Energy Efficiency and Electricity Reliability*

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May 2018

Abstract

Overloaded electrical systems are a major source of unreliable power. Using a randomized saturation design, we estimate the impact of energy efficient lightbulbs on local electricity reliability and household electricity consumption in the Kyrgyz Republic. Greater saturation of compact fluorescent lamps (CFLs) within a transformer leads to two fewer days per month without electricity, a technological externality benefitting all households regardless of individual adoption. Receiving CFLs significantly reduces households' electricity consumption, but increased reliability permits greater consumption of electricity services. At follow-up, CFL adoption spillovers are greater among control households in high saturation transformers, where reliability improves.

Keywords: Energy Efficiency, Externalities, Reliability
JEL: D01, D62, O13

*We thank Arstan Omuraliev and Ruslan Isaev for invaluable input. We are grateful to Sendhil Mullainathan, Rohini Pande, Rema Hanna, Claudia Goldin, Kelsey Jack, Sebastian Bauhoff, Jeremiah Johnson, Hunt Allcott, Raymond Guiteras, Shaun McRae, Mushfiq Mobarak, Ach Adhvaryu, Michael Moore, Catie Hausman, Judd Boomhower, Paul Ferraro, as well as many seminar participants for helpful discussions and comments. Cholpon Chargynova, Saikal Nogoibaeva, Merim Japarova, Wincy Poon, Ryoko Sato, and Daniel Velez-Lopez provided excellent research assistance. Generous funding was provided by the Harvard Sustainability Science Program, Harvard Graduate Student Grant, the University of Michigan, the Weiser Center, and the National Science Foundation (Award #1061989). AEA RCT Registry #AEARCTR-0000461. All errors are our own.

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1 Introduction

Overloaded power distribution systems are a major problem for electricity service provision. When the electrical grid is asked to deliver more power than its capacity allows, overloads may cause grid components, such as local distribution transformers,[1] to fail and result in unplanned outages and unreliable electricity services (Lawton et al., 2003; Sullivan et al., 2009; Singh and Singh, 2010).[2] This problem is likely to worsen in the future. Experts fear distribution failures will become more common as climate change and growing electricity demand put further pressure on the existing electrical grid (Wolfram, Gertler and Shelef, 2012; EOP, 2013; Auffhammer, Baylis and Hausman, 2017), requiring prohibitive investments in infrastructure (ASCE, 2011).[3]

With this in mind, programs distributing energy efficient technologies potentially provide an additional benefit beyond reducing emissions associated with electricity generation and decreasing the cost of energy services to technology adopters. Energy efficient technologies are frequently deployed via government programs with the specific goals of reducing peak demand and increasing reliability of electricity services (Osborn and Kawann, 2001; Gillingham, Newell and Palmer, 2006; World Bank, 2006). Efficient lighting technologies, such as compact fluorescent lamps (CFLs) and, more recently, light emitting diodes (LEDs), are a particularly popular technology choice of energy efficiency programs.[4] These technologies are a relatively accessible option for end-users, for whom lighting comprises 86% of electricity consumption in developing countries and 15% in the developed world (Mills, 2002).[5]

[1]Overloaded transformers are a critical binding constraint in electricity distribution systems. Transformers on the electrical grid convert high-voltage electricity to usable, low-voltage electricity for household consumption. Each transformer can transfer a certain maximum electricity load at any given time and exceeding that load may cause breakage (Glover, Sarma and Overbye, 2011).

[2]Unplanned outages are more common in developing countries, but developed nations have distribution failures too. For example, these can occur in heat or cold waves when users run cooling or heating units.

[3]In the United States, an estimated additional investment of $107 billion is needed by 2020 to keep the electricity infrastructure functioning, of which $57 billion is for distribution and $12 billion is for generation. Failure to achieve this will cost households $71 billion and businesses $126 billion by 2020 (ASCE, 2011).

[4]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 aiming to reduce peak load and increase service reliability (amongst other goals) include: 800,000 CFLs distributed 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).

[5]For industrialized countries, use of electricity for lighting ranges from 5% (Belgium, Luxembourg) to 15% (Denmark, Japan, and the Netherlands) of total electricity use, whereas in developing countries it is up to 86% (Tanzania) (Mills, 2002). Lighting is 10% of total US electricity consumption (EIA-OEA, 2018).

Moreover, consumption of lighting services tends to occur at peak times, making efficient lighting particularly pertinent for peak load reduction and avoiding overloads.

The gains from efficient lighting programs are potentially high.[6] CFLs, which are engineered to consume 75% less electricity per lumen relative to traditional incandescent bulbs, are expected to deliver important electricity savings without requiring adopters to decrease their lighting services consumed (DOE, 2009).[7] Moreover, as electricity savings reduce the stress on distribution infrastructure, a sufficient saturation of efficient lighting can induce a technological externality in the form of a more reliable electricity supply for *all* end-users served by the same transformer, regardless of their own adoption of the technology (Trifunovic et al., 2009).[8] Improved reliability would permit *all* end-users to utilize more hours of electricity services, allowing increased consumption of electricity and additional productive use.[9]

Although programs deploying efficient lighting are ubiquitous and ostensibly promising, there is fairly little evidence to date on their impacts.[10] Perhaps more notably, there is a dearth of evidence on the reliability effects of CFLs and energy efficient technologies more broadly. Whether impacts on reliability are empirically possible is nevertheless 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. The improvement in reliability resulting from CFL distribution is a form of technological externality. Technological externalities and the technology saturation threshold at which they occur are known to govern the take-up and impacts of other technologies (Miguel and Kremer, 2004; Cohen and Dupas, 2010).[11] Adoption and the benefits from adoption of en-

[6] Although we study CFLs specifically, our findings are also valid for LEDs, which are even more efficient.

[7] In practice, electricity savings may differ from engineering estimates, as they depend on the technology and the interaction of end-user behavior with such technologies (Allcott and Mullainathan, 2010).

[8] For a particular technology, adoption of the technology by others is said to generate a positive (negative) technological externality if an individual's returns to the adoption of such technology increases (decreases) in the fraction utilizing the technology (Foster and Rosenzweig, 2010). With potential for greater consumption of electricity services, the value to a given household from adopting efficient lighting is expected to increase with improved electricity reliability at some threshold of CFL saturation.

[9] This premise - that more reliable electricity service permits a household or enterprise to operate for additional hours - differs from other potential responses to energy efficiency, such as a "rebound effect" (Gillingham, Rapson and Wagner, 2016) or an increase in worker productivity during hours in which a factory operates due to less heat waste (Adhvaryu, Kala and Nyshadham, 2018).

[10] Exceptions include Costolanski et al. (2017) and Adhvaryu, Kala and Nyshadham (2018), neither of which address this technological externality.

[11] 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

ergy efficient technologies are similarly likely to hinge on the reliability externality that can result from mass distribution of these technologies.

To assess the impacts of CFLs and test for the technological externality in electricity reliability, we implemented an experimental distribution of CFLs in a district adjacent to Bishkek, the capital of the Kyrgyz Republic.[12] In a novel application of a randomized saturation design (Baird et al., 2018), we employ the electricity utility's data on its residential customers and the transformers through which these consumers are served.[13] In each transformer we sample 20% of the households into the study. We randomly assign treatment status in two stages. First, we consider the technologically-relevant level at which the reliability externality typically occurs. We randomize electricity transformers to control, low or high CFL treatment saturations, with 0, 60 or 80 percent of *study* households treated, respectively. This results in 10 to 14 (15 to 18) percent of *all* households within low (high) saturation transformers being assigned to treatment.[14] Second, we randomize households individually to treatment and control groups, according to the transformer saturation intensity assigned 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 on average 6.2 lightbulbs of which 0.2 were CFLS. Treated households received 3.2 CFLs, on average, through this intervention.

We begin by measuring the impacts of CFLs on outages and residential electricity consumption. We collect a panel of survey data on households' reported days without electricity due to unplanned outages.[15] Analysis of the electricity utility's billing data on household monthly electricity consumption, which extends for 18 months post-intervention, confirms the outage result.[16] We find that transformers with a higher CFL saturation have fewer

of price variation on the need of the marginal consumer, and (4) the presence of nonlinearities or externalities 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.

[12]The Kyrgyz Republic is a lower-middle-income developing country, in which electricity reliability is a concern. At baseline, CFLs were available in few stores and were not commonly used outside the capital.

[13]The use of multi-level randomized saturation permits the clean identification of treatment impacts when there is 'interference', namely, when a unit's outcome depends on the outcomes of other units in a same group of reference (Baird et al., 2018).

[14]Power calculations informed the design decisions regarding technology saturation, so as to detect effects.

[15]Data on outcomes related to infrastructure failure, particularly electricity reliability and incidence of outages, are typically difficult to acquire for developing countries (Klytchnikova and Lokshin, 2009). Therefore recent research on the relationship between electricity reliability and firm-level outcomes uses "shortages" or "scarcity" as proxies for reliability of electricity services. For examples, see Fisher-Vanden, Mansur and Wang (2015) and Allcott, Collard-Wexler and O'Connell (2016).

[16]Because firms may adapt to electricity shortages by adopting generators (Steinbuks and Foster, 2010),

days reported without electricity due to unplanned outages, controlling for baseline outages. We consider this positive evidence that energy efficiency programs can improve electricity reliability, if they reach sufficient levels of saturation.[17] The impacts of CFL distribution on electricity consumption vary according to whether there are effects on reliability. CFLs' energy savings are larger and significant only in low saturation transformers, where no effect on outages was found. The reduction in monthly electricity consumption observed for treated households in low saturation transformers falls within the expected range for the technology based on engineering performance estimates. Our evidence indicates that households in high saturation transformers with improved reliability are consuming greater electricity services due to fewer outages–an improvement in household welfare.

To better understand CFL adoption, we examine how control households' take-up varies with CFL saturation, and therefore with electricity reliability, within a transformer. There is evidence of spillovers in take-up, as control households in treated transformers have significantly more CFLs than the "pure" control households at follow-up. Take-up of CFLs is higher among control households in high saturation transformers compared to those in low saturation transformers. We interpret this finding with caution, given that differences in CFL adoption by transformer saturation is statistically insignificant. Nevertheless, this result is consistent with back of the envelop calculations of the expected benefits from using CFLs for scenarios with and without reliability externalities. We take these spillover findings to suggest that households *may* learn more from their neighbors and *may* value the additional electricity consumption and services supplied by CFLs, which are only possible in the presence of increased electricity reliability.

Using these results we perform a simple cost-benefit analysis, which illustrates the importance of accounting for the reliability externality in estimating the welfare impacts of CFL deployment programs. Benefit calculations that include both reductions in electricity consumption and increased electricity services are more than double the traditional estimates. Given this potential externality, an evaluation of an energy efficiency program that only focuses on its direct beneficiaries may substantially underestimate the full program impact.

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their self-reported outages suffer from systematic measurement error (Fisher-Vanden, Mansur and Wang, 2015). Our sample contains households, only one of which uses a generator for lights or appliances, eliminating this concern.

[17] This result is robust to including a number of controls and supported by calculations of expected peak load reduction.

Our experiment contributes to the literature in several ways. First, our experiment applies a recent innovation in experimental design to the estimation of technological externalities in the domain of energy efficiency. Multi-level randomized saturation designs are increasingly used by a new wave of empirical work focused on the estimation of 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 also highlighted the importance of technological externalities in the study of technology take-up and pricing (subsidization) and in the assessment of program impacts and cost-effectiveness (Miguel and Kremer, 2004; Cohen and Dupas, 2010; Ashraf, Berry and Shapiro, 2010).[18] Nevertheless, given the scale at which technological externalities typically occur, designing an experiment that can identify such externalities has been challenging.[19] As a result, there is relatively little causal empirical evidence on them.[20] We employ this novel experimental design to deliberately induce a technological externality in terms of improved electricity reliability, by taking into account the constraint within the electricity distribution system that typically causes electricity outages and randomly varying the saturation intensity of CFLs at that level. In doing so, our study contributes to various literatures concerned with energy efficiency, technological externalities, technology adoption, and program evaluation in the presence of interference.

Second, our experiment contributes to the debate regarding the impacts of energy efficient technologies, their potential to reduce household energy demand, and their promise as potentially welfare-improving. Recent experimental and quasi-experimental studies of home weatherization - a form of energy efficiency - programs in the United States suggest that

[18]In the context of these studies of health products, the technological externaltity takes the form of herd immunity (deworming pills), a decline in the mosquito population (bednets), or more general health externalities from a drinking-water disinfectant (Clorin).

[19]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."

[20]Miguel and Kremer (2004) provide experimental evidence of positive cross-school externalities from deworming medicines in Kenya, but rely on more tentative 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.

realization rates from energy efficiency upgrades can be lower than engineering predictions (Fowlie, Greenstone and Wolfram, 2017; Allcott and Greenstone, 2017).[21] Contributing to skepticism regarding the gains from energy efficiency, Davis, Fuchs and Gertler (2014) found that a refrigerator and air conditioner replacement program in Mexico also did not deliver to the engineering expectations, possibly due to increased appliance use or additional product features. Energy efficient lighting, which is a significantly different type of intervention than these, is less studied, particularly in experimental settings.[22] We contribute to this literature, finding that the estimated impacts of energy efficient technology distribution vary with the level of technology saturation, according to whether a technological externality in electricity reliability occurs. We also find that spillovers in adoption can significantly confound empirical estimates of impacts. In low saturation transformers, where no electricity reliability improvements are observed, our CFL treatment results in a statistically significant and meaningful reduction in electricity consumption. Accounting for spillovers in CFL adoption, this estimated reduction comes close in size to the expected engineering savings; that is a realization rate between 66 to 100 percent.[23] In high saturation transformers with improved reliability, electricity consumption increases due to more hours of electricity availability. This increase in consumption following the introduction of CFLs is a welfare improvement, not a sign of ineffective technology. Our study findings add nuance to the previous evidence and suggest that, given possible technological externalities and spillovers, energy efficient lighting and other energy efficient technologies should remain on the menu of policy options.

Third, our experiment contributes to the discussion regarding the adoption of energy efficient technologies and the energy efficiency gap. Cumulative research suggests an energy efficiency gap due to individuals not maximizing the net present value of their energy spending when making technology purchase decisions (Hausman, 1979).[24] A growing 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

[21]The realization rate compares engineering predictions and actual energy usage, generally relative to a control group. A 100% realization rate means that on average energy savings were as predicted.

[22]A non-experimental study of a large-scale CFL distribution program in Ethiopia found that electricity consumption was reduced by 45 kWh per household per month (Costolanski et al., 2017).

[23]This finding resembles recent machine-learning estimates from schools in the United States, with results indicating substantial electricity savings from the energy efficient lighting interventions (Burlig et al., 2017).

[24]Building upon Hausman (1979), many believe households are not using energy efficient technologies when they should. Energy 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.

and Greenstone, 2012; Gillingham and Palmer, 2014).[25] In contrast, very little attention has been paid to the role of spillovers in adoption decision and technological externalities in electricity reliability, concerning all end users, adopters and non-adopters. We show that spillovers in CFL adoption depend on exposure to the technology and intensify when electricity reliability improves. At higher CFL saturation, there are more neighbors to learn from and CFLs can get more use due to fewer outages. Therefore, adoption and the benefits from adoption of CFLs increase with the level of technology saturation within a transformer. This finding provides an additional economic rationale for mass deployments of energy efficient technologies. In our study setting, greater technology saturation is associated with improved electricity reliability. In developed contexts, where failure in distribution systems is less common, it may still lead to lower electricity costs. Overall, spillovers and technological externalities are key parameters underlying the impacts of mass deployment and subsequent adoption of energy efficient technologies. Considering these effects, the level of private investment in some energy efficient technologies may be even less optimal than previously thought.

Finally, our study connects with the literature on infrastructure and development. Research indicates that electrification is important for development (Dinkelman, 2011; Lipscomb, Mobarak 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 infrastructure does not guarantee reliable service (Klytchnikova and Lokshin, 2009). Electricity outages can impact both households (Chakravorty, Pelli and Marchand, 2014) and firms (Allcott, Collard-Wexler and O'Connell, 2016; Alam, 2013), yet low-quality electricity infrastructure can be persistent (McRae, 2015), potentially compelling demand-side interventions such as ours.

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. Sections 6 and 7 present analysis of residential electricity consumption and adoption of CFLs, and discusses evidence of technological externalities in electricity reliability and spillovers in technology take-up. Section 8 addresses external validity. Section 9 concludes.

[25]Interventions to understand or increase purchase of energy efficient technologies have included energy labeling (Newell and Siikamaki, 2015), social norms (Herberich, List, and Price, 2011), information on energy costs (Allcott and Taubinsky, 2015), and subsidies (Allcott and Sweeney, 2016).

2 Experiment setting

The Kyrgyz Republic provides a suitable context in which to study energy efficiency and electricity reliability in a developing country setting. As of 2012, this lower-middle income nation ranked 147th out of 187 countries for GDP (PPP) per capita. Nevertheless, due to its history as part of the former Soviet Union, it is highly electrified. Nearly 100 percent of Kyrgyz households are covered by formal electricity connections and the residential sector consumes 63% of the country's current electricity supply (Gassmann, 2014).

The country's utilities face growing electricity consumption while constrained by infrastructure designed for substantially lower demand. Much of the existing electricity infrastructure dates back to the Soviet Union, including all 16 power plants (Zozulinsky, 2007).[26] The distribution network was constructed for peak electricity consumption in line with limited household ownership of appliances. As households purchased more electricity-using durables following the country's 1992 independence, peak household electricity demand has increased.[27] In the years prior to our study, most of the 35/220 kV transformers - the last step in delivering electricity to homes - had a load factor of between 0.9 and 1.2, which is substantially greater than the optimal load of 0.7 (Amankulova, 2006). Electricity outages have been frequent[28] and transformer overloads serve as the primary source of these distribution failures and unreliable electricity services.[29]

In our study setting, 54 households on average receive their electricity via a single transformer. Many households heat with electricity in winter, leading to large seasonal variations in electricity consumption. On average, winter consumption is approximately three times that of summer. Unplanned outages thus typically occur in the winter months, when local distribution transformers are more likely to experience an overload. When a transformer overload results in an outage, all households sharing the transformer are without electricity services. Constrained transformer capacity is not only a concern for consumers but also for the utility, as the electricity utility is not selling electricity to households during an outage.

[26] Ninety percent of electricity generation capacity is hydroelectric.

[27] Electricity consumption by the Kyrgyz residential sector is steadily increasing, consistent with predicted pro-poor economic growth in developing countries more broadly (Obozov et al., 2013).

[28] In 2010, the country had 12,578 unplanned power outages (approximately 34 outages per day), which is considered unreliable service by international standards (USAID, 2011).

[29] According to the electricity utility, planned outages and rolling blackouts (e.g. due to fluctuations in reservoir water levels) did not occur during our study period.

In spite of low residential electricity prices ($0.02 per kWh throughout this study), household energy expenditures comprise an estimated 7.1 percent of total household expenditures (Gassmann, 2014). Worries regarding electricity bills and energy expenditures are common and households report knowing and taking actions to cut them back.

Despite both the need to reduce peak electricity demand within the distribution system and residential consumers' expressed desire to minimize energy expenditures, very few households used CFLs outside of Bishkek, the capital city, prior to this study. CFLs were available for purchase only in large home repair stores and markets within Bishek[30] and sold for prices between 100 and 170 Kyrgyz soms, depending on the quality.[31] In contrast, incandescent lightbulbs were available to purchase in both rural and urban markets for approximately 15 to 20 Kyrgyz soms. Even with these low electricity prices, the payback period for the CFLs was between 1 and 2 years.[32]

Households in our study sample are small, with an average of just under 4 members. Household monthly income per capita is on average 76 USD per month (2.45 USD per person per day) and household heads are educated, with 84 percent having finished secondary school. Most households (91 percent) live in owner-occupied homes. They comprise an average of 4.3 rooms, and are typically constructed of brick (54 percent) or a hay/adobe mix (38 percent).

Households are served by formal connections to the electrical grid, are metered individually (i.e., houses 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). On average, households have 8 electricity-using durables[33] and many households (39 percent) report heating with electricity.[34] A small proportion have an electric hot water heater (14 percent), and almost none (2 percent) have air conditioners. Only 1 household

[30]Residents of districts adjacent to the capital frequently travel to the city and could have purchased CFLs pre-intervention.

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

[32]Payback period calculations (not shown) were based on typical lightbulb use in our sample and electricity and CFL prices within the region. We show cost-benefit calculations later in the paper.

[33]Almost all homes have a television and refrigerator. Approximately three-quarters of households have electric stoves, an iron, and a clothes washing machine.

[34]Households conserve on heating. Most households report heating their houses at least sometimes with coal (80%), and on average they heat 3/4 of all their rooms during winter.

reported having an electricity generator for purposes such as lighting.

Our study households largely indicate that they both frequently worry about saving electricity (95 percent) and take measures to save electricity (86 percent). More than half the households report knowing about energy efficient lightbulbs (56 percent). However, the use of CFLs was low. Only a few households had them, and in small numbers (resulting in 0.17 CFLs per household, on average). The majority of households did not know or believe that CFLs consume less electricity (70 percent), did not expect savings in their electricity bill from replace incandescent bulbs with CFLs (72 percent), and did not believe the electricity savings would pay back the upfront costs of the CFLs (69 percent). Households were also unaware of differences in quality (88%) and in potential electricity savings (80%) between different types and brands of CFL.

3 Randomized experiment with energy efficiency

3.1 Sampling process

For our sampling procedure, we used data from electricity utility records on over 40,000 residential customers in a district adjacent to Bishkek, the country's capital. These records contain crucial information to identify each of the households in the district as well as the transformer through which each household is served.

Within the study district, we chose seven villages (comprising 248 eligible transformers) due to their accessibility from Bishkek during the winter months.[35] We further restricted the sample to the 124 eligible transformers with below median monthly household electricity consumption in the year prior to the intervention. Such households and transformers in this peri-urban setting are experiencing rapid growth in electricity demand, putting a stress on existing electricity infrastructure. To complete the sampling process, 20 percent of the households from each transformer were randomly selected to participate in the study. Because the number of households per transformer is heterogeneous, the exact number sampled in each transformer also varies.

[35] Transformers providing at least 5 households with electricity were eligible. According to the electricity utility, transformers serving fewer households likely also served industrial consumers.

3.2 Experimental saturation design

The randomized saturation design varies household exposure to the CFL technology within a transformer, to test for a technological externality effect, and its subsequent impact on CFL adoption. Transformers are first randomized to differing treatment saturations, and then households within those transformers are randomized either to receive CFLs or to control status, according to the saturation previously assigned.

Figure 1 depicts how treatment status was randomly assigned in two stages. In the first stage, the 124 sampled eligible transformers were randomized into three groups: control, lower treatment saturation, and higher treatment saturation. Due to funding constraints, households in 14 control transformers were not surveyed. This resulted in only 110 eligible transformers being finally included in the study, with 25, 45, and 40 transformers in control, lower and higher saturation groups respectively. In each transformer 20 percent of the households were sampled into the study. In control transformers, no study households were treated. In lower-saturation transformers, 60 percent of study households were treated. In higher-saturation transformers, 80 percent of study households were treated. Thus, the first stage randomization results in approximately 10 to 14 (15 to 18) percent of all households within low (high) treatment saturation transformers being assigned to treatment.

In the second stage, a total of 1,000 study households within the 110 transformers were randomized into either control or treatment status. This resulted in 457 and 543 households in each group respectively. By design, as depicted in Figure 2, treated households are found only in treated transformers, in the proportions set by each transformer's treatment intensity. Control households, however, can be in either control or treated transformers. The two stages of randomization also induced spatial heterogeneity in the location of the treated households, leading to variation in the proximity to and number of treated neighbors.

3.3 Intervention

In the spring of 2013, all study households were visited and invited to participate in a baseline survey regarding electricity use. After finishing the survey, all households were given 150 Kyrgyz soms (approximately 3.26 USD) as compensation.[36] Interaction with the control

[36] As 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).

households was complete at this time.

Households randomly assigned to the treatment group were offered the opportunity to purchase up to 4 CFLs[37] at a highly subsidized, randomly-drawn price, via a willingness to pay experiment.[38] The set of possible prices, in Kyrgyz soms, was $\{0, 5, 10, 15, 20\}$. 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. On average, treated households received 3.2 CFLs via the intervention, paying an average price of 13 KGS per CFL. The rate of non-compliance to treatment was 12%, as some treated households opted to stop after the survey, thereby receiving zero CFLs.[39]

All study households were visited again in the spring of 2014, one year after the intervention, for a follow-up survey. Of the original 1,000 study households, 101 addresses were identified as having new tenants in the year since the intervention. We interviewed all 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.[40] A total of 835 original respondents were re-interviewed for the follow-up survey. Upon completion, survey respondents were again offered 150 KGS to compensate for their time.

4 Data

We collected baseline and follow-up household data through in-person surveys prior to the intervention (March 2013) and one year after (March 2014). Baseline and follow-up data include information on various household demographics, electricity-related behaviors, appliance ownership and use, lightbulb ownership (type, wattage, etc), lightbulb use (room of use, hours used in a typical day, etc.), and perceptions and understanding of the CFL technology. We track the number of CFLs distributed to each treatment household at baseline.

Importantly, both survey rounds asked households to report the number of days in the month

[37] We 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.

[38] The experiment utilizes the Becker-de Groot-Marschak methodology to measure demand for CFLs. The use of this method to elicit demand is demonstrated in Berry, Fischer and Guiteras (2015).

[39] For intent-to-treat estimates, these households are considered treated.

[40] Survey 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.

prior that they did not have electricity due to outages. The number of outage days was chosen as proxy of electricity reliability after extensive piloting and the electricity utility's input regarding heterogeneity in outage length.[41] Because fieldwork for both survey rounds began in March, the 'month prior' captures the occurrence of outages in winter months, when the electricity demand and stress on the transformers is the greatest.[42]

We supplement our household survey data with electricity utility data for the period starting in October 2010 and continuing through September 2014. This provides observations 30 months prior to and 18 months following the intervention. One important feature of this time period is that electricity prices remained constant at 0.02 USD per kWh.[43] The utility records identify both the transformers and households served by them, as well as the monthly electricity bills for each household. The utility did not collect transformer-specific outage data; however, analysis of household electricity consumption data in transformers with high relative to low CFL saturation is an important tool to corroborate results based on self-reported outages and address concerns about misreporting.

Furthermore, we collected GPS data on the location of each residence comprised in the study. These spatial data permit the calculation of measures relevant for the analysis of potential spillovers in adoption, such as the distance to nearest treated household and the number of treated households within certain radii.

4.1 Randomization balance

We compared baseline characteristics both at the transformer and household levels to understand the outcome of randomization. Comparisons use both household survey data and data on transformer characteristics, as provided by the electricity utility.

First, we highlight the lack of systematic differences in baseline demand for CFLs by transformer-level treatment saturation. To do so, we compare baseline experimental estimates of household demand for CFLs in Table 1. To further illustrate this point, we graph the distribution

[41] 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 after a transformer overload.

[42] For this reason, outages tend to be most prevalent in winter months.

[43] A tariff reform was introduced in late 2014 and therefore we end our analysis in September to avoid conflating the CFL intervention with the tariff change.

of per CFL unit bids in Appendix Figure 1. Additional transformer-level balance test results are shown in Appendix Table 1. There are no statistically significant differences between the low saturation transformers and the control transformers, nor are there any statistically significant differences between the high saturation transformers and the control transformers. The high and low saturation transformers do have one significant difference from each other. They differ in the number of households within the transformers. We can control for this characteristic in related regressions and perform additional robustness checks.

Results from the household-level balance tests are shown in Appendix Table 2. The two household-level treatment groups are statistically identical along most dimensions. Importantly, most households in all groups have their own individual electricity meters. There are, however, two slight differences. Control households are slightly more likely than treatment households to have a household head that has completed secondary school education, and to be in homes that are single family buildings (in comparison to the multi-unit apartment buildings). This difference is about what could be expected by chance. If anything, these differences would downward bias our results.

A graph of pre-intervention electricity consumption over time, in Appendix Figure 2, highlights important heterogeneities in electricity consumption over a year and shows the same seasonal variation 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. Longer hours of lighting due to shorter days play a lesser role. The winter peak is somewhat greater among the treated households than the control in both pre-intervention winters (winter 2011 and winter 2012). To account for these patterns, our analysis will include month-by-year fixed effects and either household fixed effects or the more stringent household-by-season fixed effects.

5 Impacts of energy efficiency on electricity reliability

As common in other settings, unplanned outages in the Kyrgyz Republic typically result from overloads within the distribution system. Overloads occur at times of peak electricity consumption, when electricity demand is greatest and distribution transformers are strained, causing outages.[44] In this section, we illustrate the potential for energy efficient lightbulbs to reduce peak electricity consumption at distribution transformers and then estimate the impacts on outages using household panel data.

5.1 Benchmarking impacts on transformer outages

To better understand the extent to which replacing incandescent bulbs with CFLs could feasibly result in aggregate impacts that reduce transformer outages, we performed a set of benchmarking calculations with three different seasonal scenarios. As further demonstrated and discussed in Appendix Calculation 1, we conduct these calculations in two steps. First, we calculate the potential reductions in electricity consumption induced by the intervention's household-level CFL treatment. Second, we calculate the potential transformer-level peak load reduction resulting from the aggregate adoption of CFLs within a transformer.

Our calculations indicate that switching 3.2 incandescent lightbulbs to CFLs could substantially reduce average household monthly electricity consumption, both in absolute value (kWh) and percent of monthly electricity bill. Changing to CFLs could save between 34 kWh per month in the spring/fall months and 42 kWh per month during the winter months; seasons with substantially higher demand than the summer. This represents a non-trivial percent reduction in household average monthly electricity bills, in both winter and spring/fall scenarios (7% of the 566 kWh winter average and 10% of the 340 kWh spring/fall average).

To affect outages, energy efficiency must do more than reduce average monthly electricity consumption. Overloads, and therefore outages, typically occur due to excess demand during times of peak load. Lighting is disproportionately used "on peak," meaning that it can contribute substantially to overloads. Therefore, we need to estimate the potential impacts of lightbulb replacement on peak load.[45] In step two of our benchmarking calculations, we calculate that the CFL intervention reduces household peak load by 19% (31%) in the winter (spring/fall). In the winter, this switch from 100 W incandescent bulbs to 21 W CFLs reduces peak load by 1.337 kW. For a distribution transformer with 20% of its households treated, this represents a 4% reduction in peak load. Appendix Calculation 1 provides details.

[44] In this setting, the months of peak demand are October through April. These months, called the "heating season" by the electricity utility, are peak months due to the use of electricity for heating services.

[45] According to the electricity utility, times of peak demand within a day are 6 to 9 am and 6 to 10 pm.

Electricity utility engineers claim that the above reductions would be sufficient to reduce transformer outages. In Figure 3, we plot the reported outages at follow-up by transformer-level CFL saturation, which provides evidence suggesting this occurs.[46] As the graph shows, 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 provides suggestive evidence of a relationship between transformer-level CFL saturation and outages, motivating the regression analysis that follows.

5.2 Estimating the impacts of CFLs on outages

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

$$O_{ig} = \pi High_{ig} + \rho Low_{ig} + \beta T_{ig} + \eta X_g + \epsilon_{ig} \tag{1}$$

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; $High_{ig}$ indicates if household i is in a higher-saturation transformer, with between 15 to 18 percent of all households assigned to treatment, regardless of the household's own individual treatment status; Low_{ig} indicates whether household i is in a lower-saturation transformer, with between 10 to 14 percent of households assigned to treatment, regardless of the household's own individual treatment status;[47] T_{ig} is an indicator equal to 1 if household itself was assigned to treatment; and X_g is a vector of transformer-level controls.[48] Standard errors are clustered at the transformer level.[49]

[46] 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. 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 in this way to prevent households from conflating system outages with other reasons (e.g. bill non-payment) for which the electricity might not function at their individual household.

[47] In higher (lower) saturation transformers, 80% (60%) of study households were assigned to treatment. There is heterogeneity in the number of households across transformers, and we sampled 20% of all households within each transformer to include them in the study. Therefore, the randomized study saturation proportions result in between 15 to 18 (10 to 14) percent of all households in high (low) saturation transformers actually receiving the CFL treatment

[48] We can and have also run these regressions collapsing to the transformer level and using the average reported outages per transformer. In doing so, 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.

[49] We also correct standard errors for multiple hypothesis testing, per List, Shaikh and Xu (2016).

Results in Table 2 indicate that the energy efficient technology led to an transformer-level impact in the form of improved reliability. Table 2, Column 1 shows the basic results at the transformer level, given by π and ρ in the equation above. We see between one and two fewer days without electricity in the low and high saturation transformers, respectively. However, the reduction in days without electricity due to outages is only statistically significant for households in the high saturation treatment transformers. They report approximately half as many days with outages as households in control transformers (two in comparison to four). The estimates are robust to including a set of transformer-level controls, such as the number of households within the transformer and the baseline number of outages reported.

High saturation transformers have more treated households (by definition) and one may be concerned that those households have an incentive to report fewer outages. To address this potential concern Table 2, Column 2, controls for the reporting household's own treatment status. Accounting for individual household treatment status indicates that such differential responses, if anything, may have biased the results downward. The coefficients for the high saturation transformers, when controlling for household treatment status, are slightly larger in magnitude (i.e. more negative) and the difference in outage-day reductions between households in high and low saturation transformers (two versus one) is also statistically significant.

These findings indicate that our energy efficient lighting technology reduced distribution outages, thereby demonstrating impacts on electricity reliability. If the intense saturation of treatment households within a transformer reduces outages at the transformer-level, then household reported outages should be correlated within a given transformer. As a robustness check, we calculate the intra-cluster correlation of the number of outages reported at follow-up.[50] Our calculation results in an intra-class correlation of 0.56, indicating that responses within transformers are indeed highly correlated and supporting our interpretation.[51]

6 How energy efficiency affects electricity reliability?

In this section, we decipher how CFLs generate the transformer-level impacts. The electricity utility's monthly household billing records are used to verify the results employing self-

[50] The cluster in this analysis is the transformer.

[51] Setting aside differences in recall, we knew ex ante that responses would not be perfectly correlated with one another, as households within a single transformer were surveyed on different dates and therefore the reference point of the "past month" can differ across households within a transformer.

reported outage measures in Section 5. If impacts on outages did occur, we should see evidence in the household electricity consumption data. We decompose the CFL treatment impact on household electricity consumption employing the random variation in treatment, at both the transformer- and household-levels, 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, shown in Figure 4. We employ the utility records on household electricity consumption and plot the estimated impacts of CFL treatment on household-level electricity consumption month-by-month. We illustrate the estimated intervention impacts by plotting – in blue – the coefficients from regressing household electricity consumption on household treatment status month-by-month, controlling for baseline monthly electricity consumption, heating degree days, and the number of days within each billing period.[52] Alongside the estimated impacts in Figure 4, we plot the predicted electricity reductions in green. More refined than Appendix Calculation 1, these calculations use household-specific survey data to predict the impacts of treatment month-by-month, including the same controls used in the estimated impacts regressions.[53]

By graphing the predicted and actual effects of CFL treatment together, a number of points are evident. First, the figure shows a reduction in estimated impacts on electricity consumption for treatment households, shortly following the CFL distribution in late March and April 2013. This indicates that households installed the CFLs shortly after receiving them via the intervention, initiating electricity reductions at the household-level. Second, the estimated impacts, which are graphed with 95% confidence intervals, are quite noisy in winter months. This annual seasonal noisiness existed in the winter prior to the intervention albeit to a lesser extent than post-intervention and likely results from heterogeneities in heating fuels used.[54] Third, there are seasonal differences as to how closely the estimated electricity reductions mimic the predicted impacts. The estimated impacts closely follow the predicted expected impacts for the first six months post-intervention (April through September 2013). The two lines then diverge in the five months following (October 2013 through February 2014), with

[52]Regressions do not include household fixed effects, as impacts are calculated separately month-by-month.

[53]We use data on the number of CFLs received, hours of lighting reported by households, etc. CFL distribution began in spring 2013, making that the earliest for expected impacts.

[54]Some households heat with electricity, which would cause a large spike in their winter electricity consumption. Other households heat with coal and therefore may just have a slight increase in electricity consumption during winter, due to fewer hours of sunlight.

the estimated impacts closer to zero during that period. Interestingly, this period overlaps with the months of peak electricity demand. The predicted and estimated actual effects converge in March 2014 and remain close through the end of the study period (September 2014).

We argue that the latter two above mentioned points – the divergence between the predicted and estimated impacts and the particular noisiness of estimated impacts in post-intervention winter months – are both related to the impact of transformer-level CFL treatment and the resulting reduction in outages during these months of peak demand. The intuition is simple. That individual household effects and aggregate transformer effects could occur simultaneously was not accounted for in our predicted impacts. However, in practice they would. If CFLs reduce peak demand at the transformer level, this can result in fewer distribution outages and more hours of electricity services available within a month. Although households that received CFLs would use fewer kW per hour of lighting services (due to the greater energy efficiency of CFL technologies), they can consume more kWh of electricity per month due to electricity outages occurring with less frequency. With fewer outages, all households in such transformers with improved reliability can consume more hours of electricity services - regardless of their individual household treatment status. By the impacts depicted in Figure 4, we anticipate that treatment effects are heterogeneous across transformers depending on whether household experience individual household electricity reductions alone or those reductions in conjunction with more hours of electricity services.

6.2 Disentangling the impacts of CFLs on electricity consumption

Having implemented the event study, we estimate the impacts of CFL treatment on household electricity consumption with a basic specification and then build upon this analysis to show how differentiating between households in the high and low saturation transformers is important in understanding electricity consumption impacts.

We first estimate a simple difference-in-differences model:

$$q_{igt} = \tau T_{ig} * Post_t + \beta Post_t + \delta T_{ig} + \alpha X_{igt} + \gamma_t + \lambda_{ig} + \epsilon_{ig} \tag{2}$$

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 itself 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.[55] 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, as the coefficient on this term, τ, is the estimate of the average change in household monthly electricity consumption (in kWh) that resulted from random household assignment to treatment. Table 3 Column 1 reports intent-to-treat estimates of τ.[56] The impacts are identified from variation within households over time, controlling for month-by-year shocks.

The basic estimate in Table 3 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 Calculation 1. 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:

[55]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.

[56]Regarding compliance and attrition, potential concerns might include: (i) whether treated households took the CFLs assigned to them, and (ii) whether study households had 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). Results are consistent across these analyses.

$$
\begin{aligned}
q_{igt} = \theta THigh_{ig} * Post_t + \mu TLow_{ig} * Post_t + \omega THigh_{ig} + \psi TLow_{ig} + \\
\beta Post_t + \alpha X_{igt} + \gamma_t + \lambda_{ig} + \epsilon_{ig}
\end{aligned} \tag{3}
$$

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 Table 3 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.[57]

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, therefore, a reduction is observed in their monthly electricity consumption. In contrast, treated households in the high saturation transformers experience significantly 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 services consumed are offset by an increase in hours of electricity services consumed due to greater availability of electricity services.

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

[57]This difference is particularly meaningful given the demand results in Table 1 showed no significant difference between the two groups in the average number of energy efficient lightbulbs received (3.2 CFLs on average) via treatment.

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 bias (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.

We re-estimate the impacts of CFL treatment on household electricity consumption, addressing the potential within-transformer contamination in a fashion similar to Gine and Mansuri (2018) and Banerjee et al. (2014). We employ the following specification:

$$\begin{split} q_{igt} = \theta THigh_{ig} * Post_t + \mu TLow_{ig} * Post_t + \nu CHigh_{ig} * Post_t + \sigma CLow_{ig} * Post_t + \\ \omega THigh_{ig} + \psi TLow_{ig} + \phi CHigh_{ig} + \kappa CLow_{ig} + \beta Post_t + \alpha X_{ig} + \gamma_t + \lambda_{ig} + \epsilon_{igt} \end{split} \tag{4}$$

in which $THigh_{ig}$ and $TLow_{ig}$ remain as in the previous equation. We add $CHigh_{ig}$ and $CLow_{ig}$, which are indicators that equal 1 if the control households are located in high saturation and low saturation treatment transformers, respectively. The coefficients of interest are those on the interactions between those four variables and the $Post_t$ variable. Importantly, the omitted group in this regression is now comprised of only control households located within control transformers, which we consider a "pure control" group.

We estimate this regression in two ways. First, we estimate it with the month-by-year fixed effects, γ_t, and household fixed effects, λ_i, employed in the earlier estimations. Second, we replace the household fixed effects with household-by-season fixed effects. Results are shown in Table 3, Columns 3 and 4, respectively. The latter specification, which accounts for any potential concerns of pre-intervention seasonal differences in electricity consumption across treatment groups, is our preferred.

Results in Column 4 indicate that the CFL treatment amongst treated households in low saturation transformers reduced household electricity consumption by -37 kWh per month. The reduction amongst treated households in high saturation transformers is statistically insignificant and of a smaller magnitude at -15 kWh. Given they did not significantly differ in their take-up of CFLs, this heterogeneity across treated households in high versus low saturation transformers reflects a difference in electricity services reliability across these transformers. Compared to Column 2, the coefficients' magnitudes in Column 4 are larger, suggesting that control households in treated transformers were indeed contaminated.[58] Overall, the progression of electricity consumption results in Table 3 Columns 1 to 4 is consistent with reliability externalities and adoption spillovers within treated transformers. Section 5 provided direct evidence on reliability impacts. Section 7 will provide additional evidence of adoption spillovers.

Although our experiment design does not allow us to perform a direct test to rule out the possibility of a rebound effect, a number of analyses are inconsistent with a direct or indirect rebound in electricity consumption. For instance, the event-study graph of the impacts on electricity consumption by season (Figure 4) showed that following a winter spike, savings in electricity consumption returned to the expected amount in the spring. If a rebound occurred, a persistent change in behavior would be expected, and a reversal in the spring would have been unlikely. Furthermore, using our detailed baseline and follow-up survey data, we tested for impacts of treatment on appliance ownership and average use (results not shown).[59] We found no effects of treatment on lightbulb use (which would be a measure of a direct rebound) and only one significant effect of treatment on use of household appliances (which would be a measure of an indirect rebound) out of 25 appliances for which data were collected. Treatment households were significantly less likely to report using electric heaters at follow-up. If anything, this finding is evidence counter to a rebound effect.

7 Understanding CFL adoption

To formally test for spillovers in CFL take-up, we estimate the same panel regression with household fixed effects employed in Equation 4, but use the total number of CFLs in a house as our outcome variable and control for the number of CFLs distributed through our intervention on the right hand side. If electricity consumption reductions amongst control

[58]Indeed, the coefficient on $CLow_{ig}$ is consistent with spillovers in adoption, as control households in low saturation transformers show a reduction in electricity consumption of -36 kWh per month. Although the interpretation of the coefficient on $CHigh_{ig}$ is less clear, it is not inconsistent with the outage results.

[59]In both survey rounds we ask a number questions regarding the household use of appliances, including "On average, how many days per month do you use [the appliance]?", and "On average, how many hours per day does your HH use [the appliance]?" Important to note, these questions are asking about average use *per month* and *per day*. In contrast, our question on outages asks about the *past month*. For this reason, that we find no impacts on the use of lightbulbs is not inconsistent with our aggregate reliability results.

households in treated transformers are indeed indicative of adoption spillovers, then this should bear out in the number of CFLs within these households at follow-up.

Results are presented in Table 4 Column 1. Treated households appear not to have purchased any additional CFLs between the intervention and follow-up survey. This is not surprising. We provided them 3.2 CFLs at baseline, which was enough for the average household to replace most of its incadescent bulbs with the CFLs.[60] Instead, we do see evidence of spillovers in adoption amongst the control households in treated transformers. Regardless of transformer treatment saturation, these households have significantly more CFLs than the "pure" control households in control transformers. At follow up, control households in high saturation transformers have more CFLs than control households in low saturation transformers. However, the average CFL take-up in high saturation transformers is not statistically significantly different from adoption in low saturation transformers.

These results are noteworthy for several reasons. First, the estimated adoption spillovers are in addition to the overall increase in CFL ownership that occurred during this period, displayed by the coefficient on $Post_t$. Second, these adoption spillovers occur within the treated transformers, which means they contribute to the aggregate effect on outages shown in Table 2.[61] Third, the spillover estimates confirm that differences in outages, not in adoption of CFLs, are likely to underly the dissimilar electricity consumption impacts for control households in high and low saturation transformers.[62]

To better understand the extent to which having close-by neighbors who received CFLs through our intervention matters in generating these adoption spillovers, we run the above-mentioned regression again but differentiate control households in treated transformers by their proximity to a treated household.[63] We define a household as being "close" to a treated one if it is within 100 meters from any treated household.[64]

[60] The CFL is a durable good with a multi-year expected lifespan. Therefore, we would not anticipate that the treated households would require additional CFLs after just one year has passed.

[61] In other words, they would also contribute toward the electricity load reduction within the transformer.

[62] The control households in high saturation transformers have no reduction in monthly electricity consumption in spite of having (insignificantly) more CFLs than those in low saturation transformers.

[63] This definition of closeness between households is a distance measure of geographical proximity. 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).

[64] GPS location data, collected during the baseline household survey, are used to perform distance calculations in ArcGIS.

Results, shown in Column 2, indicate that proximity does matter for adoption spillovers. Control households that are in treated transformers but far from a treated house do not have significantly more CFLs than the pure control households at follow-up. In contrast, the number of CFLs amongst groups of 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, suggesting that the results in Column 1 could be an underestimate. 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.

Although we cannot fully disentangle the path through which adoption spillovers occur, we provide evidence that proximity matters not only in generating adoption spillovers but also in changing beliefs and preferences regarding the CFLs. Results, shown in Appendix Table 3, are similarly estimated using household panel survey data. The largest changes in beliefs and preferences occur amongst the treated households (relative to the pure control households). We do also see some evidence of spillovers in beliefs and preferences for CFLs amongst the control households in treated transformers that are close to treated households.

8 External validity

We implemented a randomized saturation design to study the impact of energy efficient lightbulbs on local electricity reliability and household electricity consumption in a lower-middle-income developing country. Our thinking about external validity is then concerned with the extent to which our results are location-specific or technology-specific.

One important feature of our study's setting, the Kyrgyz Republic, is that essentially all households are electrified, formally connected to the network and metered individually. This feature helps with the internal validity of our study without harming the external validity. If the setting were not a fully electrified country or informal connections to the network were common, we would be measuring the responses of the first households to connect, which are very likely the richest households. Also, if households were not metered for their individual electricity consumption, their incentives to adopt would be lowered. Our study setting also has an extensive electricity generation and distribution infrastructure. However, similar to other developing countries, it has a problem of insufficient infrastructure capacity relative to demand. Aggregate electricity demand relative to infrastructure capacity, not infrastructure alone, determines the probability of system overload, which results in unplanned outages. As such, this work is relevant to many developing countries in which demand for electricity is either currently pushing the infrastructure capacity or rapidly increasing such that infrastructure capacity may be binding in the near future.

Furthermore, our study setting is unique in that it allows us to generate technological externalities in electricity reliability at relatively low treatment saturation. However, we do not make the point that technological externalities can be induced at some particular saturation of energy efficiency. Instead, we show that these externalities are possible to generate and that they are crucial in understanding the welfare implications of energy efficiency programs. Although similarly low saturation levels in other settings may not induce such reliability effects, the existence of technological externalities should not be ruled out. Instead, we should ask how high the saturation ought to be to generate them. Likewise, we should ask what type of externality a program is expected to induce. The externality may not be limited to a reduction in outages, but may take other forms such as reductions in prices. The type of externality and the saturation level that induces it will depend on many factors, including the type of capacity constraint in the electricity infrastructure, the number of consumers the infrastructure serves, and the feasible engineering impacts of the technology distributed.

The relevance of our findings is not limited to developing country settings, but they also speak to developed countries. Although developed countries are less likely to have electricity reliability problems, they do experience congestion within the electricity distribution network due to peak loads, which impacts utility prices. Deployment of CFL technologies in such settings may not have similar impacts, but we believe our findings are not just specific to energy efficient lighting. A program wishing to induce an aggregate impact in a wealthier setting, such as the United States and other developed countries, where households own a greater number of electricity-using durables, may need to focus on a technology that accounts for a larger proportion of the electricity bill.

9 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 the energy efficient technology, when taken up at a high enough saturation level, can have a local effect on electricity reliability, 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 at a lower cost than traditional lightbulbs). 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. The results in Table 3 highlight ways in which estimates of the effects of energy efficiency could be biased, if we do not account for spillovers in take-up, potential externalities, and heterogeneity in impacts across seasons.

Our study also highlights that an increase in electricity consumption following the introduction of CFLs is a welfare improvement, not a sign of ineffective technology. Other technologies inducing positive externalities may create incentives for households to free-ride on the adoption by others. We show that in this case, in which the aggregate effect increases the returns to the technology, the externality may ameliorate (or even offset) the incentive to free-ride. Thinking about this interaction between technological externalities and incentivizing adoption is important for both policy design and the development of new technologies.

As a result of this analysis, we can perform several variations of cost-benefit analyses both with and without accounting for the aggregate benefits of improved electricity service reliability. Benefit calculations, shown in Table 5, that include both reductions in electricity consumption and increased electricity services are more than double the estimated benefits from electricity savings alone in the first year post-adoption (approximately $14 in estimated benefits instead of $7). Full descriptions of these calculations, included in Appendix Calculation 2, demonstrate that accounting for externalities in the welfare calculations is crucial. The benefits in year 1 of the program are substantially larger than the upfront cost of purchasing and distributing the CFLs (approximately $9 per household). These simple calculations provide a lower bound estimate of benefits from such energy efficiency distribution programs, given they do not account for other benefits, such as pollution reductions.

An energy efficiency distribution program, such as ours, looks much more favorable after making this correction.

In addition, Appendix Figure 2 and Figure 4 uncovered substantial variation by season in overall household electricity consumption and treatment impacts. This has important implications. First, when measuring impacts of energy efficient technologies, comparing outcomes in a given month (e.g. June) before and after the treatment is not sufficient to address seasonality. Because reliability impacts may occur, the savings attained by energy efficient lighting would appear to be small in peak-demand months. On the contrary, they would appear to be large in months when demand is lowest. Impacts may be better measured as the average over a year rather than at a specific month. Relatedly, the seasonality pattern suggests that the time of the year when energy efficient technologies are distributed matters. If technologies were introduced in low-demand months, end-users could observe reductions in consumption similar to the feasible engineering estimated impacts. Instead, if the technology were distributed in peak-demand months, adopters may dismiss the technology as deficient rather than one that induces a reliability externality. In our study, the fact that CFLs were distributed immediately before low-demand months may have allowed households to learn about the true effectiveness of CFLs during the summer, enabling them to understand that the smaller reductions in consumption during peak-demand months were a welfare gain.

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 a design to inform our understanding of aggregate impacts and technological externalities from various interventions. This methodology can be applied to study other topics for which decomposing private returns and technological externalities is important in measuring the impacts of technology adoption and choosing between various policy options or program subsidy levels.

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Figure 1: Randomized saturation process

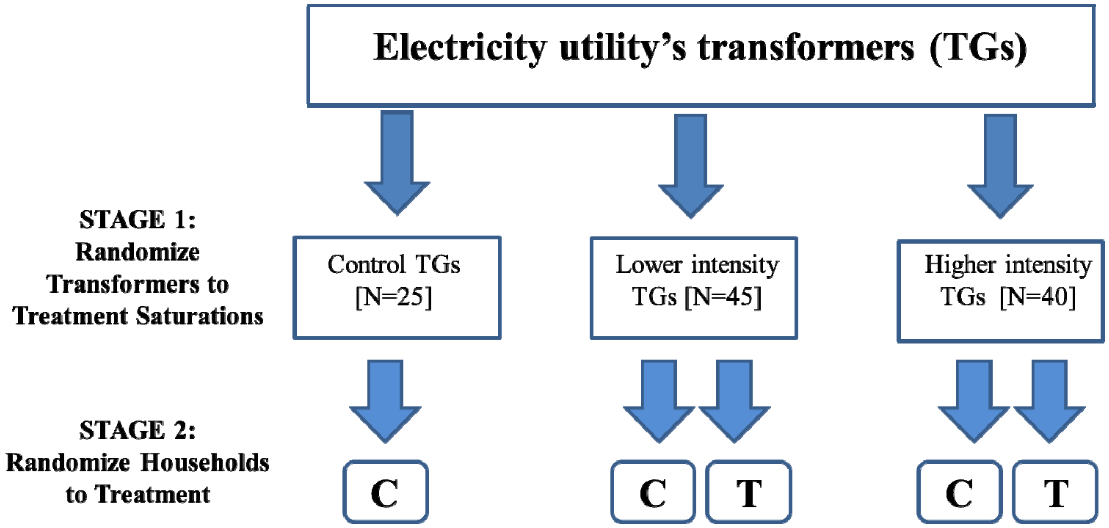


Figure 2: Stylized example of randomized saturation design

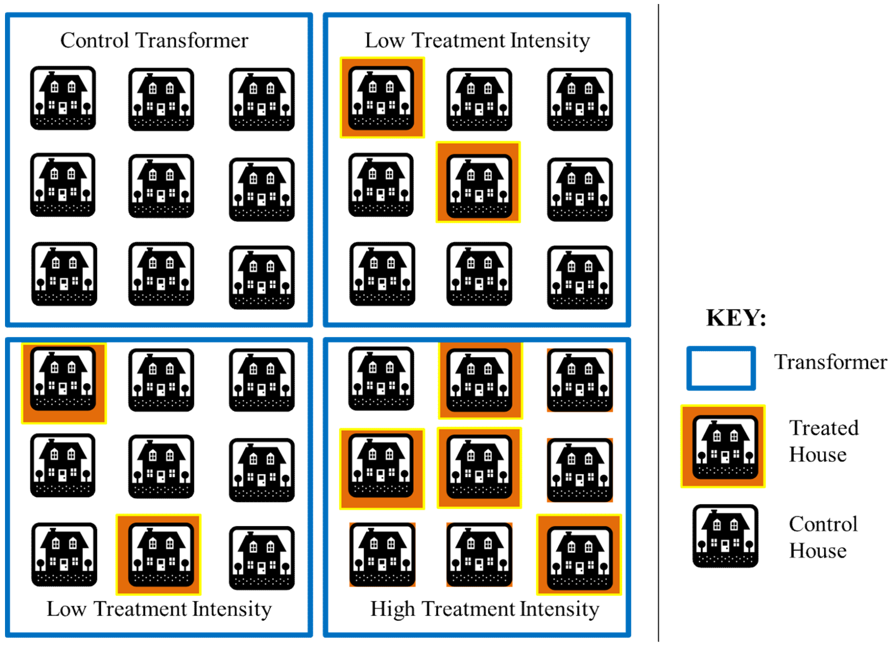
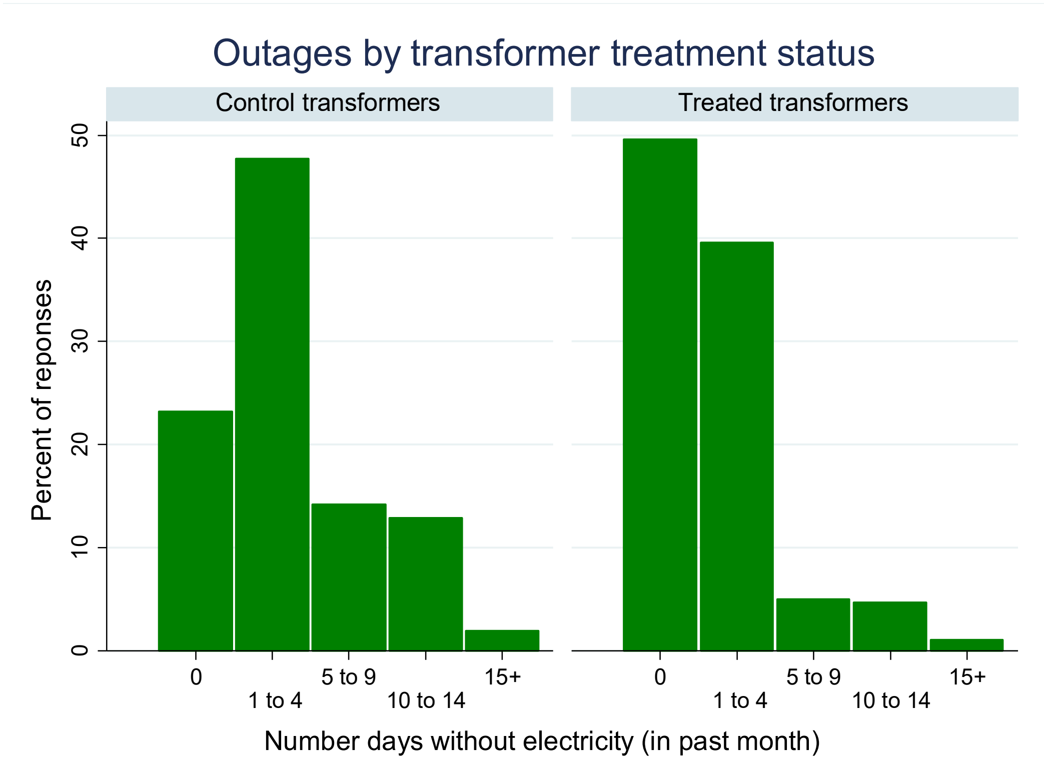


Table 1: Household demand for CFLs by transformer intensity

	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

Notes: Measurements from demand intervention in March/April 2013. Calculations made based on the experimental measures of demand. 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. There are 85 transformers in total across the high and low saturation transformers. The exchange rate in March 2013 was 1 USD = 48 KGS.

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



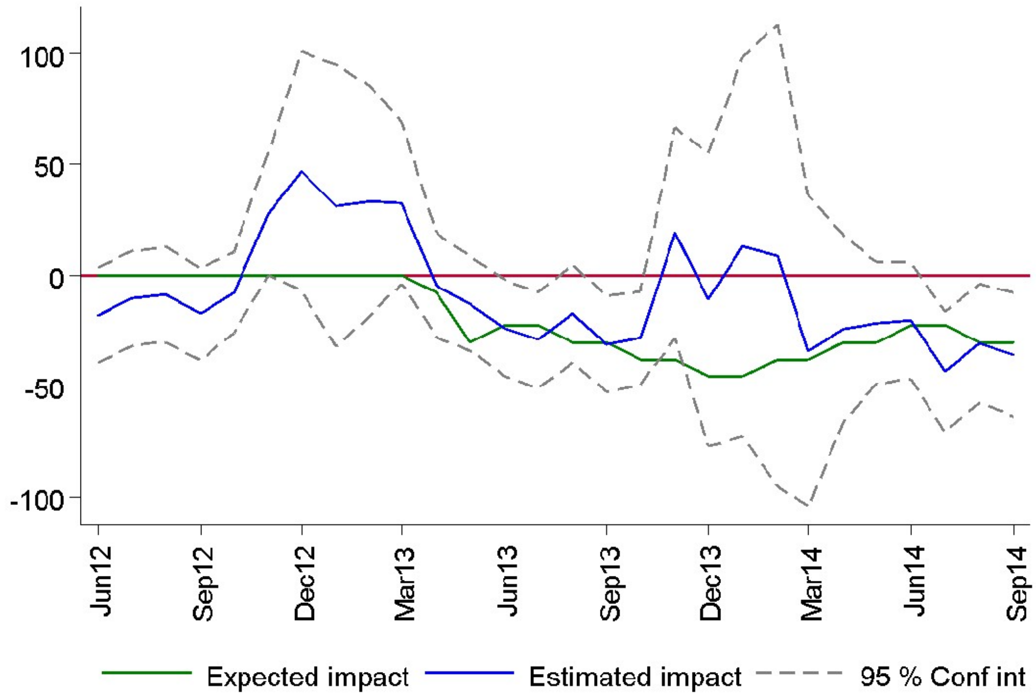
Notes: Analysis performed using data from household follow-up survey data, collected in response to the survey question, "In the past month, how many days had your household been without electricity, due to problems with the electrical system in the village?" Control transformers are transformers in 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)
TG low saturation	-1.321	-1.164
	(0.851)	(0.868)
	[0.433]	[0.434]
TG high saturation	-1.866**	-2.162***
	(0.812)	(0.822)
	[0.000]	[0.000]
Household treatment status controls	No	Yes
Constant	3.810***	3.811***
	(0.836)	(0.838)
p-value: TG low = TG high	0.228	0.047
Observations	838	838
R-squared	0.051	0.053

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 response to this question in the baseline survey, as well as 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: Analysis 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; however, all regressions include controls for the household's baseline monthly electricity consumption (for the year prior to the intervention) and the number of days within each monthly billing period. The expected 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 sublight throughout the calendar year. Distribution of CFLs began in March 2013, so by design the expected impacts are zero up until that time.

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

Dependent Variable: Monthly Household Electricity Consumption (kWh)				
	(1)	(2)	(3)	(4)
Treated household * Post	-16.679*			
	(8.780)			
Treated household in TG low * Post		-27.688***	-44.132***	-36.961**
		(10.482)	(12.696)	(15.689)
Treated household in TG high * Post		-7.175	-23.603*	-14.996
		(11.026)	(13.138)	(16.418)
Control household in TG low * Post			-44.364***	-35.729**
			(13.347)	(16.147)
Control household in TG high * Post			8.051	21.080
			(17.908)	(23.040)
Omitted group	All control houses	All control houses	Houses in control transformers	Houses in control transformers
Month-by-year FEs	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	No
Household-by-season FEs	No	No	No	Yes
Wald p-value: T in TG high = T in TG low		0.098	0.098	0.139
Wald p-value: C in TG high = C in TG low			0.003	0.011
Households	899	899	899	899
Observations	31,143	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 "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: 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)
Constant	-0.127**	-0.127**
	(0.054)	(0.054)
Omitted group	Control hhs in control TGs	Control hhs in control TGs
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. 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.

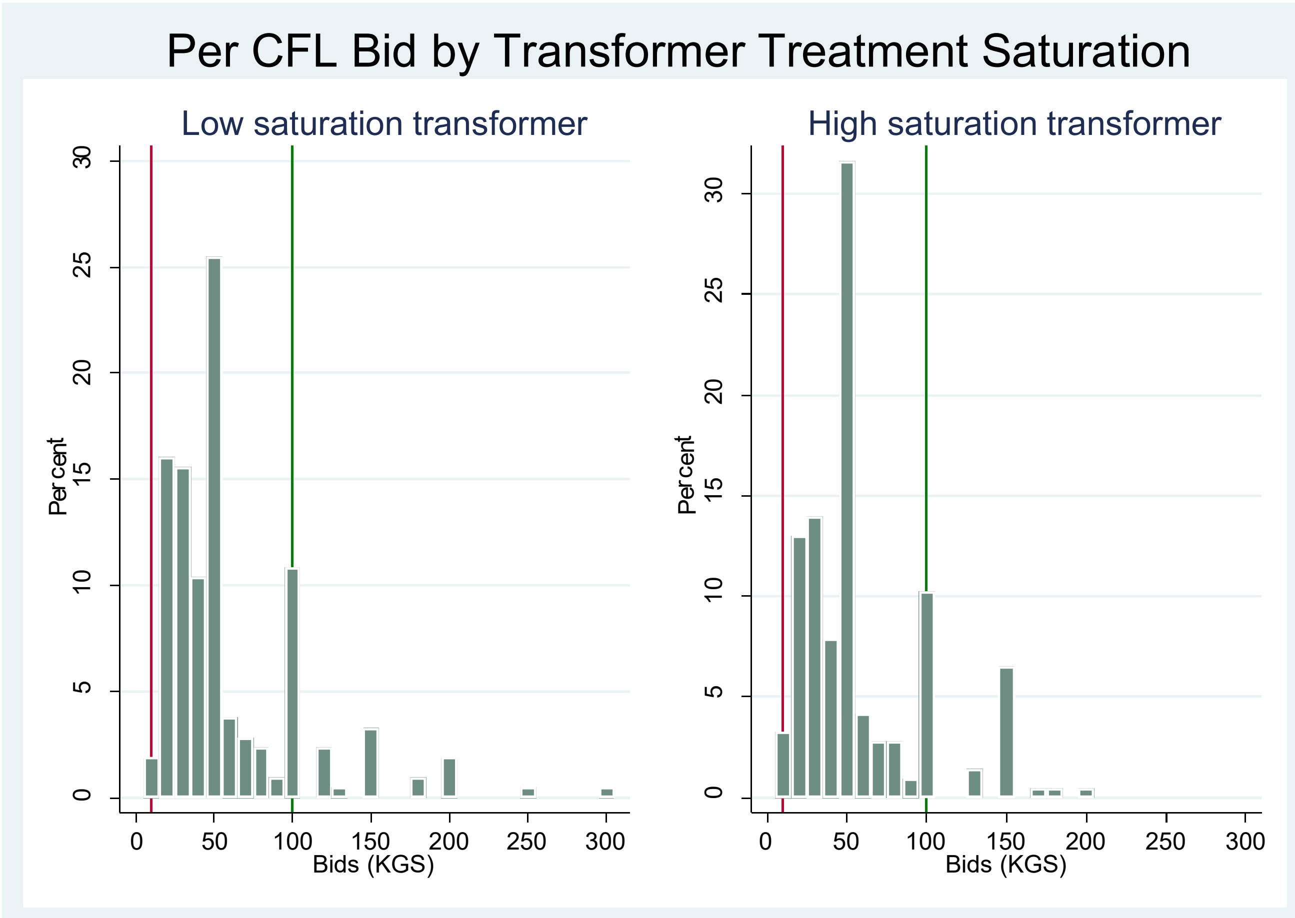
Table 5: Benefits of CFL Distribution Program

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	22	kWh/month
						Additional electricity consumption per year	264	kWh/year
						Price per kWh	0.02	USD
						Value of additional consumption	**5.28**	**USD**
TOTAL BENEFITS PER HOUSEHOLD	**$ 6.65**		**TOTAL BENEFITS PER HOUSEHOLD**	**$ 8.88**		**TOTAL BENEFITS PER HOUSEHOLD**	**$ 14.16**	

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

Appendix Figure 1: Bid per CFL Conditional on Being At or Above Randomly Drawn Price



Notes: Measurements from demand intervention in March/April 2013. Only treated households participated in the demand intervention, therefore calculations include only data for the treated households, not control households. "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. There are 85 transformers in total across the high and low saturation transformers. The exchange rate in March 2013 was 1 USD = 48 KGS.

Appendix Table 1: Transformer-level randomization check

	Number of Transformers	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: Averages of household-level data							
HH head completed seconday school	110	0.8	0.88	0.74	0.415	0.572	0.111
Household income (KGS)	110	13107.1	12647.6	13285.5	0.842	0.938	0.748
Own house	110	0.88	0.95	0.84	0.380	0.602	0.105
Private house	110	0.88	0.83	0.74	0.649	0.185	0.312
Number of rooms	110	4.32	4.50	4.14	0.584	0.582	0.203
Lightbulbs in house	110	6.96	5.83	5.88	0.110	0.142	0.890
Total incandescent bulb in house	110	6.73	5.74	5.72	0.154	0.158	0.948
Total CFls bulbs in the house	110	0.20	0.08	0.16	0.216	0.687	0.230
Outages in the past month	110	2.21	1.69	1.65	0.139	0.098	0.901
Winter electricity consumption (kWh/month)	110	491.03	586.72	584.75	0.033	0.044	0.96
Panel B: 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
Proportion of HH with 3 phase meter	110	0.28	0.28	0.34	0.951	0.102	0.068

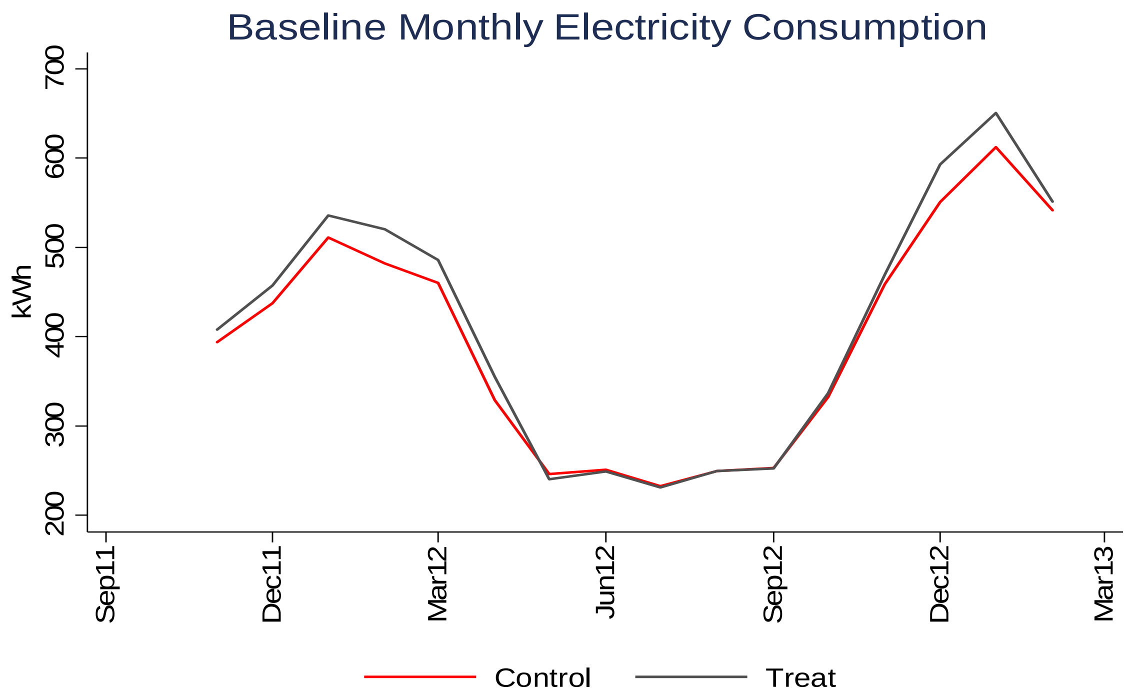
Notes: "Low saturation transformers" are those in which between 10 and 14 percent of households in the transformer were assigned to treatment. "High saturation transformers" are those in which 15 to 18 percent of households in the transformer were assigned to treatment. "Control transformers" only contain control households. Panel A calculated using responses from the baseline household survey. 20% of all households in a transformer were surveyed at baseline. 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 in March 2013 was 1 USD = 48 KGS. Winter baseline electricity consumption is calculated for the months between November 2012 and February 2013.

Appendix Table 2: 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	457	543	

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.

Appendix Figure 2: Pre-intervention seasonality of electricity consumption by household treatment status



Appendix Calculation 1: Estimates of the intervention's technologically feasible impacts

We have implemented this two-staged randomized treatment to vary 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 lighbulbs with CFLs, and (2) the expected 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.

STEP 1: Benchmarking household reductions in electricity consumption

Benchmarking the technologically feasible reduction in electricity consumption at the household-level is undertaken in two sub-steps. First, we calculate the kW reduction that occurs from replacing the original bulbs with more energy efficient ones. This is a mechanical difference and is 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, as a result of replacing 3.2 incandescent 100 W bulbs with 21 W CFLs.[65]

Second, we calculate the expected kWh reduction in monthly electricity consumption for three different scenarios (winter, spring/fall, and summer months). These different scenarios account for variations in day length (sunlight hours) and heterogeneities in appliance use across seasons.[66] Based on these calculations, we estimated electricity consumption to decrease, as a result of the intervention, by between 26.5 kWh per month in the summer and 42 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.

[65]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.

[66]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.

Benchmarking calculations

STEP 1. Benchmarking household-level reductions

1A. Reduction from changing bulbs: incandescent to CFLs

(a)	Average number of bulbs replaced	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 the actual wattage pof the lightbulbs distributed through the intervention.

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

		Winter	Spring/Fall	Summer	Baseline year avg
(p)	kW reduction	0.2528	0.2528	0.2528	0.2528
(q)	Average hours of bulb use per day	5.5	4.5	3.5	4.5
(r)	Days in month	30	30	30	30
(s)	**Expected CFL savings (kWh) [= p*q*r]**	**41.71**	**34.13**	**26.54**	**34.13**
(t)	Average monthly bill (kWh/month)	566.3	340	245	379
(u)	**Expected reduction in bill (%) [= (s/t)*100]**	**7%**	**10%**	**11%**	**9%**

Notes: These calculations are for three seasonal scenarios. 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. The average hours of use per day is calculated using the baseline survey data (Spring 2013) and data on sunrise and sunset times are used to extrapolate for the rest of the year. Average monthly electricity bill is calculated using baseline electricity use amongst the treated households in our sample during the year prior to the intervention.

STEP 2. Benchmarking transformer-level reductions

2.A Expected peak load reductions

		Winter scenario	Spring/Fall	Summer scenario
(t)	Average monthly bill (kWh/month)	566.3	340	245
(v)	Average hourly demand (kW) [= t /30 days/24 hours]	0.787	0.472	0.340
(w)	Assuming peak load is 70% > average load, calculate housheold peak (kW) [= 1.7 * v]	1.337	0.803	0.578
(x)	**Reduction in household peak demand (%) [= e/w]**	**19%**	**31%**	**44%**

Notes: The assumption 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.

STEP 2: Benchmarking peak load reductions within transformers
As common in many developing countries, unplanned outages in the Kyrgyz Republic are typically the result of overloads within the distribution system. 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. Lighting is disproportionately "on peak", in that we most often use lighting in the evenings and early mornings.

To better understand the potential aggregate impact that switching from incandescent bulbs to CFLs could have on electricity distribution, we want to estimate the impact on peak load. To do do, we carry-out the second benchmarking calculation, a back-of-the-envelope calculation based on data from our sample and some informed assumptions.[67] Given there are seasonal heterogeneities in peak load, we perform these calculations for three seasonal scenarios. Using data from our treated households on monthly electricity consumption, we estimate a 1.34 kW reduction in peak load during the winter, which reflects a 19% decrease in household peak demand. If 20% of the households within a transformer are included in the program and each household sees a 19% reduction in its peak demand, then the peak demand on the transformer is reduced by 4%.

[67]We use the U.S. Energy Information Administration's calculations for peak-to-average electricity ratios to inform our assumption that peak load is approximately 70% more than average load.

Appendix Table 3: Evidence in support of spillovers

	(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)
Constant	-0.021	-0.003	-0.007	0.021
	(0.021)	(0.027)	(0.025)	(0.019)
Omitted group	Control hhs in control TGs	Control hhs in control TGs	Control hhs in control TGs	Control hhs in control TGs
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. 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 Calculation 2: Cost-benefit analysis of the CFL program

To understand the welfare implications of such a CFL distribution program, we perform some simple cost-benefit calculations. By using the estimated impacts of CFLs on electricity savings and the aggregated impacts on reliability of electricity services, we are able to demonstrate the implications of performing these welfare calculations both with and without accounting for reliability improvements.

To simplify these calculations, we perform the cost-benefit analysis for the first year of the CFL program. The one-year analysis is sufficient to demonstrate the importance of the reliability impacts for welfare calculations. In addition, this simplification is useful for several reasons, in that we: can use the estimated coming from our experiment, which measures 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, we need not make any assumption regarding the 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 calculations, we divide costs into two components: the cost of CFL purchase and the cost of distributing the technology through the door-to-door campaign. Calculations are shown in Appendix Table 4. We base these calculations on details from our own experiment, such as the price per CFL, the number of households served by the program, the average number of CFLs distributed per household, etc. These calculations do differ from our experiment in that here we assume the government bears 100% 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 shift 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 5. 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 Table 3, 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 (see Table 3, Column 4). 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 (see Table 3, Column 4). 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 1 are nearing double the costs per household.

Appendix Table 4: 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**	