

Shedding Light: Understanding Energy Efficiency and Electricity Reliability in Developing Countries*

Eliana Carranza[†] Robyn Meeks[‡]

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Abstract

Overloaded electrical systems are a major source of unreliable power (outages) in developing countries. Using a randomized saturation design, we estimate the impact of energy efficient lightbulbs on household electricity consumption and local electricity reliability. Receiving compact fluorescent lightbulbs (CFLs) significantly reduced household electricity consumption. Estimates not controlling for spillovers in take-up underestimate the impacts of the CFLs, as control households near the treated are likely to take-up CFLs themselves. Greater saturation of CFLs within a transformer leads to aggregate reliability impacts of two fewer days per month without electricity due to unplanned outages relative to pure controls. Increased electricity reliability permits households to consume more electricity services, suggesting that CFL treatment results in technological externalities. The spillovers in take-up and technological externalities that we document may provide an additional explanation for the gap between empirical and engineering estimates of the impacts of energy efficient technologies.

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[†]World Bank. Email: ecarranza@worldbank.org

[‡]University of Michigan. Email: meeks@umich.edu (corresponding author)

1 Introduction

Overloaded systems are major source of unreliable power in developing countries. Overloads occur when the grid is asked to deliver more power than it is able, causing components of the grid to break. Such breakage results in electricity outages, a major problem for electricity service provision in developing countries. This problem is likely to worsen in the future for at least two reasons. First, residential electricity demand is expected to increase with pro-poor development, as households buy their first appliances (Wolfram et al., 2012), putting further pressure on the existing electrical grid. Additionally, in certain settings, subsidized electricity prices provide little incentive for service providers to upgrade infrastructure, resulting in persistent low quality infrastructure (McRae, 2015).

With this in mind, programs distributing energy efficient technologies in developing countries¹ potentially provide an additional benefit beyond reducing emissions and decreasing the cost of energy services to technology adopters. CFLs are frequently deployed en masse in developing countries via programs with the specific goals of reducing electricity outages and increasing reliability of electricity services.² Compact fluorescent lightbulbs (CFLs), which consume 25% of the electricity used by traditional incandescent bulbs (per lumen), can reduce overall household electricity consumption without requiring a reduction in the hours of lighting services consumed (DOE, 2009). They may also provide important aggregate impacts in the form of reduced peak electricity load and improved reliability, permitting households to consume more electricity services (World Bank, 2006).³ Such technological externalities, through which the returns to an individual adopting CFLs are increasing in the fraction of the population utilizing the technology, can be a substantial benefit from adoption of energy efficient technologies.⁴

¹There are many such programs. Just between 1990 and the mid-2000s (World Bank, 2006), the World Bank alone committed more than US\$11 billion to energy efficiency in developing countries.

²For example, 600,000 CFLs were distributed in Uganda to reduce peak load by 25 MW. In Rwanda, 400,000 CFLs were distributed to reduce peak load by 16 MW and offset the need for diesel-based power generation. In Ethiopia, 200,000 CFLs were provided to reduce peak load by 6.8 MW to increase reliability.

³At an aggregate level, energy efficient lightbulbs can help address electric power shortages, permit utilities to reach a greater number of customers with existing supplies, reduce need for investment in capacity and distribution, accommodate growth in economic activity, and reduce environmental impact.

⁴We follow the definition of technological externality employed by Foster and Rosenzweig (2010). For a particular technology, adoption of the technology by others is said to generate a positive (negative) technological externality if it increases (decreases) an individual's returns to the adoption of such technology. Miguel and Kremer (2007) discuss such effects in the context of de-worming medication. By reducing the exposure to individuals infected with worms, the net benefit of the deworming pill to an individual is small (as long as the fraction of treated individuals is reasonably high). Similarly, Dupas (2014) cites medical

The potential gains from distribution of energy efficient technologies in developing countries are highly promising; however, there is relatively little evidence to date on the empirical impact of energy efficiency on individual household electricity consumption.⁵ Perhaps more notably, there is a dearth of evidence on the technological externalities that may result from the aggregate consumption impacts of energy efficiency. This is likely due to several reasons. First, spillovers in the adoption of energy efficient technologies confound the estimated impact on individual household energy consumption. Second, data on outcomes related to infrastructure quality (such as actual outages) tend to be difficult to acquire for developing countries (Klytchnikova and Lokshin, 2009). And third, levels of energy efficiency take-up and reliability of electricity services within a community are mutually endogenous⁶ and jointly explained by community characteristics⁷, making the causal aggregate impact of energy efficiency challenging to estimate.

To overcome these empirical challenges and assess the impacts of energy efficient technologies, we implemented an experimental distribution of CFLs employing a randomized saturation design, which allows us to account for spillovers when estimating the impact of treatment on individual household electricity consumption.⁸ In a novel application of the randomized saturation design, we experimentally vary the treatment saturation at a technologically-meaningful and policy-relevant scale. Specifically, we randomize at the level of the typical infrastructure failure, the distribution transformer.⁹ While the direct aggregate impacts of CFL treatment, in the form of reduced transformer-level electricity loads, may be proportional to CFL saturation, the externality benefits are likely to vary non-linearly with CFL technology saturation. By randomizing saturation intensity at the technologically-relevant scale, we are able to test for evidence of technological externalities in the form of increased

evidence suggesting that the population of infected mosquitos decreases as the fraction of households using a high quality bednet increases, thus reducing the individual benefits from bednet use.

⁵The notable exception is a quasi-experimental evaluation of a Mexican appliance (air conditioners and refrigerators) replacement program (Davis, Gertler and Fuchs, 2014).

⁶Greater consumption of CFLs within a community increases electricity availability. Greater electricity availability increases the gains from adoption of CFLs, potentially leading households to consume more CFLs. These effects reinforce each other.

⁷For instance, CFL consumption and electricity availability may be greater in communities with higher education levels, higher incomes, etc.

⁸Baird, Bohren and Ozler (2014) use a randomized saturation design to account for spillovers.

⁹Distribution transformers, which convert higher-voltage electricity from the distribution system to low-voltage electricity for household use, are a crucial part of the electrical grid and their failure is a common source of electricity outages (Glover, Sarma and Overbye, 2011).

electricity service reliability (reduced blackouts) and increased household electricity consumption in higher saturation transformers.

We implement this experiment in Kyrgyzstan, a low income developing country which suffers from frequent electricity outages, which offers suitable conditions for research on electricity reliability. Although CFLs were available in some stores at the project onset, they were not commonly used outside of Bishkek, the capital city. The randomized saturation design employs an electricity utility’s data on its residential customers in a district adjacent to Bishkek and on the infrastructure through which these consumers are served.

Treatment status was randomly assigned in two stages. First, we randomize electricity transformers to different treatment saturations (i.e. different proportions of households to be treated within a transformer). Second, we randomize households individually to treatment and control groups, according to the transformer saturation intensity assigned in the first stage. After completing a baseline survey, the treated households receive up to four CFLs at a highly subsidized price. We follow household monthly electricity consumption via the electricity utility’s records for 18 months post-intervention to estimate the impacts on electricity consumption. To measure CFL use and spillovers in adoption, we return for a follow-up survey one year after CFL distribution.

We measure the impacts of CFLs on residential electricity consumption, both with and without controls for any potential spillovers in CFL take-up. The randomized saturation design in the initial CFL distribution allows us to test for such spillovers. In our sample, control households close to treated households are more likely to have CFLs at follow-up than pure control households in located control transformers. Not accounting for spillovers in take-up amongst the control group leads to estimates of electricity consumption reductions that are downward biased (in other words, they understate the savings from energy efficiency). When accounting for these spillovers, we find that CFLs lead to a significant reduction in monthly electricity consumption that falls within the expected range for the technology based on engineering performance estimates.

Using the transformer-level randomization of treatment intensity, we then test for externality effects resulting from the energy efficiency, in the form of improved electricity reliability. We find that households in transformers with a higher intensity of treatment (i.e., a higher sat-

uration of households within a transformer receive CFLs) have fewer days reported without electricity due to unplanned outages.¹⁰ This result is robust to a number of controls, including controlling for baseline reported outages, and is supported by calculations of expected peak load reduction. We also find evidence suggesting that households in transformers with improved reliability consume more hours of electricity services due to fewer outages, and that the household energy savings are larger after accounting for this technological externality.

Our experiment contributes to the literature on energy efficiency in several ways, and offers a novel experimental design for identifying externalities at various treatment levels.

First, it contributes to the debate regarding the impacts of energy efficient technologies and their potential to reduce energy demand. Energy efficiency depends not only on the development of relevant technologies, but also on the interaction of end-user behavior with such technologies (Allcott and Mullainathan, 2010). Prior to ours, no experimental or quasi-experimental studies existed measuring the impacts of energy efficient lighting. The one previous large-scale study of a CFL distribution program found that approximately 20% of initial electricity savings dissipated over time (Costolanski et al., 2013), thereby contributing to skepticism regarding the gains from efficient lighting technologies and from energy efficiency more generally. Our experimental finding, that CFL treatment results in a significant electricity consumption reduction very close in size to the expected technologically feasible reductions, contributes to balance the existing evidence from misidentified studies. Our finding is not only relevant for developing countries, but is also consistent with preliminary results from the United States, where lighting is a relatively smaller share of energy consumption.¹¹ This new evidence suggests that energy efficient lighting, and perhaps other energy efficient technologies as well, should not yet be removed from the menu of potential policy solutions.

Second, to our knowledge, our experiment is the first to use a randomized saturation design to provide evidence of technological externalities at multiple policy-relevant levels. Given the scale and multiple levels at which technological externalities typically occur, designing an experiment that can identify such externalities is challenging; as a result, there is relatively

¹⁰We collect data on reported days without electricity due to unplanned outages during both the baseline and follow-up surveys.

¹¹Burling et al. (2016) perform a machine-learning analysis of energy efficiency in California schools. Preliminary results indicate substantial energy savings from the energy efficient lighting interventions.

little rigorous empirical evidence on them.¹² This study designs such experiment by taking into account the constraint within the electricity distribution system that most frequently causes electricity outages and randomly varies the saturation intensity of CFLs at that level. By doing so, we are able to provide evidence of technological externality effects both on electricity reliability at the transformer level and on household electricity consumption. We gauge how the externality varies with the number of treated households within a transformer to decompose the overall effect of the technology on household energy consumption into its direct and externality components. Our results suggest that energy efficiency programs can improve electricity reliability, not only in Kyrgyzstan but also in other contexts, if they reach sufficient levels of technology saturation. More generally, they speak to the extent to which energy programs can accomplish various, and sometimes opposing, goals (for example, reducing energy consumption overall versus improving service reliability to increase electricity consumption) using a technology-based solution.

Third, our experiment contributes to the discussion regarding the energy efficiency gap. In spite of their promise as potentially welfare-improving, many believe households are not using energy efficient technologies when they should.¹³ Building upon Hausman (1979), cumulative research suggests an energy efficiency gap due to individuals not maximizing the net present value of their energy spending when making energy purchase decisions.¹⁴ There is a growing body of work investigating the factors impacting purchase decisions of energy efficient technologies, thereby causing these investment inefficiencies (Jaffe and Stavins, 1994; Allcott and Greenstone, 2012; Gillingham and Palmer, 2014). Most existing economic research on adoption of energy efficient technologies largely focuses on private adoption decisions and the returns to individual adopters. In contrast, very little attention has been paid to the role of spillovers in adoption decisions and technological externalities.¹⁵ In their presence, the level

¹²A notable exception is Miguel and Kremer (2004), who provide experimental evidence of positive cross-school externalities from deworming medicines in Kenya, but have to rely on more tentative non-experimental methods to decompose the overall effect on treated schools into a direct effect and within-school externality effect. As acknowledged by them: “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.”

¹³Energy efficient products often require a larger upfront cost than the standard products, but exhibit lower operating costs. Consumers decision to invest in energy-saving devices relies on this trade-off between initial investment and operating costs.

¹⁴Jaffe and Stavins (1994) and Gillingham and Palmer (2014) discuss the energy efficiency gap.

¹⁵ Interventions to increase uptake of energy efficient technologies have focused on energy labeling (Newell

of private investment in some energy efficient technologies may be even more sub-optimal than previously thought.

Finally, it connects with the literature on infrastructure and development. In many developing countries, lighting is a major component of residential electricity consumption. Research indicates that electrification is important for development (Dinkelman, 2011; Lipscomb, Morarak and Barnham, 2013; Rud, 2012; Van de Walle et al., 2013), and residential access to modern energy and lighting can improve living standards and productivity (World Bank, 2006). Yet access to electricity services does not guarantee reliable service (Klytchnikova and Lokshin, 2009). Electricity outages can impact both households (Chakravorty, Pelli and Marchand, 2013) and firms (Allcott, Collard-Wexler and O’Connell, 2015; Alam, 2013), yet low-quality electricity infrastructure can be persistent (McRae, 2015).

The remainder of the paper is as follows: Section 2 provides information on electricity use in Kyrgyzstan and the potential impacts of energy efficiency; Section 3 details the sampling process and randomized design; Section 4 addresses the data collected and results of the randomization and compliance checks; Section 5 estimates impacts of CFLs at the household level, both with and without spillovers; and Section 6 estimates the impacts of energy efficient technology at an aggregate level and provided additional supporting evidence of a technological externality; and Section 7 concludes.

2 Institutional setting and energy efficiency

2.1 Electricity services and infrastructure in Kyrgyzstan

Kyrgyzstan provides a suitable context in which to study energy efficiency and electricity reliability in a developing country setting.¹⁶ Due to its history as part of the former Soviet Union, the country is highly electrified, with nearly 100 percent of households covered by formal electricity connections (Gassmann, 2014). Residential electricity demand has increased since the country’s independence in 1992. Over the past two decades, the proportion of total electricity consumption comprised by the residential sector steadily increased, with 63% of

and Siikamaki, 2015), social norms (Herberich, List, and Price, 2011), information on energy costs (Allcott and Taubinsky, 2015), and subsidies (Allcott and Sweeney, 2015) in overcoming the investment inefficiencies.

¹⁶The country ranks 147th out of 187 countries for GDP (PPP) per capita (IMF, 2012).

country's current electricity supply consumed by the residential sector (Obozov et al., 2013).

Similar to many other developing countries, the electricity infrastructure is insufficient to meet current and growing electricity demand. In Kyrgyzstan, much of the existing electricity infrastructure dates back to the Soviet Union including all 16 of its power plants (Zozulinsky, 2007). Ninety percent of electricity generation within the country is hydroelectric, so supply fluctuates with annual variability in reservoir water levels.¹⁷ Technically, the capacity of both generation and transmission infrastructure could constrain household electricity services and result in unreliable electricity services (frequent electricity outages); however, during the study period, distribution constraints are the primary source of unreliable service.

Due to very low residential electricity prices (\$0.02 per kWh throughout this study), many households heat with electricity in winter. In spite of low prices, concerns regarding electricity bills and household energy expenditures are common. Household energy expenditures comprise an estimated 7.1 percent of total household expenditures in Kyrgyzstan (Gassmann, 2014), much of which is due to winter heating. Electric heating leads to large seasonal variations in electricity consumption, with average winter consumption approximately three times that of summer. The country's utilities face growing electricity consumption while constrained by a distribution system designed for substantially lower demand. As a result, the country is plagued by frequent unplanned outages particularly in winter.¹⁸

Transmission and distribution systems are consistently overloaded, acting as a binding constraint and source of unplanned outages. To put this in perspective, most of the transformers have a load factor of 0.9 - 1.2, with 0.7 being the optimal load (Amankulova, 2006).¹⁹ These constraints are a concern for both consumers and the electricity utility. Unplanned outages typically occur when local distribution systems experience an overload. The distribution network was constructed for peak electricity consumption associated with households owning only a few electricity-using durables. But peak household electricity demand has increased as households have bought more appliances, which is consistent with predictions made for pro-poor development in developing countries, more broadly (Gertler, Shelef and Wolfram, 2012).

¹⁷In years of low water availability, the country has instituted planned, rolling blackouts during the winter. This did not occur during our study period, according to the electricity utility.

¹⁸For example, in 2010 the country had 12,578 unplanned power outages (approximately 34 outages per day), which is considered unreliable services by international standards (USAID, 2011).

¹⁹This is for the 35/220 kV transformers, which the last step in delivering electricity to homes.

Transformers are a critical part of the electricity distribution infrastructure. A distribution transformer on the electrical grid converts high-voltage electricity to usable, low-voltage electricity for household consumption (Glover, Sarma and Overbye, 2011). There is a maximum electricity load that a transformer can transfer at any given time and exceeding that may lead to unplanned outages. During the study, transformer overloads were the primary source of unplanned outages. Quality of electricity services is correlated within a transformer, as households thus are exposed to the same electricity-related shocks. A transformer-level outage affects all households sharing the transformer.²⁰

2.2 Energy efficient lighting

Energy efficient technologies have the potential to decrease individual residential electricity consumption and therefore costs. Using approximately 75% less electricity than incandescent lightbulbs, CFLs are one tool for meeting lighting needs while reducing electricity consumption. If take-up rates are sufficiently high, energy efficient technologies could impact at an aggregate level. For example, CFLs could decrease aggregate electricity demand within a transformer reducing the probability of a transformer overload. By alleviating the stress on the infrastructure, energy efficiency could reduce unplanned electricity outages and increasing service reliability.

At the time of this study, CFLs were available for purchase in large home repair stores and markets located in the capital city, but not in villages. CFLs cost between 100 and 170 Kyrgyz soms, depending on the quality.²¹ In contrast, incandescent lightbulbs were available to purchase in both rural and urban markets for approximately 15 to 20 Kyrgyz soms. Even with low electricity prices, the payback period for the CFLs was between 1 and 2 years.²² This study was implemented in a district adjacent to the capital, Bishkek. Given residents of this district frequently travel to the city, they could have purchased CFLs pre-intervention; however, very few households outside of the capital used CFLs at baseline.

²⁰In our setting, 54 households on average receive their electricity via a single transformer.

²¹In March 2013, the exchange rate was approximately 1 USD = 46 Kyrgyz soms.

²²Payback period calculations were based on typical lightbulb use in our sample and electricity and CFL prices within the region.

2.3 Potential impacts of energy efficiency

Based on constraints in the electricity distribution system and the potential for energy efficient technologies to decrease demand both at the household and aggregate-level, we might expect the following impacts on electricity consumption following installation of CFLs:

1. *impacts on household electricity consumption:* This refers to the net effect of installing energy efficient lightbulbs within one's home. The obvious benefit would be a reduction in electricity consumption and the resulting electricity bill. With some basic information (for example, information on the wattage of both the original bulb and the energy efficient bulb to which one is switching, hours of lightbulb use, etc.), one can perform simple calculations to predict reductions in electricity consumption. We perform such calculations and discuss them in Section 5.

There are, however, multiple reasons residential electricity consumption might not change as expected following the installation of CFLs. These vary from CFLs not meeting their technological promise, human behavioral interactions with the technology, such as through a rebound effect,²³ or mechanical differences in the waste heat loss from energy efficient lightbulbs changing other practices, such as winter heating.

Finally, it is also possible that a reduction in electricity consumption occurs after installation of energy efficient lighting, but the impact is not detected (or muted) due to contamination of the comparison group. In other words, if the comparison group finds alternative means by which to access the technology, then they could also experience reductions in electricity consumption, thereby biasing empirical analyses including them. Such spillovers in adoption are discussed below.

2. *spillovers:* Installation of energy efficient technologies could influence others' adoption decisions via channels such as learning, imitation, etc. We tend to think that spillovers in take-up could be experienced by households with close linkages to the original adopters. However, spillovers in take-up could be positive, negative, or zero.
3. *aggregate effect:* This is the local aggregate effect of energy efficiency within the local distribution system. If a large enough proportion of households within a transformer

²³Given the electricity services associated with the energy efficient appliance are less expensive, households may respond to the new technology by using the appliance more. This is a rebound effect. For theoretical discussion of the rebound effect, see Borenstein (2015) and Chan and Gillingham (2015). Although the existing literature appears to agree on the existence of rebound effects, there is much debate over the magnitude of such an effect (Gillingham, Rapson and Wagner, forthcoming).

adopt the CFLs, there might be an aggregate reduction in electricity consumption at the transformer. This could reduce the probability of an outage due to a transformer overload, which translates into increased reliability of electricity services.

4. *technological externality*: The technological externality occurs when the private returns to an individual adopting the CFLs are increasing (or decreasing) in the fraction of the population adopting the energy efficient technology. In the case of energy efficiency and electricity service reliability, the relevant technological externality to consider is when consumers install energy efficient devices at a high saturation and demand decreases at the aggregate level to improve reliability. In this scenario, the improved reliability induced by the energy efficient technology permits residents to consume more hours of electricity services. This effect is experienced by all households within a transformer, regardless of whether the individual household adopted the technology.

This field experiment employs a randomized saturation design to address these potential impacts of energy efficiency.

3 Randomized experiment with energy efficiency

3.1 Sampling process

We implemented the following sampling procedure to select villages, transformers, and then households within the transformers. We use data from the electricity utility on all electrified households within one district near the country’s capital for our sampling procedure. The data identify each household’s address and the transformer through which it is served.²⁴ Given the importance of transformers in the reliability of electricity services, we designed our sampling procedure utilizing data on this infrastructure.

The sampling procedure was implemented as follows. Seven villages within the district were selected for the project based on accessibility during winter months.²⁵ Within the seven villages, there were 248 eligible transformers.²⁶ The mean monthly household electricity

²⁴The data were provided, through a Data Use Agreement with the electricity utility, for all 40,000 households in one district. The utility, however, was not informed as to which transformers or households were being treated through the experiment.

²⁵This was to ensure that survey enumerators could reach households in March, when weather conditions make transportation challenging.

²⁶Transformers providing at least 5 entities with electricity were eligible. According to the utility, transformers serving a smaller number of entities likely serve a business, not residential consumers.

consumption was calculated for all of these transformers. The 124 transformers with below median household electricity consumption are included in the sample.²⁷ To complete the sampling process, 20% of households from each transformer were randomly selected for the survey.²⁸ There is heterogeneity in the number of households per transformer, so the exact number sampled per transformer varies.

3.2 Experimental design with randomized saturation

The randomized saturation design varies household exposure to the CFL technology to test for evidence of the household energy efficiency effect, spillovers in take-up, and evidence of a technological externality due to aggregate impacts. The randomization occurs through a two-staged process, as shown in Figure 1. First, transformers are randomized to differing intensities of treatment saturations and then households within those transformers are randomly assigned to either receive CFLs (according to the saturation previously-assigned in the first stage) or to control status. A more detailed explanation of these stages is included in the paragraphs below.

The first stage randomization proceeded as follows. The 124 transformers were randomized into three groups: control transformers (39 in total), transformers with lower intensity of treatment (45 transformers), and transformers with higher intensity of treatment (40 transformers). As mentioned in the sampling discussion above, 20% of households in each transformer were surveyed. In control transformers, no households are treated. In transformers assigned a lower intensity of treatment, 60% of surveyed households are treated. In transformers assigned to a higher treatment intensity, 80% of surveyed households are treated. Due to heterogeneity in the number of houses per transformer, this results in approximately 12 to 16% of all households assigned to treatment within treated transformers.

In the second stage of the randomized saturation design, households were randomized into treatment and control groups, according to the transformers' previously assigned treatment saturations. This results in 457 control households and 543 treated households. By definition, all treated households are in treated transformers; they just differ as to whether they

²⁷The districts near the capital are better off than the country's other regions. The study sample is not representative of the entire country. In an effort to include households more typical of the country as a whole, the study design focused on selecting households with electricity use below the district median.

²⁸Due to funding constraints, households in only 25 of the 39 control transformers were surveyed. This resulted in households in 110 transformers being surveyed.

are in high or low saturation transformers. Control households, however, can be in either control or treated transformers. An example outcome of this randomization is depicted in Figure 2.

In Spring of 2013, the baseline household survey was implemented in all treatment and control households.²⁹ Immediately after finishing the survey, all respondents were compensated 150 Kyrgyz soms (approximately 3.26 USD) for their time completing the survey.³⁰ At that point, baseline interaction with the control households was complete. After the baseline survey, treated households were able to receive up to 4 CFLs³¹ at a highly subsidized, randomly-drawn price.³² Treated households were told only about the opportunity to receive the CFLs after the baseline survey was complete. On average, treated households received 3.2 CFLs through the intervention.³³

4 Data, randomization checks, and compliance

4.1 Data

We use several datasets for this analysis, including electricity utility data, baseline and follow-up survey data, and GIS spatial data, which are matched at the household-level. All of these data are then matched to heating degree day data from a nearby weather station.

Electricity utility data: We utilize electricity utility records to identify both transformers and households for our randomized design. In addition, we use the electricity utility’s monthly household billing records, starting in October 2010. These data continue through September 2014. This provides observations 30 months prior to and 18 months following the

²⁹At that time, households were not informed of their treatment assignment.

³⁰As of 2011, the average monthly nominal employee wage was 9,352 KGS per month (or an estimated 467 KGS per day of work) (National Statistical Committee of the Kyrgyz Republic, 2012).

³¹We provided up to four CFLs as pilot surveys indicated that, on average, households had five to six lightbulbs at baseline. We sought to replace most of their incandescent bulbs with CFLs.

³²All treatment households could purchase up to four CFLs via a willingness to pay experiment. The experiment, which utilizes the Becker-de Groot-Marschak methodology to measure demand for CFLs, is explained in Meeks (2016). The set of possible prices was $\{0, 5, 10, 15, 20\}$ for treated households. The market price for CFLs was a minimum of 100 KGS, so treated households were paying a maximum of 20% of market price. The market price for incandescent lightbulbs was between 15 and 20 KGS.

³³Take-up of CFLs was not 100% as some treated households opted to stop after the survey. In those cases, the household received zero CFLs. Compliance is discussed further below.

intervention, held in March 2013.³⁴ One important feature of this time period: electricity prices remained constant at 0.02 USD per kWh.³⁵

Household survey data: We conducted two rounds of household surveys, one immediately prior to the intervention (baseline) and one a year following the intervention (follow-up). For the baseline survey, representatives from the project visited individual households starting in late March 2013. Households in both the treatment and control groups were asked to participate in a survey regarding electricity use. The survey collected information on appliance ownership and use, lightbulb ownership (type, wattage, etc) and use (room of use, hours used in a typical day, etc), electricity-related behaviors, and various household demographics. Importantly, we ask households to report the number of days in the past month that they did not have electricity due to outages.³⁶ We also tracked the number of CFLs distributed to each treatment household.

We visited the same residential addresses one year after the intervention, in the spring of 2014. Of the original 1,000 respondents, 835 households were interviewed for the follow-up survey.³⁷ Survey respondents were again offered 150 KGS to compensate for their time. The follow-up survey repeated questions from the baseline, in addition to new questions on CFLs perception and understanding.

Spatial data: GPS data were collected on the location of each participating house during the baseline survey. These data points permit various calculations relevant to potential spillovers in adoption, including the distance to nearest treated household and the number of treated households within certain radii. In addition, we use GIS data from OpenStreetMap on locations of all buildings in the study villages. These data permit calculations of the total number of households located within various radii (e.g., 100 meters, 200 meters, and so on) of each participating household. The calculations of the total number of buildings are further

³⁴The utility was not collecting transformer-specific outage data at the time of the intervention. Because electricity consumption data are monthly, we cannot use those data to calculate timing of outages.

³⁵A tariff reform was introduced in late 2014 (see McRae and Meeks (2016) for details of reform) and therefore we end our analysis in September to avoid conflating the CFL intervention with the tariff change.

³⁶These questions were piloted extensively prior to the baseline survey. We asked about the number of days due to heterogeneity in outage length. The transformer repair required and availability of replacement parts determines the outage length after a transformer overload. According to the utility, transformer outages last between a few hours and a few days.

³⁷Survey enumerators made at least four attempts to survey the household. If enumerators were informed that the previous respondents had moved, then the new residents were surveyed.

described in Appendix Calculation 1.

4.2 Study sample

Households in the sample are highly-educated, with 84% of household heads having finished secondary school. Household monthly income per capita is an average of 76 USD per month (2.45 USD per person per day). The average household size is just under 4 individuals. Most houses (91%) are owner-occupied, the majority of which were constructed during the Soviet Union. On average, the homes are comprised of 4.3 rooms and are typically constructed of brick (54%) or a hay/adobe mix (38%).

Houses are served by formal connections to the electrical grid and metered individually (i.e., houses do not share meters). Households receive a monthly electricity bill based on readings of the meters documenting their consumption. Amongst households in our sample, the average baseline summer electricity consumption is 232 kWh per month. Average winter electricity consumption is more than double that amount (633 kWh per month). Self-reported heating fuels include coal (80% of households report heating with coal at least sometimes) and electricity (39%). Many households report trying to conserve on heating; respondents reported heating an average of 3/4 of rooms during winter.

Households, on average, have 8 electricity-using durables in their homes. Almost all homes have a television and refrigerator. Approximately three-quarters of households have electric stoves, an iron, and a clothes washing machine. A much smaller proportion have an electric hot water heater (14%) and almost no respondents (2%) have air conditioners. Saving electricity is a major concern for households. Approximately 95% of households indicated that they frequently worry about saving electricity, whereas 86% report that they take some measures to save electricity. More than half the households reported knowing about energy efficient lightbulbs. However, energy efficient technologies were rarely used; households had only 0.17 CFLs, on average, prior to the intervention.

4.3 Randomization check

To understand the outcome of randomization, baseline characteristics were compared both at the transformer and household levels. Appendix Table 1 provides results from the transformer-level balance tests, which used both household survey data and data on trans-

former characteristics, as provided by the electricity utility. There are no statistically significant differences between the transformers treated with a low intensity and the control transformers, nor were there any statistically significant differences between the high intensity transformers and the control transformers. The high and low transformers do have one significant difference from each other: the number of households within the transformers. Following Bruhn and McKenzie (2008), we chose not to re-randomize and instead control for this characteristic in related regressions and perform additional robustness checks.

Results of the household-level balance tests are shown in Appendix Table 2. The two household-level treatment groups are statistically identical along most dimensions. There are, however, two slight differences. Treated households are slightly less likely than control households to have a household head that has completed secondary school education. In addition, control households are slightly more likely to be in homes that are single family buildings (in comparison to the multi-unit apartment buildings). If anything, we believe these differences would downward bias our results. Essentially all households in all groups, however, have their own individual electricity meters.

A graph of pre-intervention electricity consumption over time (in Appendix Figure 1) highlights importance heterogeneities in electricity consumption over a year and shows the same seasonal patterns for both treatment and control households. The large spike in winter electricity consumption is due in large part to electric heating and is the reason that electricity outages are most frequent in that season.³⁸ We also note that the winter peak is somewhat greater amongst the treated households than the control in both pre-intervention winters (winter 2011 and winter 2012). For this reason, including household fixed effects and month-by-year fixed effects in our analysis will be crucial.

4.4 Compliance

There are two aspects of compliance with which we might be concerned: (1) compliance with treatment (whether or not they took the CFLs that we distributed as the treatment) and (2) inhabiting the home at time of follow-up survey. We address compliance in the following ways.

First, upon completion of the baseline survey, treatment households were asked to continue

³⁸Longer hours of lighting due to shorter days play a lesser role.

on to a module addressing energy efficiency. A portion of the treatment groups refused to continue after the baseline survey (before the households learned of their treatment assignment). These households therefore do not receive the CFLs. The rate of non-compliance was 12%. For our intent-to-treat estimates, these households are considered treated.

Second, as of spring 2014, 101 addresses (of the original 1000 surveyed households) were identified as having new tenants in the year since the intervention. We interviewed households currently living at the original addresses, as it was difficult to know exactly when residents moved or if the CFLs had moved with them. Analysis can perform the analysis two ways: including all households (movers + non-movers) and then excluding those houses with new tenants (just non-movers). Results are consistent across these analyses.

5 Establishing the impact of energy efficient lighting

Prior to estimating the intervention’s impacts, we first calculate the technologically feasible expected electricity reductions for the winter, spring/fall, and summer seasons.³⁹ Using baseline survey and intervention data, we calculate expected impacts assuming an average 3.2 incandescent lightbulbs (100 watts each) are replaced by project CFLs (21 watts each).⁴⁰ These calculations and their underlying assumptions are further described in the Appendix and results of these calculations are in Appendix Table 3. Electricity consumption is expected to decrease by between 26 and 42 kWh per month, in summer and winter respectively.

Although the technologically feasible electricity reductions are straightforward to calculate, they do not account for the interaction of behavior with the technology. The actual effect of CFLs on electricity consumption could be negative, zero, or positive. Results with impacts that are smaller than the technological feasible expected impacts or even zero or positive could be explained by channels such as a rebound in electricity consumption, a reduction in electricity outages permitting more electricity services, or an externality that is biasing estimates. The randomized saturation design helps us understand the impacts of energy efficient lighting and untangle the channels through which they operate.

³⁹Through our discussions with the electricity utility in fall 2012, we learned that the winter (or “heating season” as they refer to it) the time of greatest electricity demand and period of greatest strain on the transformers.

⁴⁰During early survey piloting, we learned that households typically used 100 watt bulbs in their homes. We provided 21 watt CFLs, because they were advertised to be equivalent to 100 watt incandescent bulbs.

We start with an event study-style graph of electricity consumption month-by-month (Figure 3), which motivates our regression analysis in the following sections. In this graph, we plot the technologically feasible expected electricity reductions, as described in the paragraphs above. Alongside that, we plot the estimated impact of CFL treatment (the result of comparing treatment relative to control households in control transformers) month-by-month.⁴¹

There are a few key points to take away from this graph. First, the figure shows a downwards shift in electricity consumption for treatment households post-intervention (with CFL distribution starting late March 2013). Second, the impacts of CFL treatment are quite noisy, particularly in the winter months. This noisiness is likely due to some households heating with electricity in the winter (which would cause a large spike in their electricity consumption), while others heat with coal. Although they indeed have reductions in electricity consumption, this noisiness might make these reductions less salient for treated households. Third, there is much heterogeneity in the impacts across seasons. We see electricity savings grow in the months following the distribution of the energy efficient lightbulbs in the spring summer, and fall of 2013. However, during the winter months, the actual impacts of the energy efficient lightbulbs diverge greatly from the predicted impacts. In the spring of 2014, the electricity savings returns to a size that is similar in magnitude to the predicted amount. To better understand the impacts of the CFL treatment, we continue with a regression analysis.

5.1 Basic estimates of impacts on electricity consumption

To estimate the reductions in electricity consumption observed in our project households, we first estimate a simple difference-in-differences model:

$$q_{it} = \tau Treat_i * Post + \beta Post_t + \delta Treat_i + \alpha X_{it} + \gamma_t + \lambda_i + \epsilon_i \quad (1)$$

where q_{it} is household electricity consumption (kWh), $Treat_i$ is an indicator of treatment status, X_{it} is a vector of household controls, γ_t are month-by-year fixed effects, and λ_i are household fixed effects.⁴² The $Treat_i * Post$ indicator in the equation above denotes the

⁴¹Because this calculating the treatment impact separately for each month, we cannot include household fixed effects here.

⁴²We could also control for heating degree days; however, The 7 villages in the study sample are all covered by one weather station. Therefore we do not have spatial variation in temperature, only variation in

assignment to T and if that treatment occurred in that month or prior months.

We report intent to treat estimates, which are identified from variation within households over time, controlling for the month-by-year shocks to all households. The coefficient on the interaction term, τ , is an estimate of the average change in household monthly electricity consumption (in kWh) that resulted from random assignment to treatment.

Table 1 Column 1 reports results from this basic estimation, in which the omitted group is comprised of all control households, regardless of whether they are in a treated or control transformer. These basic results indicate the CFL treatment reduces household electricity consumption by 16 kWh per month; however, the magnitude of this impact is only half the expected size. This regression addresses issues identified in the event study graph (potential heterogeneities in baseline electricity consumption across households, large seasonal variation in consumption). However, if there are any externalities, we may be mis-estimating the impact of adopting the energy efficient lighting technology.

5.2 Accounting for spillovers in estimated impacts

The randomized saturation process provides variation in the proportion of households treated within a transformer. We use this variation to test whether externalities may be affecting our estimates of the impacts of the CFL treatment. If there were externalities impacting control households, then our results calculated via equation 1 will be biased. For example, it is feasible that there are spillovers in take-up of CFLs amongst control households.

Externalities impacting electricity consumption

We account for the potential transformer-level externalities through specifications in a fashion similar to that used in Gine and Mansuri (2011) and Banerjee et al. (2014). The basic version of this equation is:

$$Y_{ig} = \beta Treat_{ig} + \theta C_{ig} + \sigma X_{ig} + \epsilon_{ig} \quad (2)$$

where Y_{ig} is our outcome of interest for household i located in transformer group g ; $Treat_{ig}$ is an indicator for treatment status of household i in transformer group g ; C_{ig} is an indicator

temperature over time. We do not expect, however, for there to be much spatial variation in temperatures across the villages included in the study.

that equals 1 if the household i is a control household in a treated transformer group; and X_{ig} is a vector of potential controls, including the number of houses served by a particular transformer. The coefficient θ provides an estimate of the average impact of being a control household in a treated transformer. Importantly, the omitted group in these regressions is now a “pure control” group, in that it only includes control households that are located in control transformers.

To re-estimate the impacts of household-level treatment on electricity consumption, accounting for potential externalities within the transformer, we employ the following difference-in-differences version of equation 2:

$$q_{igt} = \tau Treat_{ig} * Post + \beta Post + \delta Treat_{ig} + \theta C_{ig} * Post + \phi C_{ig} + \alpha X_{ig} + \gamma_t + \lambda_{ig} + \epsilon_{igt} \quad (3)$$

Results presented in Columns 2 and 3 of Table 1 indicate that the CFL treatment led to a reduction in electricity consumption of 30 kWh per month. When accounting for potential within transformer externalities, the impacts of the CFLs on household electricity consumption are statistically significant, substantially larger than estimates in column 1, and comparable to the expected reductions. A comparison across columns 2 and 3 shows that coefficients are significant regardless of the level at which standard errors are clustered.

It is clear that not accounting for potential externalities biased estimates of the impacts of technology adoption on electricity consumption. These biases could be caused by spillovers in take-up, a local aggregate reliability effect, or some other channel. That we also see a significant reduction in electricity consumption amongst control households in treated transformers suggests spillovers. To better understand these processes, we analyze seasonality of impacts, spillovers in take-up, and aggregate impacts on outages.

5.3 Impacts on electricity consumption by season

Based on our calculations of the expected electricity savings, ex ante we believed that electricity consumption reductions would be greatest in the winter (followed by fall/spring and then summer).⁴³ We estimate the same difference-in-differences regression as shown in equation 3, but run the regression separately for each season. We divide the months according to

⁴³These differences in expected electricity consumption across seasons are a function of differences in the hours of sunlight throughout the year.

the electricity utility’s seasonal definitions, with the winter heating months including November, December, January, and February. Results in Appendix Table 4 also show that our ex ante predictions were incorrect. The only season in which the impacts of treatment are of the magnitude expected and statistically significant is spring/fall. Impacts in the winter and summer seasons are far smaller than expected. Both the results in Table 1 and those in Appendix Table 4 highlight ways in which estimates of the effects of energy efficiency could be biased, if we do not account for potential externalities and heterogeneity in impacts across seasons.

That savings in electricity consumption returns to the expected amount in the spring (following the winter spike) suggests that this is not driven by a longer-term rebound effect. If there were a rebound effect occurring here, we would expect to see a more persistent change in behavior, rather than this reversal in the spring. We cannot rule out the possibility of a rebound; however, we performed a number of tests (results not shown) and find no evidence of a direct or indirect rebound in electricity consumption. For example, using detailed survey data on both baseline and follow-up appliance use, we find no effects of treatment on lightbulb use. We find only one significant effect of treatment on appliance use: treatment households are significantly less likely to report using electric heaters at follow-up. If anything, these results are counter to a rebound effect.

The results in Figure 3 are also consistent with a technological externality in the form of a reduction of electricity outages in the winter. Winter is when unplanned outages most frequently occur, as peak electricity demand is quite high. CFLs have the potential to reduce electricity consumption, but they also have the potential to reduce outages in winter (more than any other season). If households have more reliable electricity service (fewer outages) in the winter, then they will be able to consume more electricity services and we would not see the expected reduction in electricity consumption. Results in Appendix Table 4 are also consistent with households in higher intensity treatment transformers consuming more electricity.

5.4 Spillovers in CFL Take-up

Are there indeed spillovers in CFL take-up following the intervention (as implied by Table 1)? Table 2 shows results estimating the impact of treatment on the number of CFLs in a house at the follow-up survey, controlling for the number of CFLs distributed to the house-

holds at baseline. The omitted group is detailed at the bottom of each column. Similar to column 1 in Table 2, column 1 in this table will be biased, as the omitted group is all control households.

We expect that control households located very close to a treated household are likely to experience some spillovers.⁴⁴ We utilize the spatial variation in exposure of control households to close treated neighbors induced by the two-stage randomization.⁴⁵

We use the following equation to account for potential peer effects in technology adoption:

$$Y_{ig} = \beta Treat_{ig} + \theta C_{id} + \rho N_d + \theta X_{ig} + \epsilon_{ig} \quad (4)$$

where Y_{ig} is our outcome of interest for household i located in transformer group g ; T_{ig} is an indicator for treatment status of household i in transformer group g ; C_{ig} is an indicator for if the household i is a control household with at least one treated household within 100 meters from the house; N_d is the total number of households within 100 meters from the house; and X_{ig} is a vector of controls, including the number of CFLs the household received from our project at baseline. Standard errors are clustered at the transformer level.

Results from this specification, in column 2, indicate that both treated and control households have an average of half an additional CFL at follow-up. There are two important things to note about these results. First, the coefficient on the *Treat* variable in column 2 is dramatically different from that in column 1, making clear that estimates of the household energy efficiency effect on later take-up are downward biased when we do not account for externalities. Treatment households have a greater stock of CFLs at follow-up, controlling for the number of CFLs the households received from our project. This suggests that they likely purchased CFLs themselves between baseline and follow-up. Second, we see a positive and statistically significant relationship between being close to a treated household and the number of CFLs that household has at follow-up.

In column 3, we show an alternative way to measure potential spillovers in take-up by in-

⁴⁴We consider a control household to be “close” if the entrance is within 100 meters of a treated household. We choose 100 meters as the cutoff, as some prior analyses of peer effects on a number of outcomes variables had suggested that this distance was an important cutoff, past which the effect dissipates.

⁴⁵Our measure of a close link between households is a distance measure of proximity between households. As discussed in Breza (2015), a number of studies have used geographical proximity to measure spillovers, including Dupas (2014), Godlonton and Thornton (2012), and Cohen, Dupas and Schaner (2015).

cluding a dummy variable for control households in treated transformers. This specification is meant to mirror the specification used to correct for externalities when measuring the impacts of CFL treatment on electricity consumption, as shown in Equation 2. This result should be (and is indeed) similar to column 2, given that households within the same transformer tend to be in close proximity spatially.

6 Aggregate effects of load reduction

6.1 Reduction in outages

In this section we provide evidence of a technological externality resulting from the CFLs, in the form of fewer outages for all households within the treated transformers. As is not uncommon in developing countries, outages in this context are typically the result of overloads within the distribution system. These overloads occur most frequently in winter (and in the winter evenings, particular) when household energy demand is greatest.

To motivate this analysis, we seek to better understand the impact of energy efficient lighting on peak demand. This is important as outages are typically caused by transformer overloads during peak times and lighting is disproportionately “on peak.”⁴⁶ We perform a back-of-the-envelope calculation of the peak load reduction induced by the CFL treatment. Calculations, which are shown in the Appendix Calculation 3, indicate that switching 4 incandescent lightbulbs to CFLs could save 60 kWh per month, which would be 10% of a 600 kWh monthly bill. But if the lights are being used at peak times, as we expect them to be, it would be a 21% reduction in household peak demand.⁴⁷ For a transformer with approximately 20% of households treated, this would equal approximately a 4% reduction in peak load for the transformer.⁴⁸

Using data from the follow-up survey on the number of days without electricity (due to outage) during the month prior, we can estimate the impact of transformer-level treatment on unplanned outages.⁴⁹ First, we provide basic evidence of an aggregate impacts on outages

⁴⁶According to the utility, times of peak demand are between 6 to 9 am and 6 to 10 pm.

⁴⁷This is assuming a reduction of peak demand of 1.5 kW peak and switching from 100 W incandescent bulbs to 21 W CFLs, per our calculations in the Appendix.

⁴⁸We also “ground-truth” these results by discussing them to our utility collaborators. Engineers indicated that this would be a substantial reduction in peak demand and would very likely reduce transformer outages.

⁴⁹The follow-up survey occurred in March and April 2014, so the months in which we are measuring days

by plotting the reported outages at follow-up by treatment group. As shown in Figure 4, the distribution of reported outages amongst households in treated transformers is shifted leftward (towards zero outages) than the graphed responses from households in the control transformers. This figure provides suggestive evidence and motivates the regression analysis that follows.

We use this transformer-level randomization to estimate the impact on reported unplanned electricity outages using the following equation:

$$O_{ig} = \pi H_{ig} + \rho L_{ig} + \beta T_{ig} + \eta X_{ig} + \epsilon_{ig} \quad (5)$$

where O_{ig} is the number of days without electricity due to outages in the month prior to the follow-up survey as reported by household i in transformer g ; H_{ig} is a dummy variable if household i is in a transformer with between 15 to 18 percent of households assigned to treatment; L_{ig} is a dummy variable if household i is in a transformer with a between 10 to 14 percent of households assigned to treatment; T_{ig} remains the household’s own treatment status; and X_g is a vector of transformer controls, in particular the number of houses served by a particular transformer. Standard errors are clustered at the transformer level. We also perform the standard error correction for multiple hypothesis testing developed by List, Shaikh and Xu (2016).

Results in Table 3 indicate that the energy efficient technology led to an aggregate impact in the form of improved reliability. Column 1 shows this basic result. We see between one and two fewer days without electricity in both the low and high intensity transformers. Results are robust to including a suite of different transformer level controls, most important of which is the number of households within the transformer and the baseline number of outages reported. Column 2, in which we are controlling for the reporting household’s own treatment status, shows that the responses from the treated households are not driving results.⁵⁰

This reduction in days without electricity due to outages is only statistically significant for households in the high saturation transformers. Column 2 indicates that households in high

without electricity due to outage include February and March.

⁵⁰High saturation transformers have more treatment households (by definition), so we might have been concerned that those households have an incentive to report fewer outages. Controlling for individual household treatment shows that such an outcome is not a concern.

intensity treatment transformers report approximately half as many (2.2 in comparison to 3.8) days of outages as households in control transformers. We test for the significance of difference between the high and low intensity transformer groups and, in column 2 this difference is statistically significant.⁵¹

Lastly, we test for evidence of the technological externality, by re-estimating the impacts of CFL treatment on electricity consumption, breaking up the analysis by transformer saturation level. Importantly, these analyses still use variation induced by the randomized saturation process. Results of these regressions, shown in Table 4, are consistent with a technological externality. These results indicate a difference between the transformers with lower and higher intensities of treatment in the extent to which a technological externality is created. The households that take-up the energy efficient bulbs in a lower intensity transformer appear to create some positive externality in that they are, to some extent, reducing the load on the transformer. The reduction in the days without electricity due to outages at the transformer is smaller and insignificant for the lower intensity transformers, but has the same sign and is of a similar magnitude as the higher intensity transformers. In contrast, the households that take-up the CFLs in the higher intensity transformers generate a positive externality that is, in the aggregate, substantial enough to significantly reduce the number of days without electricity due to outages. This externality becomes closer to our working definition of a technological externality, in that the more individuals that take up the technology, the greater are the returns to the technology.⁵²

In summary, the CFLs exert a significant reduction in electricity consumption that, when controlling for potential externalities, is of a similar magnitude to that which is technologically feasible. When a large enough proportion of households take-up the CFLs, an aggregate effect is possible in the form of a technological externality: a reduction in electricity outages. These reductions are experienced by all households served by the impacted transformer, regardless of whether they themselves are treated or control households.

⁵¹We can and have also run these regressions collapsing to the transformer level and using the average reported outages per transformer. In doing, we get similar results; however, in using the transformer level average, we lose our ability to control for the respondent household's own treatment status. For this reason, the specification displayed in Table 2 is our preferred.

⁵²We think of this as an analogy to children within a school being vaccinated against a disease, such as measles. Vaccinated children provide a positive externality to non-vaccinated children. With each additional child vaccinated, it should reduce the probability of a measles outbreak within the school; however, the proportion of children within the school that are vaccinated must surpass some threshold in order for the school community to achieve herd immunity.

6.2 Robustness checks

We perform multiple robustness checks of our results to ensure that we are indeed measuring a local aggregate reliability effect. First, we calculate the intra-cluster correlation in reported outages at follow-up. We have argued that intense treatment of households within a transformer is causing a reduction in outages at the transformer-level. If this is indeed the case, then household reported outages should be correlated with other household responses within the transformer.⁵³ Our calculation indicates a intra-class correlation of 0.56, which means that responses within transformers are indeed highly correlated.

As a second robustness check, we consider the above reduction in outages in light of the difference between the expected reduction in electricity consumption and the estimated reduction in electricity consumption. Ex ante, we expected a reduction in winter electricity consumption of approximately 42 kWh per month. However, we estimated the actual reduction in monthly winter electricity consumption to be approximately 26 kWh per month. This is a difference of approximately 16 kWh per month. This is equal to approximately 14.4 hours of additional electricity consumption. Taken in conjunction with results above indicating two fewer days without electricity per month, this would mean two outages of approximately seven hours in duration each. This is a perfectly reasonable result.⁵⁴

6.3 External validity

We implemented this randomized saturation design in a developing country context in which reliability of electricity services is a substantial concern for both households and the electricity utility. Electricity reliability in this context is largely driven by congestion within the distribution network, which leads to transformer overloads. The constraints in electricity distribution networks are an issue in many developing countries and will become a greater concern as countries develop and residential electricity demand increases and exceeds the limits of existing infrastructure. As such, we believe this work is relevant to many developing countries in which demand for electricity is rapidly increasing.

⁵³Responses won't be perfectly correlated with one another, as households in a transformer were surveyed on different dates and therefore the reference point of "past month" differs.

⁵⁴Anecdotal evidence from both consumers and the utility indicate that outages can last between a few hours to a few days, depending on the repair required following the transformer overload.

7 Conclusions

Through an experiment with a randomized saturation design, we provide several substantial contributions to the literatures on energy efficiency, electrification, and electricity reliability. We show that energy efficient lightbulbs can indeed lead to significant reductions in electricity consumption. We find that controlling for spillovers is critical, suggesting that estimates of energy efficiency that do not account for such spillovers may be downward biased.

In addition, we show that the energy efficient technology, when taken up at a high enough intensity, can have a local aggregate reliability effect, in the form of fewer days without electricity due to outages at the transformer level. By improving electricity service reliability, the energy efficient technology becomes more valuable; households can use the CFL for more hours when the electricity service is more reliable (i.e. providing electricity for more hours per month). This is a classic example of a technological externality, through which the returns to a particular technology are increasing with the number of other adopters.

Finally, the paper provides a novel application of a randomized saturation design at a policy-relevant and technologically meaningful scale. In doing so, we demonstrate the usefulness of such designs to inform our understanding of aggregate impacts and technological externalities from various interventions. This methodology can be applied to the study of many other topics, for which decomposing private returns and technological externalities is important in the process of choosing between different policy options or program subsidy levels.

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Figure 1: Randomized saturation process

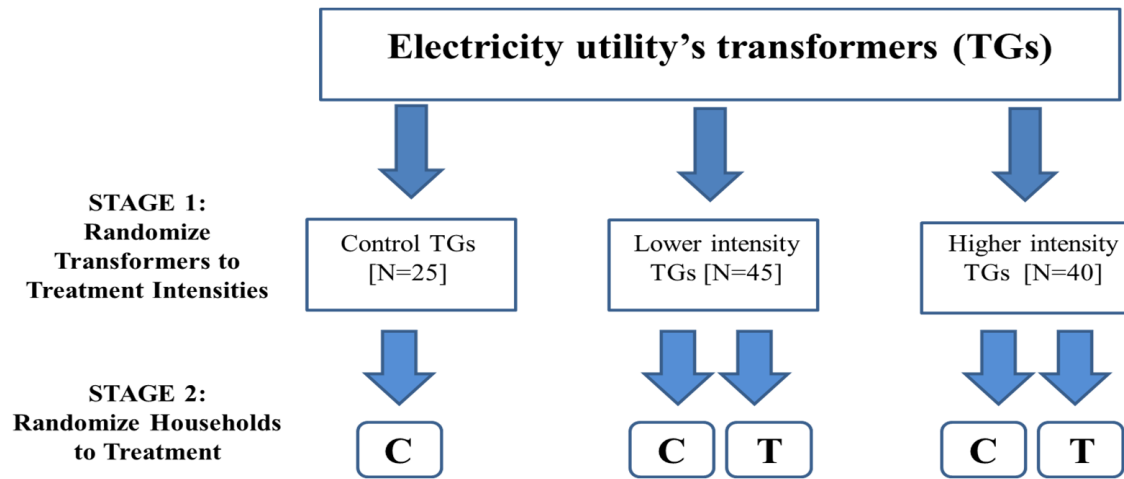


Figure 2: Example of randomized saturation design

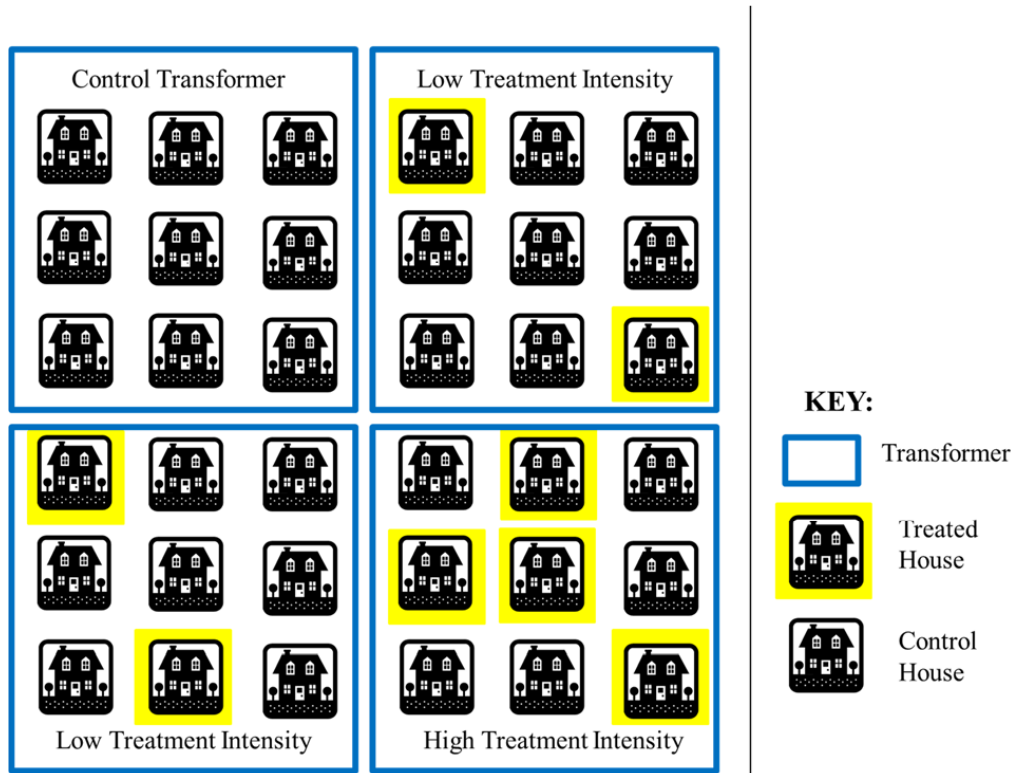


Figure 3: Predicted and actual electricity reductions (kWh per month)

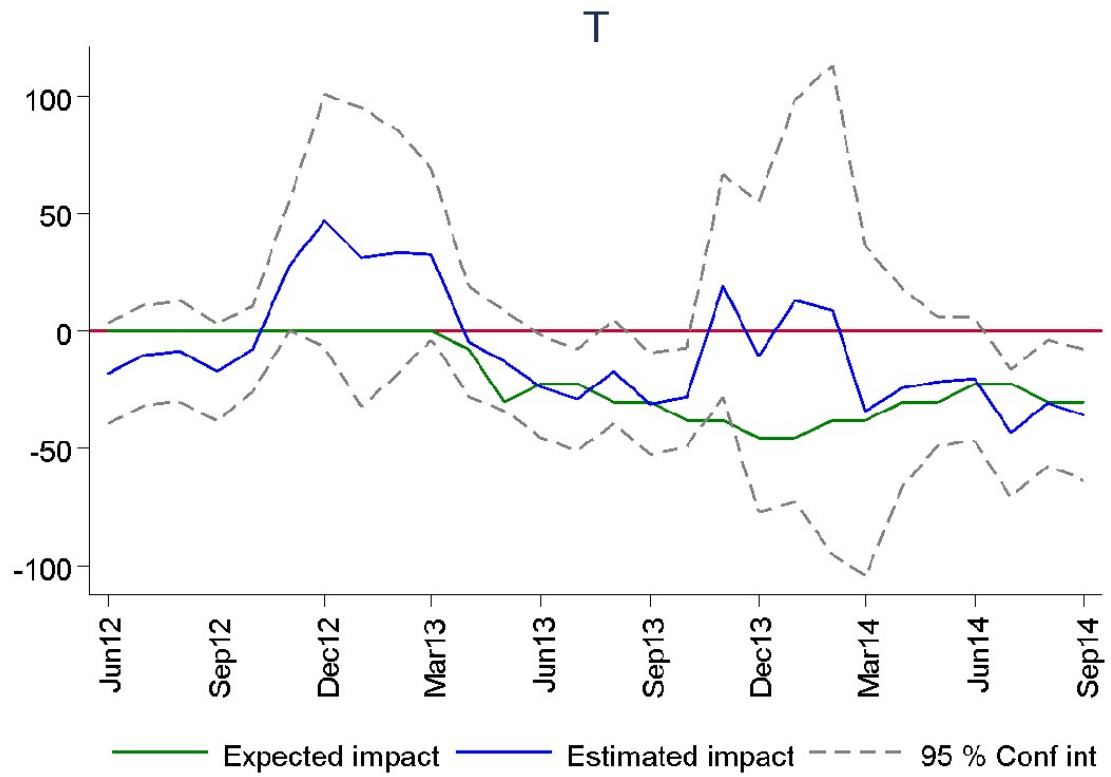


Table 1: Impacts of treatment on household electricity consumption

Dependent Variable: Monthly Household Electricity Consumption (kWh)			
	(1)	(2)	(3)
Treated*post	-16.269* (8.803)	-29.949*** (11.399)	-29.949*** (10.434)
Control in treated TG*post		-25.086** (12.579)	-25.086** (12.384)
Omitted group	All control houses	Houses in Control TGs	Houses in Control TGs
Std error cluster level	Household	Household	Transformer
Households	899	899	899
Observations	31,143	31,143	31,143

Notes: Results are intent-to-treat. All regressions include month-by-year fixed effects, household fixed effects, and controls for heating degree days, number of days in monthly billing period, whether the household uses electricity for heating, and dummy variables for Treated and Post. Columns 2 and 3 also include a dummy variable for being a control household in a treated transformer. 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). "TG" is the abbreviation for transformer group. Standard errors are in parentheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table 2: Spillovers: CFL Stock at Follow-up

Dependent Variable: Number of CFLs at Follow-up			
	(1)	(2)	(3)
Treat	0.185 (0.174)	0.442** (0.212)	0.479** (0.219)
C close to Treat		0.458** (0.207)	
Control in treated TG			0.502** (0.205)
Constant	0.617*** (0.187)	0.365* (0.204)	0.332* (0.199)
R-squared	0.012	0.013	0.012
Omitted group	All controls	Controls far from T	Controls in control TGs
Observations	834	834	834

Notes: All specifications control for the total number of households in the transformer and the number of CFLs received at baseline through the project. A "C close to Treat" is an indicator for a control household located < 100 meters from treated household. "Controls far from T" are control households location > 100 meters from a treated household. Standard errors are clustered at the transformer level, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Figure 4: Reported days without electricity per month, by transformer treatment

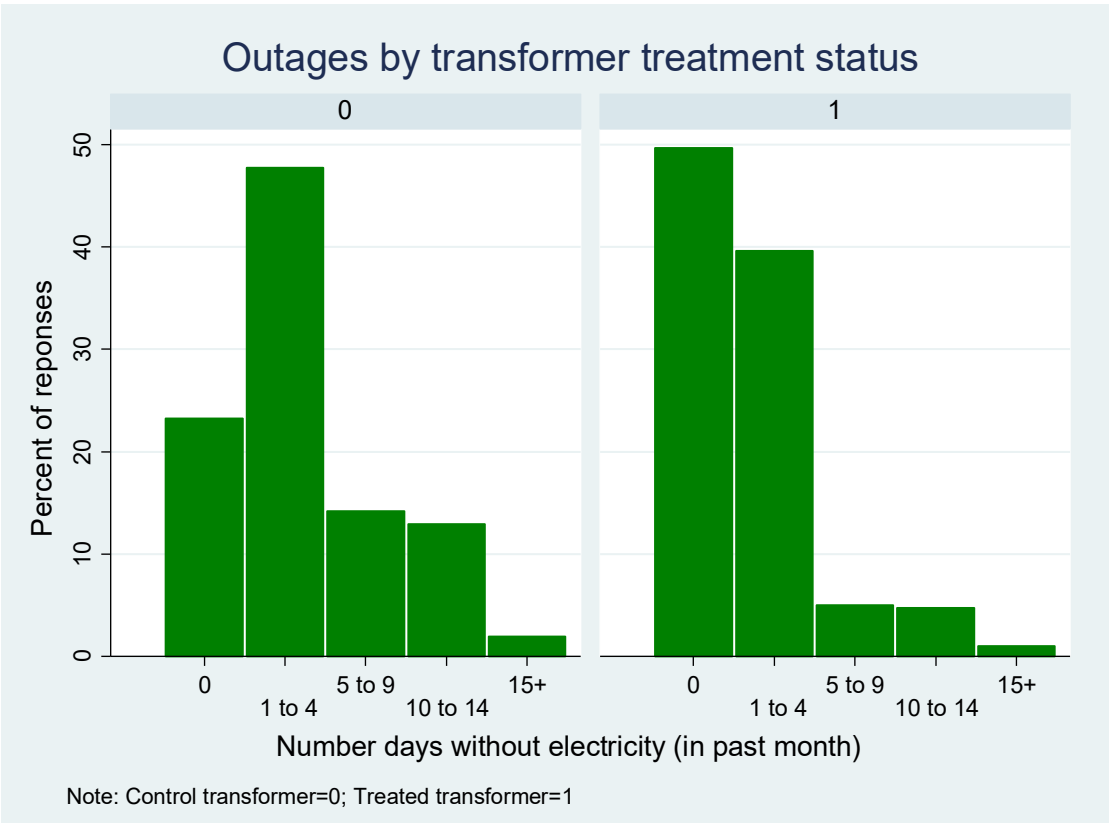


Table 3: Technological externalities: improved electricity reliability

Dependent Variable: Number of Days Without Electricity (in past month)		
	(1)	(2)
TG low saturation	-1.321 (0.851) [0.433]	-1.164 (0.868) [0.434]
TG high saturation	-1.866** (0.812) [0.000]	-2.162*** (0.822) [0.000]
Household treatment status controls	No	Yes
Constant	3.810*** (0.836)	3.811*** (0.838)
p-value: TG low = TG high	0.228	0.047
Observations	838	838
R-squared	0.051	0.053

Notes: "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. Omitted group is comprised of households in control TGs. All columns control for the number of households in the transformer. The "Household treatment status controls" are separate binary indicators that equal to one when a treated household is in either a low or high saturation transformer. 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 for accounting for multiple-hypothesis testing (List, Shaikh, and Xu, 2015) are showm in brackets.

Table 4: Technological externalities: Heterogeneous impacts by transformer treatment saturation

Dependent Variable: Monthly Household Electricity Consumption (kWh)		
	(1)	(2)
Treated household in TG low * Post	-42.798*** (12.025)	-41.392*** (13.320)
Treated household in TG high * Post	-22.269* (11.911)	-20.337 (13.752)
Control household in TG low * Post	-42.986*** (13.713)	-50.243*** (13.769)
Control household in TG high * Post	13.014 (16.355)	21.283 (17.893)
Controls for reported outages	No	Yes
Omitted group	Houses in Control Transformers	Houses in Control Transformers
Observations: households	31,143	26,043

Notes: The omitted group is comprised of houses in control transformers. "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. All regressions include time fixed effects, household fixed effects, and controls for heating degree days, number of days in monthly billing period, and the use of 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). Std errors are clustered at the transformer level, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Appendix: For on-line publication

Appendix Table 1: Transformer-level randomization check

	Number of Transformers	Control Transformer	Lower Transformer (<=14%)	Higher Transformer (>14%)	Joint F tests (p-value)		
					Control = Low	Control = High	Low = High
<i>Panel A: Household-level</i>							
HH head completed secondary school	111	0.8	0.88	0.74	0.415	0.572	0.111
Household income (Kyrgyz soms)	111	13107.08	12647.62	13285.47	0.842	0.938	0.748
Own house	111	0.88	0.95	0.84	0.380	0.602	0.105
Private house	111	0.88	0.83	0.74	0.649	0.185	0.312
Number of rooms	111	4.32	4.50	4.14	0.584	0.582	0.203
Lightbulbs in house	111	6.36	6.21	6.23	0.831	0.851	0.975
<i>Panel B: Transformer-level</i>							
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
Proportion of HH with 3 phase meter	110	0.28	0.28	0.34	0.951	0.102	0.068

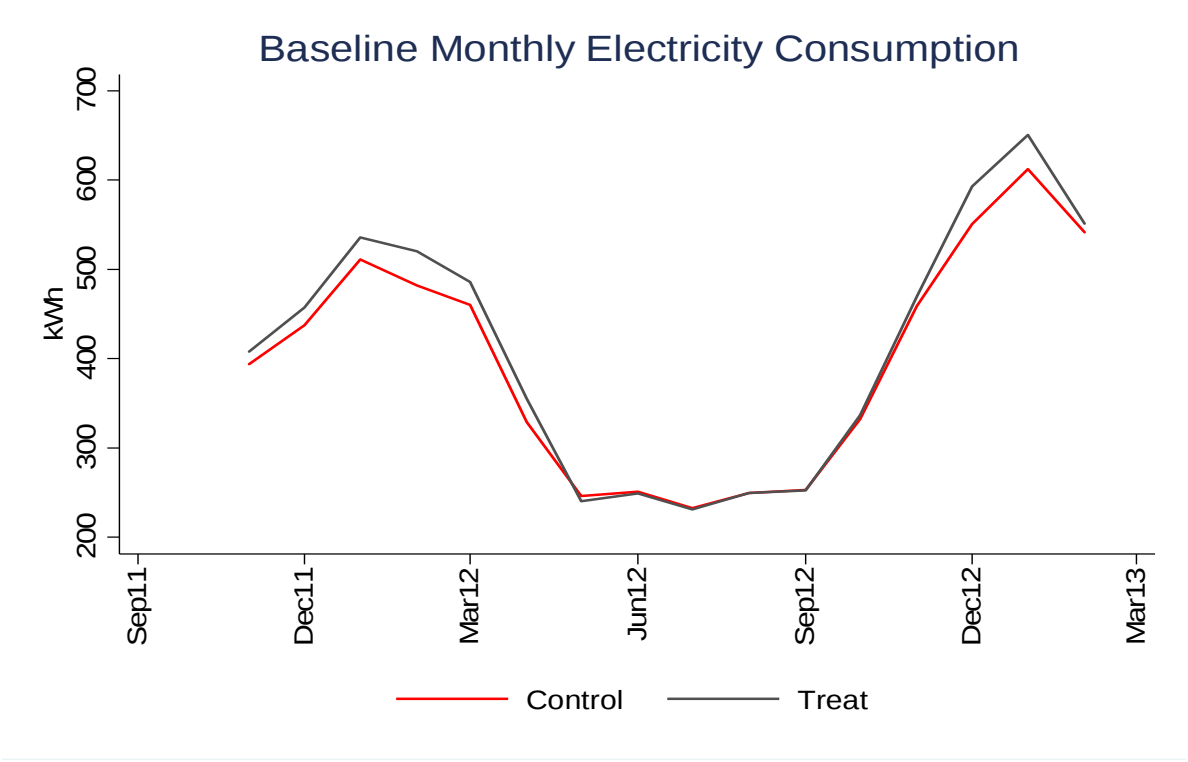
Notes: Panel A calculated using responses from the baseline household survey. 20% of all households in a transformer were surveyed at baseline. These household responses were then used to create transformer-level averages. Panel B is calculated using transformer-specific data provided by the electricity utility. Exchange rate

Appendix Table 2: Household-level randomization check

	All	Control	Treatment	Joint F tests (p-value)
	(1)	(2)	(3)	(4)
<i><u>General characteristics</u></i>				
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
<i><u>Housing characteristics</u></i>				
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
<i><u>Electricity consumption practices</u></i>				
Total number of appliances	8.393	8.578	8.238	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
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
Believe CFL use less energy	0.305	0.319	0.292	0.436
Rooms heated in winter	3.14	3.12	3.15	0.764
Days without electricity in the past month	1.66	1.58	1.75	0.338
Number of households	1000	457	543	

Note: In March 2013, the exchange was 1USD = 48 KGS. For these calculations, the winter months include November through February and summer months include May through August. Baseline surveys were implemented in the late spring and early

Appendix Figure 1: Seasonality of electricity consumption pre-treatment



Appendix Calculation 1: Number of residential buildings

To control for the total number of households within various radii from project households, we use spatial data on residential building locations available through OpenStreetMap.org. The ArcGIS building layer for Kyrgyzstan was downloaded from OpenStreetMap in March 2015. We calculate the total number of residential buildings within radii of project households. Radii were of the following sizes: 100 meters, 200 meters, 300 meters, and 400 meters.

The following building types are considered residential for the calculation: residential, house, farm, dormitory, and apartment. Industrial and commercial buildings were omitted from the residential building count. ArcGIS aerial photographs were used to cross-check the building counts and also to manual add building polygons in areas not completely covered in data from OpenStreetMap.

Calculations needed to account for multi-family buildings, which are prevalent in districts near to the capital (such as the study district). Buildings were defined to be multi-family residential buildings if (1) the building polygon has an area of 369 square meters or more or (2) at least one side of the building is longer than 19.4 meters. These thresholds were made based on a random sampling of buildings and visual interpretation of the images. Fortunately for variable construction, essentially all multi-family residential buildings in this region were constructed during the Soviet Union and were built according to very standardized specifications. This permits us to make several assumptions regarding the number of households per building. We assume these multi-family buildings have 5 floors each and that each stairwell has 3 units per floor. The number of stairwells assumed depends on the size of the building.

Appendix Calculation 2: Technologically feasible electricity savings from CFLs

The expected technologically feasible electricity savings from the treatment can be calculated through the following equation:

$$\text{Expected electricity savings/month} = \# \text{ Incandescent bulbs replaced with CFLs} * (\text{CFL wattage} - \text{Incandescent wattage}) * (\# \text{ hours Incandescent bulbs used per day}) * (\text{days in a monthly billing period})$$

We calculate the technological feasible electricity savings using data from the project pilot in Fall 2012, the baseline survey in Spring 2013, and the intervention through which CFLs were distributed. On average, treatment households received 3.2 CFLs through the intervention.

We know from piloting exercises and the baseline survey data that 100 watt incandescent bulbs were most common in households prior to the intervention. The project's 21 watt CFL replacement bulbs were selected, as they were rated to be 100 watt equivalent bulbs. Therefore we know that households, on average are shifting from 100 watt to 21 watt bulbs. The calculations also use data on the self-reported hours lighting of use at baseline.

Estimates of hours of lighting use are extrapolated using data on the timing of sunrise and sunset in the region and how it changes throughout the year. These predictions assume behavior with respect to lighting and other electricity uses remain constant after the intervention, which is consistent with our results comparing behavior at the baseline and follow-up.

These calculations of the expected impacts on electricity consumption are shown below. Based on these data, electricity consumption is estimated to decrease by between 26 kWh per month (summer) and 42 kWh per month (winter). The percent by which the electricity bill is expected to decrease in each season is also calculated.

Appendix Table 3: Expected impacts on electricity consumption

Assumptions	Winter scenario	Spring/Fall	Summer scenario
Average number of light bulbs replaced	3.2	3.2	3.2
Incandescent wattage	100	100	100
CFL wattage	21	21	21
Average hours per use per day	5.5	4.5	3.5
Average monthly bill (kWh)	586	340	245
Prop bill in lighting baseline	0.090	0.127	0.137
Expected CFL savings (kWh)	41.712	34.128	26.544
Expected reduction in bill (no rebound)	7.1%	10.0%	10.8%

Notes: These calculations are for an estimated scenario. For these calculations, the winter months include November through February; spring/fall months include March, April, September, and October; and summer months include May through August. Average number of light bulbs replaced is based on the actual numbers of CFLs distributed on average through the intervention. Average hours of use per day are calculated using the baseline survey data and data on sunrise and sunset to estimate for the rest of the year. CFL wattage is actual wattage for the light bulbs that were distributed. Incandescent wattage is the typical wattage found in households at the time of the baseline survey. Calculations are assuming an average of 30 days per month. Average monthly electricity bill is calculated using baseline electricity use during the year prior to the intervention.

Appendix Table 4: Impacts of treatment on household electricity consumption by season

	(1) Winter Electricity consumption (kWh)	(2) Spring/fall Electricity consumption (kWh)	(3) Summer Electricity consumption (kWh)
Treated*post	-25.538 (32.171)	-32.375*** (10.985)	-8.835 (6.672)
Control in treated TG*post	-26.314 (35.203)	-8.373 (13.906)	-12.114 (8.041)
Households	899	899	899
Observations	10680	9784	10679

Notes: The omitted group is comprised of households in control transformers. All regressions include time fixed effects, household fixed effects, and controls for HDD, # days in billing period, and dummy variables for Treated and Post. Columns 2 and 3 also include a dummy variable for being a control household in a treated transformer. 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 transformer levels, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Appendix Calculation 3: Back-of-the-envelope expected peak load reduction

Times of peak demand are in the early morning and in the evening. Lighting is disproportionately “on peak.” To better understand the impact that switching from incandescent bulbs to CFLs could have on peak load, we perform a back-of-the-envelope calculation based on data from our sample and some informed assumptions. The calculation is as follows:

- We assume a household’s winter monthly electricity demand is 630 kWh per month, which is based on data from our sample.
- Dividing this by the number of days per month and number of hours per day, we estimate an average hourly winter electricity demand of .875 kW.
- We assume that peak load is approximately 70% more than average load, which is in line with the U.S. Energy Information Administration’s calculations for peak-to-average electricity demand ratios. Therefore, household peak is 1.49 kW.
- We assume the household has 4 incandescent bulbs (100 W each) that replaced by CFLs (21 W) used in our project. This change would reduce peak load by 0.32 kW.
- Given our estimated peak demand of 1.49 kW, reducing peak load by 0.32 kW represents a 21% reduction in peak demand for a household.
- For a transformer with 20% of households making this shift to CFLs, this would mean a 4% reduction in peak load for the transformer.