randomize transformers to control, low or high CFL treatment saturations, with approximately 10 to 14 (15 to 18) percent of all households within low (high) treatment saturation transformers assigned to treatment.[5] Design decisions regarding CFL saturations to induce reliability effects were informed by a calibration exercise. Second, we randomize households individually to treatment and control groups, according to the saturation assigned to their transformer in the first stage. Treated households are given the opportunity to purchase up to four CFLs at a highly subsidized price. At baseline, households had 6.2 lightbulbs on average, of which only 0.2 were energy efficient. Treated households received an average of 3.2 CFLs through this intervention.

We observe three main results. First, households in transformers with a higher CFL saturation report fewer days without electricity due to unplanned outages. We consider this result positive evidence that energy efficiency programs can reduce peak loads to improve electricity reliability, if they reach sufficient levels of technology saturation. Analysis of utility's residential electricity consumption data collapsed at the transformer level confirms this result. Second, the impacts of CFL distribution on households' electricity consumption vary according to the CFL saturation within a transformer. In lower saturation transformers, there is a

[5] We employ electric utility's data on residential users and the transformers through which they are served. We sample 20 percent of households in each transformer into the study. Then, we randomize transformers to saturations of 0, 60 or 80 percent of *study* households treated, respectively. This results in the 10 to 14 (15 to 18) percent of *all* households within low (high) saturation transformers being assigned to treatment.

statistically significant and meaningful reduction in electricity consumption. In higher saturation transformers, reductions in electricity consumption are smaller and not statistically significant. This result is consistent with potential for greater electricity consumption due to improved reliability within higher saturation transformers.[6] Third, spillovers in CFL take-up occur among control households. Control households in treated transformers have significantly more CFLs than the "pure" control households in control transformers. Adoption spillovers contribute to *greater reductions* in electricity consumption within a transformer, adding to the technological externality in electricity reliability. Although at higher technology saturations there are more neighbors to learn from and more reliable electricity services, we do not find significant differences in adoption spillovers by CFL saturation.

Our study contributes to literatures concerned with technology adoption and technological externalities. Our experiment employs a recent innovation in experimental design, a multi-level randomized saturation, to study the role of technological externalities in the domain of energy efficiency. Multi-level randomized saturation designs are increasingly used by empirical work focused on estimating network, spillover and general equilibrium effects, thereby addressing their interference in the identification of program impacts (Sinclair and Green, 2012; Banerjee et al., 2014; Crepon et al., 2013; Haushofer et al., 2013; Crepon et al., 2018; Filmer et al., 2018; Muralidharan, Niehaus and Sukhtankar, 2018). Previous work on technology adoption highlighted the importance of technological externalities in technology take-up, diffusion and subsidization, and in the assessment of program impacts and cost-effectiveness (Miguel and Kremer, 2004; Cohen and Dupas, 2010; Ashraf, Berry and Shapiro, 2010). Nevertheless, given the scale at which technological externalities typically occur, designing an

[6]In low saturation transformers, electricity savings are within the expected range from engineering calculations. The smaller reductions in high saturation transformers are thus not a sign of ineffective technology. Rebound effects, increased used of electric heating, and strategic outages do not seem to drive the impacts by transformer saturation.

experiment that can identify such externalities has been challenging.[7] As a result, there has been relatively little causal empirical evidence on them.[8] By implementing a randomized saturation design at the level of frequent infrastructure failure, we provide evidence of a technological externality in the form of improved reliability of electricity services. We show that, due to this externality, the effect of CFL adoption on household energy consumption is non-monotonic. At a lower saturation, CFLs reduce household electricity consumption; but at a higher saturation, CFLs allow them to increase their electricity consumption due to fewer outages. Ignoring this externality would lead to inaccurate calculations of the electricity savings from the CFLs.

Our study also connects to the literatures on energy efficiency impacts, adoption, and the energy efficiency gap. The substantial body of work investigating the take-up of energy efficient technologies has largely focused on private adoption decisions and the returns to individual adopters (Jaffe and Stavins, 1994; Allcott and Greenstone, 2012; Gillingham and Palmer, 2014). Although programs deploying efficient lighting are ubiquitous and ostensibly promising, there is little evidence of their impacts on household electricity consumption.[9] Perhaps more notably, adoption spillovers and reliability externality effects of energy efficient technologies have received little attention. Through our CFL distribution we show that increasing household energy efficiency leads to adoption spillovers and reliability externalities, which affect many more electricity consumers. Accounting for these effects is critical.

[7]As Miguel and Kremer (2004) acknowledge: "When local treatment externalities are expected, field experiments can be purposefully designed to estimate externalities by randomizing treatment at various levels. [...] However, this multi-level design may not be practical in all contexts: for example, in our context it was not possible to randomize treatment within schools. Randomization at the level of clusters of schools also dramatically increases the sample size needed for adequate statistical power, raising project cost."

[8]Miguel and Kremer (2004) provide experimental evidence of positive cross-school externalities from deworming medicines in Kenya, but rely on non-experimental methods to decompose the overall effect on treated schools into a direct effect and within-school externality effect. Cohen and Dupas (2010) use a randomized two-stage pricing design to estimate the elasticities of demand and usage of bednets with respect to price, assuming three levels of externality in calculations of price subsidy cost-effectiveness.

[9]The exception is Iimi et al. (2017), which does not address technological externalities.

Benefit calculations that incorporate adoption spillovers and improved electricity services are more than double the calculations based solely on private electricity consumption impacts, providing an economic rationale for mass deployment of energy efficient technologies.

The remainder of the paper is as follows: Section 2 describes our experiment setting in the Kyrgyz Republic. Section 3 explains the sampling process, the randomized design, and the intervention. Section 4 details the data collected and offers randomization checks. Section 5 estimates of the aggregate impacts of CFLs on outages. Section 6 presents analysis of residential electricity consumption and discusses evidence of technological externalities in electricity reliability. Section 7 provides analysis on CFL adoption and spillovers in technology take-up. Section 8 addresses external validity. Section 9 concludes.

2 Experiment setting

The Kyrgyz Republic provides a suitable context in which to study energy efficiency and electricity reliability in a developing country setting. Due to its history as part of the former Soviet Union, this lower-middle income country is highly electrified. Nearly 100 percent of households are covered by formal electricity connections and the residential sector consumes 63 percent of the country's electricity supplied. In spite of low residential electricity prices – $0.02 per kWh throughout this study – energy expenditures comprised an estimated 7.1 percent of total household expenditures (Gassmann, 2014).

Since the country's 1992 independence, residential electricity demand has rapidly grown, straining the existing infrastructure.[10] In the years prior to our study, most local distribu-

[10]Kyrgyz households' growing electricity consumption is consistent with pro-poor economic growth in developing countries more broadly (Obozov et al., 2013). Much of the existing electricity infrastructure dates back to the Soviet Union (Zozulinsky, 2007) and was designed for substantially lower demand.

tion transformers had a load factor between 0.9 and 1.2, which is greater than the optimal load of 0.7 (Amankulova, 2006). As a result, poor reliability and unplanned outages are frequent (World Bank, 2014), particularly during the winter when residential demand is high due to electric heating (World Bank, 2017*a*). Between 2009 and 2012, the utility serving the study region reported 20 outages per day on average during winter (World Bank, 2017*b*).[11] But frequent outages are politically and economically risky for the government and utility. No strategic outages or planned rolling blackouts (e.g. from overall electricity supply shortages), occurred during the intervention period (per communication with the electric utility, 2013).

In our study setting, a peri-urban district near Bishkek, households are served by formal connections to the electrical grid. Service provision is interconnected within a transformer; when a transformer has an outage, all households connected to the transformer are without electricity.[12] On average, 54 households receive electricity via a single transformer. Households are metered individually (i.e., they do not share meters) and receive a monthly electricity bill based on their meter readings. At baseline, they use an average of 232 kWh per month in the summer (June to September) and 633 kWh per month – more than double – in the winter (November to February). Households have an average of 8 electricity-using appliances and many (39 percent) report heating with electricity.[13]

Prior to the intervention, study households indicated that they frequently worried about saving electricity (95 percent) and took measures to do so (86 percent). Nevertheless, very

[11]Such high rates of outages are not specific to only this particular utility. Between 2009 and 2012, the country's distribution companies reported 43 outages on average per day (World Bank, 2017*b*).

[12]Only 1 household reported having an electricity generator for purposes such as lighting.

[13]Almost all homes have a television and refrigerator. Approximately three-quarters have electric stoves, an iron, and a clothes washing machine. Only 2 percent have air conditioners. Households conserve on heating. Most households report heating their houses at least sometimes with coal (80 percent), and on average they heat 3/4 of all their rooms during winter.

few had CFLs and they had them in small numbers (0.17 CFLs per household, on average). CFLs were available for purchase only within Bishkek and sold for prices between 100 and 170 Kyrgyz soms, depending on the quality.[14] In contrast, incandescent lightbulbs were available in both rural and urban markets for approximately 15 to 20 Kyrgyz soms. Based on the lightbulb and electricity prices and typical lightbulb use in our sample, we calculated the payback period for CFLs to be 1 to 2 years. Although more than half the households reported knowing about CFLs (56 percent), the majority did not know or believe that CFLs consume less electricity than incandescent bulbs (70 percent) or that electricity bill savings can result from bulb replacement (72 percent).

3 Randomized experiment with energy efficiency

3.1 Sampling process

For our sampling procedure, we used electricity utility data on households' locations and the transformer through which they were served. Transformers providing at least 5 households with electricity were eligible, as those serving fewer households likely also served industrial consumers. Within the study district, we chose seven villages accessible from Bishkek during the winter months, comprising 248 eligible transformers. We further restricted the sample to the 124 eligible transformers with below median monthly household electricity consumption in the year prior to the study.[15] Then we randomly sampled 20 percent of households in each transformer. The number of households per transformer is heterogeneous, resulting in differences across transformers in the number of households included in the study.

[14]As a reference, at baseline, household monthly income per capita was on average 76 USD (2.45 USD per person per day), and the exchange rate was approximately 1 USD = 46 Kyrgyz soms.

[15]We exclude transformers with above median electricity consumption. In those transformers, households were consuming more electricity due to heating. Based on our calculation, inducing a reliability effect would have required a much higher CFL saturation than what we could afford to implement. CFLs were not the appropriate technology choice to reduce peak load in those transformers.

3.2 Experimental saturation design

Treatment status was randomly assigned in two stages. In the first stage, the 124 sampled transformers were randomized into control, and lower and higher treatment saturations. Due to funding constraints, households in 14 control transformers were not surveyed, resulting in 25, 42, and 43 eligible transformers in control, lower and higher saturation groups, respectively. In lower (higher) saturation transformers 60 (80) percent of study households were assigned to treatment, which is approximately 10 to 14 (15 to 18) percent of all households within lower (higher) treatment saturation transformers. In the second stage, households were randomized into either control or treatment status – 460 and 540 respectively – according to the previously-assigned transformer saturations.

Figure 1 shows the experimental design. Treated households are only in treated transformers; however, control households are in both control and treated transformers. Figure 2 depicts how the two-stage randomization induced spatial heterogeneity in treated households' locations and variation in the proximity to and number of nearby treated neighbors.

3.3 Intervention

In the spring of 2013, households were visited and invited to participate in a baseline survey. During the informed consent process, all households were informed that the research addressed CFLs and electricity consumption. Additionally, treated households were told that they would have the opportunity to purchase CFLs at a subsidized price after the survey. None of the participants, neither treatment nor control, were told about the variations in transformer saturations nor did they have reason to know. Moreover, the control households were not told that other households received subsidized CFLs. Upon completion of the baseline survey, all households were given 150 Kyrgyz soms (about 3.26 USD) as compensation.[16] Baseline interaction with control households ended at that time.

Households randomly assigned to treatment were offered the opportunity to purchase up to four 21 W CFLs (rated equivalent to 100 W incandescent bulbs) at a subsidized, randomly-drawn price, via a willingness to pay experiment.[17] The experiment uses the Becker-de Groot-Marschak (BDM) methodology to elicit demand, following Berry, Fischer and Guiteras (2020). The set of possible prices, in Kyrgyz soms, was $\{0, 5, 10, 15, 20\}$. At the time, the lowest market price for CFLs was 100 KGS. The number of CFLs distributed to each treatment household was recorded. On average, treated households received 3.2 CFLs via the intervention, paying an average price of 13 KGS per CFL. Of the 540 households assigned to treatment, 70 chose not to participate in the WTP game and therefore received zero CFLs. These households are non-compliers. For intent-to-treat estimates, they are considered treated.

Households were visited one year later, in the spring of 2014, for a follow-up survey. Survey enumerators made at least four attempts to survey the address. Of the 1,000 original households, 749 were found at the address visited at baseline. When original households were no longer living at the address, the new residents were surveyed instead. In total, 838 households (original and new residents) were interviewed for the follow-up survey, and 101 original households were identified as having moved in the year since the intervention. Either a new resident responded or neighbors informed enumerators that the prior resident had moved. After the survey, respondents were compensated 150 KGS for their time.

[16] As of 2011, the average monthly nominal employee wage was 9,352 KGS per month–an estimated 467 KGS per day of work (National Statistical Committee of the Kyrgyz Republic, 2012).

[17] From the survey piloting exercises in Fall 2012, we knew that 100 W incandescent bulbs were most common and that households had five to six lightbulbs, almost all of which were incandescent.

Potential concerns regarding compliance and attrition might include: (i) whether treated households participated in the CFL treatment, and (ii) whether study households moved prior to the follow-up survey. We address these issues as follows. First, in our intent-to-treat estimates, treated households that did not comply with the treatment are considered treated. Second, we obtain estimates two ways: including all households (movers and non-movers) and excluding houses with new tenants (just non-movers).[18] We also check for differential attrition by transformer treatment saturation and find no significant difference in attrition across groups (Appendix Table A1).

4 Data

Baseline and follow-up survey data include information on various household demographics, lightbulb ownership (type, wattage, etc), lightbulb use (room of use, hours used in a typical day, etc.), times of peak electricity consumption, perceptions and understanding of the CFL technology, and GPS location of each residence. Furthermore, households report the number of days in the prior month during which they did not have electricity due to outages. This is a proxy for electricity reliability.[19]

The utility does not collect transformer-specific outage data. With limited funding and capacity, electric utilities in developing countries often do not systematically document electricity reliability and outages (Klytchnikova and Lokshin, 2009). Researchers use proxies in the absence of such data. For example, Fisher-Vanden, Mansur and Wang (2015) and Allcott, Collard-Wexler and O'Connell (2016)'s research on reliability and firm-level outcomes

[18] Results are consistent across these analyses.

[19] According to the utility, transformer outages last between a few hours and a few days. The transformer repair required and availability of replacement parts determines the outage length.

use "shortages" or "scarcity." To corroborate our results based on household's self-reported outages, we also use the utility's data on household electricity consumption.

The electric utility provided data on households' service transformer and monthly electricity consumption for the period between October 2010 and September 2014, comprising 30 months prior to and 18 months following the intervention. Our analysis ends in September 2014 to avoid conflating the CFL intervention with a tariff reform introduced later in 2014. In the period examined, electricity prices were constant at 0.02 USD per kWh.

4.1 Randomization balance

Given the two-stage randomization, we perform balance tests at multiple levels. First, balance tests at the transformer level highlight the lack of systematic differences by treatment saturation in the baseline demand for CFLs. Table 1 shows balance in the number of CFLs provided by the intervention, the price households bid, and the price paid for the intervention CFLs. Appendix Table A2 provides additional transformer balance tests and indicates that transformers are similar along many other dimensions of demographics. There are three exceptions. Lower saturation transformers have marginally significantly lower household income and higher pre-intervention winter electricity consumption than control transformers, as well as significantly more households than higher saturation transformers.[20] In transformer-level regressions, we control for these covariates and use transformer fixed effects.

Household-level balance tests further show that treatment and control households are similar along most characteristics at baseline (Appendix Table A3). Control households are marginally more likely to have a household head that has completed secondary school, and

[20]Since a greater number of households is typically associated with higher electricity consumption, the direction of this difference should bias our results towards not finding a differential impact on outages.

significantly more likely to live in single family dwellings. These two differences are jointly about what could be expected by chance. If anything, these differences would downward bias our results. Appendix Figure A1 provides an additional balance check, revealing similar time trends and seasonal heterogeneity in pre-intervention electricity consumption by treatment status. Noteworthy, the peaks recorded in both pre-intervention winters (in 2011 and 2012) are not statistically significantly greater among treated than control households. Our estimations nevertheless will account for seasonal variation in electricity consumption by including either household-by-season or transformer-by-season fixed effects.

5 Impacts of energy efficiency on electricity reliability

To affect electricity reliability, energy efficiency must do more than reduce average monthly electricity consumption. Overloads and the resulting outages occur at times of peak electricity consumption, when distribution transformers are most strained. Thus, the services associated with the energy efficiency improvement must be consumed at peak times, when they can help reduce overloads. In our study setting, the electric utility reports times of daily peak demand to be 6 to 9 am and 6 to 10 pm, which overlaps with times typical for lighting service consumption and when CFLs could make a difference. Times of peak demand are corroborated by the study households' self-reported peak consumption times (Appendix Figure A2). The months of peak demand are October through April, due to electric heating and longer hours of lighting.

5.1 Benchmarking impacts on transformer outages

We start by illustrating the potential for energy efficient lightbulbs to lower peak electricity consumption and reduce transformer outages. We perform benchmarking calculations by season, informed by household baseline survey and electricity consumption data (Appendix

A1). Our calculations indicate that replacing 3.2 incandescent lightbulbs (100 W each) with equivalent CFLs (21 W each) could substantially reduce average household monthly electricity consumption, saving between 42 kWh per month during the winter and 34 kWh per month in the spring/fall. This represents a non-trivial percent reduction in household average monthly electricity bills, of about 7 percent of the 566 kWh winter average and 10 percent of the 340 kWh spring/fall average. Considering peak-to-average load ratios by season, we calculate household peak load could be reduced by 23 percent in the winter and 25 percent in the spring/fall.[21] For a distribution transformer with 20 percent of its households treated, this represents a 4 to 4.5 percent reduction in peak load. If adoption spillovers occur, additional reductions in peak load are expected.[22]

Consulted about the above peak load reductions, the electric utility's engineers sustained they would be sufficient to reduce transformer outages. Figure 3 shows that households' self-reported outage counts at follow-up, differentiated by transformer-level CFL saturation, supports their assessment.[23] The distribution of reported outages among households in treated transformers is shifted leftward (towards zero outages) in comparison to the graphed responses of households in the control transformers. This evidence suggests a relationship between transformer-level CFL saturation and outages, motivating the analysis that follows.

[21]The peak-to-average load ratios are informed by hourly residential electricity consumption smart meter data from a nearby but different district (see Appendix A1).

[22]Section 7 explores adoption spillovers. Benchmarking calculations are redone to account for those.

[23]Data on reported outages are collected in both the baseline and follow-up surveys in response to the question: "In the past month, how many days has your household been without electricity, due to problems with the electrical system in the village?" The question was asked this way to avoid households conflating distribution system outages with other reasons for which household electricity service might cease (e.g. bill non-payment). The follow-up survey occurred in March and April 2014, so the months in which we are measuring days without electricity due to outage include February and March.

5.2 Estimating the impacts of CFLs on outages

To examine the impact of this CFL intervention on electricity outages, we draw on the transformer-level randomization. We begin by estimating the following basic specification:

$$O_{ig} = \beta_1 High_{ig} + \beta_2 Low_{ig} + \beta_3 X_g + \epsilon_{ig} \tag{1}$$

where O_{ig} is the number of days without electricity due to unplanned outages in the month prior to the follow-up survey, as reported by household i in transformer g; $High_{ig}$ and Low_{ig} indicate if the household is in a higher- or lower-saturation transformer; and X_g is the number of households within a transformer. In alternative specifications, we further include the household treatment status, T_{ig}; interactions between the household and transformer treatment status, $T_i * High_{ig}$ and $T_i * Low_{ig}$; and the latter plus a control for the number of outages reported at baseline. Standard errors are clustered at the transformer level. We correct standard errors for multiple hypothesis testing, per List, Shaikh and Xu (2016).

In Table 2, across all specifications, households in both higher and lower saturation transformers report fewer days without electricity, relative to households in control transformers. The negative number of reported outages is statistically significant only for households in higher saturation transformers. Higher saturation transformers have more treated households (by definition). To address concerns that treated households may have an incentive to report fewer outages, Column 2 controls for household treatment status. Columns 3 and 4 interact household and transformer treatment status, to allow treated households differential impacts depending on the transformer saturation. Results after allowing for such a differential response indicate that, if anything, estimates in Columns 1 and 2 may be downward biased. In Columns 3 and 4, the coefficients on high saturation transformers are more negative (i.e. there are fewer outage days) than those on low saturation transformers and the difference between coefficients is statistically significant in these specifications.

Our preferred specification is Column 4 of Table 2, as it both allows for differential impacts by transformer treatment status and controls for baseline reported number of days without electricity. These results indicate that households in higher (lower) saturation transformers report 2.1 (1.1) fewer outage-days in the month prior, relative to the 3.24 days without electricity reported by households in control transformers. The significant and larger reduction in outage-days among the higher saturation transformers reflects that the gradient of treatment saturation, in moving from lower to higher treatment transformers, is sufficient to improve reliability in our setting, where transformers operate close to capacity.

5.3 Additional evidence on outages

Supporting evidence that the CFLs reduced distribution outages comes from an intra-cluster correlation analysis of the number of outages reported at follow-up. If saturation within a transformer reduces outages at the transformer-level, then household reported outages should be correlated within a transformer. Given different survey dates, responses are not expected to be perfectly correlated. Our calculation results in an intra-class correlation of 0.56, indicating that responses within transformers are indeed highly correlated.

Providing further support, we check that the estimated reduction in outages is not due to strategic or planned outages implemented purposefully by the utility. Strategic or planned outages occur at the level of the electricity feeder line – one level higher than the transformer in the electricity distribution system – so we would be concerned if control and treated transformers were differently distributed across feeder lines. The 110 treated and control transformers in our study are equally spread across 20 different feeder lines. We check utility maps and find no clustering of transformer treatment type by feeder line.

Finally, impacts on transformer-level electricity consumption corroborate the outage impacts presented earlier (Appendix Table A4). We use a monthly panel of electricity consumption data for all residential consumers within a transformer, including those not sampled or surveyed (as sampled households are only 20 percent of households within each transformer).[24] We collapse these data at the transformer-level. Controlling for transformer fixed effects, we estimate a substantial and significant reduction in electricity consumption for low saturation transformers, but no reduction in electricity consumption for high saturation transformers.

6 How does energy efficiency affect reliability?

If differential impacts on outages by transformer treatment saturation occur, monthly household electricity consumption should be consistent with those differences. To better understand how CFLs' reliability impacts interact with their impacts on household electricity consumption, we use the electric utility's monthly household billing records and exploit the random variation in treatment at both the transformer and household levels, as induced by the two-stage randomization.

6.1 Event study of household electricity consumption

We illustrate the intuition of our analysis in an event study-style graph. In Figure 4, we plot the estimates and 95 percent confidence intervals for the month-by-month impacts of our CFL intervention on household-level electricity consumption, controlling for baseline monthly electricity consumption, heating degree days, and days within each billing period. Alongside, we plot ex ante predicted month-by-month electricity reductions.

[24]The electricity consumed within the transformer also includes industrial and commercial consumers, for which we do not have data.

A number of points are evident. First, a reduction in electricity consumption is observed for treated households shortly following the intervention. Second, the estimated impacts are quite noisy in winter months, albeit to a lesser extent prior to the intervention than post intervention. Third, the estimated impacts diverge from the predicted impacts during the months of peak electricity demand, and track them closely otherwise.[25] The first point suggests that households installed the CFLs soon upon receiving them in spring 2013. We confirm the timing of CFL installation with follow-up survey data. The latter points underscore the CFLs' reliability effects, which were not accounted for in ex ante predicted impacts.

Basic estimates of CFL impacts in Figure 4 are downward biased (i.e. less negative than they should be). We anticipate heterogeneous household-level treatment effects by transformer treatment saturation, depending on the occurrence of reliability effects at the transformer level. Although treated households with CFLs use fewer kW per hour of lighting services consumed, fewer outages mean they can utilize more hours of electricity services, making additional consumption of electricity services per month possible. Indeed, this additional consumption is similarly possible for control households within transformers where the CFL treatment resulted in fewer outages. Adoption spillovers may also exist, if control households in both high and low saturation transformers adopt CFLs on their own. Thus, differentiating between treated and control households in high versus low saturation transformers is important in understanding CFL's electricity consumption impacts.[26]

[25] The estimates closely follow the predicted impacts for first six months post-intervention (April through September 2013), diverge in the five months following (October 2013 through February 2014) with the estimated impacts near zero, then converge and remain close for the remainder of the study (March through September 2014).

[26] Appendix A2 shows basic regression specifications that do not differentiate households by transformer saturation. The basic regression results are in Appendix Table A5. Estimated impacts are substantially smaller in magnitude than the results presented here.

6.2 Disentangling the impacts of CFLs on electricity consumption

To address the confounding effects of the reliability externality as well as potential within-transformer contamination due to adoption spillovers, we employ a specification similar to that of Gine and Mansuri (2018) and Banerjee et al. (2014) to estimate the impacts of the CFL intervention on household electricity consumption:

$$
\begin{aligned}
q_{igt} = {} & \beta_1 THigh_{ig} * Post_t + \beta_2 TLow_{ig} * Post_t + \beta_3 CHigh_{ig} * Post_t + \beta_4 CLow_{ig} * Post_t + \\
& \beta_5 THigh_{ig} + \beta_6 TLow_{ig} + \beta_7 CHigh_{ig} + \beta_8 CLow_{ig} + \beta_{10} Post_t + \alpha X_{ig} + \gamma_t + \lambda_{ig} + \epsilon_{igt}
\end{aligned}
\tag{2}
$$

where q_{igt} is electricity consumption (kWh) in month t, for household i in transformer g; $THigh_{ig}$ and $TLow_{ig}$ ($CHigh_{ig}$ and $CLow_{ig}$) indicate whether i is a treated (control) household in a higher- or lower saturation transformer; $Post_t$ indicates whether t is the month of treatment or any of the months that follow; and X_{igt} are household-level control variables.[27] Month-by-year and household fixed effects, γ_t and λ_i, control for fixed seasonal and household patterns of electricity consumption. In alternative specifications, we replace the household fixed effects with household-by-season fixed effects to account for possible differential seasonal consumption patterns across households; or we add transformer-by-season fixed effects to address concerns of differential transformer performance across seasons. Standard errors are clustered at the household level.

Table 3 reports intent-to-treat estimates. The coefficients of interest are those on the interactions between the indicators of household treatment by transformer saturation, $THigh_{ig}$,

[27]Controls include the number of days in the monthly billing period, whether the household uses electricity for heating, and heating degree days. The latter only entails variation in temperature over time, as all study villages are covered by a single weather station and data are reported at that level. However, we do not expect much spatial variation in temperatures across villages in the study, given their size and proximity.

$TLow_{ig}$, $CHigh_{ig}$ and $CLow_{ig}$, and the $Post_t$ variable. Importantly, the omitted group is comprised of only control households in control transformers, which we consider a "pure control" group. Column 3 is our preferred specification. It not only controls for fixed household characteristics and month-by-year fixed effects, but also accounts for any fixed transformer characteristics that result in differential performance across seasons. In addition to balance tables presented in Section 4, Appendix Table A6 provides support that these groups are balanced in the pre-intervention period for this particular specification.

The results in Column 3 indicate that the CFL treatment reduced household electricity consumption by -37 kWh per month amongst treated households in low saturation transformers. In high saturation transformers, the reduction amongst treated households is statistically insignificant and of a smaller magnitude at -14 kWh. The difference between the impacts on treated households in higher and lower saturation transformers is marginally statistically insignificant; however it is meaningful in magnitude. Given that treated households in higher and lower saturation transformers received a similar number of CFLs via treatment (Table 1), we argue that the heterogeneous impacts on treated households reflect differences in electricity service reliability by transformer saturation.[28] Impacts among control households are similarly consistent with reliability improvements in higher but not lower saturation transformers. In higher saturation transformers, control households show a statistically insignificant increase of 18 kWh per month in electricity consumption. In lower saturation transformers, they show a reduction of -37 kWh per month. The difference between the two is statistically significant.

Event study graphs of household monthly electricity consumption by transformer satura-

[28] Appendix Figure A3, a re-creation of the original event study graph, shows only treated households and differentiates between those in high versus low saturation transformers. This illustrates that these differential impacts over time are consistent with outage reductions among the high saturation transformers.

tion offer more nuance and lend support to our interpretation (Appendix Figure A4). In higher saturation transformers both treatment and control groups exhibit an increase in consumption of electricity in the winter, which is consistent with improved electricity reliability. Meanwhile in transformers with lower treatment saturation, both treatment and control exhibit similar reductions in electricity consumption.

That control households in lower saturation transformers reduce electricity consumption, and that they reduce it by the same amount as treated households (-37kWh), suggests that control households are either adopting CFLs or taking additional actions to generate savings, or both. When we examine CFL adoption, we observe control households are indeed taking up CFLs but not at the same rate as treated households. Consistent with this, spring/fall reductions in electricity consumption are larger – albeit insignificantly – among treated than control households (-40 vs. -27 kWh) (Appendix Table A8). We do not find evidence of other behavior changes such as a consumption rebound and changes in heating practices, but we cannot disprove that households undertake additional energy saving actions. We discuss these findings further in the next sections.

6.3 Other possible behaviors changes

Other potential byproducts of energy efficiency have been highlighted in the literature, such as a rebound effect (Davis, Fuchs and Gertler, 2014) or less heat given off from lightbulbs, thereby reducing temperatures (Adhvaryu, Kala and Nyshadham, 2018). We consider the role these might play and assess their plausibility in the context of our intervention.

6.3.1 Rebound effects

Increased consumption of lighting services (a direct rebound) or increased use of other appliances (an indirect rebound) may be a response to CFLs' greater energy efficiency. This impact would vary with transformer saturation. While we cannot rule out the possibility of a rebound, our analysis shows no clear evidence of a rebound. In the absence of metering data for individual appliances, we employ panel survey data on the household ownership and usage of 3 types of lightbulbs and 24 different appliances. We estimate treatment impacts on the hours *per day* the household uses each lightbulb or appliance, and assess whether they are consistent with a rebound. Results indicate no significant effects of treatment on lightbulb use nor on the use of household appliances (Appendix Table A9).

Moreover, the event study of electricity consumption presented earlier does not provide evidence of a rebound (Figure 4). Following a winter spike in electricity consumption, it returns to the predicted amount in the spring. In contrast, a rebound would have implied a persistent change in behavior. Taken together, we found no evidence that a direct or indirect rebound is driving the differences across transformers.

6.3.2 Temperature, waste heat, and electric heating

All estimates of the CFL intervention's impacts on monthly electricity consumption (at the household-level and collapsed at the transformer-level) control for the number of heating degree days within each month to account for seasonal heterogeneity and the use of heating during the winter.

Still, one possibility is that because CFLs produce less heat waste (i.e. they emit less heat) than incandescent lightbulbs, switching to CFLs made it necessary for households to consume more electric heating to maintain a given comfort level. In particular, our CFL intervention could have induced adoption of electric heating on the extensive margin or greater use on the intensive margin (e.g. heating more of rooms or heating to a warmer temperature). We test for both using our panel survey data and find no evidence of differential changes in heating practices by treatment group and transformer saturation (Table 4).

It is also possible that households may respond differently to the CFL intervention depending on whether they use electric heating or not. We re-estimate impacts on household electricity consumption by transformer saturation, additionally differentiating by their self-reported use of electric heating at baseline. Overall, our estimates are consistent with reliability impacts and greater opportunities for consumption of electricity services in high saturation transformers (Appendix Table A10).[29] Taken together, the results indicate that electric heating plays a role, but it is not driving the impacts on household electricity consumption across transformer saturations.

7 Understanding CFL adoption

7.1 Spillovers in adoption

If reductions in electricity consumption among control households in treated transformers are indicative of adoption spillovers, this should bear out in the number of CFLs they have at follow-up. Moreover, having close neighbors who received CFLs should matter for adoption by control households. As a check, we first estimate a panel regression with household fixed effects similar to Equation 2, but with the number of CFLs as the outcome variable, and controlling for the number of CFLs distributed through the intervention. Then, we

[29]In the specification with household fixed effects only (column 1), the coefficient on treated households in high saturation transformers that heat with electricity does not seem to conform to the expected effects. However, once we account for household-specific seasonal patterns of consumption (column 2), the results are consistent with differences in reliability effects across transformers. The latter specification is also preferred in our main analysis of household electricity consumption (Table 3).

re-estimate the regression differentiating control households in treated transformers by their proximity to a treated household.[30]

Results in Table 5 provide positive evidence of adoption spillovers (Column 1). Control households in treated transformers–regardless of treatment saturation–have significantly more CFLs than "pure" control households in control transformers at follow-up. Moreover, control households have more CFLs in higher than lower saturation transformers, although the difference is not statistically significant. In contrast, treated households have not acquired additional CFLs between the intervention and follow-up survey. This is not surprising, given our experiment provided sufficient CFLs for the average household to replace more than half of its lightbulb stock. The CFL is a durable good with a multi-year expected lifespan. Therefore, treated households would not require replacement CFLs after just one year.

These findings are noteworthy for multiple reasons. First, the estimated adoption spillovers are additional to the overall increase in CFL ownership between baseline and follow-up (the coefficient on $Post_t$). Second, adoption spillovers contribute toward the electricity load reduction and thus to the reduction in outages within treated transformers (as shown in Table 2). Third, the spillover estimates support our argument that differences in electricity reliability, not in adoption of CFLs, explain the heterogeneous impacts on household electricity consumption by transformer saturation. The control households in higher saturation transformers have no reduction in monthly electricity consumption despite having (insignificantly) more CFLs than those in lower saturation transformers.

[30] As discussed in Breza (2016), a number of studies have used geographical proximity to measure spillovers, including Dupas (2014), Godlonton and Thornton (2012), and Cohen, Dupas and Schaner (2015). We define a household as being "close" to a treated one if it is within 100 meters from any treated household. Baseline GPS location data are used to perform distance calculations in ArcGIS.

The results in Table 5 also suggest that proximity does matter for adoption spillovers (Column 2). Control households that are in treated transformers but far from a treated household do not have significantly more CFLs than the pure controls at follow-up. In contrast, the number of CFLs found in control households that are both in treated transformers and close to treated households is significantly larger than among pure controls. The adoption estimates for control households in treated transformers increase once we account for close proximity to a treated household. No statistically significant difference by transformer saturation level is found among control households who have close-by treated neighbors. Nevertheless, the adoption estimates are larger in magnitude for control households in high saturation transformers relative to those in low saturation transformers.

Proximity matters not only in generating adoption spillovers but also in changing beliefs and preferences regarding CFLs, suggesting a path through which adoption spillovers occur (Appendix Table A11). The largest changes in beliefs and preferences occur amongst the treated households relative to the pure controls, indicating learning about the technology over time. We also see some evidence of changes in beliefs and preferences for CFLs amongst the control households that are in treated transformers and close to treated households.

7.2 Adoption spillovers and peak load reduction

High saturation transformers have more treated households from which to generate adoption spillovers and to contribute to peak load reductions. Although only 15 to 18 (10 to 14) percent of all households in high (low) saturation transformers received the CFL treatment through our experiment, higher effective saturation proportions can be reached after accounting for the spillovers attributed to our experimental distribution. Spillovers are thus critical in assessing the extent to which our transformer-level treatments can induce reliability improvements, and to which differences between low and high saturation treatments can result in differential peak load reductions and impacts on outages.

We re-do the calculations for expected peak load reductions, this time differentiating explicitly between the low and high saturation transformers and incorporating the adoption spillovers (Appendix A3). These revisions result in estimated peak load reductions of 6 percent for the low saturation transformers and 8 percent for high saturation transformers, well beyond the 4 to 4.5 percent benchmarking estimates in Appendix A1. Given that the internal heating effects that cause transformers to overload are a square function of current (ANSI/IEEE, 1981), reductions in load below the transformer rated capacity have non-linear impacts on transformer failure. A peak reduction of 8 percent in an overloaded system can yield a significantly larger reduction in outages when compared to a 6 percent reduction in peak and certainly when compared to no reduction at all.

8 External validity

Our study setting is unique in that it allows us to generate technological externalities in the form of improved electricity reliability using energy efficient lightbulbs at relatively low treatment saturations. We do not claim that the same infrastructure constraint, same form of technological externality, same type of technology, and same level of technology saturation would be relevant in a different context. Instead, we argue that the potential for energy efficiency distribution programs to generate technological externalities should not be ignored. We provide evidence that these externalities are possible to generate, and we show they are crucial in understanding the welfare implications of energy efficiency programs. These points remain valid to a large extent in a variety of settings.

Our experiment is generally relevant to developing and developed contexts in which demandside management is a potentially important tool to reduce electricity consumption. These include settings where infrastructure capacity is insufficient for current demand–such as our study setting; where infrastructure will bind in the near future due to a rapidly increasing demand; where demand for electricity is congesting the infrastructure capacity; or where constraints are not related to distribution capacity, but to electricity generation. These constraints may be seasonal. For example, in developed countries failures can occur in heat or cold waves when users run cooling or heating units. In developing countries that rely on hydropower systems, generation capacity may be insufficient during a dry season.

The replication of our experiment would require determining the design that works in a different setting. The right design depends on many factors, including the source of the constraint, the feasible engineering impacts of the technology distributed, the contribution of the technology to on-peak electricity savings, and the number of consumers the infrastructure serves.

In our study setting, where failure in distribution systems leads to unplanned outages, greater technology saturation is associated with improved electricity reliability. However, the type of externality may not be limited to a reduction in outages. Where failure in distribution systems is less common, such as in developed contexts, electricity reliability problems are less likely to occur. However, congestion within the electricity distribution network due to peak loads can impact utility prices, depending on the marginal electricity generation source. In those settings, energy efficiency may induce externalities in the form of lower electricity costs.

Although we study CFLs specifically, our findings are also valid for other energy efficient technologies. Recent programs are deploying light emitting diodes (LEDs), which are even more efficient than CFLs. For developing countries, the use of electricity for lighting can be up to 86 percent (Tanzania), whereas in industrialized countries it ranges from 5 percent

(Belgium, Luxembourg) to 15 percent (Denmark, Japan, and the Netherlands) of total electricity use (Mills, 2002).[31] Therefore, savings generated by efficient lighting are pertinent for reducing peak demand and avoiding overloads. In settings where households own more electricity-using durables, such as the United States and other developed countries, the focus has been primarily on the individual household-level effects of other "high impact" energy efficiency technologies.[32] Programs designed to induce an aggregate savings could expect similar externality effects to the extent that these technologies contribute to a larger proportion of the on-peak electricity consumption.

Finally, the source of the electricity constraint and technology of choice determine the optimal technology saturation. In our study, the local distribution transformer is the constraint within the electricity system that typically causes electricity outages. We calibrated the CFL saturation necessary to bring peak loads below the transformers rated capacity, so as to induce reliability effects. Because the transformers operated close to overload, implementing a sufficient saturation of CFLs was feasible. A lower (greater) technology saturation would be required to induce an externality effect the smaller (larger) the factor by which peak loads exceed distribution capacity, the more (less) efficient is a technology, and the larger (smaller) its contribution to electricity consumption on peak.

9 Conclusions

Electrification can have positive impacts on many indicators of development (Dinkelman, 2011; Rud, 2012; Lipscomb, Mobarak and Barnham, 2013; Van de Walle et al., 2013), yet electricity service reliability is a major concern in achieving them (Pargal and Banerjee,

[31] Lighting is 10 percent of total US electricity consumption (EIA-OEA, 2018).

[32] One quasi-experimental study measured impacts of an appliance replacement program in Mexico (Davis, Fuchs and Gertler, 2014).

2014; World Bank, 2014; Klytchnikova and Lokshin, 2009). Unreliable electricity service is a potential reason for heterogeneities in the impacts of electrification, given frequent electricity outages can impact both households (Chakravorty, Pelli and Marchand, 2014; Samad and Zhang, 2017) and firms (Allcott, Collard-Wexler and O'Connell, 2016; Alam, 2013).

Through a randomized saturation experiment, we increase the energy efficiency of households by implementing a distribution of energy efficient lightbulbs. We show that, in our study context, a high enough CFL saturation leads to improvements in the reliability of electricity services for all consumers within the transformer, regardless of whether they themselves adopt the technology. This improved electricity reliability is a classic example of a technological externality through which the returns to a particular technology are increasing in the number of adopters. More reliable electricity services permit households who own CFLs to consume lighting for more hours per month at a lower cost than traditional light bulbs. Proximity matters in generating adoption spillovers, and adoption spillovers contribute to the electricity reliability impacts. Other technologies inducing positive externalities have been found to reduce the need for private investment in the technology, creating incentives for households to free-ride on the adoption by others (Miguel and Kremer, 2004; Cohen and Dupas, 2010; Dupas, 2014). Instead, the externality effect on reliability increases the returns to the technology, thereby ameliorating (or even offsetting) the incentive to free-ride.

Thinking about interactions between technological externalities, technology impacts and techonolgy adoption is important for program design and the deployment of new technologies. The seasonality pattern in electricity consumption impacts by CFL saturation suggests that if the technology were distributed in peak-demand months and adopters were not aware of reliability improvements, they may dismiss the technology as deficient. Instead, introducing technologies in low-demand months would allow end-users to observe reductions in consumption similar to the technology's feasible engineering impacts, enabling them to understand that the smaller reductions in consumption during peak-demand months are a welfare gain, not a sign of ineffective technology.

Lastly, accounting for the technological externality effects of energy efficient technology distribution is also crucial for program evaluation. Benefit calculations that include reductions in private electricity consumption and increased electricity services are more than double the calculations based on private electricity savings. This is the difference between approximately $14 in benefits instead of $7 in the first year post-adoption (Table 6). When these effects are taken into account, benefits are substantially larger than the upfront cost of purchasing and distributing the CFLs, which was approximately $9 per household (Appendix Table A13) in our experiment. This illustrates the importance of accounting for the positive externality in the economic rationale for mass deployment of energy efficient technologies.

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Figure 1: Randomized saturation process

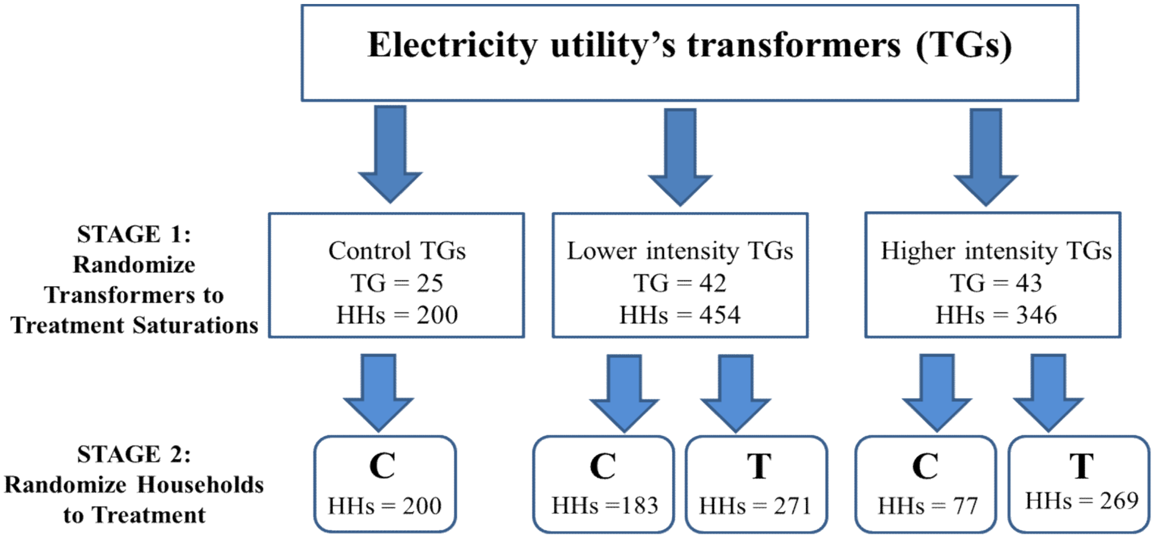


Figure 2: Stylized example of randomized saturation design

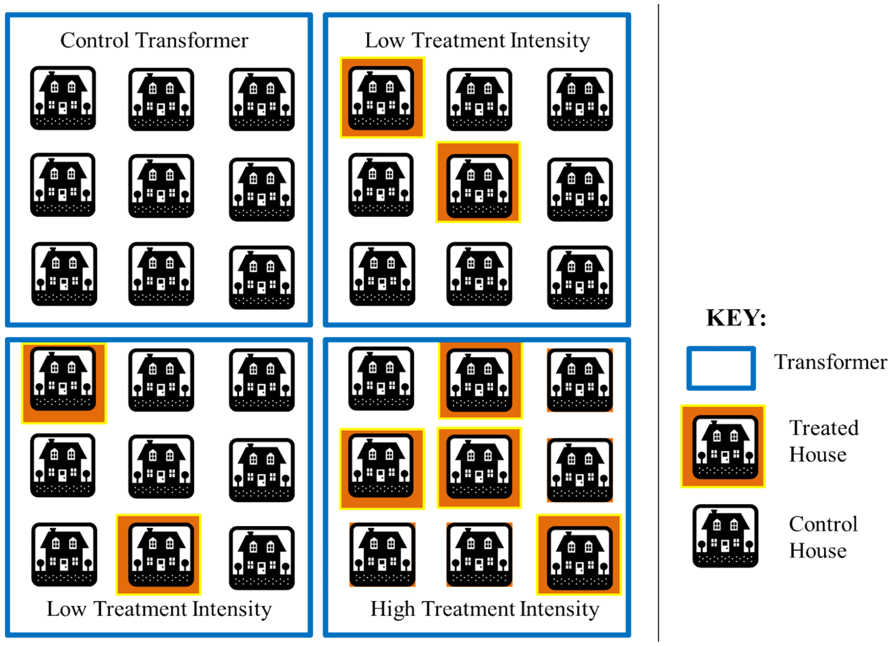
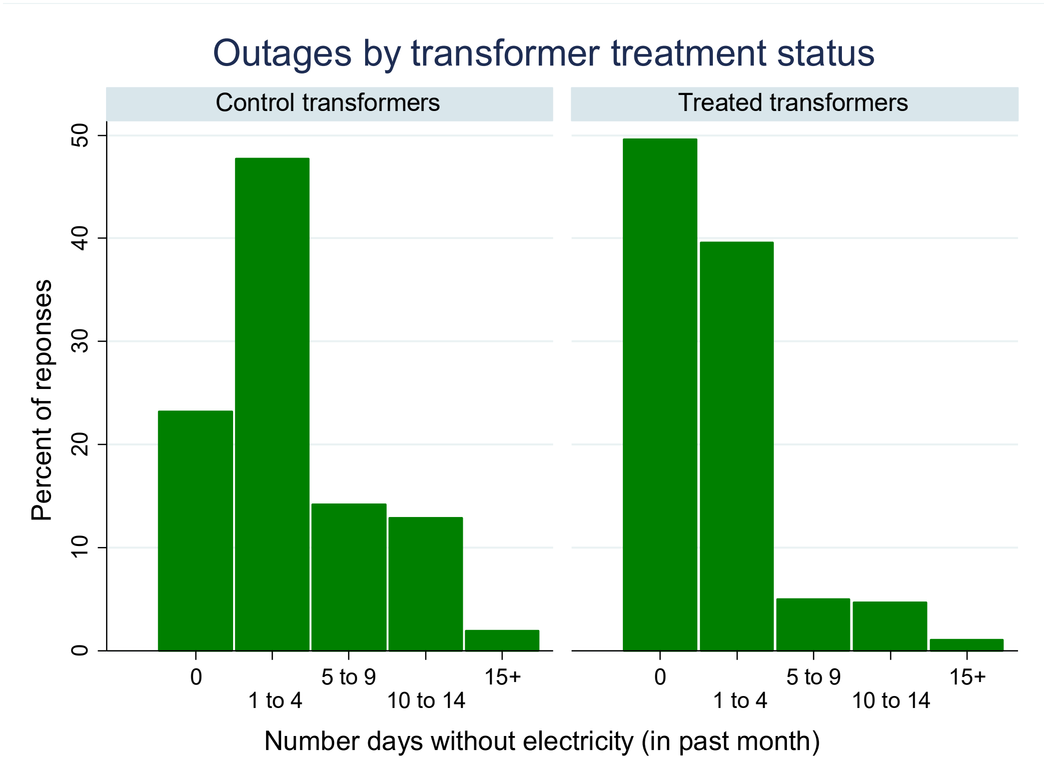


Table 1: Household demand for CFLs by transformer intensity

	All transformers	Low saturation transformers	High saturation transformers	Joint F tests (p-value) Low saturation = High saturation
	(1)	(2)	(3)	(4)
Averages of treated households:				
Number of CFLs received	3.17	3.34	3.00	0.125
Bid made for 1 CFL (KGS/CFL)	51.70	55.22	49.42	0.385
Price paid for 1 CFL (KGS/CFL)	12.56	12.69	12.44	0.747
Households	800	454	346	
Transformers	85	42	43	

Notes: Calculations made based on the experimental measures of demand from March/April 2013. Only treated households participated in the demand intervention, therefore calculations include only data for the treated households, not control households. "Treated households" is an intent to treat and includes all households assigned to the treatment, regardless of whether they actually received CFLs. "Low saturation transformers" are those in which between 10 and 14 percent of households in the transformer were assigned to treatment. "High saturation transformers" are those in which 15 to 18 percent of households in the transformer were assigned to treatment. The exchange rate in March 2013 was 1 USD = 48 KGS.

Figure 3: Number of days without electricity, by transformer-level treatment status



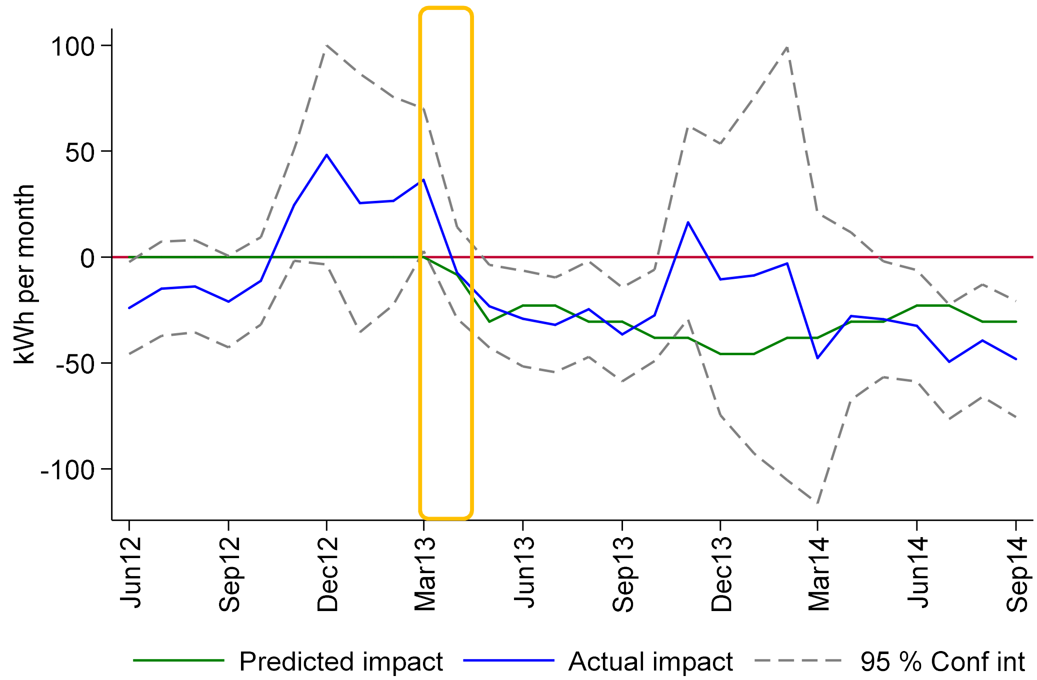
Notes: Analysis performed using data from household follow-up survey, collected in response to the survey question, "In the past month, how many days had your household been without electricity, due to problems with the electrical system in the village?" Control transformers are transformers in which no households received the intervention CFLs. Treated transformers are transformers in which some proportion of households received the intervention CFLs.

Table 2: Aggregate effect of CFLs: improved electricity reliability

Dependent Variable: Number of Days Without Electricity (in past month)				
	(1)	(2)	(3)	(4)
TG low saturation	-1.321	-1.302	-1.164	-1.108
	(0.851)	(0.862)	(0.868)	(0.864)
	[0.433]	[0.426]	[0.434]	[0.434]
TG high saturation	-1.866**	-1.841**	-2.162***	-2.111**
	(0.812)	(0.815)	(0.822)	(0.814)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated household		-0.032		
		(0.159)		
Treated household in TG low			-0.262	-0.280
			(0.186)	(0.186)
Treated household in TG high			0.381	0.391
			(0.279)	(0.276)
Constant	3.810***	3.810***	3.811***	3.587***
	(0.836)	(0.837)	(0.838)	(0.814)
Control: baseline days without electricity	No	No	No	Yes
p-value: TG low = TG high	0.228	0.227	0.047	0.047
Omitted group mean	3.24	3.24	3.24	3.24
Observations	838	838	838	836
R-squared	0.051	0.051	0.053	0.057

Notes: Analysis performed using data from both baseline and follow-up household surveys. Outcome variable is created in response to the survey question, "In the past month, how many days had your household been without electricity, due to problems with the electrical system in the village?" All regressions control for the number of households within the transformer. "TG low" is a indicator variable that equals 1 if 10 to 14 percent of households in a transformer were assigned to treatment. "TG high" is a indicator variable that equals 1 if 15 to 18 percent of households in a transformer were assigned to treatment. The omitted group is comprised of households in control TGs. The "Household treatment status controls" are separate binary indicators that equal one for treated households. Standard errors are clustered at the transformer level and shown in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level. P-values accounting for multiple-hypothesis testing, as discussed in List, Shaikh, and Xu (2015), are shown in brackets.

Figure 4: Predicted and actual effects on electricity consumption (kWh per month)



Notes: Orange block demarks time period when CFLs were distributed. Distribution of CFLs began in March 2013, so by design the predicted impacts are zero up until that time. The predicted impact is calculated based on the number of CFLs distributed to the households, the number of hours of lighting reported by households in the baseline survey, as well as the shifting hours of sunlight throughout the calendar year. Analysis of actual impacts performed using household-level panel of monthly electricity consumption data, as provided from the electricity utility's billing records. The graph of the estimated impact was created by plotting the coefficients from regressing household electricity consumption (kWh) on household treatment status on a month-by-month basis. The resulting regressions for each month within the study period mean that we cannot include household fixed effects (as is included through much of the paper's analysis) in creating these graphs. All regressions include controls for (1) the control households in treated transformers, making this estimate a comparison of treated households against pure control households (control households in control transformers), (2) the household's baseline monthly electricity consumption (for the year prior to the intervention), and (3) the number of days within each monthly billing period.

Table 3: Household electricity consumption effects: results consistent with outage reduction and adoption spillovers

	Monthly Household Electricity Consumption (kWh)		
	(1)	(2)	(3)
Treated household in TG low * Post	-44.174***	-36.998**	-36.628**
	(12.701)	(15.693)	(14.984)
Treated household in TG high * Post	-23.604*	-14.997	-14.419
	(13.138)	(16.418)	(15.701)
Control household in TG low * Post	-44.322***	-35.709**	-37.188**
	(13.344)	(16.145)	(15.270)
Control household in TG high * Post	8.050	21.079	18.116
	(17.908)	(23.040)	(20.193)
Post	45.006***	42.590**	40.684**
	(16.271)	(17.634)	(17.198)
Omitted group baseline mean	328.10	328.10	328.10
Month-by-year FEs	Yes	Yes	Yes
Household FEs	Yes	No	Yes
Household-by-season FEs	No	Yes	No
Transformer-by-season FEs	No	No	Yes
Wald p-value: T in TG high = T in TG low	0.097	0.138	0.110
Wald p-value: C in TG high = C in TG low	0.003	0.011	0.004
Households	899	899	899
Observations	31,143	31,143	31,143

Notes: Analysis performed using household-level panel of monthly electricity consumption data for the period between April 2011 to September 2014, as provided from the electricity utility's billing records. The omitted group is comprised of households in control tranformers. The "post" period are the months after the intervention implementation (from April 2013 onwards). "Treated" households were offered to receive up to 4 CFLs through the intervention. "Control" households were not offered CFLs through the intervention. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control transformers" only contain control households. All regressions include controls for monthly heating degree days, number of days in each monthly billing period, and the use of an electric heater. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Standard errors are clustered at the household level and resported in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table 4: Effects on heating practices

	Dependent Variables: Heating-related practices		
	(1)	(2)	(3)
	Use electricity to heat	Proportion rooms heated	Number of rooms heated
T household in TG low * Post	-0.026	-0.038	-0.056
	(0.055)	(0.069)	(0.337)
T household in TG high * Post	0.052	-0.010	0.057
	(0.057)	(0.064)	(0.293)
C household in TG low * Post	-0.017	-0.044	-0.198
	(0.044)	(0.064)	(0.314)
C household in TG high * Post	0.026	-0.003	-0.019
	(0.085)	(0.081)	(0.374)
Post	0.089***	0.079	0.610**
	(0.031)	(0.050)	(0.236)
Omitted group baseline mean	0.247	0.729	2.890
Observations	1498	1426	1426
R-squared	0.87	0.72	0.81

Notes: Data were collected via the baseline (March 2013) and follow-up (March 2014) surveys, forming a panel dataset. The omitted group is comprised of households in control transformers. All specifications include household fixed effects. Column 3 includes controls for the total number of rooms in the house. Regressions include only households for which there are both baseline and follow-up data; households that moved during the period between the intervention and the follow-up survey are dropped. The "post" period data were collected via the follow-up survey in March 2014. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control TGs" only contain control households. Standard errors are clustered at the transformer level and in parentheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table 5: Spillovers: CFL stock at follow-up

Dependent Variable: Total number of CFL bulbs in home	(1)	(2)
T household in TG low * Post	0.319	0.319
	(0.260)	(0.260)
T household in TG high * Post	0.139	0.139
	(0.299)	(0.299)
C household in TG low * Post	0.689***	
	(0.257)	
C household in TG high * Post	0.843***	
	(0.303)	
C household in TG low and close to T * Post		0.706**
		(0.288)
C household in TG high and close to T * Post		0.910***
		(0.308)
C household in treated TG and far from T * Post		0.447
		(0.392)
Post	0.253**	0.253**
	(0.108)	(0.108)
Omitted group baseline mean	0.224	0.224
Wald p-value: T in TG high = T in TG low	0.618	0.618
Wald p-value: C in TG high = C in TG low	0.675	0.603
Households	749	749
Observations	1498	1498

Notes: Data on the total number of CFLs in homes were collected via the baseline (March 2013) and follow-up (March 2014) surveys, forming a panel dataset. The omitted group is comprised of households in control transformers. All specifications include household fixed effects and control for the number of CFLs given to the treated households through the intervention. Regressions include only households for which there are both baseline and follow-up data; households that moved during the period between the intervention and the follow-up survey are dropped. The "post" period data were collected via the follow-up survey in March 2014. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control TGs" only contain control households. Being "close to T" is an indicator that equals 1 when a control household is located < 100 meters from a treated household. Control households that are "far from T" are located > 100 meters from a treated household. Standard errors are clustered at the transformer level and in parentheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table 6: Benefits of CFL distribution program

BENEFITS OF CFL DISTRIBUTION PROGRAM IN YEAR 1								
VERSION A: Accounting for heterogeneous impacts			**VERSION B: Accounting for heterogeneous impacts and adoption spillovers**			**VERSION C: Accounting for technological externalities, adoption spillovers, and additional electricity services**		
Uses estimate of kWh reduction from Table 3, Col 2.			Uses estimates for Treated households in low saturation transformers from Table 3, Col 4.			Uses estimates for Treated households in both high and low saturation transformers from Table 3, Col 4.		
Part 1: electricity savings due to CFLs			**Part 1: electricity savings due to CFLs**			**Part 1: electricity savings due to CFLs**		
Average monthly savings	-27.7	kWh/month	Average monthly savings	-37	kWh/month	Average monthly savings	-37	kWh/month
Savings in a year	-332.4	kWh/year	Savings in a year	-444	kWh/year	Savings in a year	-444	kWh/year
Price per kWh	0.02	USD	Price per kWh	0.02	USD	Price per kWh	0.02	USD
Value of savings	-6.648	USD	Value of savings	-8.88	USD	Value of savings	-8.88	USD
Absolute value of benefits	**6.65**	**USD**	**Absolute value of benefits**	**8.88**	**USD**	**Absolute value of benefits**	**8.88**	**USD**
						Part 2: additional electricity consumed		
						Additional electricity consumption per month	21	kWh/month
						Additional electricity consumption per year	252	kWh/year
						Price per kWh	0.02	USD
						Value of additional consumption	**5.04**	**USD**
TOTAL BENEFITS PER HOUSEHOLD	**$ 6.65**		**TOTAL BENEFITS PER HOUSEHOLD**	**$ 8.88**		**TOTAL BENEFITS PER HOUSEHOLD**	**$ 13.92**	

Notes: Calculations of benefits are just for the first year after installation. We value the additional electricity consumed at the price per kWh in the Kyrgyz Republic during the study period. The exchange rate in March 2013 was 1 USD = 48 KGS.

APPENDIX: FOR ON-LINE PUBLICATION

Table A1: Check for differential attrition, by treatment status

	No follow-up survey from household originally surveyed at baseline
Treated household in TG low	-0.035
	(0.041)
Treated household in TG high	-0.037
	(0.041)
Control household in TG low	-0.030
	(0.045)
Control household in TG high	0.026
	(0.062)
Constant	0.271***
	(0.031)
Wald p-value: T in TG high = T in TG low	0.9573
Wald p-value: C in TG high = C in TG low	0.3591
Observations: Households	1000

Notes: Data include all 1,000 households surveyed at baseline. Households for which we have no follow-up survey data are those that (1) did not respond to the follow-up survey when approached, and (2) those households that had moved from the address between the baseline and follow-up surveys. Standard errors are resported in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table A2: Transformer-level randomization check

	Number of Obs.	Control Transformer	Low saturation transformers	High saturation transformers	Joint F tests (p-value) Control = Low	Control = High	Low = High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Household-level data							
HH head completed seconday school	1000	0.865	0.83	0.84	0.41	0.49	0.94
Household income (KGS)	1000	12251.7	10396.6	10780.4	0.07	0.18	0.66
Own house	1000	.925	0.91	0.90	0.68	0.54	0.74
Number of rooms	1000	4.255	4.22	4.44	0.85	0.45	0.21
Lightbulbs: incandescents in house	1000	6.90	5.78	5.95	0.130	0.221	0.647
Lightbulbs: CFls in house	1000	0.34	0.09	0.17	0.185	0.382	0.176
Outages in the past month	997	2.45	1.90	1.91	0.346	0.326	0.961
Panel B: Household electricity consumption (kWh/month)							
Winter [Nov 2012-Feb 2013]	1000	493.81	571.13	568.64	0.075	0.114	0.948
Fall [Sept 2012 - Oct 2012]	1000	284.49	291.15	302.86	0.669	0.234	0.390
Summer [May 2012 - Aug 2012]	1000	234.97	239.96	253.83	0.723	0.184	0.244
Spring [March 2012 - April 2012]	1000	376.25	417.54	415.91	0.129	0.151	0.947
Panel C: Transformer-level data							
Years since last maintenance	102	3.38	3.03	3.90	0.568	0.385	0.101
Total # of households	110	51.80	63.12	47.58	0.126	0.565	0.015
Total # of households with 3 phase meter	110	12.92	15.36	15.81	0.324	0.240	0.829
Households		200	454	346			
Transformers		25	42	43			

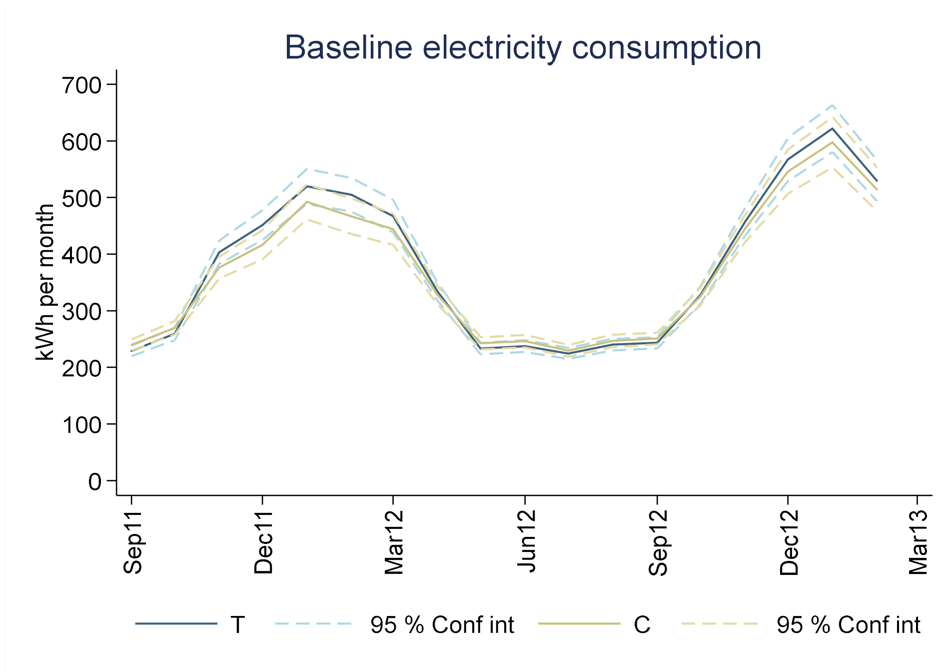
Notes: "Low saturation transformers" are those in which between 10 and 14 percent of households in the transformer were assigned to treatment. "High saturation transformers" are those in which 15 to 18 percent of households in the transformer were assigned to treatment. "Control transformers" only contain control households. Panel A calculated using responses from the baseline household survey. 20% of all households in a transformer were surveyed at baseline. To estimate differences in outages during the past month, we control for the month in which the survey data were collected. Panel B is calculated using the monthly household electricity consumption data from the electricity utility. Panel C is calculated using transformer-specific data provided by the electricity utility. Exchange rate in March 2013 was 1 USD = 48 KGS.

Table A3: Household-level randomization check

	All	Control	Treatment	**Joint F tests (p-value)** Control = Treatment
	(1)	(2)	(3)	(4)
General characteristics				
Household head completed secondary school	0.840	0.867	0.818	0.090
Household income past month (KGS)	10900	11463	10427	0.138
Household income past month per capita (KGS/person)	3668	3740	3608	0.603
Owner-occupied house	0.912	0.919	0.906	0.506
Number of people living in the home	3.6	3.7	3.5	0.218
Time at address (months)	203	201	204.137	0.789
Housing characteristics				
Single-family dwelling	0.793	0.829	0.762	0.053
Number of rooms	4.302	4.245	4.35	0.409
Home made from brick	0.535	0.569	0.507	0.100
Floors that are wood	0.877	0.864	0.887	0.388
Age of dwelling (years)	41.29	41.27	41.30	0.987
Electricity meter for single house	0.991	0.993	0.989	0.546
Electricity consumption practices				
Outages in the past month	1.66	1.58	1.75	0.338
Winter electricity consumption (kWh/month)	554.80	541.11	566.33	0.379
Total number of appliances	8.4	8.6	8.2	0.210
Lighting hours per day	17.5	17.9	17.2	0.643
Think about saving electricity	0.946	0.934	0.955	0.500
Do something to save electricity	0.86	0.829	0.885	0.185
Rooms heated in winter	3.14	3.12	3.15	0.764
Total light bulbs in house	6.2	6.5	6.0	0.128
Total incandescent bulb in house	6.1	6.3	5.8	0.177
Total CFls bulbs in the house	0.2	0.2	0.1	0.353
Believe CFL use less energy	0.305	0.319	0.292	0.436
Number of households	1000	460	540	

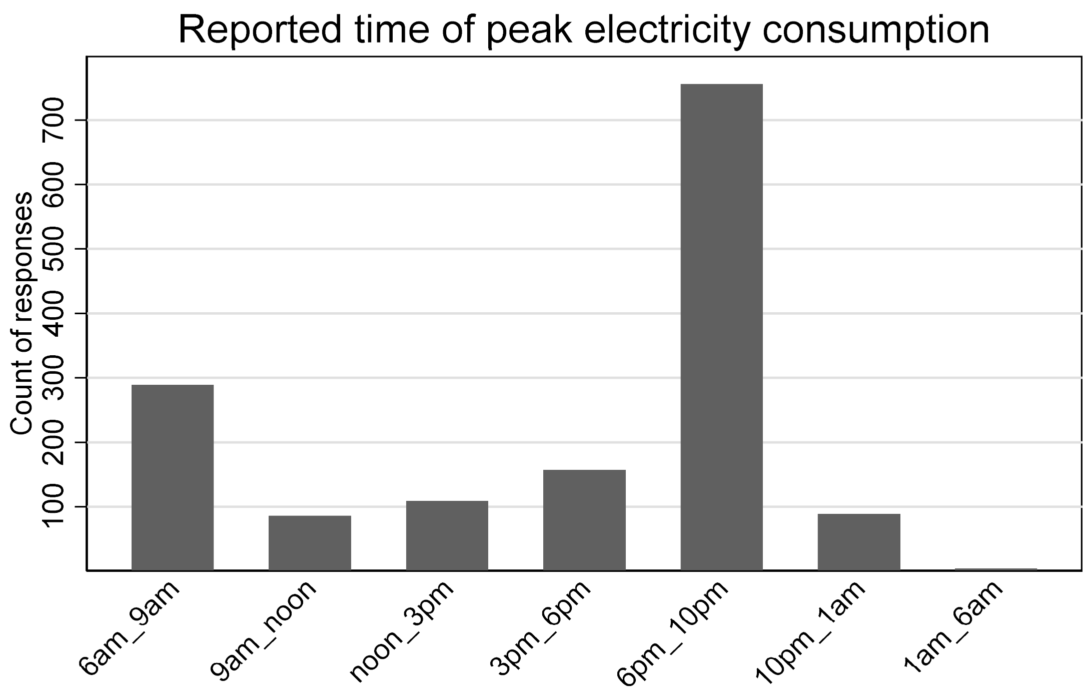
Note: All calculations performed using baseline survey data, except for electricity consumption (kWh), which was calculated using the electricity utility's billing records. Winter baseline electricity consumption is calculated for the months between November 2012 and February 2013. In March 2013, the exchange was 1USD = 48 KGS.

Figure A1: Baseline electricity consumption by household treatment status



Notes: Graph made by plotting average monthly electricity consumption (kWh) and confidence intervals for households assigned to treatment and control groups.

Figure A2: Self-reported household peak electricity consumption



Notes: Graph based on reponse to the question: "During which time frame does peak electricity consumption occur in your home?" Respondents were permitted to inlcude more than one time category in their response. Responses collected via survey during follow-up survey in Spring 2014.

Appendix A1: Bench-marking calculations of the intervention's technologically feasible impacts

Transformers are designed for a rated capacity and experience significant loss of life based on the frequency, duration, and magnitude of overloads. The transformer heating effects that lead to failure are a square function of current. This means that increases in load above the rated capacity of a transformer have a disproportionately large impact on transformer failure. The overload-driven failure modes of distribution transformers are well recognized (see, for example, American National Standards Institute IEEE C57.91). This phenomenon is particularly acute in developing country contexts where distribution transformers are overloaded frequently, for long durations, and to high values relative to their rating capacity. The nonlinear impacts of overloads also mean that peak reductions of overloaded systems can yield disproportionately large reductions in distribution-level outages (ANSI/IEEE, 1981).

We have implemented this two-staged randomized treatment to vary the distribution of the CFLs at the household-level and the intensity of CFL saturation at the transformer-level. To benchmark our findings, we calculate (1) the potential household-level reductions in electricity consumption resulting from replacing incandescent lightbulbs with CFLs, and (2) the expected household-level peak load reduction from implementing this lightbulb replacement en mass within the electricity distribution system. These calculations are shown on the following pages in Steps 1 and 2, respectively. The details of the calculations are shown in the accompanying table.

Step 1: Benchmarking household reductions in electricity consumption

Benchmarking the technologically feasible reduction in electricity consumption at the household-level is undertaken in three sub-steps. First, we calculate the power reduction (kW) that occurs from replacing the original bulbs with more energy efficient ones (found in Step 1A of the following table). This is a mechanical difference and a function of the number of lightbulbs changed, the wattage of the original bulbs that are being replaced, and the wattage of the bulbs to which they are changed. We calculate a potential 0.253 kW reduction per household, as a result of replacing 3.2 incandescent 100 W bulbs with 21 W CFLs.[33]

Second, we calculate the expected energy reduction (kWh) in monthly electricity consumption for three different scenarios (winter, spring/fall, and summer months). Calculations shown below in Step 1B. These different scenarios account for variations in day length (sunlight hours) and heterogeneities in appliance use across seasons.[34] Based on these calculations, we estimated electricity consumption to decrease, as a result of the intervention, by between 22.8 kWh per month in the summer and 41.7 kWh per month in the winter. These estimates provide a sense as to the magnitude by which monthly residential electricity consumption could change via this intervention.

[33]From the survey piloting exercises in Fall 2012 and the baseline survey data collected in Spring 2013, we know that 100 watt incandescent bulbs were most common in households prior to the intervention. We selected 21 watt CFLs as the replacement bulbs, due their rating as 100 watt equivalent bulbs. Therefore, we know that the typical household in our treated group is shifting from 100 watt incandescent to 21 watt CFLs. On average, treated households received 3.2 CFLs through the intervention.

[34]Hours of lighting calculations are performed with data on hours of lightbulb use, as collected via the baseline survey. Estimates of hours of lighting use throughout the year are extrapolated using data on the timing of sunrise and sunset in the region. These predictions assume behavior with respect to lighting and other electricity uses remain constant post-intervention, which is consistent with the evidence on a lack of rebound effect and other related behaviors.

Appendix A1 calculation details: benchmarking household load peak reductions

STEP 1. Benchmarking household-level reductions

1A. Household power reduction from changing bulbs: incandescent to CFLs

(a)	Average number of bulbs replaced per treated household	3.2
(b)	Original bulb: Incandescent bulb wattage (W)	100
(c)	Replacement bulb: CFL bulb wattage (W)	21
(d)	**Watt reduction: [= a*(b - c)]**	**252.8**
(e)	**kW reduction: [= (a*(b - c))/1000]**	**0.2528**

Notes: Average number of light bulbs replaced is based on the actual numbers of CFLs distributed through the intervention. Incandescent wattage is the typical wattage found in households at the time of piloting the project and the baseline survey. CFL wattage is based on the lightbulbs distributed through the intervention.

1B. Scenarios of expected household reductions in monthly electricity bill, by season

		Winter scenario	Spring/Fall	Summer scenario
(p)	kW reduction per household	0.2528	0.2528	0.2528
(q)	Average hours of bulb use per day	5.5	4.5	3
(r)	Days in month	30	30	30
(s)	**Expected CFL savings per month (kWh) [= p*q*r]**	**41.71**	**34.13**	**22.75**
(t)	Average monthly bill (kWh/month)	566.3	340	245
(u)	**Expected reduction in bill (%) [= (s/t)*100]**	**7%**	**10%**	**9%**

Notes: For these calculations, the winter scenario includes November through February; spring/fall scenario includes March, April, September, and October; and summer scenario includes May through August. The average hours of use per day is calculated using the baseline survey data (Spring 2013). Data on sunrise and sunset times are used to extrapolate to the other seasons. Average monthly electricity bill is calculated using baseline electricity consumption data for the treated households in our sample during the year prior to the intervention.

STEP 2. Expected household peak load reductions

		Winter scenario	Spring/Fall	Summer scenario
(t)	Average monthly household bill (kWh/month)	566.3	340	245
(v)	Average hourly demand per household (kW) [= t /30 days/24 hours]	0.787	0.472	0.340
(w)	Ratios of peak-to-average load (see notes below)	1.410	2.150	1.290
(x)	Peak load estimate per household (kW) [= w * v]	1.109	1.015	0.439
(y)	**Reduction in household peak demand (%) [= e/x]**	**23%**	**25%**	**58%**

Notes: These household calculations include only treated households receiving CFLs through the intervention and do not account for any spillovers in adoption by other households (either control households or other households not included in this surveyed sample) within a transformer. To provide estimates for the ratios of peak-to-average load, we use smart meter hourly electricity consumption data from a pilot of 10 transformers that are served by the same electricity utility and located near (but not in) our project sample. Given the proximity to our project sample, these transformers are subject to similar seasonal weather fluctuations and load patterns over the course of a day. Smart meter data availability vary by transformer; approximately half the transforrmers provide data covering March 2015 to April 2016 and the other half cover from October 2015 to April 2016.

Step 2: calculations of peak load reductions

Reducing peak load at the transformer level is key to reducing outages. To better understand the potential aggregate impact that switching from incandescent bulbs to efficient lighting could have on electricity distribution, we calculate the expected impact on peak load. To do so, we perform calculations based on data from our sample and informed assumptions. Overloads occur during times of peak electricity consumption. In a setting in which electricity is used for heating, overloads are most common in the winter, particularly winter evenings, when household energy demand is greatest. Times of peak demand are the early mornings and the evenings, meaning lighting disproportionately "on peak".

An important assumption for these calculations is the peak-to-average load ratio. Using real data from proximate transformers – 10 transformers located near (but not in) our project sample – we calculated the peak-to-average load by season. Given the proximity to our project sample, these transformers are subject to similar weather fluctuations and load patterns. These transformers were also located in the same service area of the electric utility managing the location in this project. These data provide hourly electricity consumption data at the transformer level. For half of the transformers, we have data for the period between March 2015 and April 2016, whereas for the other half of transformers, we have data only from October 2015 to April 2016. This means we have the greatest number of observations for the winter and spring/fall months, the period when peak consumption occurs. We use these transformer-level smart meter data to calculate the peaks and average loads across this time period.

Given seasonal heterogeneities in peak load, we perform these calculations for three scenarios (winter, spring/fall, and summer). Using data from our treated households on monthly electricity consumption, we estimate a 0.252 kW reduction in a peak load of 1.109 kW during the winter (1.015 kW in the spring/fall), which reflects a 23 percent (25 percent) decrease in household peak demand. If 20 percent of the households within a transformer are included in the program and each household sees a 23 to 25 percent reduction in its peak demand during these crucial months, then the peak demand on the transformer is reduced by 4.6 to 5 percent.

These calculations, however, only include the treated households in the calculations of the expected peak load reduction. If spillovers in adoption of the energy efficient technology occur within a transformer, then this 4.6 to 5 percent expected reduction will be an underestimate of the overall peak load reduction within a transformer.

Table A4: Transformer-level monthly electricity consumption effects

	(1)	(2)
	Transformer monthly electricity consumption (kWh)	Transformer monthly electricity consumption (kWh)
TG low*post	-1964.391**	-1964.391**
	(874.195)	(768.237)
TG high*post	43.921	43.921
	(880.357)	(574.674)
Month-year FEs	Yes	Yes
Transformer FEs	Yes	Yes
Cluster standard errors	Transformer	Village
Wald p-value: TG high = TG low	0.012	0.046
Omitted group	Control TGs	Control TGs
Observations: TG level	3850	3850
R-squared	0.85	0.85

Notes: Regressions use a panel of monthly electricty billing data, collapsed at the transformer level. The monthly electricity consumption for a transformer includes all residential consumers within a transformer, not just the ones survyed for the experiment. All columns include controls for "post" period, the number of HDD each month, the average number of days in billing period for the transformer, the total number of residential consumers being by the transformer in that month. "TG low" is a dummy variable that equals 1 if 10 to 14 percent of households in a transformer were assigned to treatment. "TG high" is a dummy variable that equals 1 if 15 to 18 percent of households in a transformer were assigned to treatment. Standard errors indicated with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Appendix A2: Basic estimates of impacts on electricity consumption

In the paper, we estimate the impacts of the intervention on electricity consumption, accounting for externalities. In this appendix, we additionally report estimated impacts of CFL treatment on household electricity consumption with two more basic specifications. We first estimate a simple difference-in-differences model:

$$q_{igt} = \beta_1 T_{ig} * Post_t + \beta_2 Post_t + \beta_3 T_{ig} + \alpha X_{igt} + \gamma_t + \lambda_{ig} + \epsilon_{ig} \tag{A1}$$

where q_{igt} is the electricity consumption (kWh) in month t for household i within transformer g; T_{ig} is an indicator of treatment status for household i in transformer g that equals 1 if the household was assigned to CFL treatment and the opportunity to receive up to 4 CFLs through the intervention; $Post_t$ is an indicator equaling 1 in the month of treatment and all months that follow; and X_{igt} is a vector of household-level control variables.[35] Month-by-year fixed effects, γ_t, address the seasonal variations that occur throughout the year and affect all households, such as hours of sunlight and climate. Household fixed effects, λ_i, control for household-level characteristics that are fixed over time. Standard errors are clustered at the household level.

The interaction, $T_{ig} * Post_t$, is the term of interest here, as the coefficient on this term, β_1, is the estimate of the average change in household monthly electricity consumption (in kWh) that resulted from random household assignment to treatment. Table A5, Column 1, reports intent-to-treat estimates of β_1. The impacts are identified from variation within households

[35] These include controls for number of days in monthly billing period and whether the household uses electricity for heating. We also control for heating degree days; however, we only have variation in temperature over time, as the 7 villages in the study sample are all covered by one weather station and data are reported at that level. Nevertheless, we do not expect for there to be much spatial variation in temperatures across villages included in the study given their size and proximity.

over time, controlling for month-by-year shocks.

The basic estimate in Appendix Table A5 Column 1 indicates that the CFL treatment reduces household electricity consumption by 16.7 kWh per month. The magnitude of this coefficient is less than half the expected reduction, as calculated in the first step of our benchmarking calculations in Appendix A1. This estimate, however, is flawed in several respects. First, it is does not differentiate between treated households in high versus low saturation transformers. Second, the omitted group in this regression is comprised of all control households, regardless of whether they are located in control transformers, low saturation transformers, or high saturation transformers.

To address the first concern mentioned above, we estimate the impacts of CFL treatment on household electricity consumption, differentiating by treated households in higher versus lower treatment saturation transformers. We estimate:

$$\begin{aligned} q_{igt} = \beta_1 THigh_{ig} * Post_t + \beta_2 TLow_{ig} * Post_t + \beta_3 THigh_{ig} + \beta_4 TLow_{ig} + \\ \beta_5 Post_t + \alpha X_{igt} + \gamma_t + \lambda_{ig} + \epsilon_{ig} \end{aligned} \tag{A2}$$

where $THigh_{ig}$ is an indicator equal to 1 for treated households located in high saturation transformers and $TLow_{ig}$ is an indicator equal to 1 for treated households located in low saturation transformers. The omitted group in this regression is still comprised of all control households, regardless of transformer treatment saturation.

The results of this estimation are presented in Appendix Table A5 Column 2. In low saturation transformers, the CFL household treatment led to a 27.7 kWh per month reduction in electricity consumption, on average. This reduction is statistically significant and close in magnitude to our benchmarking calculation of the expected reduction in the summer scenario. In contrast, treated households in high saturation transformers did not significantly reduce electricity consumption. As indicated by the Wald p-value, the coefficients for the two groups of treated households are statistically significantly different from one another.

The difference in estimated impacts for low and high saturation transformers is consistent with the outage results in Table 2. Treated households in low saturation transformers experience no significant change in outages (no increase in hours of electricity services available), but they benefit as a result of replacing incandescent bulbs with CFLs. CFLs use fewer kW per hour of lighting services and, thus, a reduction is observed in their monthly electricity consumption. In contrast, treated households in high saturation transformers experience fewer outages as a result of the transformer treatment. There is no significant or large reduction in kWh per month of electricity consumed amongst this group, but not because the CFLs did not work. Rather, reductions in kW per hour of lighting consumed are offset by an increase in hours of electricity services consumed due to greater availability of electricity.

The estimation in Column 2 is preferable to that in Column 1, but nonetheless problematic. The omitted group is still comprised of all control households, regardless of transformer treatment status. When either reliability externalities or adoption spillovers exist, the control households within treated transformers would be contaminated. If control households in both high and low saturation transformers adopt CFLs on their own, then the impacts estimated for treated households in Columns 1 and 2 are downward biased (i.e. less negative than they should be). This bias is less certain in high saturation transformers, where control households' electricity savings from a CFL adoption spillover may be mitigated by an increase in electricity consumption due to improved electricity reliability.

Table A5: Household electricity consumption effects, basic estimates

	Monthly Household Electricity Consumption	
	(1)	(2)
Treated household * Post	-16.679*	
	(8.780)	
Treated household in TG low * Post		-27.688***
		(10.482)
Treated household in TG high * Post		-7.175
		(11.026)
Omitted group	All control houses	All control houses
Month-by-year FEs	Yes	Yes
Household FEs	Yes	Yes
Household-by-season FEs	No	No
Transformer-by-season FEs	No	No
Wald p-value: T in TG high = T in TG low		0.098
Households	899	899
Observations	31,143	31,143

Notes: Analysis performed using household-level panel of monthly electricity consumption data for the period between April 2011 to September 2014, as provided from the electricity utility's billing records. The "post" period are the months after the intervention implementation (from April 2013 onwards). "Treated" households were offered to receive up to 4 CFLs through the intervention. "Control" households were not offered CFLs through the intervention. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. All regressions include controls for monthly heating degree days, number of days in each monthly billing period, and the use of an electric heater. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Standard errors are clustered at the household level and resported in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table A6: Baseline balance in monthly electricity consumption, by treatment status

	Monthly Household Electricity Consumption (kWh)
Treated household in TG low	148.603
	(112.499)
Treated household in TG high	88.138
	(117.814)
Control household in TG low	87.168
	(118.166)
Control household in TG high	63.326
	(117.814)
Omitted group baseline mean	328.10
Month-by-year FEs	Yes
Household FEs	Yes
Transformer-by-season FEs	Yes
Wald p-value: T in TG high = T in TG low	0.151
Wald p-value: C in TG high = C in TG low	0.668
Households	899
Observations	14237

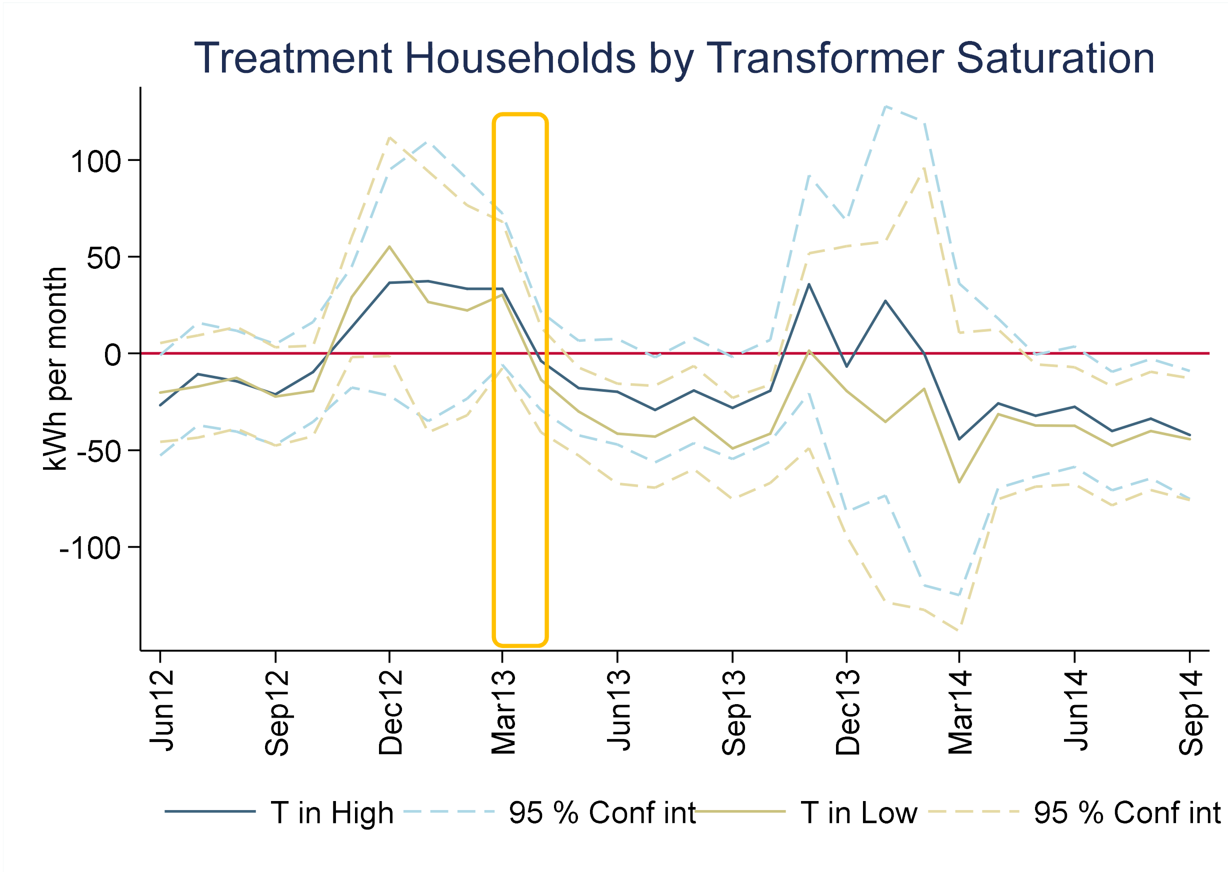
Notes: Analysis performed using household-level panel of monthly electricity consumption data as provided by the utility's billing records. Data are for the period between April 2011 to March 2013, which is the pre-intervention period. The omitted group is comprised of households in control tranformers. "Treated" households were offered to receive up to 4 CFLs through the intervention. "Control" households were not offered CFLs through the intervention. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control transformers" only contain control households. All regressions include controls for monthly heating degree days, number of days in each monthly billing period, and the use of an electric heater. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Standard errors are clustered at the household level and resported in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table A7: Household electricity consumption effects, dropping top 5 percent of observations

Dependent Variable: Monthly Household Electricity Consumption (kWh)			
	(1)	(2)	(3)
Treated household in TG low * Post	-40.348***	-28.671**	-30.555***
	(10.290)	(12.004)	(11.600)
Treated household in TG high * Post	-20.597**	-13.623	-11.334
	(9.954)	(11.825)	(11.515)
Control household in TG low * Post	-40.675***	-29.915**	-31.563***
	(11.326)	(12.554)	(12.208)
Control household in TG high * Post	16.594	32.082	26.744
	(16.515)	(21.055)	(18.183)
Post	32.194**	29.087**	29.574**
	(13.117)	(13.634)	(13.311)
Omitted group baseline mean	305.08	305.08	305.08
Month-by-year FEs	Yes	Yes	Yes
Household FEs	Yes	No	Yes
Household-by-season FEs	No	Yes	No
Transformer-by-season FEs	No	No	Yes
Wald p-value: T in TG high = T in TG low	0.039	0.170	0.066
Wald p-value: C in TG high = C in TG low	0.001	0.003	0.001
Households	899	899	899
Observations	29874	29874	29874

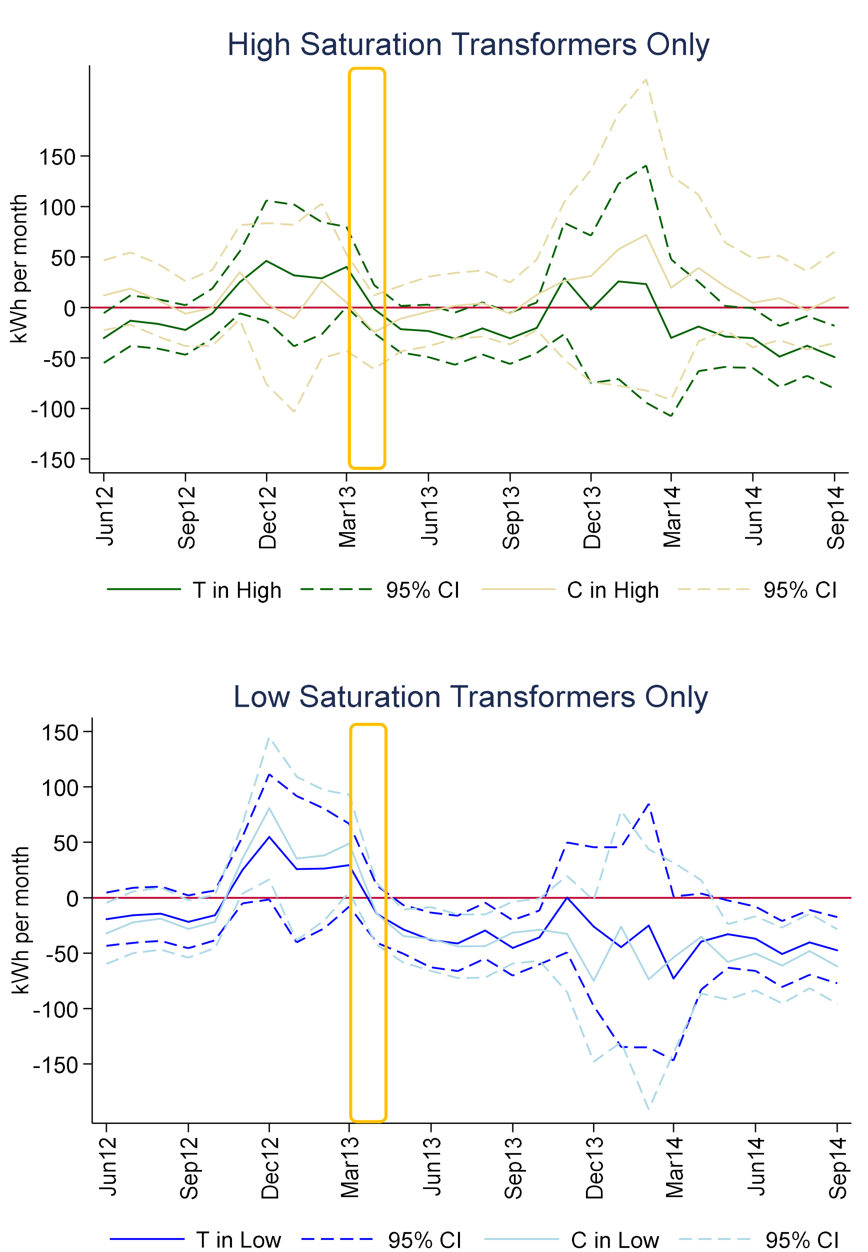
Notes: Analysis performed using household-level panel of monthly electricity consumption data for the period between April 2011 to September 2014, as provided from the electricity utility's billing records. The "post" period are the months after the intervention implementation (from April 2013 onwards). The omitted group is comprised of households in control tranformers. "Treated" households were offered to receive up to 4 CFLs through the intervention. "Control" households were not offered CFLs through the intervention. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control transformers" only contain control households. All regressions include controls for monthly heating degree days, number of days in each monthly billing period, and the use of an electric heater. Each month drops the top 5% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Standard errors are clustered at the household level and resported in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Figure A3: Household monthly electricity consumption effects, treatment households differentiated by transformer saturation



Notes: Orange block demarks time period when CFLs were distributed, beginning in March 2013. Analysis of these actual impacts are performed using household-level panel of monthly electricity consumption data, as provided from the electricity utility's billing records. The graph of the estimated impact was created by plotting the coefficients from regressing household electricity consumption (kWh) on household treatment status on a month-by-month basis. The resulting regressions for each month within the study period mean that we cannot include household fixed effects (as is included through much of the paper's analysis) in creating these graphs. All regressions include controls for (1) the control households in treated transformers, making this estimate a comparison of treated households against pure control households (control househols in control transformers), (2) the household's baseline monthly electricity consumption (for the year prior to the intervention), and (3) the number of days within each monthly billing period.

Figure A4: Household monthly electricity consumption effects, by transformer saturation



Notes: Orange block demarks time period when CFLs were distributed, beginning in March 2013. Analysis of these actual impacts are performed using household-level panel of monthly electricity consumption data, as provided from the electricity utility's billing records. The graph of the estimated impact was created by plotting the coefficients from regressing household electricity consumption (kWh) on household treatment status on a month-by-month basis. The resulting regressions for each month within the study period mean that we cannot include household fixed effects (as is included through much of the paper's analysis) in creating these graphs. All regressions include controls for (1) the control households in treated transformers, making this estimate a comparison of treated households against pure control households (control housholds in control transformers), (2) the household's baseline monthly electricity consumption (for the year prior to the intervention), and (3) the number of days within each monthly billing period.

Table A8: Household monthly electricity consumption effects, by season

	Monthly Household Electricity Consumption (kWh)		
	Winter	Spring/fall	Summer
	(1)	(2)	(3)
Treated household in TG low * Post	-56.101*	-39.764***	-15.448**
	(33.703)	(13.066)	(7.209)
Treated household in TG high * Post	-10.265	-31.002**	-2.678
	(35.687)	(13.152)	(7.267)
Control household in TG low * Post	-67.568**	-26.534*	-14.528*
	(34.215)	(15.362)	(8.072)
Control household in TG high * Post	46.827	24.001	-8.388
	(49.140)	(20.304)	(11.902)
Post	219.011***	44.124***	32.234
	(36.406)	(16.212)	(59.137)
Omitted group baseline mean	438.10	321.08	226.35
Month-by-year FEs	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes
Wald p-value: T in TG high = T in TG low	0.151	0.449	0.083
Wald p-value: C in TG high = C in TG low	0.015	0.016	0.623
Households	899	899	899
Observations	10603	9697	10581

Notes: For estimates, the winter includes November through February; spring/fall includes March, April, September, and October; and summer includes May through August. The omitted group is comprised of households in control tranformers. Analysis performed using household-level panel of monthly electricity consumption data for the period between April 2011 to September 2014, as provided from the electricity utility's billing records. The "post" period are the months after the intervention implementation (from April 2013 onwards). "Treated" households were offered to receive up to 4 CFLs through the intervention. "Control" households were not offered CFLs through the intervention. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control transformers" only contain control households. All regressions include controls for monthly heating degree days, number of days in each monthly billing period, and the use of an electric heater. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Standard errors are clustered at the household level and resported in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table A9: Tests for evidence of direct and indirect rebound

	(1) Direct Rebound: Hours of lighting use per day	(2) Indirect rebound: Hours of appliance use per day
T household in TG low * Post	3.376	2.839
	(3.133)	(3.340)
T household in TG high * Post	2.686	4.297
	(3.241)	(3.747)
C household in TG low * Post	3.875	0.310
	(3.640)	(3.260)
C household in TG high * Post	2.232	0.995
	(4.068)	(3.650)
Post	-1.510	4.280
	(2.755)	(2.625)
Omitted group baseline mean	18.61	30.46
Wald p-value: T in TG high = T in TG low	0.7608	0.6667
Wald p-value: C in TG high = C in TG low	0.6674	0.8293
Observations	1498	1498
Households	749	749

Notes: Data were collected via the baseline (March 2013) and follow-up (March 2014) surveys, forming a panel dataset. The omitted group is comprised of households in control transformers. All specifications include household fixed effects. Regressions include only households for which there are both baseline and follow-up data; households that moved during the period between the intervention and the follow-up survey are dropped. The "post" period data were collected via the follow-up survey in March 2014. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control TGs" only contain control households. Standard errors are clustered at the transformer level and in parentheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table A10: Household electricity consumption effects, by use of electric heating

Dependent Variable: Monthly Household Electricity Consumption (kWh)		
	(1)	(2)
Treated household in TG low * Post * Heat	-40.701**	-17.006
	(17.800)	(21.778)
Treated household in TG low * Post * No Heat	-46.170***	-48.748***
	(13.810)	(16.750)
Treated household in TG high * Post * Heat	-37.821**	-13.630
	(17.981)	(22.906)
Treated household in TG high * Post * No Heat	-16.797	-15.623
	(14.716)	(18.113)
Control household in TG low * Post * Heat	-47.154**	-13.992
	(18.908)	(22.563)
Control household in TG low * Post * No Heat	-42.930***	-46.880***
	(14.883)	(17.541)
Control household in TG high * Post * Heat	27.801	61.543*
	(28.947)	(36.610)
Control household in TG high * Post * No Heat	-2.963	-1.416
	(20.153)	(25.734)
Omitted group	Houses in control transformers	Houses in control transformers
Month-by-year FEs	Yes	Yes
Household FEs	Yes	No
Household-by-season FEs	No	Yes
Households	899	899
Observations	31,143	31,143

Notes: Analysis performed using household-level panel of monthly electricity consumption data for the period between April 2011 to September 2014, as provided from the electricity utility's billing records. "Heat" refers to households that reported using electricity for heating at baseline. "No heat" are the households that reported not using electricity for heating at baseline. The "post" period are the months after the intervention implementation (from April 2013 onwards). "Treated" households were offered to receive up to 4 CFLs through the intervention. "Control" households were not offered CFLs through the intervention. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control transformers" only contain control households. All regressions include controls for monthly heating degree days, number of days in each monthly billing period, and the use of an electric heater. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Standard errors are clustered at the household level and resported in parantheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table A11: Changes in beliefs and preferences

	(1)	(2)	(3)	(4)
	Prefer CFLs to other lightbulb types	Believe CFLs consume less electricity than incandescent bulbs	Believe savings from CFLs show on electricity bill	Believe CFLs use pays back purchase cost by saving electricity
T household in TG low * Post	0.469***	0.216**	0.127	0.279***
	(0.071)	(0.095)	(0.093)	(0.089)
T household in TG high * Post	0.386***	0.328***	0.180*	0.361***
	(0.061)	(0.086)	(0.098)	(0.076)
C household in TG low and close to T * Post	0.188***	0.001	0.003	0.049
	(0.072)	(0.107)	(0.098)	(0.090)
C household in TG high and close to T * Post	0.143	0.095	0.129	0.245**
	(0.112)	(0.138)	(0.122)	(0.121)
C household in treated TG and far from T * Post	0.059	0.093	-0.214	-0.009
	(0.101)	(0.258)	(0.266)	(0.213)
Post	0.041	0.007	0.014	-0.041
	(0.042)	(0.055)	(0.050)	(0.038)
Omitted group baseline mean	0.048	0.253	0.212	0.205
Households	749	749	749	749
Observations	1498	1498	1498	1498

Notes: Data on the outcomes measures were collected via the baseline (March 2013) and follow-up (March 2014) surveys, forming a panel dataset. The omitted group is comprised of households in control transformers. All specifications include household fixed effects. Regressions include only households for which there are both baseline and follow-up data; households that moved during the period between the intervention and the follow-up survey are dropped. The "post" period data were collected via the follow-up survey in March 2014. "TG low" are transformers for which 10 to 14 percent of households in the transformer were assigned to treatment. "TG high" are transformers for which 15 to 18 percent of households in the transformer were assigned to treatment. "Control TGs" only contain control households. Being "close to T" is an indicator that equals 1 when a control household is located < 100 meters from a treated household. Control households that are "far from T" are located > 100 meters from a treated household. Standard errors are clustered at the transformer level and in parentheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Appendix A3: Estimates of technologically feasible transformer peak load reductions, by transformer treatment intensity and incorporating spillovers

We redo the calculations for expected peak load reductions, this time making three crucial adjustments. First, we approach these calculations holistically, at the transformer-level. Second, we differentiate explicitly between the low and the high saturation intensity transformers throughout the calculations. Third, we incorporate the spillovers in adoption amongst control households in treated transformers. Altogether the last two adjustments are critical for attaining a more realistic estimate of the expected peak load reductions, not only assisting in the assessment as to whether the transformer-level treatment was sufficient to induce improvements in reliability, but also to determine whether the expected peak load reductions across low and high treatment saturations are sufficiently different to support the interpretation that differential impacts on outages resulted.

Details of the calculations are in Appendix Table A12. We first estimate the number of households within high and low saturation transformers that might be acquiring CFLs, including treated households, control households that are "close" to treated households and control households that are "far" from treated households. Differentiating between the close and far households is important given the results in Section 7 highlighted the role of proximity in generating adoption spillovers. We use the average number of households in high and low transformers (A) from the baseline balance table (previously shown in Appendix Table A2, Panel C). We know the number of treated households, on average for high and low saturations, from intervention data. Based on the local density of houses, we assume for (D) that each treated household has 5 control households that are "close" (within 100 m or less). Given the density of housing within the sample region, this is a conservative assumption so as to account for the control households that are "close" to multiple treated households (and therefore might be at a risk of being double-counted).

From the estimates throughout the paper, we know approximately the number of CFLs households of each type have. For example, the number of CFLs in "close" and "far" households are based on the spillover results in Table 5 Column 2. Knowing the number of households in each of these groups and the average number of CFLs each household type has, we can calculate the total number of CFLs within a transformer.

In Appendix A1, we estimated the peak load per household (using data from a separate smart meter pilot in a village outside of our study), which we use here to estimate the peak load per transformer. On average 100 W incandescent bulbs were replaced by 21 W CFLs. We multiply this reduction (79W) by the average number of CFLs in the transformer. We calculate a reduction of 6 percent in electricity consumption for the low saturation transformers and 8 percent for high saturation transformers. The internal heating effects of the transformer are a square function of current. These nonlinear impacts of overloads mean that peak reductions of overloaded systems can yield disproportionately large reductions in distribution-level outages (ANSI/IEEE, 1981). It is therefore both reasonable and expected that an 8 percent reduction in peak would yield a significantly larger reduction in outages when compared to a 6 percent reduction in peak and certainly when compared to no reduction at all.

Two important points are made salient from these calculations. First, high saturation transformer not only have a greater proportion of households that are treated, but also a greater proportion of their control households are close to the treated. Second, the difference between the high and low saturation transformers in percent peak load reduction is not inconsequential and could result in differential impacts in outages.

Table A12: Appendix A3 calculation details: benchmarking peak load reductions within transformers

Transformer peak load reductions in winter, by transformer treatment intensity

		Source	Low Transformers	High Transformers
Household numbers - Average number of:				
(A)	total households per transformer	[see notes]	63	48
(B)	treated households per transformer	[see notes]	6.5	6.3
(C)	untreated households per transformer	[= A - B]	56.5	41.7
(D)	"close" untreated households per transformer	[= B * 5]	32.3	31.3
(E)	"far" untreated households per transformer	[= C - D]	24.3	10.5
CFL numbers - Average number of:				
(F)	CFLs received per treated household	[see notes]	3.3	3
(G)	CFLs attained per "close" untreated households	[see notes]	0.704	0.910
(H)	CFLs attained per "far" untreated households	[see notes]	0.447	0.447
Transformer peak load reduction:				
(I)	Number of CFLs per transformer	[=B*F+D*G+E*H]	54.86	51.91
(J)	Electricity consumption reduction per transformer (kW)	[=(I*79W/bulb)/1000]	4.33	4.10
(K)	Peak load per transformer (kW)	[=1.109*A]	69.3	52.8
(L)	**Transformer peak load reduction (%)**	**[=(J/K)*100]**	**6%**	**8%**

Notes: These transformer calculations include not only treated households receiving CFLs through the intervention as well as spillovers in adoption by other households (either control households or other households not included in this surveyed sample) within a transformer. The average number of households in high and low transformers (A) is based on Appendix Table A1, Panel C. (B) is based on calculations from intervention. Based on the local density of houses, we assume for (D) that each treated household has 5 control households that are "close" (within 100 m or less). Number of CFLs in (F) is based on results in Table 1. Number of CFLs for "close" and "far" households in (G) and (H), respectively, are based on the spillover results in Table 4, Column 2. For (J) the 79W/bulb reduction is based on [b-c] in Step 1A of the prior benchmarking calculations. Household peak load for (K) is based on the winter estimate for (x) in the prior benchmarking calculations (which were informed using smart meter data and explained in Step 1C).

Appendix A4: Cost-benefit analysis of the CFL program

We demonstrate the implications of performing cost-benefit calculations for our CFL distribution, with and without accounting for the aggregated impacts on electricity reliability, in addition to the estimated impacts of CFLs on household electricity savings.

To simplify these calculations, we perform the cost-benefit analysis for the first year of the CFL intervention. The one-year analysis is sufficient to show the importance of the reliability impacts for these calculations. In addition, this simplification is useful for several reasons, in that we can use the estimates from our experiment, which measure impacts over the course of 18 months following the CFL distribution; avoid having to make assumptions about the life span of the CFLs; do not have to worry about multi-year equilibrium adjustments in consumption; and, finally, need not make any assumption regarding discount rates.

Cost calculations

We perform program cost calculations from the perspective of a government entity implementing an energy efficiency program through a door-to-door campaign. These calculations are made based on a CFL distribution program with the design of our experiment: in which CFLs are distributed through individual house visits, at which time information on the benefits of CFL adoption are provided to households. Incandescent bulbs currently in-use at the households are not taken from the households. To encourage households to install the CFLs quickly, the entity distributing the CFLs can remove the packaging at the time of distribution. Although such door-to-door campaigns may be effective at inducing technology take-up, this is one of the more expensive distribution options available. Cheaper distribution programs include ones that distribute coupons at stores or through mailings, which permit households to receive the technology for free or a subsidized price.

In the calculation details in Appendix Table A13, we divide costs into two components: the cost of CFL purchase and the cost of distributing the technology through the door-to-door campaign. We base these calculations on details from our own experiment, such as the price per CFL, the number of households served by the program, and the average number of CFLs distributed per household. An organization buying energy efficient lightbulbs in bulk would likely be able to acquire them at a lower cost than this project.

These cost calculations do differ from our experiment in that here we assume the government bears 100 percent of the program costs. This need not be the case given that we find households are willing to pay a positive price for the CFLs. We can adjust the assumptions as to the number of households such a door-to-door campaign can reach per day, but such shifts do not alter the costs substantially.

Benefit calculations

We perform three versions of benefit calculations for such a CFL distribution program, as shown in Table 6. Important to note, these calculations do not include the value of any reductions in pollution resulting from the CFL adoption.

Version A is our most simplified calculation of average benefits for households in all transformers. This is based on the estimate of electricity consumption impacts from Appendix Table A5, Column 2. This estimate does not account for any aggregate impacts in reliability of electricity services and is therefore an underestimate of the benefits. Even so, the benefits per household in the first year are approximately $1.16 less than the costs per household.

Version B estimates the benefits from the CFLs among households that do not have any changes in reliability of electricity services. These calculations use estimated electricity savings amongst treated households in transformers not experiencing any reliability improvements (Table 3, Column 2). Here the benefits per treated household in year 1 are greater than the costs per household.

Finally, Version C of the calculation includes the benefits from the CFLs amongst households that experience improvements in the reliability of electricity services. These calculations use the reduction in electricity consumption amongst treated households experiencing reliability improvements (Table 3, Column 2). Part 2 of these calculations are still likely an underestimate of household benefits given that electricity prices were very low. In this calculation, the benefits per treated household in year one are nearing double the costs per household.

Table A13: Appendix A4 calculation details: costs of CFL distribution program

	COSTS FOR CFL DISTRIBUTION PROGRAM		
Part 1:	**CFL purchase cost**		
	Average # CFLs distributed	3.2	per household
	Cost per CFL	120	KGS
	Cost per household	384	KGS
	Number of households	543	
	Total CFL purchase cost	208512	KGS
Part 2:	**CFL Distribution cost**		
	Number of households	543	
	Households visited per day	12	
	Time to distribute CFLs	45	Days
	Cost per workday	467	KGS
	Total distribution cost	21132	KGS
Total Program Cost (Purchase+ Distribution):			
	Costs	229643.75	KGS
	Exchange rate	48.00	KGS = 1 USD
	Costs	4784.24	USD
Cost of Program Per Household		**$ 8.81**	