Shedding Light: Understanding the Role of Externalities in Energy Efficient Technology Adoption

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Abstract

Through a two-stage randomized control trial, we estimate the impact of energy efficient lightbulbs (compact fluorescent lightbulbs or CFLs) on household electricity consumption and show that household-level efficiency creates a technological externality, in the form of increased electricity reliability. The CFL treatment leads to a reduction in household electricity consumption of approximately 30 kWh per month, which is within the range of the technologically feasible expected electricity savings. Estimates not controlling for externalities are substantially downward biased. The distribution of CFLs can result in transformer-level technological externalities: more intense distribution of CFLs within a transformer leads to two fewer days without electricity per month due to transformer-level outages, a statistically and technologically significant result. This reduction in outages permits households to consume more electricity services. Finally, we investigate the channels through which externalities impact technology adoption and find interactions between peer effects and technological externalities to be critical in inducing take-up. This is the first study to experimentally disentangle the roles of multiple externalities and their interactions in technology adoption.

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1 Introduction

An individual's consumption of a technology can affect another individual's decision to adopt through many channels, both indirect, such as through learning spillovers, imitation or mimicking, and peer pressure,[1] and direct, by increasing (or decreasing) the utility an individual derives from adopting the technology themselves. Since Manski (1993), experimental evidence has amassed on the importance of peer effects in a number of economic decisions.[2] Technological externalities – through which the private returns to an individual adopting a particular technology are increasing (or decreasing) in the fraction of the population utilizing the technology[3] – also can play a crucial role in technology adoption (Griliches, 1957); however, there is much less existing rigorous evidence on these externalities.[4]

An additional complexity arises when multiple externalities (such as peer effects and technological externalities) are present and potentially impacting adoption decisions. There is relatively little work disentangling the effects of multiple simultaneous externalities in technology adoption. Distinguishing between these channels is important in several respects. First, the externalities may have opposite signs and therefore counteract one another in their impact on technology adoption. Second, instead of being additive, externalities may interact with one another in a multiplicative sense and lead to heterogeneous returns to technology adoption. Distinguishing between externalities and estimating the impacts of their interactions is challenging empirically. If both externalities are present, then exposure tends to be overlapping (Foster and Rosenzweig, 2010). To disentangle the roles of multiple externalities in technology adoption, one must find a context or develop an experiment through which they are not completely overlapping.

Energy efficient lightbulbs are an ideal good through which to study externalities in technology adoption. Energy efficient technologies can reduce the cost of energy services to

[1]Foster and Rosenzweig (1995), in introducing their "learning-by-doing" model, distinguish between these different external peer effects and how they can impact productivity.

[2]The peer effects literature has focused primarily on randomized studies since Manski (1993). Examples of randomized studies measuring the impact of peer effects include research on the following topics: financial decisions (Duflo and Saez, 2002; Banarjee et al, 2013); bednet adoption (Dupas, 2014*a*); taking deworming medicine (Kremer and Miguel, 2007); learning about HIV status (Godlonton and Thornton, 2012); and insurance take-up (Cai, de Janvry and Sadoulet, 2015). Jackson (2010) and (n.d.) review the field.

[3]We follow the definition of technological externality employed by Foster and Rosenzweig (2010).

[4]A notable exception is the Miguel and Kremer (2004) randomized experiment, in which they find evidence of positive externalities (in the form of a reduced disease burden) from deworming medicines in Kenya.

adopters of the technology. In addition, some energy efficient technologies may provide important technological externalities in the form of reduced peak electricity load leading to fewer electricity outages (thereby increasing reliability).[5] With this in mind, there have been a number of mass deployment programs in developing countries with the specific goal of peak load reduction and increased reliability of electricity services.[6] Improved reliability can permit households to consume more electricity services, a benefit that many households may value (WorldBank, 2006).

To test for evidence of externalities resulting from energy efficient technologies and to distinguish between the effects of multiple externalities in later adoption decisions, we implement a two-staged randomized study on the adoption of compact fluorescent light bulbs (CFLs). CFLs, which consume 25% of the electricity used by traditional incandescent bulbs per lumin, can reduce overall household electricity consumption without requiring a reduction in the hours of lighting services consumed (DOE, 2009). As a result, CFLs are one common energy efficient technology promoted en masse in developing countries during the past two decades.[7]

We implement this experiment in collaboration with an electricity utility in Kyrgyzstan.[8] The two-staged randomization employs the utility's data on 40,000 consumers and details on the electricity infrastructure through which these consumers are served. First, we randomize electricity transformers to different intensities of treatment. A distribution transformer, which is a crucial part of the electrical grid, converts higher-voltage electricity from the distribution system to low-voltage electricity for household use (Glover, Sarma and Overbye, 2011). In the second stage, we randomize households to individual treatment and control assignments, according to the transformer intensity assigned in the first stage. After completing a baseline survey, the treated households receive up to four CFLs at a highly subsidized price. We follow household electricity consumption (via the electricity utility's records) for

[5]At an aggregate level, energy efficient light bulbs can help address electric power shortages, permit utilities to reach a greater number of customers with existing supplies, reduce need for investment in capacity, accommodate growth in economic activity, and reduce environmental impact (WorldBank, 2006).

[6]These programs include efforts in Uganda, Rwanda, and Ethiopia. In Uganda, 600,000 CFLs were deployed in an effort to reduce the peak load by 25 MW. In Rwanda, 400,000 CFLs were distributed to reduce the load by 16 MW, with the goal of offsetting the need for diesel-based power generation. In Ethiopia, 200,000 CFLs were provided to reduce the peak load by an expected 6.8 MW, with the goal of increasing reliability.

[7]The World Bank alone committed more than US$11 billion to energy efficiency in developing countries between 1990 and the mid-2000s.

[8]Like many developing countries, Kyrgyzstan, suffers from frequent electricity outages, making it ideal for research on electricity reliability.

18 months after the intervention to estimate the impacts on electricity consumption. To measure CFL adoption, we return for a follow-up survey one year later and offer all households the opportunity to purchase CFLs at full market price.

By experimentally varying the initial CFL distribution, we can measure the impacts of CFLs on residential electricity consumption, both with and without controls for any potential externalities. We find that, when accounting for potential externalities, CFLs lead to a significant reduction in monthly electricity consumption that is of the magnitude expected for the technology. Not accounting for potential externalities leads to estimates of electricity consumption reductions that are downward biased (in other words, they understate the savings from energy efficiency). Impacts are heterogeneous across seasons, regardless of whether we control for externalities.

Using the transformer-level randomization of treatment intensity, we test for evidence of a technological externality resulting from the energy efficiency, in the form of improved electricity reliability. We find that transformers with a higher intensity of treatment (i.e. a larger proportion of households within a transformer receive CFLs) have fewer days without electricity due to unplanned outages. All households, both treated and control, within a transformer benefit from this improvement in electricity reliability. Results indicate that households in transformers with improved electricity reliability are able to consume more hours of energy services because they experience fewer outages.

The two-stage randomization induces spatial heterogeneity in the location of the treated households, which leads to variation in the exposure of control households to both technological externalities and potential peer effects. Importantly, these two externalities do not perfectly overlap.[9] We use this variation in exposure to externalities to decompose the channels through which they impact later adoption of the technology. We find evidence of significant interactions between the technological externality and the peer effects, particularly when the technological externality is strong enough to induce an aggregate reliability effect. In contrast, households only exposed to the technological externality show signs of free-riding behavior. These results suggest that accounting for interactions between externalities is important in understanding technology adoption.

[9] For example, households can be exposed to peer effects from close neighbors that received the CFLs, regardless of whether or not they are served by the same electricity transformer.

These findings contribute to the literature on infrastructure and development. In many developing countries, lighting is a major component of residential electricity consumption. Research indicates that electrification is important for development (Dinkelman, 2011; Lipscomb, 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 (WorldBank, 2006). Yet developing countries often face electricity constraints, resulting in outages. Electricity outages can impact both households (Chakravorty, Pelli and Marchand, 2013) and firms (Allcott, Collard-Wexler and O'Connell, 2015; Alam, 2013), yet low-quality electricity infrastructure can be persistent (McRae, 2015). This is a concern given expectations that pro-poor growth in the developing world will result in increases in household appliance ownership and, therefore, residential electricity demand (Gertler, Shelef and Wolfram, 2012).

Our experiment is the first to vary treatment intensities of an energy efficient technology in an effort to measure impacts on electricity service reliability. Given the scale at which technological externalities typically occur, experimentally inducing exposure to such an effect is challenging. By designing the experiment to take into account the constraint within the electricity distribution system that most frequently causes electricity outages, we provide evidence of an aggregate energy efficiency impact at a technologically significant level.

In addition to the technology adoption literature more broadly, this study provides important insight into the role of externalities in the adoption of an energy efficient technologies specifically. In spite of their promise as a potentially welfare-improving technology, many believe households are not using energy efficient technologies when they should.[10] Building upon Hausman (1979), cumulative research suggests an energy efficiency gap due to individuals not maximizing the net present value of their energy spending when making energy purchase decisions.[11] There is a growing body of work investigating the factors impacting purchase decisions of energy efficient technologies, thereby causing these investment inefficiencies (Jaffe and Stavins, 1994; Allcott and Greenstone, 2012; Gillingham and Palmer, 2014). Most existing economic research on adoption of energy efficient technologies largely

[10]Consumers face a variety of choices when it comes to new appliances, lighting system and other energy consuming equipment. 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.

[11]For examples of work on the energy efficiency gap, see Jaffe and Stavins (1994) and Gillingham and Palmer (2014).

focuses on private adoption decisions and the returns to individual adopters. In contrast, very little attention has been paid to the role of externalities in adoption decisions.[12] We find not only that externalities are important in the adoption decision, but that interactions between the technological externalities and peer effects induce adoption.

Finally, we contribute to the literature on the impacts of energy efficient technologies. Energy efficient technologies are promising; however, the impacts depend not only on the development of the relevant technologies, but also on the choices of the user (Allcott and Mullainathan, 2010). We find the CFL treatment results in a significant electricity consumption reduction, very close in size to the expected reductions, but only when controlling for potential externalities. This finding is particularly important given that recent studies have found energy efficiency interventions to fall short of the technologically-feasible engineering calculations.[13]

The remainder of the paper is as follows: Section 2 provides information on electricity use in Kyrgyzstan and the study context; Section 3 details the experimental design, the data collected, and results of the randomization and compliance checks; Section 4 establishes impacts of CFLs at the household and transformer-levels; and Section 5 estimates the role of various channels in the adoption of the energy efficient technology; and Section 6 concludes.

[12] For example, empirical evidence regarding reasons for low uptake of energy efficient technologies has focused on the role of 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, 2015) in overcoming the investment inefficiencies.

[13] A quasi-experimental evaluation of a Mexican appliance replacement program (Davis, Gertler and Fuchs, 2014) finds some electricity savings result from the program, but less than expected. Results were indicative of old appliances being replaced by modern appliances having additional features, which also consume more electricity. A non-experimental evaluation of CFL distribution in Ethiopia suggests approximately 20% of the initial electricity savings dissipated (Costolanski et al., 2013). A recent working paper on a weatherization program in the mid-western United States also found energy reductions to be far less than predicted (Fowlie, Greenstone and Wolfram, 2015).

2 Institutional setting and energy efficiency

2.1 Electricity in Kyrgyzstan

Kyrgyzstan provides an ideal setting to study energy efficiency and electricity reliability in a developing country setting.[14] Due to its history as part of the former Soviet Union, the country is highly electrified, with nearly 100 percent of households covered by formal electricity connections (Gassmann, 2012). Residential electricity demand has increased since the country's independence in 1992. Over the past two decades, the proportion of total electricity consumption comprised by the residential sector steadily increased, with 63% of country's current electricity supply consumed by the residential sector (Obozov et al., 2013).

Similar to many other developing countries, the electricity infrastructure is insufficient to meet current and growing electricity demand. In Kyrgyzstan, much of the existing electricity infrastructure dates back to the Soviet Union including all 16 of the existing power plants (Zozulinsky, 2007). Ninety percent of electricity generation within the country is hydroelectric, meaning that supply fluctuates with annual variability in reservoir water levels.[15] Technically, the capacity of both generation and transmission infrastructure could constrain household electricity services and result in unreliable electricity services (frequent electricity outages); however, during the period of study, distribution constraints are the primary source of unreliable electricity service.

Due to very low residential electricity prices (approximately $0.02 per kWh at the time of this study), many heat their houses with electric heaters in winter. This leads to large seasonal variations in electricity consumption, with average winter consumption approximately three times that of summer. As a result, the country's electricity utilities must address the growing electricity demand while faced a distribution system designed for much lower levels of residential electricity demand. As a result, the country is plagued by frequent unplanned outages[16] particularly in the winter (USAID, 2011).

[14] The country ranks 147th out of 187 countries (between Cambodia and Cameroon) for GDP (PPP) per capita (IMF, 2012).

[15] In years of low water availability, the country has instituted planned, rolling blackouts during the winter; however, this was not a tool employed during the time period included in this study.

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

Transmission and distribution systems are consistently overloaded, acting a binding constraint and source of unplanned outages. To put this in perspective, most of the transformers have a load factor of 0.9 - 1.2, with 0.7 being the optimal load (Amankulova, 2006).[17] These constraints are a concern for both consumers and the electricity utility. Unplanned outages typicaly occur when local distribution systems experience an overload. As in many developing countries, the distribution network was constructed for peak electricity consumption associated with households owning only a few electricity-using durables. The peak household electricity demand has increased, as households have bought more appliances.

Transformers are a critical part of the electricity distribution infrastructure. A distribution transformer on the electrical grid converts high-voltage electricity to usable, low-voltage electricity for household consumption (Glover, Sarma and Overbye, 2011). Electricity service is highly correlated at the transformer level, as households served by a single transformer are exposed to the same electricity-related shocks. For example, when there is a transformer-level outage, it affects all households within the transformer. There is a maximum electricity load that a transformer can transfer at any given time and exceeding that may lead to unplanned blackouts. In the study region, 54 households on average receive their electricity via a single transformer. During this time period, there were no planned or rolling outages; transformer overloads were the primary source of unplanned outages.[18]

In spite of low electricity prices, concerns regarding the electricity bills and the proportion of household expenditures directed to energy expenses are common. Household energy expenditures comprise an estimated 7.1 percent of total household expenditures in Kyrgyzstan (Gassmann, 2012), much of which is due to heating during the winter months.

2.2 Energy efficiency promise

Energy efficient technologies have the potential to decrease individual residential electricity costs. Using approximately 75% less electricity than incandescent light bulbs, CFLs are one tool through which to meet lighting needs while reducing electricity consumption. If take-up rates are sufficiently high, energy efficient technologies have the potential to have an impact at an aggregate level. For example, CFLs could decrease cumulative electricity demand at

[17] This is for the 35/220 kV transformers, which the last step in delivering electricity to homes.
[18] This information was provided via personal communication with the electricity utility (March 2014).

the transformer level, thereby reducing unplanned electricity outages and increasing service reliability.

At the time of this study, CFLs were available for purchase in large home repair stores and markets located in the capital city, but not in villages. CFLs cost between 100 and 170 Kyrgyz soms (depending on the quality). In contrast, incandescent light bulbs were available to purchase in both rural and urban markets for approximately 15 to 20 Kyrgyz soms. Even with low electricity prices, the payback period for the energy efficient light bulbs was between 1 and 2 years.[19] Yet, outside of the capital, very few households were using CFLs at the start of this project.

2.3 Categories of potential impact

Based on constraints in the electricity distribution system and the potential for energy efficient technologies to decrease demand, we expect the following impacts from energy efficient technology adoption in a developing country setting, such as ours. These include:

1. *household energy efficiency effect:* this refers to the private returns to adopting energy efficient light bulbs within one's home. The obvious benefit would be a reduction in electricity consumption (and resulting electricity bill). There could be a rebound effect, resulting in a zero or positive impact on electricity consumption. This is the overall net effect of the energy efficient technology on household electricity consumption.

2. *technological externality:* this category is the local aggregate effect of energy efficiency within the local distribution system. It is the likelihood of an outage due to an overload at the transformer. A reduction in the probability of an outage translates into increased reliability of electricity services. This effect is experienced by all households within a transformer, regardless of whether the individual household adopted the technology. This effect could be positive, negative or zero.

3. *peer effect:* this is the effect of CFL adoption on others' adoption of the energy efficient bulbs and could be due to channels such as learning, imitation, etc. This effect is

[19] Calculations on payback period were based on typical light bulb use in our sample, as well as electricity and CFL prices in the region.

experienced by households with close linkages to adopters.[20] This effect could be positive, negative or zero.

4. *aggregate regional electricity demand:* this is the effect of energy efficiency on aggregate demand within a particular geographic region. This would occur at a higher level than the transformer, such as a village or district. The study is not designed to measure aggregate regional impacts.

This field experiment was designed to randomly vary household exposure to the first three of these expected impacts from CFL adoption. This heterogeneity in exposure to peer effects and technological externalities will allows us to disentangle the roles of each as well as better understand how the two externalities interact.

3 Randomized experiment with energy efficiency

3.1 Sampling process

In collaboration with an electricity utility in Kyrgyzstan, we implemented the following sampling procedure to select villages, transformers, and then households within the transformers. We use data from the electricity utility on all electrified households within one district (which includes over 40,000 residential customers) for our sampling procedure. Crucial for the experimental design, the data identify each household's address and the transformer by which it is served.

The sampling procedure was implemented as follows. Seven villages within the district were selected for the project. Village selection was based on accessibility during winter months.[21] Within the seven villages, there were 248 eligible transformers.[22] The mean monthly house-

[20] Our measure of a close link between households is a distance measure of proximity between households. As discussed in (n.d.), a number of studies have used geographical proximity to measure spillovers, including Dupas (2014*b*), Godlonton and Thornton (2012), and Cohen, Dupas and Schaner (2015).

[21] This was to ensure that survey enumerators could get from the survey office in Bishkek out to survey the households in the villages in March, when weather conditions are winter-like and snow makes transportation challenging. The districts near the capital are considered to be better off than the other regions in the country. The study sample is not representative of the country as a whole.

[22] Transformers were considered eligible if they had more than 5 entities receiving electricity from it. From conversations with the electricity utility, we understood that transformers serving a small number of entities were likely serving a business and therefore not comprised of the residential consumers that we were seeking to target for this project.

hold electricity consumption was calculated for the eligible transformers. We included the 124 transformers with below median household electricity consumption in the study process.[23] To complete the sampling process, 20% of households from each transformer were randomly selected for the survey.[24]

3.2 Experimental design with two-staged randomization

A two-stage randomization process was designed to randomly vary household exposure to the following potential categories of impacts (as described in section 2) of energy efficiency technology: the household energy efficiency effect, the technological externality, and the peer effect. The two-stage process, as shown in Figure 1, first randomizes transformers to differing intensities of household treatment and then randomizes households within those transformers to receive CFLs (according to the proportion assigned to that transformer).

The first stage randomization proceeded as follows. The 124 transformers were randomized into three groups: control transformers, transformers with lower intensity of treatment, and transformers with higher intensity of treatment. This resulted in the following randomized assignment: 39 control, 45 lower intensity, and 40 higher intensity transformers. Control transformers are those in which no households are treated. In transformers assigned a lower intensity of treatment, 60% of surveyed households are treated. In transformers assigned to a higher treatment intensity, 80% of surveyed households are treated. Due to differences in the number of houses per transformer, this results in between 10 to 18% of all households being assigned to treatment within the treated transformers.

In the second stage, the 1,000 surveyed households were randomized into treatment or control assignments according to the transformers' randomly assigned treatment intensities. As a result of the two-stage randomization, we end up with 457 control households and 543 treated households. By definition, all treatment households are in treated transformers. However, control households can be located in either control or treated transformers.

[23]In an effort for the study to include households more typical for the country as a whole, the study design focused on selecting households with electricity use below the district median. Even so, the study sample is not representative of the country as a whole.

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

We implemented the same household survey in both treatment and control households. Immediately after completing the survey, households were given 150 Kyrgyz soms to compensate them for their time. They were given this money. At the time of the survey, households were not informed of their assignment into a specific treatment arm.

After the baseline survey, treated households were able to receive up to 4 CFLs[25] at a highly subsidized, randomly-drawn price.[26] Treated households were not told about the opportunity to receive the CFLs until after the baseline survey was complete. Some treated households were not interested in continuing after the baseline survey, in which case they received zero CFLs.[27] All households, regardless of their original transformer-level or household-level treatment status, were given the opportunity to purchase up to two CFLs at the full market price after the follow-up survey in 2014.

3.3 Randomized exposure to an energy efficient technology

As a result of this two-stage randomization, households are exposed to different combinations of three potential effects from energy efficiency: the individual household energy efficiency effect, the local aggregate reliability effect, and the peer effect. Treated households will be exposed to the household level energy efficiency effect, through which they may or may not experience reductions in electricity consumption.

If a large enough proportion of households within a transformer do adopt the energy efficient technology and have reductions in electricity consumption, then there may be a local aggregate reliability effect. This would be a reduction in unplanned electricity outages, resulting in more hours of available electricity services. If a control household is in close proximity to

[25]We decided to provide up to four CFLs because other sources and our own pilot surveys suggested that households had on average five to six light bulbs prior to our intervention. Our goal was to replace most of their incandescent bulbs with CFLs, so we allowed households to receive up to four CFLs.

[26]The set of possible prices was {0, 5, 10, 15, 20} for treated households. At the time of the experiment, the market price for incandescent light bulbs was between 15 and 20 KGS. The market price for CFLs at the time was a minimum of 100 KGS, so treated households were paying a maximum of 20% of market price. All treatment households were offered the opportunity to purchase up to four CFLs by playing a willingness to pay game. The game, which utilizes the Becker-de Groot-Marschak methodology to measure willingness to pay for the CFLs, is further explained in a separate paper (Carranza and Meeks, 2015).

[27]For this reason, we do not have 100% take-up of the CFL technology, even when the CFLs would have been offered at a zero price. For the purposes of our intent-to-treat estimates, these households are considered treated. Further discussion of compliance is included below.

a treated household, then it may learn about the technology from those neighbors. Whether there will be positive or negative peer effects will depend on the direction of the individual household energy efficiency effect. There are control households that are both exposed to both of these potential effects. However, crucial for our empirical estimation, there is not complete overlap in exposure to both the aggregate reliability and the peer effects. A control household located in a control transformer (and therefore having no potential exposure to local aggregate reliability effects) may still be exposure to peer effects. This variation in exposure permits us to separate out these effects on later adoption of the technology.

Although not receiving CFLs themselves, control households may also be exposed to effects of energy efficiency adoption via either the technological externality or the peer effects. How the two-staged randomization resulted in control households' differing exposure to impacts is portrayed in Figure 2. For example, a control household can be located in a treated transformer (and thus exposed to potential technological externalities) and close to a treated household (and thus also exposed to potential peer effects). Other control households may be located in a control transformer (and therefore not exposed to any potential technological externalities), but close to a treated household (and thus still exposed to potential peer effects). Because exposure to the two externalities is not completely overlapping, we are able to decompose the effects of each.

3.4 Disentangling the role of multiple externalities

What is the impact of externalities on CFL adoption? Any control household in a treated transformer could potentially experience this improved electricity reliability. There is also potential for peer effects, through which control households located close to treatment households are exposed to the technology through learning, imitation, peer pressure, or other related mechanisms. How the two-stage randomization enables us to disentangle these effects is shown through a "road map" in Figure 3. Panel A shows this varying exposure when we consider all treated transformers together. Panel B shows the varying exposure to externalities when we differentiate between high and low treated transformers.

All treated transformers

Figure 3 Panel A provides a road map for an analysis with all treatment transformers analyzed together, regardless of transformer treatment intensity. The first stage of randomization, which assigns transformers to treatment, determines which transformers may potentially experience impacts on electricity reliability. In the second stage, households are randomized into treatment and control households. Treated households are exposed to the household energy efficiency effect. This group is shown as group E in Figure 3.

What results are four types of control households, designated in Panel A as Groups P, Q, R, and S. These groups are exposed to different categories of impact as a result of the experimental design. Groups R and S are located in treated transformers, and therefore are exposed to a potential technological externality. Groups P and R are located close to a treated household and therefore potentially exposed to peer effects. As a result of the overlap, Group R is exposed to both potential externalities. Group Q is the pure control group, as it was neither exposed to the peer effect nor the technological externality, and will be the omitted group in the regression specifications that pool together all treated transformers.

We want to understand the roles of these externalities on later adoption of the energy efficient technology (Z). We define the components of the change in adoption of the energy efficient technology over time for each group:

$\Delta Z_P = \Delta$ peer effects $+ \, \Delta$ overall trend
$\Delta Z_Q = \Delta$ overall trend
$\Delta Z_R = \Delta$ peer effects $+ \, \Delta$ tech externalities $+ \, \Delta$ overall trend
$\Delta Z_S = \Delta$ tech externalities $+ \, \Delta$ overall trend

By estimating the impacts for these groups, we can use the results to calculate the specific channels impacting later adoption of the energy efficiency technology. Specifically, we can separately estimate the role of the technological externality and peer effects, accounting for heterogeneity in peer effects depending on the presence of a technological externality. The intuition of identifying these channels is the following:

Δ technological externality = $[\Delta Z_S - \Delta Z_Q]$
Δ peer effects with no technological externality = $[\Delta Z_P - \Delta Z_Q]$
Δ peer effects with a potential technological externality = $[\Delta Z_R - \Delta Z_S]$

Given how this analysis groups together transformers of all treatment intensities, the role of technological externalities remains unclear. Households in transformers below some intensity of treatment (and therefore do not experience any change in electricity service reliability) might behave differently than households above such a threshold (and therefore do experience improved reliability). We address the potential importance of this threshold in the technological externality, by performing this analysis again, differentiating between high and low intensity transformers.

Distinguishing between transformer treatment intensities

To better understand the importance of surpassing this threshold and inducing the technological externality, we refine our above analysis of the channels to allow for heterogeneity in transformer treatment intensity.

Panel B of Figure 3 has similar intuition to Panel A, but differentiates between transformers with a lower intensity of treatment and those with a higher intensity of treatment. We define the components of the change in adoption of the energy efficient technology over time for each group:

$\Delta Z_A = \Delta$ peer effects + Δ overall trend
$\Delta Z_B = \Delta$ overall trend
$\Delta Z_C = \Delta$ peer effects + Δ tech externalities + Δ overall trend
$\Delta Z_D = \Delta$ tech externalities + Δ overall trend
$\Delta Z_F = \Delta$ peer effects + Δ tech externalities + Δ above threshold + Δ overall trend
$\Delta Z_G = \Delta$ tech externalities + Δ above threshold + Δ overall trend

With these point estimates, we can estimate the channels of impact:

Δ Weak technological externality = [ΔZ_C - ΔZ_B]
Δ Strong technological externality = [ΔZ_F - ΔZ_B]
Δ Peer effects with no technological externality = [ΔZ_A - ΔZ_B]
Δ Peer effects with weak technological externality = [ΔZ_C - ΔZ_D]
Δ Peer effects with strong technological externality = [ΔZ_F - ΔZ_G]

By differentiating between the different intensities of transformer treatment, we are able to better understand the heterogeneity in the peer effects channels and the interactions between externalities in technology adoption.

4 Data, randomization checks, and compliance

4.1 Data

We use several datasets for this analysis, which are matched at the household-level and then matched to data on temperature and heating degree days collected from a nearby weather station.

Electricity utility data

As mentioned above, we utilize electricity utility records to identify both transformers and households within the the transformers for our two-stage randomization. In addition, we use the electricity utility's monthly household billing records, starting in October 2010. These data continue through September 2014. This provides observations 30 months prior to and 18 months following the intervention, held in March 2013. One important feature of this time period: electricity prices remained constant at 0.02 USD per kWh.

Household survey data

We conducted two rounds of household surveys, one immediately prior to the intervention (baseline) and one a year following the intervention (follow-up). For the baseline survey, representatives from the project visited individual households starting in March 2013. Households in both the treatment and control groups were asked to participate in a survey regarding electricity use.[28] The survey included detailed questions to collect information on appliance ownership and use, light bulb ownership and use, electricity-related behaviors, and various household demographics. In addition, we tracked the number of CFLs distributed to each treatment household.

We visited the same residential address one year after the intervention, in the spring of 2014. Of the original 1,000 respondents, 835 households were interviewed for the follow-up survey.[29]

[28]Respondents were offered 150 Kyrgyz soms (approximately 3.26 USD) for their time spent answering the survey. 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). Therefore, this payment was equivalent to one third of a work day.

[29]Survey enumerators made at least four attempts to survey the household. If enumerators were informed that the previous respondents had moved out of the house, then the new residents were surveyed. Survey

The follow-up survey repeated questions from the baseline, in addition to new questions on CFLs perception and understanding. Importantly, we ask households to report the number of days in the past month that they did not have electricity due to outages.[30] We also track each household's follow-up purchase decision.

Spatial data

GPS data were collected on the location of each participating house during the baseline survey. These data points permit various calculations relevant to potential peer effects, including the distance to nearest treated household and the number of treated households within certain radii.

In addition, we use GIS data from OpenStreetMap on locations of all buildings in the study villages. These data permit calculations of the total number of households located within various radii (e.g. 100 meters, 200 meters, and so on) of each participating household. These calculations are further described in the Appendix. These variables serve as important controls for specifications utilizing the spatial data.

4.2 Study sample

Households in the sample are highly-educated, with approximately 84% of households having finished secondary school. Household monthly income per capita is an average of 76 USD per month (2.45 USD per person per day). Most houses (91%) are owner-occupied and the average family size living in a single household is just under 4 individuals. Approximately 80% of homes are single-family dwellings and the majority of this housing stock was constructed during the Soviet Union. On average, the homes are comprised of 4.3 rooms and are typically constructed of either brick (54%) or a mud and hay/adobe mix (38%).

Houses are served by formal connections to the electrical grid and metered individually (i.e. houses do not share meters). Households receive a monthly electricity bill based on

respondents were again offered 150 KGS to compensate for the time taken to participate in the survey. This was enough to be able to purchase 1.5 bulbs at full price.

[30]This question was carefully worded and tested. We asked about the number of days because of the heterogeneity in the length of outages. From discussions with the electricity utility, we knew ex ante that transformer outages could last between a few hours to a few days. The extent of the transformer repair required and availability of replacement parts determined the length of time that a transformer would not be functioning after an overload had caused an outage. We did not think it reasonable to expect respondents to recall the number of hours without electricity.

the meter readings of their consumption. Amongst households in our sample, the average baseline summer electricity consumption is 232 kWh per month. Average winter electricity consumption is more than double that amount (633 kWh per month). Self-reported heating fuels include coal (80% of households report heating with coal at least sometimes) and electricity (39%). Households do try to conserve energy when heating; on average respondents reported heating only 3 rooms during winter (out of the 4 rooms in the average house).

Households, on average, have 8 electricity-using durables in their homes. Almost all homes have a television and refrigerator. Approximately three-quarters of households have electric stoves, an iron, and a clothes washing machine. A much smaller proportion have an electric hot water heater (14%) and almost no respondents (2%) have air conditioners.

Although residential electricity prices were low at the time of this study, saving electricity is a large concern for households in the region. Approximately 95% of households indicated that they frequently worry about saving electricity, whereas 86% report that they take some measures to save electricity. More than half the households reported knowing about energy efficient light bulbs, even though energy efficient lighting was rarely used prior to the intervention. Only 3% of households reported to prefer CFL bulbs over incandescent bulbs.

A lack of information on CFLs was the norm at baseline. Overall, households did not know or believe that CFLs consume less electricity than traditional incandescent bulbs (70%), did not expect electricity bill reductions immediately upon CFL installation (72%), and did not believe CFLs could pay back their cost through electricity savings (69%).

4.3 Randomization check

To determine whether the two-stage randomization worked, baseline characteristics were compared both at the transformer and household levels. Appendix Table 1 provides results from the transformer-level balance tests, which used both household survey data and data on transformer characteristics, as provided by the electricity utility. There are no statistically significant differences between the transformers treated with a low intensity and the control transformers, nor were there any statistically significant differences between the high intensity transformers and the control transformers. The high and low transformers do have one significant difference from each other: the number of households within the transformers.

We will control for this in related regressions and perform additional robustness checks.

A graph of pre-intervention electricity consumption over time (in Figure 4) shows the same seasonal patterns for both treatment and control households. The large spikes in winter electricity consumption is due in large part to electric heating. Longer hours of lighting due to shorter days play a much lesser role. Results of the household-level balance tests are shown in Appendix Table 2. The two household-level treatment groups are statistically identical along most dimensions, including baseline electricity use. There are, however, two slight differences. Treated household are slightly less likely than control households to have a household head that has completed secondary school education. In addition, control households are slightly more likely to be in homes that are single family buildings (in comparison to the multi-unit apartment buildings). It is important to note, however, that essentially all households in all groups have their own individual electricity meters.

4.4 Compliance

There are two sources of compliance with which we are concerned: (1) compliance with treatment (whether or not they took the CFLs that we distributed as the treatment) and (2) inhabiting home at time of follow-up survey.

Upon completion of the baseline survey, interaction with control households was complete. Treatment households were asked to continue on to a module addressing energy efficiency. A portion of the treatment groups refused to continue on to participate in the energy efficiency module after the baseline survey (before the households learned of their treatment assignment). These households therefore were not able to receive the CFLs. The rate of non-compliance was 12%.

On average, treated households received 3.2 CFLs from the intervention (out of a maximum of 4 CFLs permitted); however, this average includes the households that refused to continue to the energy efficiency module. Given that households had between 5 and 6 incandescent bulbs at baseline, the average treated household received enough CFLs to replace slightly more than half of the bulbs in the house.

At time of the follow-up survey in spring 2014, 101 addresses (of the original 1000 households) were identified as having new tenants in the year since the intervention. At the outset of the follow-up survey, it was unclear as to whether relocating families would leave CFLs when they moved. We interviewed all households currently living at the original addresses. To test whether this affects the results, we perform the analysis two ways: first, including the houses that have been identified as having new residents since the intervention (movers + non-movers) and then excluding those houses (just non-movers).

5 Establishing the impact of energy efficient lighting

Prior to estimating the intervention's impacts, we first calculate the technologically feasible expected electricity reductions for the winter, spring/fall, and summer seasons. Using baseline survey and intervention data, we calculate expected impacts assuming an average 3.2 incandescent light bulbs (100 watts each) are replaced by project CFLs (21 watts each).[31] These calculations and their underlying assumptions are further described in the Appendix. Based on these data, electricity consumption is estimated to decrease between 26 kWh per month (summer) and 42 kWh per month (winter).

Although the technologically feasible electricity reductions are relatively straightforward to calculate, those do not account for the interaction of human behavior with the technology. The actual effect of CFLs on electricity consumption could empirically be negative, zero, or positive. Smaller than the technological feasible expected impacts, negative, zero, or positive impacts could be explained by channels, such as a rebound in electricity consumption, a reduction in electricity outages permitting more electricity services, or an externality that is biasing estimates.

5.1 Basic estimates of impacts on electricity consumption

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

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

[31] From piloting the survey in November and December 2012, we knew that households typically used 100 watt bulbs in their homes. We decided to provide them with 21 watt CFLs, because they were advertised to be equivalent to 100 watt incandescent bulbs.

where q_{it} is household electricity consumption (kWh), $Treat_i$ is an indicator of treatment status, X_{it} is a vector of household controls, γ_t are month-by-year fixed effects, and λ_i are household fixed effects. We also control for heating degree days.[32] The $Treat_i * Post$ indicator in the equation above denotes the assignment to T and if that treatment occurred in that month or prior months.

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

Table 1 Column 1 reports results from this basic estimation. The naive results indicate the CFL treatment reduces household electricity consumption by 16 kWh per month; however, the magnitude of this impact is only half the expected size. If there are any externalities, we may be mis-estimating the impact of adopting the energy efficient lighting technology.

5.2 Accounting for externalities in estimated impacts

The two-stage randomization process provides variation in the proportion of households treated within a transformer. We use this variation to test whether externalities may be affecting our estimates of the impacts of energy efficient light bulbs. If there were externalities impacting control households, then our results calculated via equation 1 will be biased.

Externalities impacting electricity consumption

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

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

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

[32] The 7 villages in the study sample are all covered by one weather station. Therefore we do not have spatial variation in temperature, only variation in temperature over time. We do not expect, however, for there to be much spatial variation in temperatures across the villages included in the study.

for if the household i is a control household in a treated transformer group; and X_{ig} is a vector of potential controls, including the number of houses served by a particular transformer. The coefficient θ provides an estimate of the average impact of being a control household in a treated transformer.

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

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

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

It is clear that not accounting for potential externalities biased estimates of the impacts of technology adoption on electricity consumption. These biases could be caused by peer effects, a local aggregate reliability effect, or some other channel. To better understand how externalities impact the control households, we look for evidence of different forms of externalities.

Impacts on electricity consumption by season

Given the seasonality of energy use, we estimate the impacts of treatment on electricity consumption throughout the year. Based on our calculations of the expected electricity savings, ex ante we believed that electricity consumption reductions would be greatest in the winter (followed by fall/spring and then summer). These differences in expected electricity consumption across seasons are a function of differences in the hours of sunlight throughout the year.

To further explore the impacts of treatment over time, we plot both the expected impact based on the technologically feasible calculations and the estimated impact using study data. Results are shown in Figure 5. There are a few key points to take away from this graph.

First, the impacts of CFL treatment are quite noisy, particularly in the winter months. This noisiness is likely due to some households heating with electricity in the winter (which would cause a large spike in their electricity consumption), while others heat with coal. Although they indeed have reductions in electricity consumption, this noisiness might make these reductions less salient for treated households. Second, there is much heterogeneity in the impacts across seasons.

We see electricity savings grow in the months following the distribution of the energy efficient light bulbs (March 2013). In the autumn of 2013 and the spring of 2014, the electricity savings is similar in magnitude to the predicted amount. However, during the winter heating months, the actual impacts of the energy efficient light bulbs diverge greatly from the predicted impacts. Heterogeneity in impacts across seasons is reasonable, given that there are seasons in which one typically consumes more of other, non-lighting forms of electricity services.

The results in Figure 5 are also consistent with a technological externality in the form of a reduction of electricity outages in the winter. Winter is when unplanned outages most frequently occur, as peak electricity demand is quite high. CFLs have the potential to reduce electricity consumption, but they also have the potential to reduce outages in winter too (more than any other season). If households have more reliable electricity service (fewer outages) in the winter, then they will be able to consume more electricity services and we would not see the expected reduction in electricity consumption. That savings in electricity consumption returns to the expected amount in the spring (following the winter spike) suggests that this is not driven by a longer-term rebound effect.[33]

In addition, we estimate the same difference-in-differences regression as shown in equation 3, but run the regression separately for different seasons. We divide the months according the electricity utility's seasonal definitions, with the winter heating months including Novem-

[33] If there were a rebound effect occurring here, we would expect to see a more persistent change in behavior, rather than thus reversal in the spring. We cannot rule out the possibility of a rebound; however, we perform many tests and find no evidence of a direct or indirect rebound in electricity consumption. Using detailed survey data on both baseline and follow-up appliance use, we only find no effects of treatment on light bulb use. We find only one significant effect of treatment on appliance use (both whether or not appliance is used and the amount of time for which the appliance is reported to be in use): treatment households are significantly less likely to report using electric heaters at follow-up. If anything, these results are counter to a rebound effect.

ber, December, January, and February. The months shouldering the winter, the spring/fall seasons, include September, October, March and April are particularly interesting, as temperatures may be warmer, but days are short and residents are often still heating their homes.

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

5.3 Evidence of local aggregate reliability effects

The above results have shown significant negative impacts of household level treatment on electricity consumption; however, estimates are highly dependent on controlling for potential within transformer externalities. In this section we provide evidence indicating that this is a technological externality, in the form of fewer outages for all households within the treated transformers.

As is not uncommon in developing countries, outages in this context are typically the result of overloads within the distribution system. These overloads occur most frequently in winter, when household energy demand is the greatest. We use data from the follow-up survey on the number of days without electricity (due to outage) during the month prior, to measure whether transformer level treatment has an impact on unplanned outages.[34]

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

$$O_{ig} = \pi H_{ig} + \rho L_{ig} + \beta T_{ig} + \eta X_{ig} + \epsilon_{ig} \tag{4}$$

[34]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. If reductions in outages due to a reduced electricity load are possible, this is the time when we would expect to see them. Also, we can rule out the possibility that these days without electricity would be due to planned transformer maintenance, as the electricity performs that type of work in the summer, as they prepare for the winter heating season.

Where O_{ig} is the number of days without electricity due to outages in the month prior to the follow-up survey as reported by household i in transformer g; H_{ig} is a dummy variable if household i is in a transformer with a between 15 to 18 percent of households assigned to treatment; L_{ig} is a dummy variable if household i is in a transformer with a between 10 to 14 percent of households assigned to treatment; T_{ig} remains the households own treatment status; and X_g is a vector of transformer controls, in particular the number of houses served by a particular transformer. Standard errors are clustered at the transformer level.

Results in Table 2 indicate that the energy efficient technology led to a technological externality in the form of improved reliability. Column 1 shows this basic result. We see between one and two fewer days without electricity in both the low and high intensity transformers. Results are robust to including a suite of different transformer level controls, most important of which is the number of households within the transformer, and controlling for the reporting households own treatment status. Columns 2 and 3 show that the responses from the treated households are not driving results.[35]

This reduction in days without electricity due to outages is only statistically significant for households in the high intensity transformers. Column 3 indicates that households in high intensity treatment transformers report more than half as many (2.2 in comparison to 3.8) days of outages as households in control transformers. We test for the significance of difference between the high and low intensity transformer groups. In column 3 this difference is statistically significant.[36]

These results indicate a difference between the transformers with lower and higher intensities of treatment in the extent to which a technological externality is created. The households that take-up the energy efficient bulbs in a lower intensity transformer are creating some positive externality in that they are, to some extent, reducing the load on the transformer. The reduction in the days without electricity due to outages at the transformer is smaller and insignificant for the lower intensity transformers, but has the same sign and is of a similar

[35]High intensity transformers have more treatment households (by definition), so we might have been concerned that those households have an incentive to report fewer outages. By controlling for individual household treatment shows that such a story is not a concern.

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

magnitude as the higher intensity transformers. In contrast, the households that take-up the energy efficient technology in the higher intensity transformer groups generate a positive externality that is, in the aggregate, substantial enough to surpass some transformer load threshold, permitting a significant reduction in the number of days without electricity due to outages. In surpassing this threshold in take-up, this externality becomes closer to our working definition of a technological externality, in that the more individuals that take up the technology the greater are the returns to the technology.[37]

We perform three robustness checks of our results to ensure that we are indeed measuring a local aggregate reliability effect. First, we calculate the intra-cluster correlation in reported outages at follow-up. We have argued that intense treatment of households within a transformer is causing a reduction in outages at the transformer-level. If this is indeed the case, then household reported outages should be correlated with other household responses within the transformer.[38] Our calculation indicates a intra-class correlation of 0.56, which means that responses within transformers are indeed highly correlated.

As second robustness check, we consider the above reduction in outages in light of the difference between the expected reduction in electricity consumption and the estimated reduction in electricity consumption. Ex ante, we expected a reduction in winter electricity consumption of approximately 42 kWh per month. However, we estimated the actual reduction in monthly winter electricity consumption to be approximately 26 kWh per month. This is a difference of approximately 16 kWh per month. This is equal to approximately 14.4 hours of additional electricity consumption. Take in conjunction with results above indicating two fewer days without electricity per month, this would mean two outages of approximately seven hours in duration each. This is a perfectly reasonable result.[39]

Third, we seek to better understand the impact of energy efficient lighting on peak demand.

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

[38]We don't expect responses to be perfectly correlated with one another, because all households in a transformer were not surveyed on the same day and therefore the reference point of "past month" should differ, at least slightly.

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

This is important as outages are typically caused by transformer overloads during peak times and lighting is disproportionately "on peak."[40] We perform a back-of-the-envelope calculation of the peak load reduction induced by the CFL treatment. Calculations, which are shown in the Appendix, indicate that switching 4 incandescent light bulbs to CFLs could save 60 kWh per month, which would be 10% of a 600 kWh monthly bill. But if the lights are being used at peak times, it would be a 21% reduction in household peak demand.[41] For a transformer with approximately 20% of households treated, this would equal approximately a 4% reduction in peak load for the transformer.

Lastly, we also "ground-truth" these results by reporting them to our collaborators at the electricity utility in Kyrgyzstan. Engineers working at the electricity utility indicated that this would be a substantial reduction in peak demand at the transformer-level and would most certainly lead to a reduction in transformer outages.[42]

In summary, the results of this section indicate that the energy efficient light bulbs can have a significant impact on electricity consumption that, when controlling for potential externalities, is of a similar magnitude to that which is technologically feasible. And, when a large enough proportion of households take-up this energy efficient technology, an aggregate effect is possible, in the form of a technological externality. A technological externality, such a reduction in electricity outages, is experienced by all households in the impacted transformer, regardless of whether they themselves are treated or control households.

6 Interactions between multiple externalities in technology adoption

In section 5, we provided evidence of a household energy efficiency effect (the private returns) and a local aggregate reliability effect (a technological externality), as a result of the distribution of the energy efficient lightbulbs. Here we measure the impact of externalities on CFL adoption at follow-up. Specifically, we seek to answer the questions: What is the

[40] According to the utility, times of peak demand in Kyrgyzstan are 6 to 9 am and 6 to 10 pm.

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

[42] As a result of these findings and the utility's concerns regarding electricity service reliability, in October 2015 our utility collaborators reported to be promoting energy efficient lighting.

impact of the technological externality (more reliable electricity service) on CFL adoption? What is the impact of peer effects on CFL adoption?

Existing studies have disentangled the roles of direct effects and some combination of externalities in technology adoption, but they do not disentangle the roles of multiple externalties: technological externalities and peer effects (Foster and Rosenzweig, 2010).[43] In many studies the two externalities are completely overlapping, making it impossible to disentangle. In such cases, estimates of technological externalities (which confound peer effects) or peer effects (which confound technological externalities) might be biased.

Even the private effects depend on correctly identifying the externalities. How important this interaction between externalities is likely depends on which side of the technological externality threshold the study sample is.[44] We contribute to this literature by disentangling the effects of these two externalities in the adoption of CFLs.

We have two primary measures of technology adoption at follow-up: the number of CFLs in-use when we return for the follow-up survey in spring 2014 (a "stock" measure) and the number of CFLs the household purchases when offered CFLs following the follow-up survey (a "flow" measure).[45] It is also useful to think about the stock plus the flow in understanding CFL adoption, so we add the two for some analyses.

6.1 CFL stock and flow: naive estimates

What are the roles of the technological externality and peer effects on CFL adoption? We start with naive regressions of the role of these impacts on technology adoption. Table 3 panels A and B show regressions in which the outcome variable is our measure of stock and flow, respectively. The omitted group is detailed at the bottom of each column. Panel A

[43] Foster and Rosenzweig (2010) discuss how this is addressed in existing studies on the microeconomics of technology adoption. Some studies choose a technology in which one externality (typically the technological externality) is not present.

[44] If the study sample is below the technological externality threshold, it might not be as important to disentangle the peer effects from the technological externality.

[45] We offered households the opportunity to purchase up to 2 CFLs at full market price. For treated households, these 2 additional CFLs should have permitted the average house to fully replace all of their incandescent bulbs, given the average household had 6 bulbs at baseline and they were provided 4 CFLs at that time.

Column 1 shows the direct effect of being given the CFLs on later technology adoption. This is positive but not statistically significant; of course, this does not control for the fact that some control households might be contaminated by externalities.

We expect that control households located very close to a treated household are likely to experience some peer effects.[46] We utilize the spatial variation in exposure of control households to close treated neighbors induced by the two-stage randomization. We use the following equation to account for potential peer effects in technology adoption:

$$Y_{ig} = \beta Treat_{ig} + \theta C_{id} + \rho N_d + \theta X_{ig} + \epsilon_{ig} \tag{5}$$

where Y_{ig} is our outcome of interest for household i located in transformer group g; T_{ig} is an indicator for treatment status of household i in transformer group g; C_{ig} is an indicator for if the household i is a control household with at least one treated household within 100 meters from the house;[47] N_d is the total number of households within 100 meters from the house; and X_{ig} is a vector of controls, including the number of CFLs the household received from our project at baseline. Standard errors are clustered at the transformer level.

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

In column 3, we include a dummy variable for control households in treated transformers,

[46] We consider a control household to be "close" if the entrance is within 100 meters of a treated household.

[47] Household GPS coordinates were collected at the time of the baseline survey, allowing these distance calculations.

which should capture control households experiencing any technological externality. We have already shown that the technological externality is positive and significant, indicating that where electricity services are available for more hours per day, households consume more CFLs. More hours of electricity means there is more potential for savings, making CFLs even more valuable. This estimate of the technological externality, however, is confounded with the peer effect.

Given that some control households are exposed to both the potential peer effect and the technological externality, in column 4 we include dummies for both control households in treated transformers and control households close to treated households. In this specification, we now have the correct omitted group. This column represents the "typical" fully specified regression model. This is a contribution itself, by correctly separating the direct effect of receiving the technology from the externality. However, with this specification, we are not able to disentangle the separate roles of the two externalities or account for any interactions between the two.

Table 3 Panel B focuses on the flow of CFLs at follow-up. Although 23% of households purchase a CFL at full market price, there is no statistically significant relationship between exposure to CFLs and the follow-up purchase decision in any of the naive regressions.

Our diagram in Figure 3 also helps us to better understand how we are mis-estimating in the naive regressions in Table 3. Column 1 uses all control households (P, Q, R, S) as the omitted group. Column 2 uses groups Q and S as the control group. Column 3 uses groups P and Q as the omitted group. Column 4 gets the control group (Q) correct, but is still not able to disentangle the different effects of the externalities.

6.2 Disentangling the role of multiple externalities

As described earlier, the two staged randomization resulted in control households being potentially exposed to some combination of two types of externalities: technological externalities and peer effects. Our "road map" in Figure 3 portrayed how the externalities only partially overlap, allowing us to disentangle the roles of different externalities in CFL adoption. Panel A shows this varying exposure when we consider all treated transformers together. Panel B shows the varying exposure to externalities when we differentiate between high and low treated transformers.

All treated transformers

By estimating the impacts for these groups, we can use the heterogeneity in exposure to various combinations of externalities to estimate the specific channels impacting CFL adoption at follow-up. Specifically, we can separately estimate the role of the technological externality and peer effects, accounting for heterogeneity in peer effects depending on the presence of a technological externality. Coefficients from the regressions estimating the impacts for each of group of contorl households are located in Appendix Table 5, Panel A.

Results of these estimations, presented in Table 4 Panel A, differentiate between the technological externality effect, peer effects in the absence of a technological externality, and peer effects with a technological externality present. These results suggest that the peer effect potentially does interact with the technological externality.

Given how this analysis groups together transformers of all treatment intensities, it is unclear to what extent this matters. Households in transformers below some intensity of treatment might behave differently than households exposed to a technological externality. We address the potential importance of this difference in exposure to the technological externality, by performing this analysis again, differentiating between high and low intensity transformers.

Distinguishing between transformer treatment intensities

Earlier results showed a statistically significant reduction in days without electricity due to outages amongst households in higher intensity transformers. The reduction in outages reported by households in the lower intensity transformers was not statistically significant. These results suggest that the technological externality threshold is critical in understanding take-up of energy efficient technologies. To better understand the importance of surpassing this threshold and inducing the technological externality, we refine our analysis of the channels to allow for heterogeneity in transformer treatment intensity.

Results showing the calculations of these channels are in Table 4, Panel B. We start with the technological externality channels. The weak technological externality channel does not have a significant impact on CFL stock or flow. In contrast, the strong technological externality channel (above the threshold) in absence of any potential peer effects leads to a negative and significant stock of CFLs at follow-up. This is consistent with free-riding behavior. Households that experience the improved reliability as a result of others' CFL adoption are significantly less likely to adopt CFLs themselves. This is intuitive and makes clear why exposure to the technological externality alone will not necessarily induce adoption of energy efficient technologies.

There is indeed heterogeneity in the peer effects channels, depending on the interaction with the technological externality. Results indicate that the positive peer effects are driven by those households also experiencing the technological externality above the threshold at which they experience impacts on electricity reliability. Households that both learn about the private returns to CFLs and experience the increased electricity reliability have approximately one more CFL at follow-up than the pure control households. Control households that are exposed to the peer effect, but not a technological externality, buy 0.2 fewer CFLs, on average, than the pure control households. This is potentially because these households learned about the highly subsidized prices at which their neighbors received their CFLs at baseline. There is some evidence of a negative peer effect in the absence of a technological externality. In contrast, there is no evidence of a significant peer effects for the households exposed to the weak technological externality.

In assessing the results on these channels in Table 4 Panel B and comparing them with the naive results in Table 3, three points are clear. First, the interactions between the externalities are indeed critical. Second, there is much heterogeneity in the technological externality channel and interactions with peer effects appear important to induce positive take-up of the technology. Lastly, we see clearly how interpreting the naive results in Table 3 as either the technological externality or the peer effects would be misleading.

6.3 Evidence on the channels

To support the results on channels presented in the previous section, we provide evidence on the relationship between these externalities and household knowledge of and preference towards CFLs. Specifically, we use household responses to questions on whether they prefer CFLs over incandescent bulbs, know about CFLs, and believe that CFLs save electricity. In addition, we collected their responses on their maximum willingness to pay for CFLs at follow-up.[48]

Results are shown in Appendix Table 6, with Panels A and B arranged in the same format as Table 4 results. We find that the relationships between the channels and knowledge of and preference for CFLs are remarkably consistent with our results in Table 4. The strong technological externality channel, which had a negative effect on CFL stock at follow-up, also has a negative and statistically significant relationship with understanding that CFLs save electricity and willingnessto-pay for CFLs at follow-up.

Similar to the heterogeneity across peer effects channels (depending on the strength of the technological externalities) seen in Table 4 results, there is also heterogeneity across peer effects in knowledge of and preference towards CFLs. The peer effects channel in the absence of a technological externality, which showed some evidence of a negative relationship to CFL purchase at follow-up, is negative and significantly related to knowledge of CFLs and willingness to pay. In contrast, the peer effects channel in the presence of a strong technological externality has a positive and statistically significant impact on all of these indicators measuring knowledge of and preference towards CFLs. Taken together, the results in this table strongly support our findings in the prior section.

6.4 External validity

An important point to note concerns the external validity of our findings. We implement this two-staged randomized design in a developing country context in which reliability of electricity services is a substantial concern for both households and the electricity utility. Electricity reliability in this context is largely drive by congestion within the distribution network, which leads to transformer overloads. The constraints in electricity distribution networks are an issue in many developing countries and, we believe, will become a greater concern as countries develop and residential electricity demand increases and exceeds the limits of existing infrastructure. However, in developed countries, such as the United States, circumstances are different. Electricity systems typically face a different set of constraints and households own a greater number of electricity-using durables. For these reasons, a

[48] Immediately following the follow-up survey, but before we offered households the opportunity to purchase CFLs at market price (which was 100 KGS at the time), we asked a few questions on the price of CFLs in the market. We then asked them the maximum that they would be willing to pay for a CFL (in KGS). We use the value that they provided as an outcome measure. This measure was not elicited experimentally.

similar experiment in a developed country might have very different result with respect to electricity consumption.

7 Conclusions

Through a two-staged randomized experiment, we provide several substantial contributions to the literatures on both technology adoption in general and energy efficiency specifically. We show that energy efficient light bulbs can indeed lead to significant reductions in electricity consumption. These effects, however, are heterogeneous across seasons, making the impacts noisy and perhaps less salient for households. In addition, we find that controlling for potential externalities is critical, suggesting that estimates of energy efficiency that do not account for externalities may be downward biased.

In addition, we show that the energy efficient technology, when taken up at a high enough intensity, can have a local aggregate reliability effect, in the form of fewer days without electricity due to outages at the transformer level. By improving electricity service reliability, the energy efficient technology becomes more valuable. 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 two-stage randomized design permits us to decompose the different channels through which these externalities may impact adoption of an energy efficient technology. Exposure to the technological externality alone may induce free-riding. Interactions between peer effects and the technological externality can lead to heterogeneity in technology adoption, depending on whether the technological externality is present and can induce an aggregate reliability effect.

These results provide an important contribution to the microeconomics of technology adoption, by highlighting the importance of accounting for the interaction between the technological externalities and peer effects. This suggests that results not accounting for these interactions may be estimating an average of the externalities, thereby masking these important interactions and heterogeneities.

Much of the existing literature on the impediments to take-up of energy efficient technologies has focused on issues such as information problems and discount rates. This study highlights the importance of accounting for externalities both in estimating the impacts of energy efficient technologies and in understanding the adoption of these technologies.

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Figure 1: Two-stage randomization process

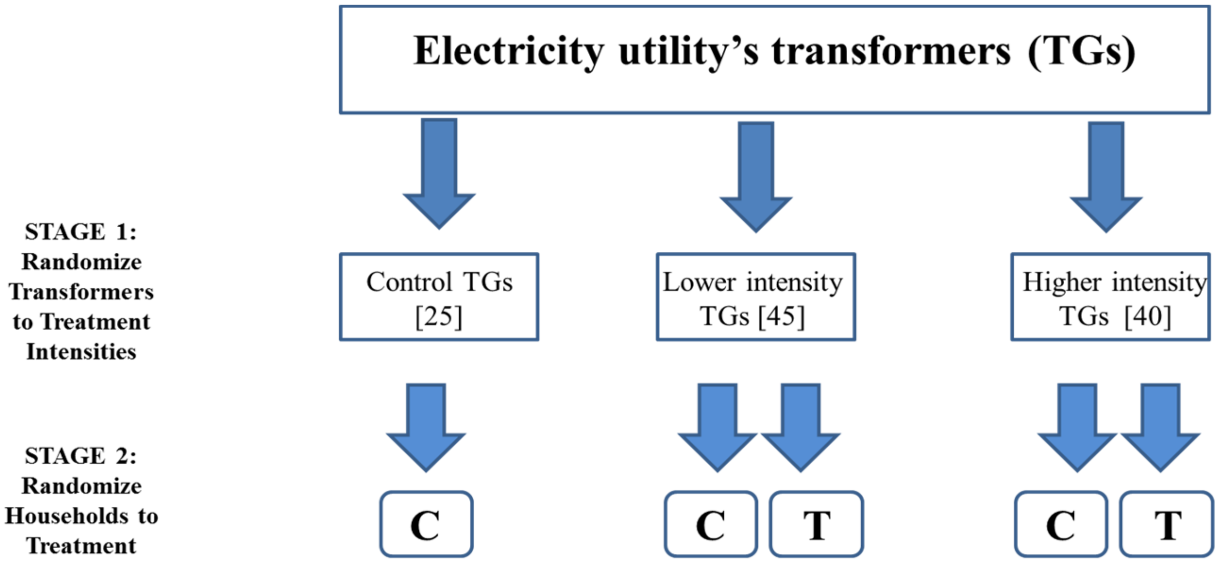

Figure 2: Example of exposure to externalities resulting from randomization

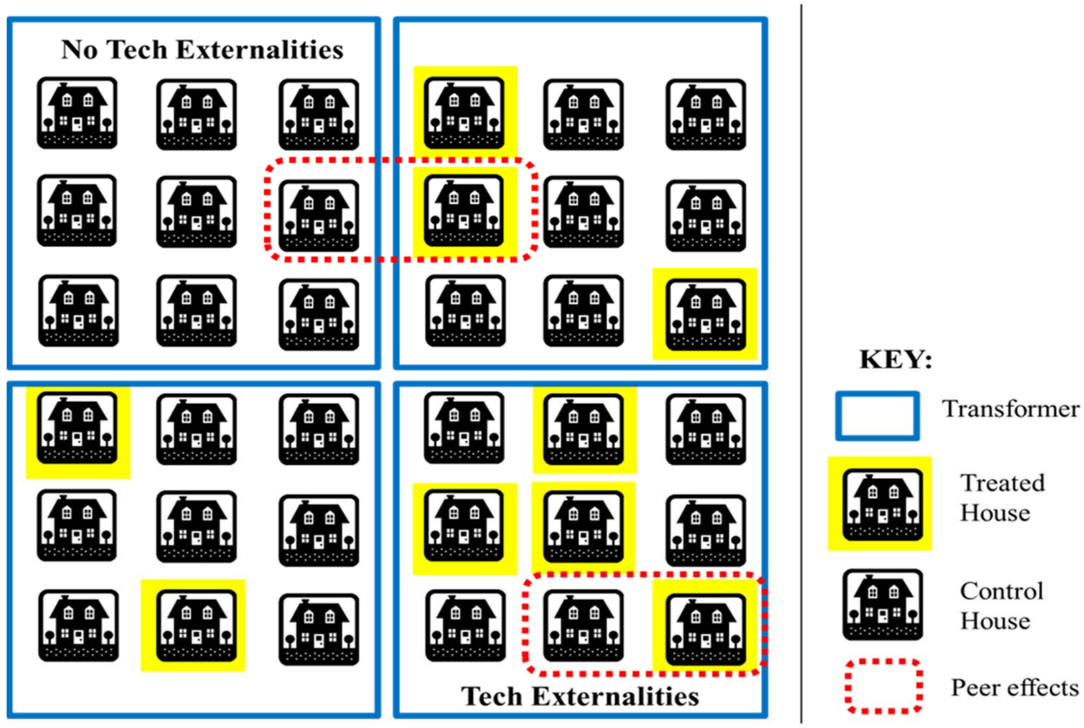

Figure 3: Experimental road map

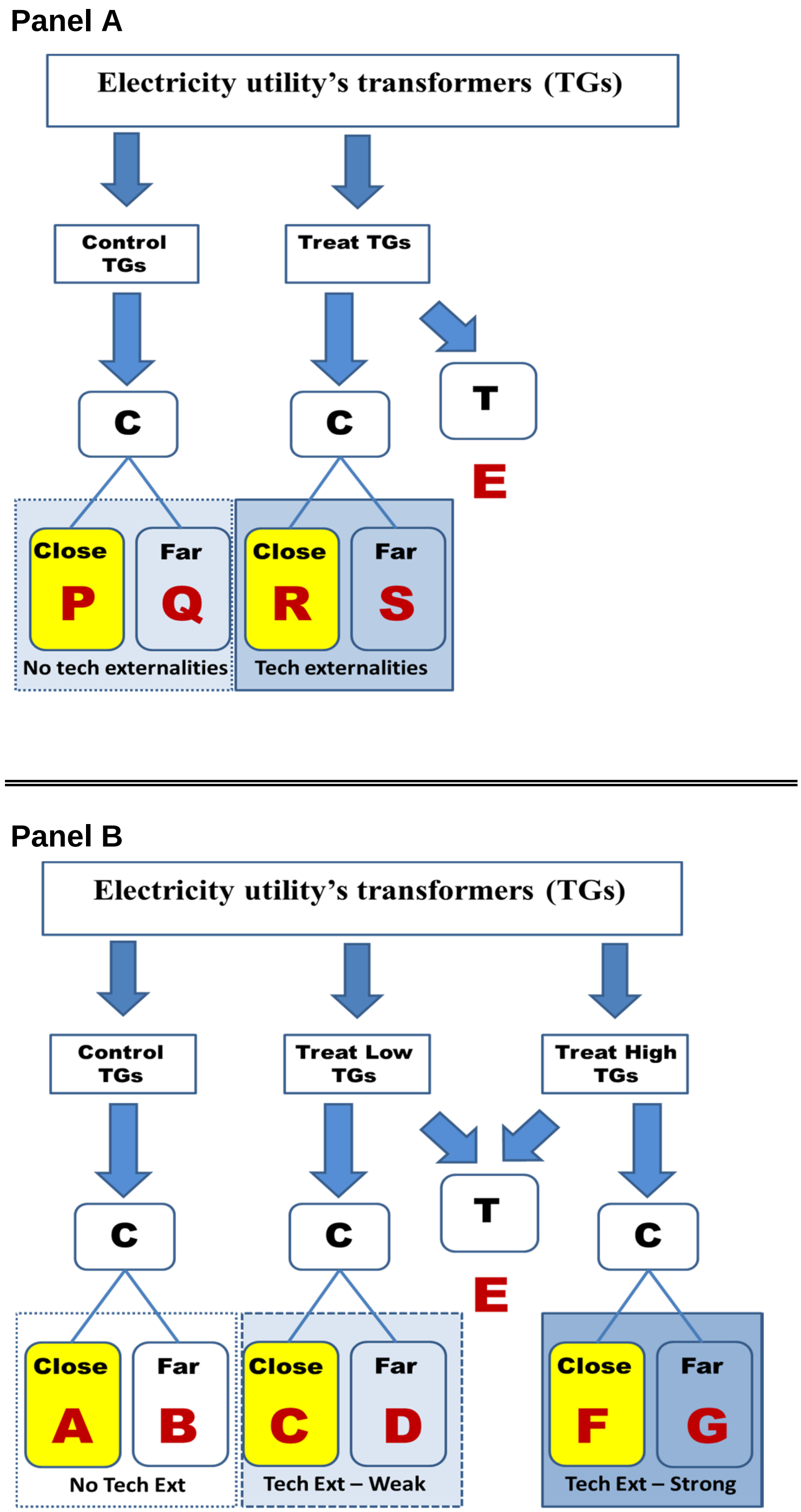

Figure 4: Seasonality of electricity consumption pre-treatment

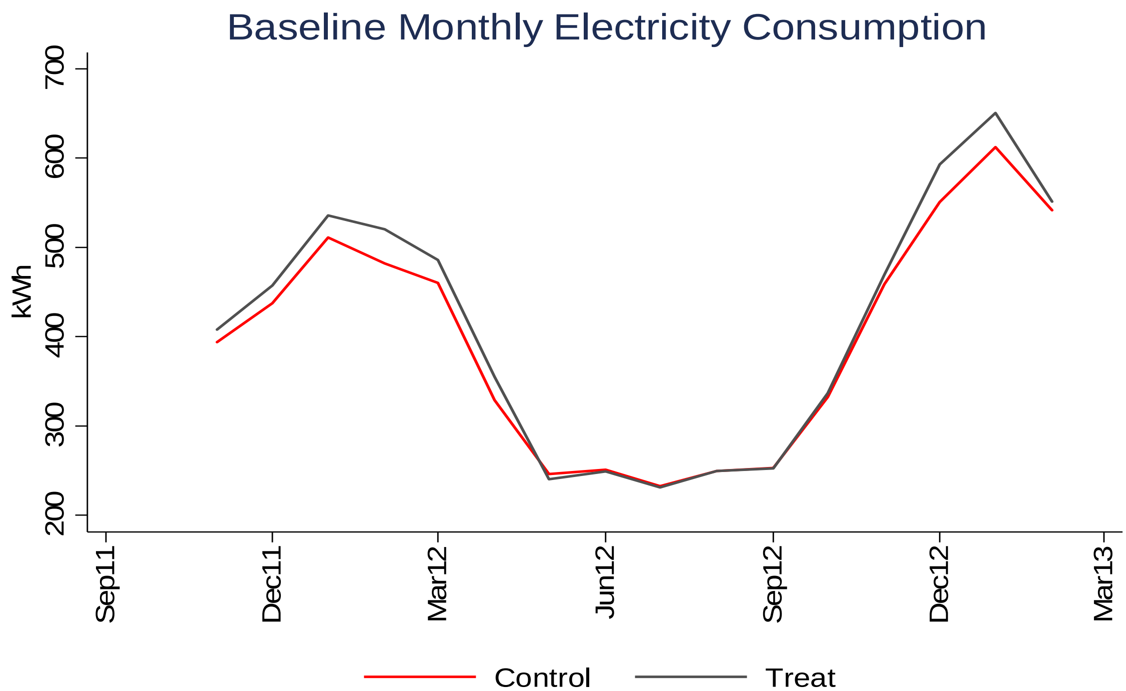

Table 1: Impacts of treatment on household electricity consumption

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

Notes: Results are intent-to-treat. All regressions include month-by-year fixed effects, household fixed effects, and controls for heating degree days, number of days in monthly billing period, whether the household uses electricity for heating, and dummy variables for Treated and Post. Columns 2 and 3 also include a dummy variable for being a control household in a treated transformer. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). "TG" is the abbreviation for transformer group. Standard errors are in parentheses, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Figure 5: Predicted and actual electricity reductions (kWh per month)

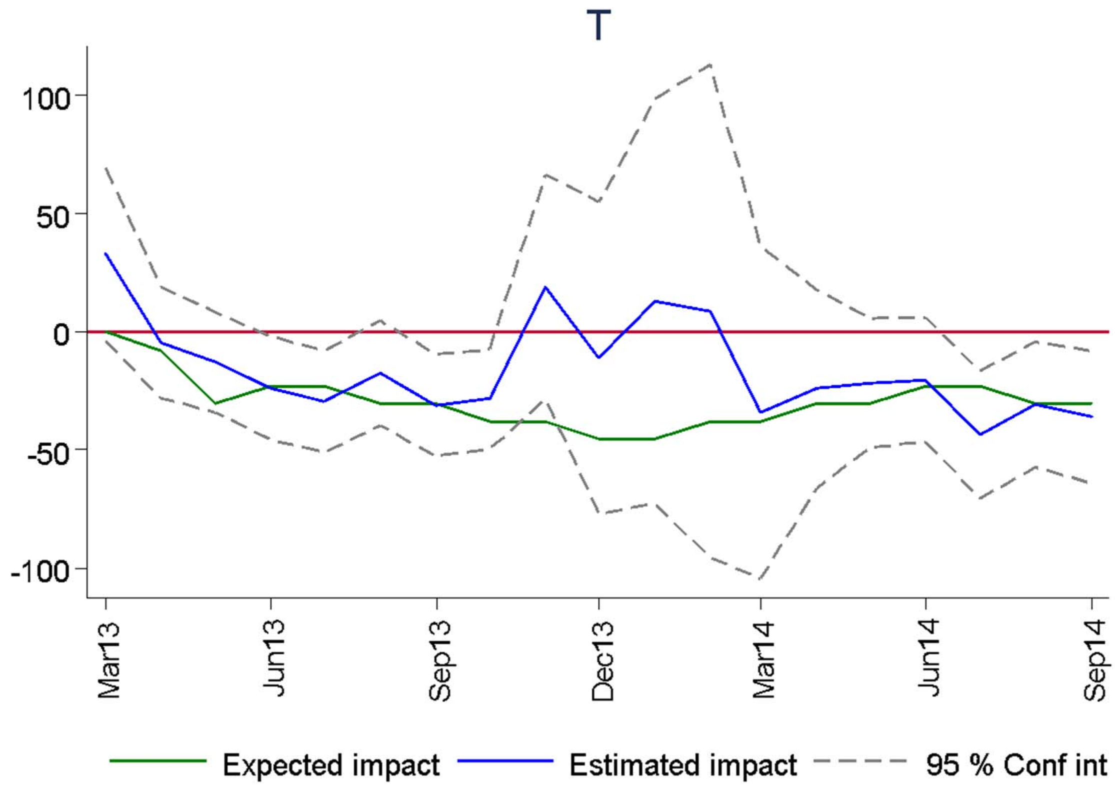

Table 2: Technological externalities: improved electricity reliability

Dependent Variable: Number of Days Without Electricity (in past month)			
	(1)	(2)	(3)
TG low	-1.321	-1.302	-1.164
	(0.851)	(0.862)	(0.868)
TG high	-1.866**	-1.841**	-2.162***
	(0.812)	(0.815)	(0.822)
Treated household		-0.032	
		(0.159)	
Treated household in TG low			-0.262
			(0.186)
Treated household in TG high			0.381
			(0.279)
Constant	3.810***	3.810***	3.811***
	(0.836)	(0.837)	(0.838)
P-value: TG low = TG high	0.228	0.227	0.047
Observations	838	838	838
R-squared	0.051	0.051	0.053

NOTES: "TG low" is a dummy variable that equals 1 if 10 to 14 percent of households in a transformer were assigned to treatment. "TG high" is a dummy variable that equals 1 if 15 to 18 percent of households in a transformer were assigned to treatment. Omitted group is comprised of households in control TGs. All columns control for the number of households in the transformer. Twenty percent of households were surveyed for each transformer. Std errors are clustered at the transformer level, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Table 3: CFL Stock and Flow: Naive estimates

	(1)	(2)	(3)	(4)
Panel A Dependent Variable: Number of CFLs at Follow-up ("stock")				
Treat	0.185	0.442**	0.479**	0.493**
	(0.174)	(0.212)	(0.219)	(0.223)
Control in treated TG			0.502**	0.373*
			(0.205)	(0.209)
C close to Treat		0.458**		0.158
		(0.207)		(0.215)
Constant	0.617***	0.365*	0.332*	0.319
	(0.187)	(0.204)	(0.199)	(0.205)
Panel B Dependent Variable: Number of CFLs Purchased at Follow-up ("flow")				
Treat	-0.002	-0.030	-0.007	-0.018
	(0.069)	(0.091)	(0.095)	(0.095)
Control in treated TG			-0.008	0.092
			(0.080)	(0.092)
C close to Treat		-0.049		-0.123
		(0.072)		(0.075)
Constant	0.137**	0.164**	0.142*	0.153*
	(0.068)	(0.079)	(0.080)	(0.080)
R-squared	0.012	0.013	0.012	0.014
Omitted group	All controls	Controls far from T	Controls in control TGs	Controls in control TGs, far from T
Observations	834	834	834	834

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

Table 4: Channels of technology adoption

	(1) CFL stock at follow-up	(2) Number of CFLs purchased	(3) Stock and flow
Panel A: Channels of effects			
Technological externality effect	0.176	0.031	0.207
(Condition S - Condition Q)	(0.303)	(0.135)	(0.308)
Peer effects with no technological externality	-0.159	-0.221***	-0.380
(Condition P - Condition Q)	(0.233)	(0.068)	(0.248)
Peer effects with technological externality	0.349	-0.064	0.284
(Condition R - Condition S)	(0.296)	(0.110)	(0.286)
Panel B: Heterogeneity in channels			
Weak technological externality effect	0.316	0.030	0.346
(Condition D - Condition B)	(0.339)	(0.149)	(0.336)
Strong technological externality effect	-0.453**	0.036	-0.418
(Condition G - Condition B)	(0.174)	(0.226)	(0.286)
Peer effects with no technological externality	-0.159	-0.221***	-0.380
(Condition A - Condition B)	(0.233)	(0.069)	(0.249)
Peer effects with weak technological externality	0.153	-0.061	0.092
(Condition C - Condition D)	(0.353)	(0.123)	(0.336)
Peer effects with strong technological externality	1.106***	-0.074	1.032***
(Condition F - Condition G)	(0.221)	(0.225)	(0.305)
Observations	834	834	834
R-squared	0.13	0.015	0.13

Notes: All specifications also included dummies for the private effect (not shown here). All regressions control for the total number of households in the transformer and the number of CFLs received at baseline through the project. The omitted group is comprised of the control households in control transformers that are more than 100 meters from any treated households (in Panel A this is is Condition Q; in Panel B this is Condition B). Treatment households are considered to be "close" if they are within 100 meters. Standard errors are clustered at the transformer level, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Appendix

Appendix Calculation 1: Number of residential buildings

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

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

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

Appendix Calculation 2: Technologically feasible electricity savings from CFLs

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

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

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

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

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

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

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

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

- We assume a household's winter monthly electricity demand is 630 kWh per month, which is based on data from our sample.

- Dividing this by the number of days per month and number of hours per day, we estimate an average hourly winter electricity demand of .875 kW.

- We assume that peak load is approximately 70% more than average load, which is in line with the U.S. Energy Information Administration's calculations for peak-to-average electricity demand ratios. Therefore, household peak is 1.49 kW.

- We assume the household has 4 incandescent bulbs (100 W each) that replaced by CFLs (21 W) used in our project. This change would reduce peak load by 0.32 kW.

- Given our estimated peak demand of 1.49 kW, reducing peak load by 0.32 kW represents a 21% reduction in peak demand for a household.

- For a transformer with 20% of households making this shift to CFLs, this would mean a 4% reduction in peak load for the transformer.

Appendix Table 1: Transformer-level randomization check

	Number of Transformers	Control Transformer	Lower Transformer (<=14%)	Higher Transformer (>14%)	Joint F tests (p-value) Control = Low	Control = High	Low = High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Household-level							
HH head completed seconday school	111	0.8	0.88	0.74	0.415	0.572	0.111
Household income (Kyrgyz soms)	111	13107.08	12647.62	13285.47	0.842	0.938	0.748
Own house	111	0.88	0.95	0.84	0.380	0.602	0.105
Private house	111	0.88	0.83	0.74	0.649	0.185	0.312
Number of rooms	111	4.32	4.50	4.14	0.584	0.582	0.203
Total bulb in house	111	6.36	6.21	6.23	0.831	0.851	0.975
Total CFL bulb in house	111	0.4	1.10	0.84	0.101	0.299	0.477
Total incandescent bulb in house	111	5.96	5.10	5.40	0.217	0.417	0.616
Panel B: Transformer-level							
Years since last maintenance	102	3.38	3.03	3.90	0.568	0.385	0.101
Total # of households	110	51.80	63.12	47.58	0.126	0.565	0.015
Total # of households with 3 phase meter	110	12.92	15.36	15.81	0.324	0.240	0.829
Proportion of HH with 3 phase meter	110	0.28	0.28	0.34	0.951	0.102	0.068

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

Appendix Table 2: Household-level randomization check

	All	**Control**	**T**	**Joint F tests (p-value)**
	(1)	(2)	(3)	(4)
General characteristics				
Household head completed seconday 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				
Total number of appliances	8.393	8.578	8.238	0.210
Lighting hours per day	17.5	17.9	17.2	0.643
Think about saving electricity	0.946	0.934	0.955	0.500
Do something to save electricity	0.86	0.829	0.885	0.185
Total light bulbs in house	6.2	6.5	6.0	0.128
Total incandescent bulb in house	6.1	6.3	5.8	0.177
Believe CFL use less energy	0.305	0.319	0.292	0.436
Rooms heated in winter	3.14	3.12	3.15	0.764

Note: In March 2013, the exchange was 1USD = 48 KGS. For these calculations, the winter months include November through February and summer months include May through August.

Appendix Table 3: Expected impacts on electricity consumption

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

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

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

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

Notes: The omitted group is comprised of households in control transformers. All regressions include time fixed effects, household fixed effects, and controls fir HDD, # days in billing period, and and dummy variables for Treated and Post. Columns 2 and 3 also include a dummy variable for being a control household in a treated transformer. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Standard errors are clustered at the transformer levels, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Appendix Table 5: CFLs stock and flow estimates

	(1) CFL stock at follow-up	(2) CFLs purchased	(3) Stock and flow
Panel A: Estimated effects by treatment status			
Treated *(Condition E - Condition Q)*	0.466**	-0.026	0.441*
	(0.229)	(0.097)	(0.249)
Peer effects alone *(Condition P - Condition Q)*	-0.159	-0.221***	-0.380
	(0.233)	(0.068)	(0.248)
Peer effects and technological externalities combined *(Condition R - Condition Q)*	0.525**	-0.033	0.492**
	(0.225)	(0.084)	(0.238)
Technological externalities alone *(Condition S - Condition Q)*	0.176	0.031	0.207
	(0.303)	(0.135)	(0.308)
Panel B: Heterogeneous estimated effects by treatment status			
Treated *(Condition E - Condition B)*	0.466**	-0.026	0.441*
	(0.230)	(0.097)	(0.249)
Peer effects alone *(Condition A - Condition B)*	-0.159	-0.221***	-0.380
	(0.233)	(0.069)	(0.249)
Peer effects and strong technological externalities combined *(Condition F - Condition B)*	0.653**	-0.038	0.615**
	(0.263)	(0.097)	(0.275)
Peer effects and weak technological externalities combined *(Condition C - Condition B)*	0.468*	-0.031	0.437*
	(0.250)	(0.088)	(0.263)
Strong technological externalities *(Condition G - Condition B)*	-0.453**	0.036	-0.418
	(0.174)	(0.226)	(0.286)
Weak technological externalities *(Condition D - Condition B)*	0.316	0.030	0.346
	(0.339)	(0.149)	(0.336)
Constant	0.358*	0.165*	0.524**
	(0.215)	(0.085)	(0.236)
Observations	834	834	834
R-squared	0.13	0.015	0.13

Notes: All specifications control for the total number of households in the transformer and the number of CFLs received at baseline through the project. The omitted group, comprised of the control households in control transformers that are not close to any treated households (in Panel A this is is Condition Q; in Panel B this is Condition B). Treatment households are considered to be "close" if they are within 100 meters. Standard errors are clustered at the transformer level, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.

Appendix Table 6: Supporting evidence of learning

	(1) Prefer CFLs	(2) Know CFLs save electricity	(3) Know about CFLs	(4) WTP (KGS) at follow-up
Panel A: Channels of effects				
Technological externality effect	0.006	-0.045	0.064	-20.13
(Condition S - Condition Q)	(0.069)	(0.096)	(0.082)	-16.82
Peer effects with no technological externality	-0.015	-0.006	-0.084**	-45.54***
(Condition P - Condition Q)	(0.093)	(0.171)	(0.035)	(7.98)
Peer effects with technological externality	0.156	0.152	0.082	10.20
(Condition R - Condition S)	(0.067)**	(0.089)*	(0.077)	(12.46)
Panel B: Heterogeneity in channels				
Weak technological externality effect	0.024	-0.004	0.098	-14.79
(Condition D - Condition B)	(0.079)	(0.111)	(0.096)	(17.82)
Strong technological externality effect	-0.078	-0.234***	-0.099**	-59.41***
(Condition G - Condition B)	(0.048)	(0.058)	(0.041)	(8.05)
Peer effects with no technological externality	-0.015	-0.008	-0.087**	-46.04***
(Condition A - Condition B)	(0.093)	(0.171)	(0.035)	(8.02)
Peer effects with weak technological externality	0.135*	0.125	0.078	8.627
(Condition C - Condition D)	(0.079)	(0.105)	(0.092)	(16.80)
Peer effects with strong technological externality	0.245***	0.309***	0.177**	39.961***
(Condition F - Condition G)	(0.062)	(0.068)	(0.060)	(7.08)
Observations	834	834	834	427

Notes: All specifications also included dummies for the private effect and the technological effect (not shown here). All regressions include controls for: the total number of households in the transformer, the proportion of households in the transformer with a 3 phase meter, and size of the household. The omitted group is comprised of the control households in control transformers that are more than 100 meters from any treated households. Standard errors are clustered at the transformer level, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level. Column (4) has fewer observations due to imperfect response rate to the question related to willingness to pay.

Appendix Table 7: Technological externalities and private benefits

Dependent Variable: Monthly Household Electricity Consumption (kWh)	(1)	(2)
Treated household in TG low * Post	-42.798***	-41.392***
	(12.025)	(13.320)
Treated household in TG high * Post	-22.269*	-20.337
	(11.911)	(13.752)
Control household in TG low * Post	-42.986***	-50.243***
	(13.713)	(13.769)
Control household in TG high * Post	13.014	21.283
	(16.355)	(17.893)
Use electricity to heathouse	69.286***	69.286***
	(0.000)	(0.000)
Number days with outages		-88.657***
		(0.000)
Controls for reported outages	No	Yes
Omitted group	Houses in Control Transformers	Houses in Control Transformers
Observations: households	31,143	26,043

Notes: The omitted group is comprised of houses in control transformers. "TG low" is a dummy variable that equals 1 if 10 to 14 percent of households in a transformer were assigned to treatment. "TG high" is a dummy variable that equals 1 if 15 to 18 percent of households in a transformer were assigned to treatment. All regressions include time fixed effects, household fixed effects, and controls for heating degree days, number of days in monthly billing period, and the use of electric heater. Each month drops the top 1% of observations with respect to electricity use. All regressions drop households that moved during period between intervention and follow-up survey (101 households). Std errors are clustered at the transformer level, with * significant at 10% level; ** significant at 5% level; and *** significant at 1% level.