

ENERGY EFFICIENCY AND ELECTRICITY RELIABILITY

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

I. Introduction

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

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

Whether impacts on electricity reliability are empirically possible is a first-order question that speaks directly to the optimal scale of programs delivering efficient technologies and the extent to which these programs can accomplish the various goals they are set to deliver. An improvement in reliability resulting from energy efficiency distribution is a form

of a technological externality.¹ Technological externalities are known to govern the take-up and impacts of other technologies (Miguel & Kremer, 2004; Cohen & Dupas, 2010).² Similarly, the adoption of energy-efficient technologies and the benefits from their adoption are likely to hinge on such externalities.

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

Designed to alleviate a constraint within the electricity distribution system that causes electricity outages—transformer overloads—we distribute CFLs to reduce peak loads and induce a technological externality. Transformers convert high-voltage electricity to usable, low-voltage electricity for household consumption. Each transformer can transfer a certain maximum electricity load at any given time, and exceeding that load may cause transformer breakage, resulting in an outage (Glover, Sarma, & Overbye, 2011).⁴ Local distribution transformers in the Kyrgyz Republic are regularly operating at a load factor that substantially exceeds the optimal, making them close to overload (Amankulova, 2006).

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

²Cohen and Dupas (2010) identify the following factors that govern technology uptake and impacts: (a) the elasticity of demand with respect to price, (b) the elasticity of usage with respect to price, (c) the impact of price variation on the need of the marginal consumer, and (d) the presence of nonlinearities or externalities in the production function. Their experiment focused on factors a through c, and assume three levels of externality in calculations of cost-effectiveness of a price subsidy. We directly test for the fourth factor.

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

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

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Given that transformer failure is a nonlinear function of load, peak reductions of overloaded transformers can yield disproportionately large impacts on supply reliability (ANSI/IEEE, 2006).

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

We observe three main results. First, households in transformers with a higher-CFL saturation report fewer days without electricity due to unplanned outages. We consider this result positive evidence that energy efficiency programs can reduce peak loads to improve electricity reliability if they reach sufficient levels of technology saturation. Analysis of a utility's residential electricity consumption data collapsed at the transformer level confirms this result. Second, the impacts of CFL distribution on households' electricity consumption vary according to the CFL saturation within a transformer. In lower-saturation transformers, there is a statistically significant and meaningful reduction in electricity consumption. In higher-saturation transformers, reductions in electricity consumption are smaller and not statistically significant. This result is consistent with the potential for greater electricity consumption due to improved reliability within higher-saturation transformers.⁶ Third, spillovers in CFL take-up occur among control households. Control households in treated transformers have significantly more CFLs than the "pure" control households in control transformers. Adoption spillovers contribute to greater reductions in electricity consumption within a transformer, adding to the technological externality in electricity reliability. Although at higher-technology saturations there are more neighbors to learn from and more reliable electricity services, we do not find significant differences in adoption spillovers by CFL saturation.

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

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

Our study contributes to the literature concerned with technology adoption and technological externalities. Our experiment employs a recent innovation in experimental design, a multilevel randomized saturation, to study the role of technological externalities in the domain of energy efficiency. Multilevel randomized saturation designs are increasingly used by empirical work focused on estimating network, spillover, and general equilibrium effects, thereby addressing their interference in the identification of program impacts (Sinclair, McConnell, & Green, 2012; Banerjee et al., 2021; Crepon et al., 2013, 2018; Haushofer et al., 2013; Filmer et al., 2018; Muralidharan, Niehaus, & Sukhtankar, 2018). Previous work on technology adoption highlighted the importance of technological externalities in technology take-up, diffusion, and subsidization, and in the assessment of program impacts and cost-effectiveness (Miguel & Kremer, 2004; Cohen & Dupas, 2010; Ashraf, Berry, & Shapiro, 2010). Nevertheless, given the scale at which technological externalities typically occur, designing an experiment that can identify such externalities has been challenging.⁷ As a result, there has been relatively little causal empirical evidence on them.⁸ By implementing a randomized saturation design at the level of frequent infrastructure failure, we provide evidence of a technological externality in the form of improved reliability of electricity services. We show that due to this externality, the effect of CFL adoption on household energy consumption is nonmonotonic. At a lower saturation, CFLs reduce household electricity consumption, but at a higher saturation, CFLs allow them to increase their electricity consumption due to fewer outages. Ignoring this externality would lead to inaccurate calculations of the electricity savings from the CFLs.

Our study also connects to the literatures on energy efficiency impacts, adoption, and the energy efficiency gap. The substantial body of work investigating the take-up of energy-efficient technologies has largely focused on private adoption decisions and the returns to individual adopters (Jaffe & Stavins, 1994; Allcott & Greenstone, 2012; Gillingham & Palmer, 2014).

Although programs deploying efficient lighting are ubiquitous and ostensibly promising, there is little evidence of their impacts on household electricity consumption.⁹ Perhaps more notable, adoption spillovers and reliability externality

⁷As 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."

⁸Miguel and Kremer (2004) provide experimental evidence of positive cross-school externalities from deworming medicines in Kenya, but rely on nonexperimental 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 bed nets with respect to price, assuming three levels of externality in calculations of price subsidy cost-effectiveness.

⁹The exception is Iimi et al. (2019), which does not address technological externalities.

effects of energy-efficient technologies have received little attention. Through our CFL distribution, we show that increasing household energy efficiency leads to adoption spillovers and reliability externalities, which affect many more electricity consumers. Accounting for these effects is critical. Benefit calculations that incorporate adoption spillovers and improved electricity services are more than double the calculations based solely on private electricity consumption impacts, providing an economic rationale for mass deployment of energy-efficient technologies.

The remainder of the paper is as follows: Section II describes our experiment setting in the Kyrgyz Republic. Section III explains the sampling process, the randomized design, and the intervention. Section IV details the data collected and offers randomization checks. Section V estimates the aggregate impacts of CFLs on outages. Section VI presents analysis of residential electricity consumption and discusses evidence of technological externalities in electricity reliability. Section VII provides analysis of CFL adoption and spillovers in technology take-up. Section VIII addresses external validity. Section IX concludes.

II. Experiment Setting

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

Since the country's 1992 independence, residential electricity demand has rapidly grown, straining the existing infrastructure.¹⁰ In the years prior to our study, most local distribution transformers had a load factor between 0.9 and 1.2, which is greater than the optimal load of 0.7 (Amankulova, 2006). As a result, poor reliability and unplanned outages are frequent (World Bank, 2014), particularly during the winter when residential demand is high due to electric heating (World Bank, 2017a). Between 2009 and 2012, the utility serving the study region reported twenty outages per day on average during winter (World Bank, 2017b).¹¹ But frequent outages are politically and economically risky for the government and utility. No strategic outages or planned rolling blackouts (e.g., from overall electricity supply shortages) oc-

curred during the intervention period (per communication with the electric utility, 2013).

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

Prior to the intervention, study households indicated that they frequently worried about saving electricity (95%) and took measures to do so (86%). Nevertheless, very few had CFLs, and they had them in small numbers (0.17 CFLs per household, on average). CFLs were available for purchase only within Bishkek and sold for prices between 100 and 170 Kyrgyz soms (KGS), depending on the quality.¹⁴ In contrast, incandescent lightbulbs were available in both rural and urban markets for approximately KGS 15 to KGS 20. Based on the lightbulb and electricity prices and typical lightbulb use in our sample, we calculated the payback period for CFLs to be one to two years. Although more than half the households reported knowing about CFLs (56%), the majority did not know or believe that CFLs consume less electricity than incandescent bulbs (70%) or that electricity bill savings can result from bulb replacement (72%).

III. Randomized Experiment with Energy Efficiency

A. Sampling Process

For our sampling procedure, we used electricity utility data on households' locations and the transformer through which they were served. Transformers providing at least five households with electricity were eligible, as those serving fewer households likely also served industrial consumers. Within the study district, we chose seven villages accessible from Bishkek during the winter months, comprising 248 eligible transformers. We further restricted the sample to the 124 eligible transformers with below-median monthly household

¹²Only one household reported having an electricity generator for purposes such as lighting.

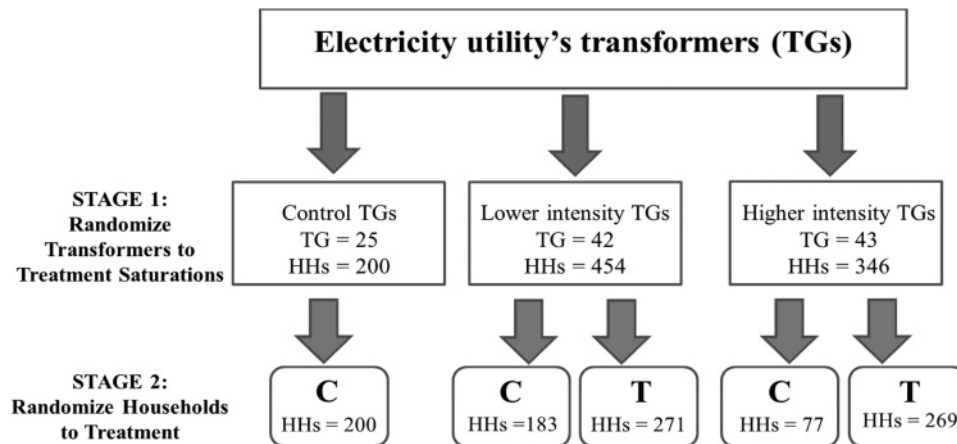
¹³Almost all homes have a television and refrigerator. Approximately three-quarters have electric stoves, an iron, and a clothes washing machine. Only 2% have air-conditioners. Households conserve on heating. Most report heating their houses at least sometimes with coal (80%) and, on average, they heat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

¹⁴At baseline, household monthly income per capita was on average US\$76 (US\$2.45 per person per day), and the exchange rate was approximately US\$1 = KGS 46.

¹⁰Kyrgyz households' growing electricity consumption is consistent with pro-poor economic growth in developing countries (Obozov et al., 2013). Existing electricity infrastructure was mostly built during the Soviet Union (Zozulinsky, 2007) and designed for lower demand.

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

FIGURE 1.—RANDOMIZED SATURATION DESIGN



electricity consumption in the year prior to the study.¹⁵ Then we randomly sampled 20% of households in each transformer. The number of households per transformer is heterogeneous, resulting in differences across transformers in the number of households included in the study.

B. Experimental Saturation Design

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

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

C. Intervention

In spring 2013, households were visited and invited to participate in a baseline survey. During the informed-consent

process, all households were informed that the research addressed CFLs and electricity consumption. Additionally, treated households were told that they would have the opportunity to purchase CFLs at a subsidized price after the survey. None of the participants, neither treatment nor control, were told about the variations in transformer saturations and had no reason to know. Moreover, the control households were not told that other households received subsidized CFLs. Upon completion of the baseline survey, all households were given KGS 150 (about US\$3.26) as compensation.¹⁶ Baseline interaction with control households ended at that time.

Households randomly assigned to treatment were offered the opportunity to purchase up to four 21 W CFLs (rated equivalent to 100 W incandescent bulbs) at a subsidized, randomly drawn price, via a willingness-to-pay experiment.¹⁷ The experiment uses the Becker-de Groot-Marschak (BDM) methodology to elicit demand, following Berry, Fischer, and Guiteras (2020). The set of possible prices, in Kyrgyz soms, was {0, 5, 10, 15, 20}. At the time, the lowest market price for CFLs was KGS 100. The number of CFLs distributed to each treatment household was recorded. On average, treated households received 3.2 CFLs via the intervention, paying an average price of KGS 13 per CFL. Of the 540 households assigned to treatment, 70 chose not to participate in the WTP game and therefore received no CFLs. These households are noncompliers. For intent-to-treat estimates, they are considered treated.

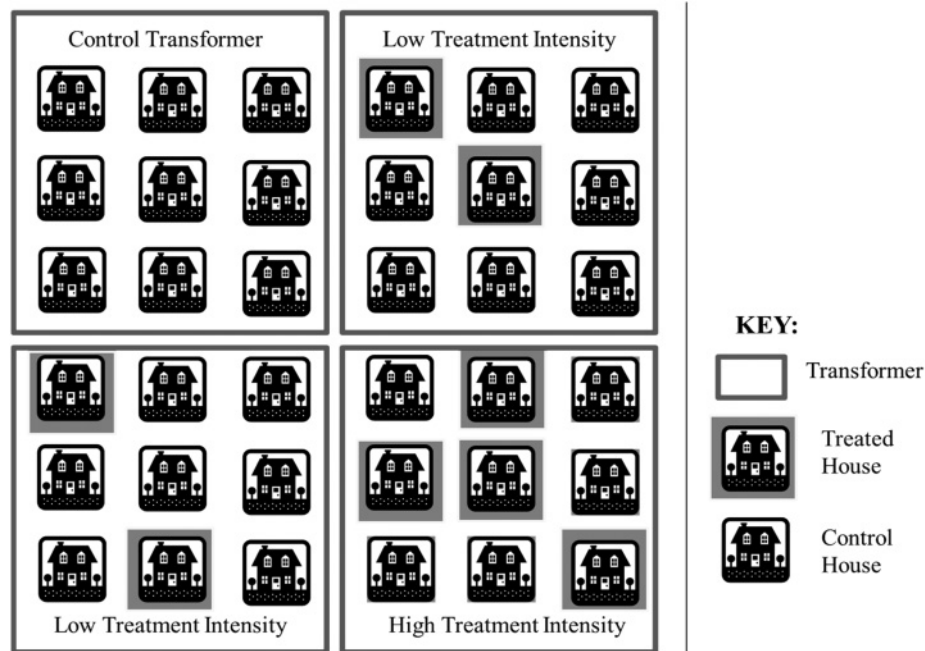
Households were visited one year later, in spring 2014, for a follow-up survey. Survey enumerators made at least four attempts to survey the address. Of the 1,000 original households, 749 were found at the address visited at baseline. When original households were no longer living at the address, the

¹⁵We exclude transformers with above-median electricity consumption. In those transformers, households consumed more electricity due to heating. Based on our calculation, inducing a reliability effect would require a higher CFL saturation than the project could afford. CFLs were not the appropriate technology to reduce peak load in those transformers.

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

¹⁷Through piloting in fall 2012, we knew that 100 W incandescent bulbs were most common and that households had five to six lightbulbs, almost all of them incandescent.

FIGURE 2.—STYLIZED EXAMPLE OF RANDOMIZED SATURATION DESIGN



new residents were surveyed instead. In total, 838 households (original and new residents) were interviewed for the follow-up survey, and 101 original households were identified as having moved in the year since the intervention. Either a new resident responded or neighbors informed enumerators that the prior resident had moved. After the survey, respondents were compensated KGS 150 for their time.

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

IV. Data

Baseline and follow-up survey data include information on various household demographics, lightbulb ownership (e.g., type, wattage), lightbulb use (e.g., room of use, hours used in a typical day), times of peak electricity consumption, perceptions and understanding of the CFL technology, and GPS location of each residence. Furthermore, households report the number of days in the prior month during which they

did not have electricity due to outages. This is a proxy for electricity reliability.¹⁹

The utility does not collect transformer-specific outage data. With limited funding and capacity, electric utilities in developing countries often do not systematically document electricity reliability and outages (Klychnikova & Lokshin, 2009). Researchers use proxies in the absence of such data. For example, Fisher-Vanden, Mansur, and Wang (2015) and Allcott, Collard-Wexler, and O'Connell's (2016) research on reliability and firm-level outcomes use "shortages" or "scarcity." To corroborate our results based on households' self-reported outages, we also use the utility's data on household electricity consumption.

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

A. Randomization Balance

Given the two-stage randomization, we perform balance tests at multiple levels. First, balance tests at the transformer level highlight the lack of systematic differences by treatment saturation in the baseline demand for CFLs. Table 1

¹⁸Results are consistent across these analyses.

¹⁹According to the utility, transformer outages last between a few hours and a few days, as determined by the transformer repair required and availability of replacement parts.

TABLE 1.—HOUSEHOLD DEMAND FOR CFLS BY TRANSFORMER INTENSITY

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

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

shows balance in the number of CFLs provided by the intervention, the price households bid, and the price paid for the intervention CFLs. Appendix table A2 provides additional transformer balance tests and indicates that transformers are similar along many other dimensions of demographics. There are three exceptions. Lower-saturation transformers have marginally significantly lower household income and higher pre-intervention winter electricity consumption than control transformers, as well as significantly more households than higher-saturation transformers.²⁰ In transformer-level regressions, we control for these covariates and use transformer fixed effects.

Household-level balance tests further show that treatment and control households are similar along most characteristics at baseline (appendix table A3). Control households are marginally more likely to have a household head who has completed secondary school, and significantly more likely to live in single-family dwellings. These two differences are jointly about what could be expected by chance. If anything, these differences would downward bias our results. Appendix figure A1 provides an additional balance check, revealing similar time trends and seasonal heterogeneity in pre-intervention electricity consumption by treatment status. Noteworthy, the peaks recorded in both pre-intervention winters (in 2011 and 2012) are not statistically significantly greater among treated than control households. Our estimations nevertheless account for seasonal variation in electricity consumption by including either household-by-season or transformer-by-season fixed effects.

V. Impacts of Energy Efficiency on Electricity Reliability

To affect electricity reliability, energy efficiency must do more than reduce average monthly electricity consumption. Overloads and the resulting outages occur at times of peak electricity consumption, when distribution transformers are most strained. Thus, the services associated with the energy efficiency improvement must be consumed at peak times,

when they can help reduce overloads. In our study setting, the electric utility reports times of daily peak demand to be 6 to 9 a.m. and 6 to 10 p.m., which overlaps with times typical for lighting service consumption and when CFLs could make a difference. Times of peak demand are corroborated by the study households' self-reported peak consumption times (appendix figure A2). The months of peak demand are October through April due to electric heating and longer hours of lighting.

A. Benchmarking Impacts on Transformer Outages

We start by illustrating the potential for energy-efficient lightbulbs to lower peak electricity consumption and reduce transformer outages. We perform benchmarking calculations by season, informed by household baseline survey and electricity consumption data (appendix A1). Our calculations indicate that replacing 3.2 incandescent lightbulbs (100 W each) with equivalent CFLs (21 W each) could substantially reduce average household monthly electricity consumption, saving between 42 kWh per month during the winter and 34 kWh per month in the spring and fall. This represents a nontrivial reduction in household average monthly electricity bills: about 7% of the 566 kWh winter average and 10% of the 340 kWh spring and fall average. Considering peak-to-average load ratios by season, we calculate that household peak load could be reduced by 23% in the winter and 25% in the spring and fall.²¹ For a distribution transformer with 20% of its households treated, this represents a 4% to 4.5% reduction in peak load. If adoption spillovers occur, additional reductions in peak load are expected.²²

Consulted about the above-peak load reductions, the electric utility's engineers sustained they would be sufficient to reduce transformer outages. Figure 3 shows that households' self-reported outage counts at follow-up, differentiated by transformer-level CFL saturation, support their assessment.²³

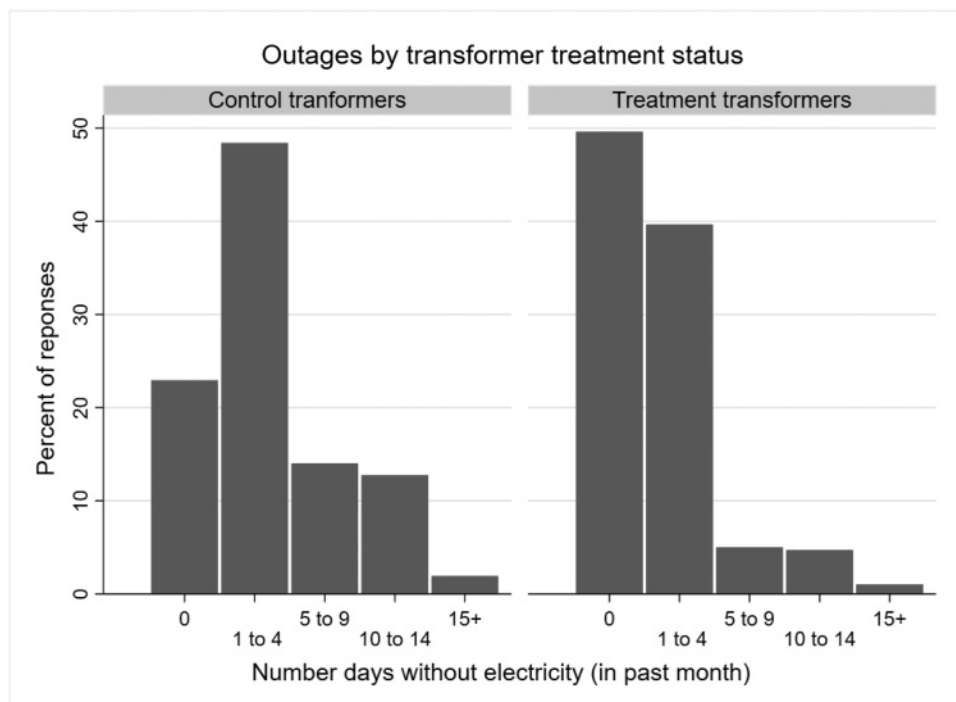
²¹The peak-to-average load ratios are informed by hourly residential electricity consumption smart meter data from a nearby but different district (see appendix A1).

²²Section VII explores adoption spillovers. We redo benchmarking calculations accordingly.

²³Data on reported outages are collected in both the baseline and follow-up surveys in response to the question: "In the past month, how many

²⁰A greater number of households is typically associated with higher electricity consumption; this difference should bias results toward no differential impact on outages.

FIGURE 3.—NUMBER OF DAYS WITHOUT ELECTRICITY, BY TRANSFORMER-LEVEL TREATMENT STATUS



Graph uses household follow-up survey data from the question, “In the past month, how many days was your household without electricity due to problems with the electrical system in the village?” Control transformers have no households that received intervention CFLs. In treated transformers, some proportion received intervention CFLs.

The distribution of reported outages among households in treated transformers is shifted leftward (toward zero outages) in comparison to the graphed responses of households in the control transformers. This evidence suggests a relationship between transformer-level CFL saturation and outages, motivating the analysis that follows.

B. Estimating the Impacts of CFLs on Outages

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

$$O_{ig} = \beta_1 High_{ig} + \beta_2 Low_{ig} + \beta_3 X_g + \epsilon_{ig}, \quad (1)$$

where O_{ig} is the number of days without electricity due to unplanned outages in the month prior to the follow-up survey, as reported by household i in transformer g ; $High_{ig}$ and Low_{ig} indicate if the household is in a higher- or lower-saturation transformer; and X_g is the number of households within a transformer. In alternative specifications, we further include the household treatment status, T_{ig} ; interactions between the

household and transformer treatment status, $T_i \times High_{ig}$ and $T_i \times Low_{ig}$; and the latter plus a control for the number of outages reported at baseline. Standard errors are clustered at the transformer level. We correct standard errors for multiple hypothesis testing, per List, Shaikh, and Xu (2016).

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

Our preferred specification is column 4 of table 2, as it allows for differential impacts by transformer treatment status and controls for baseline reported number of days without electricity. These results indicate that households in higher- (lower-) saturation transformers report 2.1 (1.1)

days has your household been without electricity due to problems with the electrical system in the village?” The question was asked this way to avoid households conflating distribution system outages with other reasons for which household electricity service might cease (e.g., bill nonpayment). 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.

TABLE 2.—AGGREGATE EFFECT OF CFLS: IMPROVED ELECTRICITY RELIABILITY

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

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 was household without electricity due to problems with the electrical system in the village?” All regressions control for the number of households within the transformer. “TG low” is an indicator variable that equals 1 if 10% to 14% of households in a transformer were assigned to treatment. “TG high” is an indicator variable that equals 1 if 15% to 18% of households in a transformer were assigned to treatment. The omitted group comprises households in control TGs. The “Household treatment status controls” are separate binary indicators that equal 1 for treated households. Standard errors are clustered at the transformer level and shown in parentheses. Significant at * 10%, ** 5%, and *** 1%. P-values accounting for multiple-hypothesis testing, as discussed in List, Shaikh, and Xu (2015), are shown in brackets.

fewer outage-days in the month prior, relative to the 3.24 days without electricity reported by households in control transformers. The significant and larger reduction in outage-days among the higher-saturation transformers reflects that the gradient of treatment saturation, in moving from lower- to higher-treatment transformers, is sufficient to improve reliability in our setting, where transformers operate close to capacity.

C. Additional Evidence on Outages

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

Providing further support, we check that the estimated reduction in outages is not due to strategic or planned outages implemented purposefully by the utility. Strategic or planned outages occur at the level of the electricity feeder line (one level higher than the transformer in the electricity distribution system), so we would be concerned if control and treated transformers were differently distributed across feeder lines. The 110 treated and control transformers in our study are

equally spread across twenty different feeder lines. We check utility maps and find no clustering of transformer treatment type by feeder line.

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

VI. How Does Energy Efficiency Affect Reliability?

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

A. Event Study of Household Electricity Consumption

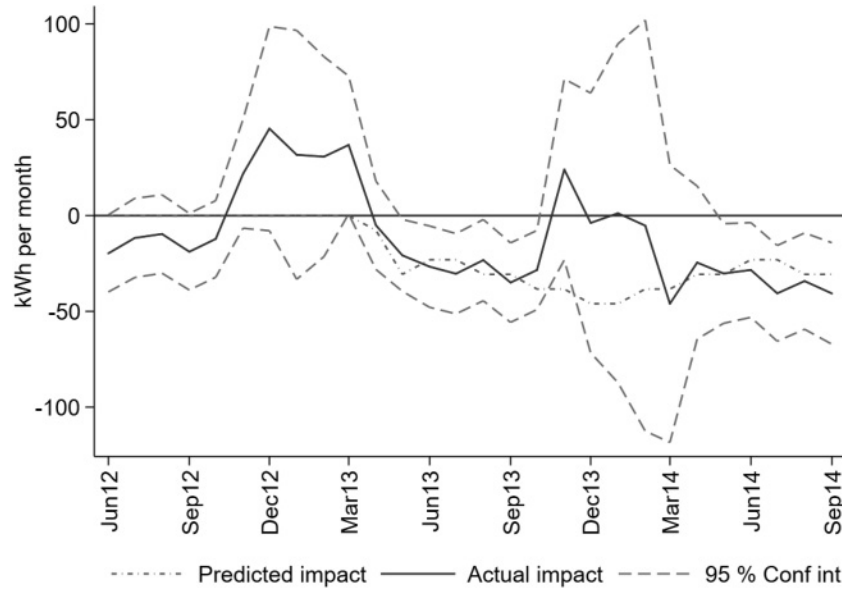
We illustrate the intuition of our analysis in an event study-style graph. In figure 4, we plot the estimates and 95% confidence intervals for the month-by-month impacts of our CFL intervention on household-level electricity consumption, controlling for baseline monthly electricity consumption, heating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

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

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

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

FIGURE 4.—PREDICTED AND ACTUAL EFFECTS ON ELECTRICITY CONSUMPTION (kWh PER MONTH)



The predicted impact is based on the number of CFLs distributed, the number of lighting hours reported at baseline, and changes in sunlight hours over a year. CFL distribution began in March 2013, so predicted impacts are 0 until then. Actual impacts are estimated using household monthly electricity consumption. We plot coefficients from regressing household electricity consumption (kWh) on household treatment status month-by-month, controlling for (a) control households in treated transformers (omitted group is control households in control transformers), (b) household's baseline monthly electricity consumption for one year prior, and (c) number of days within each monthly billing period.

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

B. Disentangling the Impacts of CFLs on Electricity Consumption

To address the confounding effects of the reliability externality as well as potential within-transformer contamination due to adoption spillovers, we employ a specification similar to that of Gine and Mansuri (2018) and Banerjee et al. (2021) to estimate the impacts of the CFL intervention on household

electricity consumption:

$$q_{igt} = \beta_1 THigh_{ig} \times Post_t + \beta_2 TLow_{ig} \times Post_t + \beta_3 CHigh_{ig} \times Post_t + \beta_4 CLow_{ig} \times Post_t + \beta_5 THigh_{ig} + \beta_6 TLow_{ig} + \beta_7 CHigh_{ig} + \beta_8 CLow_{ig} + \beta_{10} Post_t + \alpha X_{igt} + \gamma_t + \lambda_{ig} + \epsilon_{igt}, \quad (2)$$

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

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

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

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

TABLE 3.—HOUSEHOLD ELECTRICITY CONSUMPTION EFFECTS: RESULTS CONSISTENT WITH OUTAGE REDUCTION AND ADOPTION SPILLOVERS

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

Analysis performed using household-level panel of monthly electricity consumption data for the period between April 2011 and September 2014, as provided from the electricity utility's billing records. The omitted group comprises households in control transformers. The "post" period refers to the months after the intervention implementation (from April 2013 on). "Treated" households were offered up to four CFLs through the intervention. "Control" households were not offered CFLs through the intervention. "TG low" are transformers for which 10% to 14% of households in the transformer were assigned to treatment. "TG high" are transformers for which 15% to 18% of households in the transformer were assigned to treatment. "Control transformers" contain only 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 the period between intervention and follow-up survey (101 households). Standard errors are clustered at the household level and reported in parentheses. Significant at *10%, **5%, and ***1%.

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

The results in column 3 indicate that the CFL treatment reduced household electricity consumption by −37 kWh per month among treated households in low-saturation transformers. In high-saturation transformers, the reduction among treated households is statistically insignificant and of a smaller magnitude, at −14 kWh. The difference between the impacts on treated households in higher- and lower-saturation transformers is marginally statistically insignificant; however, it is meaningful in magnitude. Given that treated households in higher- and lower-saturation transformers received a similar number of CFLs via treatment (table 1), we argue that the heterogeneous impacts on treated households reflect differences in electricity service reliability

by transformer saturation.²⁸ Impacts among control households are similarly consistent with reliability improvements in higher- but not lower-saturation transformers. In higher-saturation transformers, control households show a statistically insignificant increase of 18 kWh per month in electricity consumption. In lower-saturation transformers, they show a reduction of −37 kWh per month. The difference between the two is statistically significant.

Event study graphs of household monthly electricity consumption by transformer saturation offer more nuance and lend support to our interpretation (appendix figure A5). In higher-saturation transformers, both treatment and control groups exhibit an increase in consumption of electricity in the winter, which is consistent with improved electricity reliability. Meanwhile, in transformers with lower-treatment saturation, both treatment and control exhibit similar reductions in electricity consumption.

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

C. Other Possible Behavior Changes

Other potential by-products of energy efficiency have been highlighted in the literature, such as a rebound effect (Davis, Fuchs, & Gertler, 2014) or less heat given off from lightbulbs, thereby reducing temperatures (Adhvaryu, Kala, & Nyshadham, 2020). We consider the role these might play and assess their plausibility in the context of our intervention.

Rebound effects. Increased consumption of lighting services (a direct rebound) or increased use of other appliances (an indirect rebound) may be a response to CFLs' greater energy efficiency. This impact would vary with transformer saturation. While we cannot rule out the possibility of a rebound, our analysis shows no clear evidence of a rebound.

In the absence of metering data for individual appliances, we employ panel survey data on the household ownership

²⁸ Appendix figure A4, a re-creation of the original event study graph, shows only treated households and differentiates between those in high-versus low-saturation transformers. This illustrates that these differential impacts over time are consistent with outage reductions among the high-saturation transformers.

TABLE 4.—EFFECTS ON HEATING PRACTICES

Dependent Variables: Heating-related practices	Dependent Variables: Heating-related practices		
	(1) Use Electricity to Heat	(2) Proportion Rooms Heated	(3) Number of Rooms Heated
T household in TG low \times Post	−0.026 (0.055)	−0.038 (0.069)	−0.056 (0.337)
T household in TG high \times Post	0.052 (0.057)	−0.010 (0.064)	0.057 (0.293)
C household in TG low \times Post	−0.017 (0.044)	−0.044 (0.064)	−0.198 (0.314)
C household in TG high \times Post	0.026 (0.085)	−0.003 (0.081)	−0.019 (0.374)
Post	0.089*** (0.031)	0.079 (0.050)	0.610** (0.236)
Omitted group baseline mean	0.247	0.729	2.890
Observations	1,498	1,427	1,427
R-squared	0.87	0.72	0.77

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

and usage of three types of lightbulbs and 24 different appliances. We estimate treatment impacts on the hours per day the household uses each lightbulb or appliance and assess whether they are consistent with a rebound. Results indicate no significant effects of treatment on lightbulb use or on the use of household appliances (appendix table A9).

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

Temperature, waste heat, and electric heating. All estimates of the CFL intervention’s impacts on monthly electricity consumption (at the household level and collapsed at the transformer level) control for the number of heating degree days within each month to account for seasonal heterogeneity and the use of heating during the winter. Still, one possibility is that because CFLs produce less heat waste (i.e., they emit less heat) than incandescent lightbulbs, switching to CFLs made it necessary for households to consume more electric heating to maintain a given comfort level. In particular, our CFL intervention could have induced adoption of electric heating on the extensive margin or greater use on the intensive margin (e.g., heating more of rooms or heating to a warmer temperature). We test for both using our panel survey data and find no evidence of differential changes in heating practices by treatment group and transformer saturation (table 4).

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

VII. Understanding CFL Adoption

A. Spillovers in Adoption

If reductions in electricity consumption among control households in treated transformers are indicative of adoption spillovers, this should bear out in the number of CFLs they have at follow-up. Moreover, having close neighbors who received CFLs should matter for adoption by control households. As a check, we first estimate a panel regression with household fixed effects similar to equation (2), but with the number of CFLs as the outcome variable, and controlling for the number of CFLs distributed through the intervention. Then we re-estimate the regression differentiating control households in treated transformers by their proximity to a treated household.³⁰

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

These findings are noteworthy for multiple reasons. First, the estimated adoption spillovers are additional to the overall increase in CFL ownership between baseline and follow-up (the coefficient on $Post_t$). Second, adoption spillovers

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

³⁰A number of studies have used geographical proximity to measure spillovers, including Dupas (2014), Godlonton and Thornton (2012), and Cohen, Dupas, and Schaner (2015). Here a “close” household is 100 meters or less from a treated household.

TABLE 5.—SPILLOVERS: CFL STOCK AT FOLLOW-UP

Dependent Variable: Total number of CFL bulbs in home		
	(1)	(2)
T household in TG low \times Post	0.319 (0.260)	0.319 (0.260)
T household in TG high \times Post	0.139 (0.299)	0.139 (0.299)
C household in TG low \times Post	0.689*** (0.257)	
C household in TG high \times Post	0.843*** (0.303)	
C household in TG low and close to T \times Post		0.706** (0.288)
C household in TG high and close to T \times Post		0.910*** (0.308)
C household in treated TG and far from T \times Post		0.447 (0.392)
Post	0.253** (0.108)	0.253** (0.108)
Omitted group baseline mean	0.224	0.224
Wald p -value: T in TG high = T in TG low	0.618	0.618
Wald p -value: C in TG high = C in TG low	0.675	0.603
Households	749	749
Observations	1,498	1,498

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 data set. The omitted group comprises households in control transformers. All specifications include household fixed effects and control for the number of CFLs given to the treated households through the intervention. Regressions include only households for which there are both baseline and follow-up data; households that moved during the period between the intervention and the follow-up survey are dropped. The "post" period data were collected via the follow-up survey in March 2014. "TG low" are transformers for which 10% to 14% of households in the transformer were assigned to treatment. "TG high" are transformers for which 15% to 18% of households in the transformer were assigned to treatment. "Control TGs" contain only control households. Being "close to T" is an indicator that equals 1 when a control household is located less than 100 meters from a treated household. Control households that are "far from T" are located more than 100 meters from a treated household. Standard errors are clustered at the transformer level and in parentheses. Significant at *10%, **5%, and ***1%.

contribute toward the electricity load reduction and thus to the reduction in outages within treated transformers (as shown in table 2). Third, the spillover estimates support our argument that differences in electricity reliability, not in adoption of CFLs, explain the heterogeneous impacts on household electricity consumption by transformer saturation. The control households in higher-saturation transformers have no reduction in monthly electricity consumption despite having (insignificantly) more CFLs than those in lower-saturation transformers.

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

Proximity matters not only in generating adoption spillovers but also in changing beliefs and preferences re-

garding CFLs, suggesting a path through which adoption spillovers occur (appendix table A11). The largest changes in beliefs and preferences occur among the treated households relative to the pure controls, indicating learning about the technology over time. We also see some evidence of changes in beliefs and preferences for CFLs among the control households that are in treated transformers and close to treated households.

B. Adoption Spillovers and Peak Load Reduction

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

We redo the calculations for expected peak load reductions, this time differentiating explicitly between the low- and high-saturation transformers and incorporating the adoption spillovers (appendix A3). These revisions result in estimated peak load reductions of 6% for the low-saturation transformers and 8% for high-saturation transformers, well beyond the 4% to 4.5% benchmarking estimates in appendix A1. Given that the internal heating effects that cause transformers to overload are a square function of current (ANSI/IEEE, 2006), reductions in load below the transformer rated capacity have nonlinear impacts on transformer failure. A peak reduction of 8% in an overloaded system can yield a significantly larger reduction in outages when compared to a 6% reduction in peak and certainly when compared to no reduction at all.

VIII. External Validity

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

Our experiment is generally relevant to developing and developed contexts in which demand-side management is a

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

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

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

Although we study CFLs specifically, our findings are also valid for other energy-efficient technologies. Recent programs are deploying light-emitting diodes (LEDs), which are even more efficient than CFLs. For developing countries, the use of electricity for lighting can be up to 86% (Tanzania), whereas in industrialized countries, it ranges from 5% (Belgium, Luxembourg) to 15% (Denmark, Japan, and the Netherlands) of total electricity use (Mills, 2002).³¹ Therefore, savings generated by efficient lighting are pertinent for reducing peak demand and avoiding overloads. In settings where households own more electricity-using durables, such as the United States and other developed countries, the focus has been primarily on the individual household-level effects of other “high-impact” energy efficiency technologies.³² Programs designed to induce an aggregate savings could expect similar externality effects to the extent that these technologies contribute to a larger proportion of the on-peak electricity consumption.

Finally, the source of the electricity constraint and technology of choice determine the optimal technology saturation. In our study, the local distribution transformer is the constraint within the electricity system that typically causes electricity outages. We calibrated the CFL saturation necessary to

bring peak loads below the transformers’ rated capacity so as to induce reliability effects. Because the transformers operated close to overload, implementing a sufficient saturation of CFLs was feasible. A lower (greater) technology saturation would be required to induce an externality effect the smaller (larger) the factor by which peak loads exceed distribution capacity, the more (less) efficient is a technology, and the larger (smaller) its contribution to electricity consumption on peak.

IX. Conclusion

Electrification can have positive impacts on many indicators of development (Dinkelman, 2011; Rud, 2012; Lipscomb, Mobarak, & Barnham, 2013; van de Walle et al., 2013), yet electricity service reliability is a major concern in achieving them (Banerjee & Pargal, 2014; World Bank, 2014; Klytchnikova & Lokshin, 2009). Unreliable electricity service is a potential reason for heterogeneities in the impacts of electrification, given that frequent electricity outages can have an impact on households (Chakravorty, Pelli, & Marchand, 2014; Samad & Zhang, 2017) and firms (Allcott et al., 2016).

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

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

³¹Lighting is 10% of total U.S. electricity consumption (EIA-OEA, 2018).

³²Davis et al. (2014) estimate the impacts of a Mexican appliance replacement program.

TABLE 6.—BENEFITS OF CFL DISTRIBUTION PROGRAM IN YEAR 1

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

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 US\$1 = KGS 48.

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

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