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 local electricity reliability. The CFL treatment reduces household electricity consumption by a quantity within the range of the technologically feasible savings. Estimates not controlling for externalities are downward biased. CFL distribution results in technological externalities: more intense distribution leads to two fewer days per month without electricity due to transformer-level outages. Increased electricity reliability permits households to consume more electricity services. Finally, we find interactions between technological externalities and peer effects are critical in inducing take-up.

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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 itself. 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). Technological externalities are often endogenous to a group, making their impacts particularly difficult to measure. As a result, there is relatively little existing rigorous empirical evidence on technological 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 tech-

[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] Examples of randomized studies measuring 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); and insurance take-up (Cai, de Janvry and Sadoulet, 2015). Jackson (2010) and Breza (2015) review the field.

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

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

nology adoption. Energy efficient technologies can reduce the cost of energy services to 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 (World Bank, 2006). As a result, CFLs are one common energy efficient technology promoted en masse in developing countries during the past two decades.[7]

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 lightbulbs (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).

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 in one district 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

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

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

[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.

electricity utility's records) for 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 the improved electricity reliability. Households in transformers with improved reliability consume more hours of electricity services due to 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 (World Bank, 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 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 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

[10]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]Jaffe and Stavins (1994) and Gillingham and Palmer (2014) discuss the energy efficiency gap.

[12]Interventions to increase uptake of energy efficient technologies have focused on energy labeling (Newell

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 relevant given that recent studies have found energy efficiency interventions to fall short of the technologically-feasible engineering calculations.[13]

Given the electricity services associated with the energy efficient appliance are less expensive, households may respond to the new technology by using the appliance more. This is a rebound effect.[14] Although the existing literature appears to agree on the existence of rebound effects, there is much debate over the magnitude of such an effect (Gillingham, Rapson and Wagner, forthcoming). Our analyses of both electricity consumption records and appliance use data, however, provide no evidence of direct or indirect rebound effects.

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 and expected impacts of CFL exposure; Section 4 covers the data collected and results of the randomization and compliance checks; Section 5 establishes impacts of CFLs at the household and transformer-levels; and Section 6 estimates the role of various channels in the adoption of the energy efficient technology; and Section 7 concludes.

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) found electricity reductions to be less than expected. A non-experimental evaluation of CFL distribution in Ethiopia suggests approximately 20% of initial electricity savings dissipated (Costolanski et al., 2013). Graff Zivin and Novan (2016) found that a weatherization program in San Diego led to substantially smaller energy savings than expected, ex ante. An experimental evaluation of a weatherization program in Michigan found energy reductions to be less than predicted (Fowlie, Greenstone and Wolfram, 2015).

[14] For theoretical discussion of the rebound effect, see Borenstein (2015) and Chan and Gillingham (2015).

2 Institutional setting and energy efficiency impacts

2.1 Electricity in Kyrgyzstan

Kyrgyzstan provides an ideal setting to study energy efficiency and electricity reliability in a developing country setting.[15] 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 its power plants (Zozulinsky, 2007). Ninety percent of electricity generation within the country is hydroelectric, so supply fluctuates with annual variability in reservoir water levels.[16] Technically, the capacity of both generation and transmission infrastructure could constrain household electricity services and result in unreliable electricity services (frequent electricity outages); however, during the study period, distribution constraints are the primary source of unreliable service.

Due to very low residential electricity prices ($0.02 per kWh throughout this study), many households heat with electricity in winter. In spite of low prices, concerns regarding electricity bills and household energy expenditures are common. Household energy expenditures comprise an estimated 7.1 percent of total household expenditures in Kyrgyzstan (Gassmann, 2012), much of which is due to winter heating. Electric heating leads to large seasonal variations in electricity consumption, with average winter consumption approximately three times that of summer. The country's utilities face growing electricity consumption while constrained by a distribution system designed for substantially lower demand. As a result, the country is plagued by frequent unplanned outages particularly in winter.[17]

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

[16] In years of low water availability, the country has instituted planned, rolling blackouts during the winter; however, this did not occur during our study period.

[17] 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 as a binding constraint and source of unplanned outages. To put this in perspective, most of the transformers have a load factor of 0.9 - 1.2, with 0.7 being the optimal load (Amankulova, 2006).[18] These constraints are a concern for both consumers and the electricity utility. Unplanned outages typically 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. But 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). There is a maximum electricity load that a transformer can transfer at any given time and exceeding that may lead to unplanned outages. During the study, there were no planned rolling outages; transformer overloads were the primary source of unplanned outages. Electricity service is correlated within a transformer, as households are exposed to the same electricity-related shocks. A transformer-level outage affects all households sharing the transformer.[19]

2.2 Energy efficiency promise

Energy efficient technologies have the potential to decrease individual residential electricity costs. Using approximately 75% less electricity than incandescent lightbulbs, CFLs are one tool for meeting lighting needs while reducing electricity consumption. If take-up rates are sufficiently high, energy efficient technologies could impact at an aggregate level. For example, CFLs could decrease cumulative electricity demand at 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 lightbulbs were available to purchase in both rural and urban markets for approximately 15 to 20 Kyrgyz soms. Even with low electricity prices, the payback period for the CFLs was between 1 and 2 years.[20]

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

[19] In our sample, 54 households on average receive their electricity via a single transformer.

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

Yet, outside of the capital, very few households used CFLs prior to 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 might expect the following impacts from energy efficient technology adoption in a developing country setting, such as ours:

1. *household energy efficiency effect:* this refers to the private returns to adopting energy efficient lightbulbs 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 CFLs 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 reduced probability of an outage due to a transformer overload, which 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, and could be positive, negative or zero. The presence of a technological externality can then impact later adoption decisions. For example, control households that benefit from more reliable electricity services may free-ride on other households' adoption of CFLs.

3. *peer effect:* this is the effect of CFL adoption on others' adoption decision and is experienced by households with close linkages to adopters.[21] This effect could be positive, negative or zero and could occur via channels such as learning, imitation, etc.

4. *aggregate regional electricity demand:* this is the effect of energy efficiency on aggregate demand within a particular geographic or service region. This would occur at a level higher than the transformer and is therefore outside of our study scope.

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 their individual roles and understand how the two externalities interact.

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

3 Randomized experiment with energy efficiency

3.1 Sampling process

We implemented the following sampling procedure to select villages, transformers, and then households within the transformers. We use data from the electricity utility on all electrified households within one district near the country's capital (which includes over 40,000 residential customers) for our sampling procedure.[22] 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 based on accessibility during winter months.[23] Within the seven villages, there were 248 eligible transformers.[24] The mean monthly household electricity consumption was calculated for these transformers. The 124 transformers with below median household electricity consumption are included in the sample.[25] To complete the sampling process, 20% of households from each transformer were randomly selected for the survey.[26]

3.2 Experimental design with two-staged randomization

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

The first stage randomization proceeded as follows. The 124 transformers were randomized into three groups: control transformers, transformers with lower intensity of treatment, and

[22]The districts near the capital are better off than the country's other regions. The study sample is not representative of the entire country.

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

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

[25]In an effort to include households more typical of the country as a whole, the study design focused on selecting households with electricity use below the district median.

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

transformers with higher intensity of treatment, with 39, 45, and 40 transformers, respectively. In control transformers, no households are treated. In transformers assigned a lower intensity of treatment, 60% of surveyed households are treated. In transformers assigned to a higher treatment intensity, 80% of surveyed households are treated. Within the treated transformers, between 10 to 18% of all households are assigned to treatment, with differences due to heterogeneity in the number of houses per transformer.

In the second stage, households were randomized into treatment and control groups, according to the transformers' randomly assigned treatment intensities. This results in 457 control households and 543 treated households. By definition, all treated households are in treated transformers; however, control households can be in either control or treated transformers.

In 2013, we implemented a household survey in both treatment and control households.[27] Immediately after completing the survey, all households were given 150 Kyrgyz soms to compensate them for their time. After the baseline survey, treated households were able to receive up to 4 CFLs[28] at a highly subsidized, randomly-drawn price.[29] Treated households were not told about the opportunity to receive the CFLs until after the baseline survey was complete. On average, treated households received 3.2 CFLs from the intervention.[30] After the follow-up survey in 2014, all households, regardless of their original treatment status, were given the opportunity to purchase up to 2 CFLs at the full market price.

3.3 Randomized exposure to an energy efficient technology

As described in Section 2, the two-stage randomization resulted in household exposure 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 propor-

[27] At that time, households were not informed of their treatment assignment.

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

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

[30] We did not have 100% take-up of the CFL technology. Some treated households did not continue after the baseline survey, in which case they received zero CFLs. Further discussion of compliance is below.

tion of households within a transformer adopt the CFLs and reduce electricity consumption, a local aggregate reliability effect may result. This would be a reduction in unplanned electricity outages, resulting in more hours of available electricity services.

Although not receiving CFLs themselves, control households may also be exposed to effects of externalities from other households' adoption. Figure 1 depicts how the two-staged randomization resulted in control households' differing exposure to externalities. 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. 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 these externalities on CFL adoption? How the two-stage randomization enables us to disentangle these effects is shown through a "road map" in Figure 2. 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 2 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 2.

Four types of control households are generated, designated in Panel A as Groups P, Q, R, and S. These groups are exposed to different combinations of externalities 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 CFLs over time for each group:

$\Delta Z_P = \Delta$ peer effects + Δ overall trend
$\Delta Z_Q = \Delta$ overall trend
$\Delta Z_R = \Delta$ peer effects + Δ tech externalities + Δ overall trend
$\Delta Z_S = \Delta$ tech externalities + Δ 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 = [ΔZ_S - ΔZ_Q]
Δ peer effects with no technological externality = [ΔZ_P - ΔZ_Q]
Δ peer effects with a potential technological externality = [ΔZ_R - ΔZ_S]

Given that this analysis groups together transformers of all treatment intensities, the role of technological externalities remains unclear. Households in transformers with a lower intensity of treatment might behave differently than households with a higher intensity of treatment (and therefore experiencing greater improvement in reliability).

Distinguishing between transformer treatment intensities

To better understand the importance of heterogeneity in treatment, we refine our above analysis to allow for heterogeneity in transformer treatment intensity. Panel B of Figure 2 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 weaker tech externalities + Δ overall trend
$\Delta Z_D = \Delta$ weaker tech externalities + Δ overall trend
$\Delta Z_F = \Delta$ peer effects + Δ stronger tech externalities + Δ overall trend
$\Delta Z_G = \Delta$ stronger tech externalities + Δ overall trend

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

Δ Weaker technological externality = [ΔZ_C - ΔZ_B]
Δ Stronger technological externality = [ΔZ_F - ΔZ_B]
Δ Peer effects with no technological externality = [ΔZ_A - ΔZ_B]
Δ Peer effects with weaker technological externality = [ΔZ_C - ΔZ_D]
Δ Peer effects with stronger 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 heating degree day data from a nearby weather station.

Electricity utility data: We utilize electricity utility records to identify both transformers and households for our 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.[31] One important feature of this time period: electricity prices remained constant at 0.02 USD per kWh.

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

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.[32] The survey collected information on appliance ownership and use, lightbulb ownership and use, electricity-related behaviors, and various household demographics. We tracked the number of CFLs distributed to each treatment household.

We visited the same residential addresses one year after the intervention, in the spring of 2014. Of the original 1,000 respondents, 835 households were interviewed for the follow-up survey.[33] 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.[34] 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.

4.2 Study sample

Households in the sample are highly-educated, with 84% of household heads having finished secondary school. Household monthly income per capita is an average of 76 USD per month

[32]Respondents were offered 150 Kyrgyz soms (approximately 3.26 USD) for their time spent on 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).

[33]Survey enumerators made at least four attempts to survey the household. If enumerators were informed that the previous respondents had moved, then the new residents were surveyed. Survey respondents were again offered 150 KGS to compensate for their time.

[34]We asked about the number of days due to heterogeneity in outage length. The transformer repair required and availability of replacement parts determines the outage length after a transformer overload. According to the utility, transformer outages last between a few hours and a few days.

(2.45 USD per person per day). The average household size living is just under 4 individuals. Most houses (91%) are owner-occupied.[35] On average, the homes are comprised of 4.3 rooms and are constructed of brick (54%) or a hay/adobe mix (38%).

Houses are served by formal connections to the electrical grid and metered individually (i.e., houses do not share meters). Households receive a monthly electricity bill based on 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%).[36]

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

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 2 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 Appendix Figure 2) shows

[35] The majority of the housing stock was constructed during the Soviet Union.

[36] Households conserve on heating; respondents reported heating an average of 3/4 of rooms during winter.

the same seasonal patterns for both treatment and control households. The large spike in winter electricity consumption is due in large part to electric heating. 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 the home at time of follow-up survey. First, upon completion of the baseline survey, treatment households were asked to continue on to a module addressing energy efficiency. A portion of the treatment groups refused to continue after the baseline survey (before the households learned of their treatment assignment). These households therefore do not receive the CFLs. The rate of non-compliance was 12%. For our intent-to-treat estimates, these households are considered treated.

Second, as of spring 2014, 101 addresses (of the original 1000 households) were identified as having new tenants in the year since the intervention. We interviewed households currently living at the original addresses and can perform the analysis two ways: including all households (movers + non-movers) and then excluding those houses with new tenants (just non-movers). Results are consistent across these analyses.

5 Establishing the impact of energy efficient lighting

Prior to estimating the intervention's impacts, we first calculate the technologically feasible expected electricity reductions for the winter, spring/fall, and summer seasons. Using baseline survey and intervention data, we calculate expected impacts assuming an average 3.2

incandescent lightbulbs (100 watts each) are replaced by project CFLs (21 watts each).[37] These calculations and their underlying assumptions are further described in the Appendix and results of these calculations are in Appendix Table 4. Electricity consumption is expected to decrease by between 26 and 42 kWh per month, in summer and winter respectively.

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

5.1 Basic estimates of impacts on electricity consumption

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

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

where q_{it} is household electricity consumption (kWh), $Treat_i$ is an indicator of treatment status, X_{it} is a vector of household controls, γ_t are month-by-year fixed effects, and λ_i are household fixed effects. We also control for heating degree days.[38] 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.

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

[38] 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.

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 the CFL treatment. 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 that equals 1 if the household i is a control household in a treated transformer group; and X_{ig} is a vector of potential controls, including the number of houses served by a particular transformer. The coefficient θ provides an estimate of the average impact of being a control household in a treated transformer.

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:

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

Results presented in Columns 2 and 3 of Table 1 indicate that the CFL treatment led to a reduction in electricity consumption of 30 kWh per month. When accounting for potential within transformer externalities, the impacts of the CFLs on household electricity consumption are statistically significant, substantially larger than estimates in column 1,

and comparable to the expected reductions. A comparison across columns 2 and 3 shows that coefficients are significant regardless of the level at which standard errors are clustered.

It is clear that not accounting for potential externalities biased estimates of the impacts of technology adoption on electricity consumption. These biases could be caused by peer effects, a local aggregate reliability effect, or some other channel. To better understand how externalities impact the control households, section 5.3 provides evidence on the presence 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. We plot both the impact expected of the technology and the estimated impact using study data. Results are shown in Figure 3. 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 lightbulbs (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 lightbulbs 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 3 are also consistent with a technological externality in the form of a reduction of electricity outages in the winter. Winter is when unplanned outages most frequently occur, as peak electricity demand is quite high. CFLs have the potential to reduce electricity consumption, but they also have the potential to reduce outages in winter (more than any other season). If households have more reliable electricity service (fewer outages) in the winter, then they will be able to consume more electricity services and we

would not see the expected reduction in electricity consumption. Results in Appendix Table 4 are consistent with households in higher intensity treatment transformers consuming more electricity.

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

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).[39] We estimate the same difference-in-differences regression as shown in equation 3, but run the regression separately for each season. We divide the months according to the electricity utility's seasonal definitions, with the winter heating months including November, December, January, and February. Results in Appendix Table 5 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

In this section we provide evidence of a technological externality resulting from the CFLs, in the form of fewer outages for all households within the treated transformers. As is not uncommon in developing countries, outages in this context are typically the result of over-

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

loads within the distribution system. These overloads occur most frequently in winter, when household energy demand is 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.[40]

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

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

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

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 household's own treatment status. Columns 2 and 3 show that the responses from the treated households are not driving results.[41]

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 approximately half as many (2.2 in comparison to 3.8) days of outages as households in control transformers. We test for the significance of difference between the high and low intensity transformer groups and, in column 3 this dif-

[40]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.

[41]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. Controlling for individual household treatment shows that such an outcome is not a concern.

ference is statistically significant.[42]

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 magnitude as the higher intensity transformers. In contrast, the households that take-up the CFLs in the higher intensity transformers generate a positive externality that is, in the aggregate, substantial enough to significantly reduce the number of days without electricity due to outages. This externality becomes closer to our working definition of a technological externality, in that the more individuals that take up the technology, the greater are the returns to the technology.[43]

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.[44] Our calculation indicates a intra-class correlation of 0.56, which means that responses within transformers are indeed highly correlated.

As a second robustness check, we consider the above reduction in outages in light of the difference between the expected reduction in electricity consumption and the estimated reduction in electricity consumption. Ex ante, we expected a reduction in winter electricity

[42]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.

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

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

consumption of approximately 42 kWh per month. However, we estimated the actual reduction in monthly winter electricity consumption to be approximately 26 kWh per month. This is a difference of approximately 16 kWh per month. This is equal to approximately 14.4 hours of additional electricity consumption. Taken in conjunction with results above indicating two fewer days without electricity per month, this would mean two outages of approximately seven hours in duration each. This is a perfectly reasonable result.[45]

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

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

6 Multiple externalities and 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

[45] 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.

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

[47] 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.

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

on CFL adoption at follow-up. Specifically, we seek to answer the questions: What is the impact of the technological externality (more reliable electricity service) on CFL adoption? What is the impact of peer effects on CFL adoption? Do the two interact?

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).[49] typically, 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. The private effects also depend on correctly identifying the externalities. How important this interaction between externalities is likely depends on the magnitude and sign of the technological externality.[50] 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).[51] 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. 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 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.

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

[50] If the technological externality is weak, then disentangling these externalities might be less important.

[51] Households could purchase up to 2 CFLs at full market price. The average household had 6 bulbs at baseline. For treated households, which were provided 4 CFLs at baseline, the two purchase opportunities could replace all of their incandescent bulbs.

We expect that control households located very close to a treated household are likely to experience some peer effects.[52] 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; 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, 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

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

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.

Our diagram in Figure 2 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.

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.

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 2 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 var-

ious 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 group of control households are located in Appendix Table 6, 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 some 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 survey questions on whether they prefer CFLs over incandescent bulbs, know about CFLs, believe that CFLs save electricity, and their maximum willingness to pay for CFLs at follow-up.[53]

Results are shown in Appendix Table 7, 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

[53]Immediately following the follow-up survey, we asked respondents the maximum that they would be willing to pay for a CFL. This measure was not elicited experimentally.

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 willingness to 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, these results strongly support our findings in the prior section.

6.4 External validity

We implemented 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 driven by congestion within the distribution network, which leads to transformer overloads. The constraints in electricity distribution networks are an issue in many developing countries and, 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 similar experiment in a developed country might have very different results with respect to electricity consumption.

7 Conclusions

Through a two-staged randomized experiment, we provide several substantial contributions to the literatures on technology adoption in general and energy efficiency specifically. We show that energy efficient lightbulbs 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 poten-

tial 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 later adoption of the 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 a technological externality is present and induces 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 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.

References

Alam, M. 2013. "Coping with Blackouts: Power Outages and Firm Choices." *Working paper.*

Allcott, H., A. Collard-Wexler, and S. O'Connell. 2015. "How Do Electricity Shortages Affect Industry? Evidence from India." *American Economic Review*, forthcoming.

Allcott, H., and D. Taubinsky. 2015. "Evaluating Behaviorally-Motivated Policy: Experimental Evidence from the Lightbulb Market." *American Economic Review*, 105(8).

Allcott, H., and M. Greenstone. 2012. "Is there an Energy Efficiency Gap?" *Journal of Economic Perspectives*, 26(1).

Allcott, H., and R. Sweeney. 2015. "The Role of Sales Agents in Information Disclosure? Evidence from a Field Experiment." *Management Science*, forthcoming.

Allcott, H., and S. Mullainathan. 2010. "Behavior and Energy Policy." *Science*, 327(5970).

Amankulova, K. 2006. "Transmission and Congestion Management in the Kyrgyz Republic." National Agency for Anti-Monopoly Policy and Development of Competition (NAAPDC), Bishkek, Kyrgyzstan.

Banerjee, A., R. Chattopadhyay, E. Duflo, D. Keniston, and N. Singh. 2014. "Improving Police Performance in Rajasthan, India: Experimental Evidence on Incentives, Managerial Auronomy, and Training." *Working Paper*.

Borenstein, S. 2015. "A Microeconomic Framework for Evaluating Energy Efficiency Rebound And Some Implications." *Energy Journal*, 36(1).

Breza, E. 2015. "Field Experiments, Social Networks, and Development." *Working paper*.

Cai, J., A. de Janvry, and E. Sadoulet. 2015. "Social Networks and the Decision to Insure." *American Economic Journal: Applied Economics*, 7(2).

Chakravorty, U., M. Pelli, and B. Marchand. 2013. "Does the Quality of Electricity Matter? Evidence from Rural India." *Working Paper*.

Chan, N., and K. Gillingham. 2015. "The Microeconomic Theory of the Rebound Effect and its Welfare Implications." *Journal of the Association of Environmental & Resource Economists*, 2(1).

Cohen, J., P. Dupas, and S. Schaner. 2015. "Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial." *The American Economic Review*, 105(1).

Costolanski, P., R. Elahi, A. Iimi, and R. Kitchlu. 2013. "Impact of Evaluating a Free-of-Charge CFL Bulb Distribution in Ethiopia." *World Bank Working Paper*, 6383.

Davis, L., P. Gertler, and A. Fuchs. 2014. "Cash for Coolers: Evaluating a Large-Scale Appliance Replacement Program in Mexico." *American Economic Journal: Economic Policy*, 6(4).

Dinkelman, T. 2011. "The Effects of Rural Electrification on Employment: New Evidence from South Africa." *American Economic Review*, 101(7).

DOE. 2009. "How Compact Fluorescents Compare with Incandescents." U.S. Department of Energy, Washington, D.C.

Duflo, E., and E Saez. 2002. "Participation and Investment Decisions in a Retirement Plan: The Influence of Colleagues' Choices." *Journal of Public Economics*, 2002.

Dupas, P. 2014*a*. "Getting Essential Health Products to the End Users: Subsidize, But How Much?" *Science*, 345(6202).

Dupas, P. 2014*b*. "Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment." *Econometrica*, 82.

Foster, A., and M. Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy*, 103(6).

Foster, A., and M. Rosenzweig. 2010. "Microeconomics of Technology Adoption." *Annual Review of Economics*, 2010(1).

Fowlie, M., M. Greenstone, and C. Wolfram. 2015. "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program." *E2E Working Paper*.

Gassmann, F. 2012. "Switching the Lights Off: The Impact of Energy Tariff increases on Households in the Kyrgyz Republic." *UNU-MERIT Working Paper Series*, 2012(066).

Gertler, P., O. Shelef, and C. Wolfram. 2012. "How Will Energy Demand Develop in the Developing World?" *Journal of Economic Perspectives*, 26(Winter).

Gillingham, K., and K. Palmer. 2014. "Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Analysis." *Review of Environmental Economics & Policy*, 8(1).

Gillingham, K., D. Rapson, and G. Wagner. forthcoming. "The Rebound Effect and Energy Efficiency Policy." *Review of Environmental Economics & Policy*, forthcoming.

Gine, X., and G. Mansuri. 2011. "Together We Will: Experimental Eidence on Demale Voting Behavior in Pakistan." *World Bank Policy Research Working Paper*, 5692.

Glover, J.D., M.S. Sarma, and T. Overbye. 2011. *Power Systems Analysis and Design.* . 5th ed., Stamford, CT:Cengage Learning.

Godlonton, S., and R. Thornton. 2012. "Peer Effects in Learning HIV Status." *Journal of Development Economics*, 97.

Graff Zivin, J., and K. Novan. 2016. "Upgrading Efficiency and Behavior: Electricity Savings from Residential Weatherization Programs." *The Energy Journal*.

Griliches, Z. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, 25(4).

Hausman, J.A. 1979. "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *The Bell Journal of Economics*, 10(1).

Jackson, M.O. 2010. "An Overview of Social Networks and Economic Applications." *The Handbook of Social Economics*.

Jaffe, A., and R. Stavins. 1994. "The Energy Efficiency Gap." *Energy Policy*.

Kremer, M., and E. Miguel. 2007. "The Illusion of Sustainability." *The Quarterly Journal of Economics*.

Lipscomb, M., A.M. Mobarak, and T. Barnham. 2013. "Development Effects of Electrification: Evidence from the Geological Placement of Hydropower Plants in Brazil." *American Economic Review: Applied Economics*.

Manski, C.F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies*, 60(3).

McRae, S. 2015. "Infrastructure Quality and the Subsidy Trap." *American Economic Review*, 105(1).

Meeks, R. 2016. "Demand for Energy Efficiency: Can Stated Preference Values Predict Revealed Preference Choices?" *Working Paper*.

Miguel, E., and M. Kremer. 2004. "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities." *Econometrica*, 72(1).

Newell, N., and J.V. Siikamaki. 2015. "Individual Time Preferences and Energy Efficiency." *The American Economic Review*, 105(5).

Obozov, A., R. Isaev, V. Valiyev, Y. Hasanov, I. Mirzaliyev, and F. Imamverdiyev. 2013. "Prospects of use of renewable energy resources and energy-efficient technologies in Azerbaijan and Kyrgyzstan." EcoMod Network Report, Baku, Azerbaijan.

Rud, J.P. 2012. "Electricity Provision and Industrial Development: Evidence from India." *Journal of Development Economics*, 97(2).

Van de Walle, D, M Ravallion, V Mendiratta, and G Koolwal. 2013. "Long-term Impacts of Household Electrification in Rural India." *World Bank Working Paper*.

World Bank. 2006. "Improving Lives: Program on Renewable Energy and Energy Efficiency." The World Bank Group, Washington, D.C.

Zozulinsky, A. 2007. "Kyrgyzstan: Power Generation and Transmission." BISNIS, Washington, D.C.

Figure 1: Example of exposure to externalities resulting from randomization

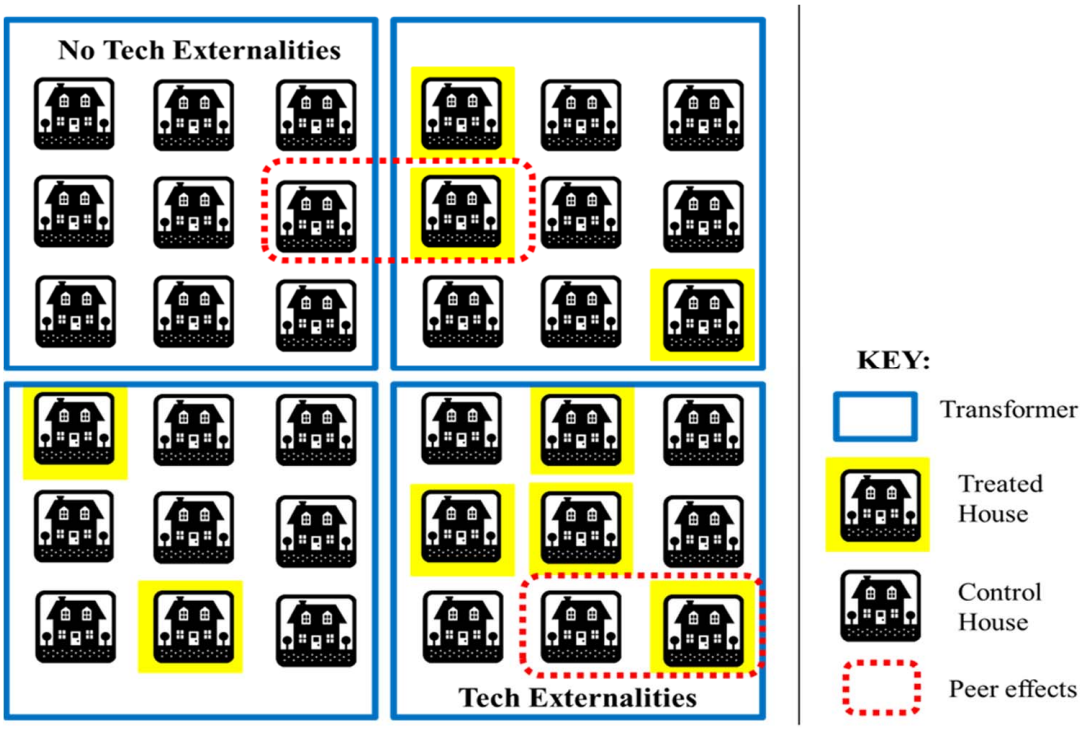


Figure 2: Experimental road map

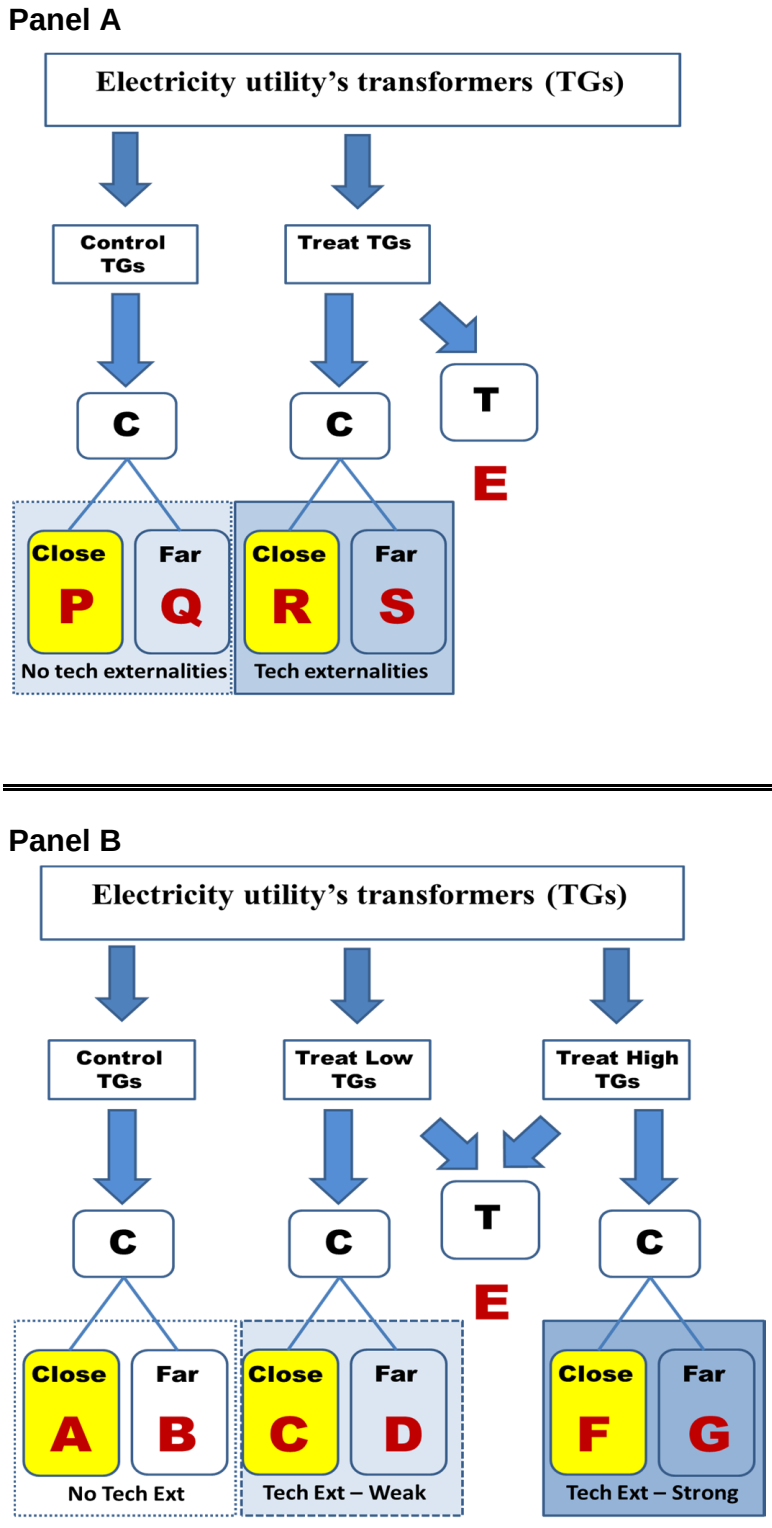


Table 1: Impacts of treatment on household electricity consumption

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

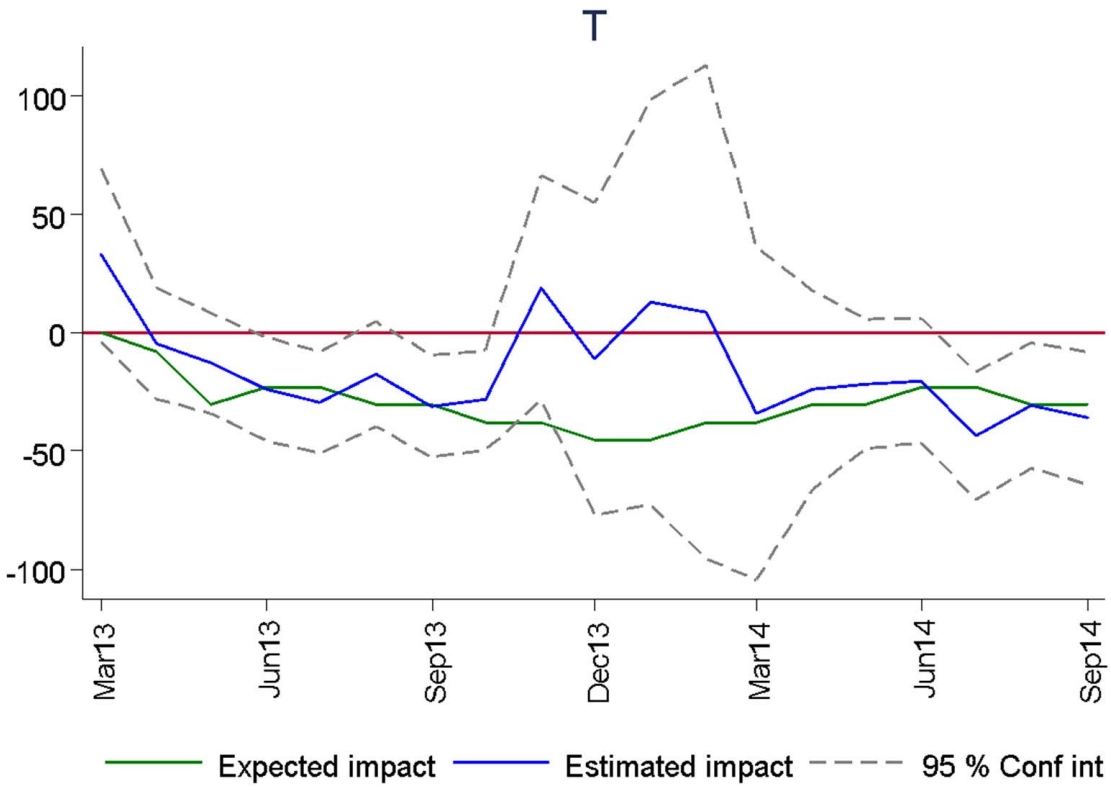


Table 2: Technological externalities: improved electricity reliability

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. Standard 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: For on-line publication

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

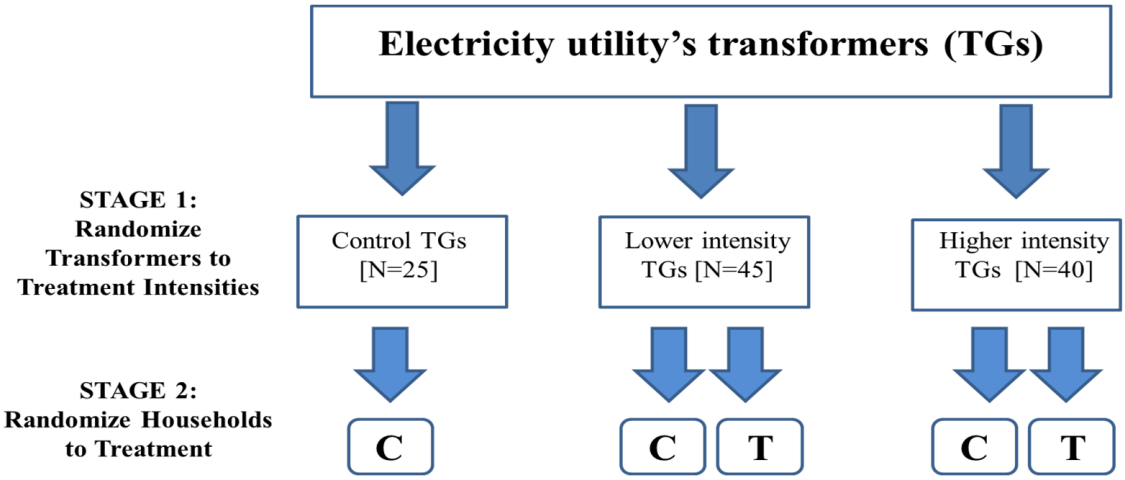
Times of peak demand are in the early morning and in the evening. Lighting is disproportionately "on peak." To better understand the impact that switching from incandescent bulbs to CFLs could have on peak load, we perform a back-of-the-envelope calculation based on data from our sample and some informed 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 Figure 1: Two-stage randomization process

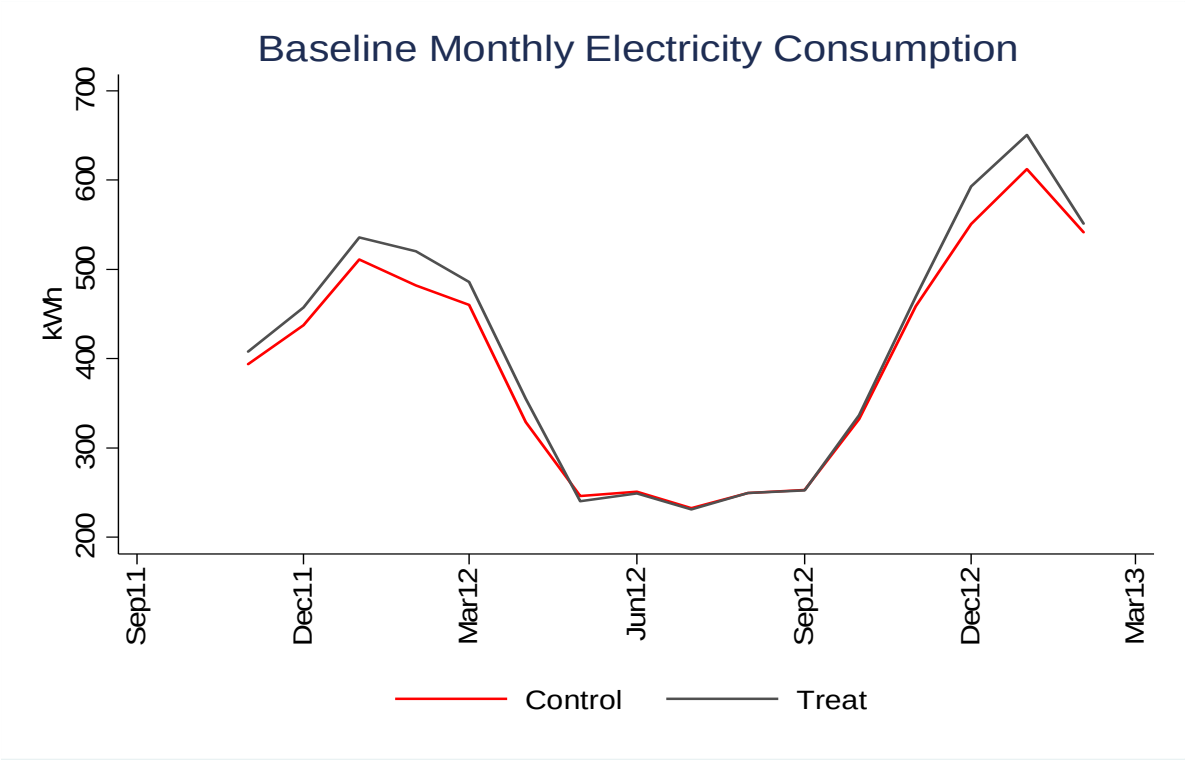


Appendix Table 1: Transformer-level randomization check

					Joint F tests (p-value)		
	Number of Transformers	Control Transformer	Lower Transformer (<=14%)	Higher Transformer (>14%)	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
Lightbulbs in house	111	6.36	6.21	6.23	0.831	0.851	0.975
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. Exchange rate

Appendix Figure 2: Seasonality of electricity consumption pre-treatment



Appendix Table 2: Household-level randomization check

	All	Control	Treatment	Joint F tests (p-value)
	(1)	(2)	(3)	(4)
General characteristics				
Household head completed secondary school	0.840	0.867	0.818	0.090
Household income past month (KGS)	10900	11463	10427	0.138
Household income past month per capita (KGS/person	3668	3740	3608	0.603
Owner-occupied house	0.912	0.919	0.906	0.506
Number of people living in the home	3.6	3.7	3.5	0.218
Time at address (months)	203	201	204.137	0.789
Housing characteristics				
Single-family dwelling	0.793	0.829	0.762	0.053
Number of rooms	4.302	4.245	4.35	0.409
Home made from brick	0.535	0.569	0.507	0.100
Floors that are wood	0.877	0.864	0.887	0.388
Age of dwelling (years)	41.29	41.27	41.30	0.987
Electricity meter for single house	0.991	0.993	0.989	0.546
Electricity consumption practices				
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
Number of households	1000	457	543	

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

Appendix Table 3: Expected impacts on electricity consumption

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

Notes: These calculations are for an estimated scenario. For these calculations, the winter months include November through February; spring/fall months include March, April, September, and October; and summer months include May through August. Average number of light bulbs replaced is based on the actual numbers of CFLs distributed on average through the intervention. Average hours of use per day are calculated using the baseline survey data and data 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: 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.

Appendix Table 6: 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 7: 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.