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Sustainability of a Residential CFL Distribution Program

Evidence from Ethiopia

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Abstract

Energy-efficient products generally offer a win-win proposition, because they pay for themselves. End users can reduce their energy costs, and power utilities can avoid costly investments in extra generation capacity. Moreover, energy efficiency can contribute to mitigating global warming. This paper casts light on the sustainability of the residential use of compact fluorescent lamps after the free compact fluorescent lamp distribution program in Ethiopia. It is found that the direct program effect has been sustained for at least four years after the program. The effect of the distributed compact fluorescent lamps may taper off, if some of the program beneficiaries reinstall relatively cheap incandescent bulbs when the compact fluorescent lamps are burned out. However, many households replaced burned out compact fluorescent lamps with new compact fluorescent lamps. This effect is found to be statistically significant, particularly among relatively low-income households, whose demand is more price-elastic. All the indications are that program participants were generally convinced that compact fluorescent lamp bulbs are more cost-effective in the long run and the program effect is sustained over time.

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Sustainability of a Residential CFL Distribution Program Evidence from Ethiopia

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Key words: Energy efficiency program; fixed- and random-effects least-squares; instrumental variable regression.

JEL Classification: C33; C36; L94.

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I. Introduction

Energy efficiency has long been recognized as a win-win solution for both end-users and utilities. While end-users can reduce their energy consumption and spending, energy suppliers may also be able to avoid costly investment in extra supply capacity. The latter is of particular importance where there remains significant unmet demand but available resources are limited. In Sub-Saharan Africa, for instance, the electrification rate is about 32 percent: More than 600 million people still live without access to electricity (IEA 2015). Improved energy efficiency can also contribute to mitigating global warming. For instance, compact fluorescent lamps (CFLs) can reduce greenhouse gases by 75 percent compared with incandescent lamps (Ramroth 2008), although the use of CFL bulbs in developing countries may raise environmental concerns, since each CFL bulb contains about 4-5 mg of mercury (e.g., Sahakian 2010; Aman et al. 2013).

In theory, energy-efficient products, such as CFL and light-emitting diode (LED) bulbs, could pay for themselves. End-users have to bear relatively high initial costs but can reduce their energy spending over time. Despite its significant potential, however, the residential sector generally tends to lag behind in improving energy efficiency, as often referred to as the "energy efficiency paradox" (Jaffe and Stavins, 1994). Even in the United States, for instance, many people still use incandescent bulbs. Only 28 percent of residential sockets that could hold CFLs actually held them (US Department of Energy, 2010).

There are a variety of constraints that are faced by households (see Ramos et al. (2015) for the latest comprehensive literature review). The literature has intensively discussed the effect of information, labeling and certificates. Many empirical studies are supportive of this. Newell and Siikamaki (2014) show that providing information on the economic value of saving energy can affect households' choice of central water heater. By contrast, Allcott and Taubinsky (2015) did not find any statistically significant impact of information on CFL market share. How to provide information may matter. Fowlie et al. (2015) also point out administrative barriers. The Federal Weatherization Assistance Program (WAP) is the largest residential energy efficiency program in the United States. The program offers no-cost subsidies to low-income households who adopt energy efficiency measures, such as insulation, window replacements and furnace replacement. But it is found that the take-up only marginally increased despite various intensive encouragement efforts, suggesting that significantly high nonmonetary costs still exist associated with the application process.

Households also face financial constraints and people's time preferences tend to be high. In the United States, the mean discount rate is estimated at 19 percent, and the payback threshold is 3.5 years (Newell and Siikamaki, 2015). In developing countries, the threshold is likely to be much shorter than this, because many households are poor. For this reason, many CFL bulb distribution programs in developing countries (e.g., Rwanda, Thailand, Uganda and Vietnam) distribute CFL bulbs free of charge or at deep discounts (World Bank 2006; ESMAP 2009). However, sustainability remains a matter of concern when distributed bulbs burn out. A survey indicates that many people do not believe that CFLs saved money even after they actually used CFLs (Reynolds et al. 2012).

Using data from a free CFL distribution program in Ethiopia, the current paper recasts light on sustainability of the residential use of CFL bulbs. Our previous study (Costolanski et al. 2013) shows that the country's first CFL program reduced household electricity consumption by 45-50 kilowatt hours a month, but about 20 percent of these energy savings seem to have disappeared within one year and half after the program. The current paper aims at examining why this happened. With additional household data collected, it shows that the energy saving impact was largely sustained when taking into account the effect of new CFL bulbs installed after the CFLs distributed under the program burned out. It is also shown that after six years, program beneficiaries still use relatively more CFLs than non-beneficiaries do. The evidence supports long-term effectiveness of the program.

The following sections are organized as follows: Section II provides an overview of the recent CFL distribution program in Ethiopia. Section III develops our empirical models and explain our data. Section IV presents main estimation results and discusses policy implications. Section V examines robustness of the estimates. Finally, Section VI concludes.

II. CFL Distribution Program in Ethiopia

Ethiopia is one of the poorest countries in Africa. Although the country has been experiencing remarkable economic growth in the last decade, gross domestic product (GDP) per capita is still US$570 and about 30 percent of the total population live below the national poverty line. The national electrification rate is estimated at 24.3 percent. In rural areas, only 10.4 percent of the population has access to electricity (IEA 2015). The Government of Ethiopia, with the support of the international donor community, has been ramping up their efforts in two areas: universal electric access and demand-side management. While the EEU has been expanding electricity access in rural areas, a series of energy efficiency measures have also been implemented at the end user level.

In the residential sector, three CFL distribution programs were implemented in recent years. The program was not targeted but implemented on a voluntary basis. This has important implications not only from a policy point of view but also for empirical purposes, as discussed below. The first program was carried out from June to August, 2009, distributing 350,000 CFL bulbs free of charge to approximately 90,000 households (Table 1). The bulbs were distributed nationwide but practically focused on Addis Ababa, because CFLs were allocated based on the number of existing customers per service center. The vast majority of the existing EEU customers live around Addis Ababa.

Table 1. Numbers of CFL bulbs distributed

Incandescent bulb	CFL bulb	Savings per bulb	Distributed CFLs	
			Phase 1	Phase 2
40W	11W	29W	192,500	2,802,000
60W	15W	45W	154,000	1,672,000
100W	20W	80W	3,500	38,000
			350,000	4,512,000

Sources: EEU.

Theoretically, there is no enforcement issue in the program, because customers had to bring their old lightbulbs to the nearest EEU service center. Each customer obtained a maximum of four CFL bulbs in exchange for old incandescent bulbs. Still, sustainability may remain questionable, because there is no guarantee that people would continue using the distributed CFLs. When they burn out, people need to purchase new CFLs or traditional incandescent bulbs in the market.

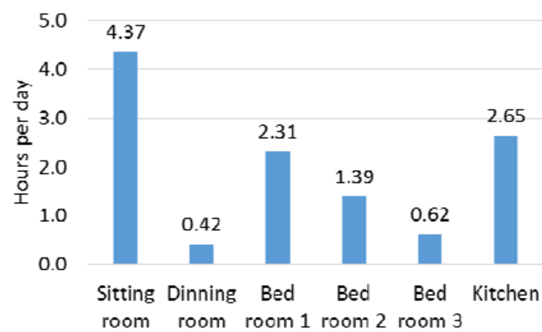
In our previous work (Costolanski et al. 2013), a dummy variable for program participants was used to estimate the impact of the program. Thus, it was implicitly assumed that the distributed CFLs would continue to be used over time. However, this may not be the case. Some beneficiaries may have stopped using CFLs for various reasons, for instance, CFLs are more costly than incandescent bulbs in Ethiopia (Table 2). Since average daily lamp usage is fairly limited to about 1 to 4 hours (Figure 1), the payback period is estimated at 12 to 20 months, which is fairly long in a developing country context.

Table 2. CFL bulb market and subsidized prices

Incandescent	Market Price (birr)	CFL	Market Price (birr[1])	Price under CFL Programs: Phase 1 (birr)	Phase 2 (birr)
40W	3.83	11W	25.00	0	7.00
60W	4.00	15W	27.00	0	8.00

Sources: Central Statistical Agency (CSA); EEU and authors' own data.

Figure 1. Average daily hours of light usage by type of room



Sources: Authors' survey data.

The following analysis is focused on this first phase of the program. Our sample data come from one of the major EEU service areas in Addis Ababa, Bole-Kazanchis Service Area, which covers 13,000 customers in total. Out of this, about 3,500 customers received CFL bulbs under the first phase of the program. Most of the beneficiaries can be identified through the program application number and the Customer Contract Number. A household survey was carried out in October to December, 2015, which randomly selected 522 households. Half of them are those who benefited from the first phase program and received up to four CFLs free of charge. While the survey was a one-time cross-sectional household survey but covers the historical information about household ownership and use of CFL bulbs and other major appliances collected basic household characteristics, such as demographics as well as appliance ownership

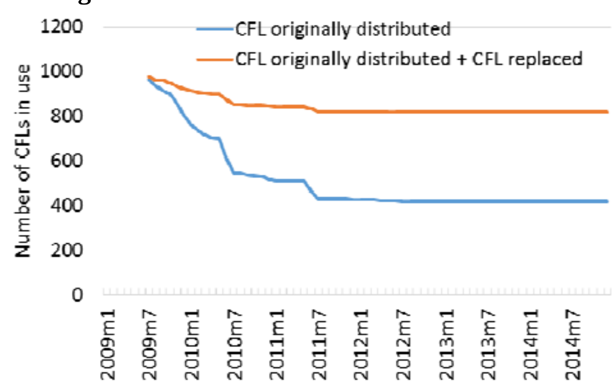
[1] The official exchange rate changed from Birr 9.0 per US$ in 2007 to Birr 20.1 per US$ in 2015

and usage, the EEU customer database is used to derive households' monthly electricity consumption and billing data.

In this sub-sample, a total of 977 CFL bulbs were distributed to 252 program participants. The household survey indicates that about half of the distributed CFLs burned out in less than three years (Figure 2). Given the observed light usage in Ethiopia (see Figure 1), this looks relatively short compared with a commonly believed norm of CFL life, which is 5,000-10,000 hours or 3-6 years. About 420 CFLs are still in use at the time of survey, i.e., 6 years after the program.

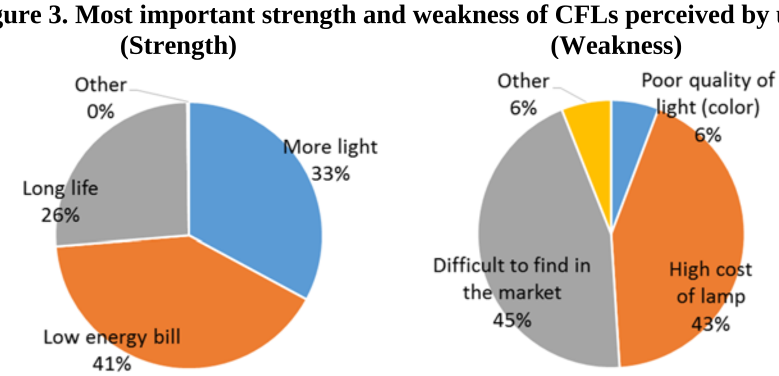
When the distributed CFLs burned out, about 70 percent were replaced with another CFL. The rest were replaced with incandescent lightbulbs, largely because they are cheaper or the perceived quality of the CFLs is not really good. While the most important strength of CFLs is savings of energy bills, two major weaknesses are market unavailability and high prices (Figure 3). In the following analysis, two types of the program effects are estimated separately: One is the direct program effect, which is observed when the program replace old incandescent lamps with CFLs. The other is the learning effect of the program. This is observed when a distributed CFL was replaced with another CFL after the program and thus considered as a long-term impact indicating how sustainable the program effect is. The two effects are different and can be measured separately because our data tell when each CFL was installed and replaced.

Figure 2. Number of CFLs distributed in use



Sources: Authors' survey data.

Figure 3. Most important strength and weakness of CFLs perceived by users



Sources: Authors' survey data.

III. Empirical Models

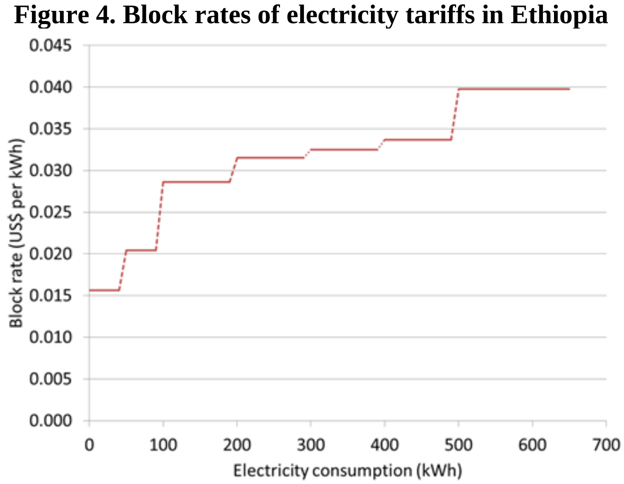
The empirical model follows our previous work (Costolanski, et al. 2013). The following demand equation is considered:

$$kwh_{it} = \alpha_1 CFL1_{it} + \alpha_2 CFL2_{it} + X_{it}'\beta + \varepsilon_{it} \qquad (1)$$

where kwh_{it} is the amount of electricity consumed by household i at time t. $CFL1_{it}$ is the number of CFL bulbs that were provided to household i under the program and are still in use at time t. $CFL2_{it}$ is the number of the program CFLs that burned out and were replaced with another CFL. X_{it} is a set of household characteristics and other covariates.

As discussed by Costolanski et al. (2013), there are two important empirical issues to estimate this demand equation. First, price information, included in X_{it}, is likely to be endogenous, because the Ethiopian tariff structure uses increasing block tariffs to curb overconsumption of energy (Figure 4).[2] In theory, therefore, people's consumption depends on marginal prices (*MP*), and the marginal price applied depends on how much electricity people use. Thus, there is potentially the endogeneity problem. To deal with this, the Nordin's (1976) difference variable, *D*, is used, which represents the amount of implicit consumer surplus generated by the difference between the actual bill and what would be paid if the final block rate were applied to total consumption (Taylor 1975; Nordin 1976; Hausman *et al.* 1979). With billing data, two instrumental variables can be constructed by regressing the amount of actual payment on a constant term and the quantity of consumption (Hewlett 1977; Deller *et al.* 1986). See Costolanski et al. (2013) for more detailed discussion.

Figure 4. Block rates of electricity tariffs in Ethiopia



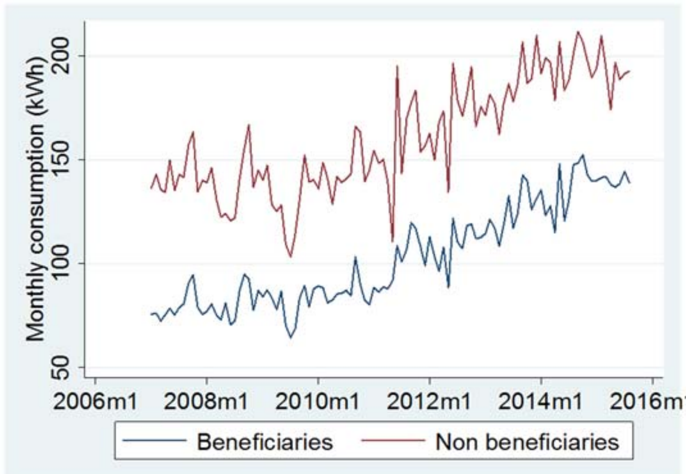
Source: EEU.

Second, the program participation was not targeted but voluntary, which causes the self-selection problem. It is program participants who decided to bring old incandescent bulbs to

[2] Taking the inflationary effect into account, the marginal rate is defined in real terms.

the utility service office to receive free CFLs. In the case of Ethiopia, program beneficiaries turned out to be low-income households and low-volume energy users. The amounts of electricity consumption clearly differ between the two groups: program beneficiaries and non-beneficiaries (Figure 5). Though, they move in parallel over time, reflecting common seasonality and supply disruptions. If $CFL1_{it}$ and $CFL2_{it}$ are correlated with people's unobservable preferences, which are included in the error term ε_{it}, the ordinary least squares (OLS) estimator will be biased.

Figure 5. Average daily hours of light usage by type of room



Sources: Authors' survey data.

To mitigate this risk, the fixed-effects model is used (e.g., Holl 2004; Khandker et al. 2009; Khandker and Koolwal 2011). Our sample data are balanced for 522 customers over the 104-month period (from January 2007 to August 2015). Thus, the individual- and time-specific fixed effects can be included (c_i and c_t). These can help to control for unobserved time-invariant factors. Note that there are several time-variant household characteristics, such as ownership of several home appliances, which are still included in the model, W_{it}:

$$kwh_{it} = \alpha_1 CFL1_{it} + \alpha_2 CFL2_{it} + \beta_P MP_{it} + \beta_D D_{it} + W_{it}'\beta_W + c_i + c_t + \varepsilon_{it} \quad (2)$$

Although the empirical efficiency of this specification may or may not be as high as the fixed-effects model, it is practically interesting to include time-invariant household characteristics and see how they affect the electricity demand. Note that in our survey, household characteristics are generally cross-sectional. Thus, there is little time variation in them, except for ownership of three home appliances: iron, hot plates and water boilers. These were selected because they have become increasingly widespread in recent years. The summary statistics are shown in Table 3.

To incorporate time-invariant characteristics Z, the following random-effects model is considered:

$$kwh_{it} = \alpha_1 CFL1_{it} + \alpha_2 CFL2_{it} + \beta_P MP_{it} + \beta_D D_{it} + W_{it}'\beta_W + Z_i'\beta_Z + c_i + T_t + month_t + \varepsilon_{it} \quad (3)$$

where the time trend is included as T. Given the fact that our sample data are monthly, a set of monthly dummy variables is also included. Normally, the electricity demand has seasonality.

These demand equations are estimated consistently by the fixed- or random-effects instrumental variable (IV) estimator. The model specification needs to be tested by the conventional test statistics, such as Hausman test. α_1 and α_2 are our primary variables of interest to investigate the impacts of the CFL distribution program. In order to examine sustainability of these effects, the CFL variables are replaced with their lagged variables, i.e., $CFL1_{it\text{-}s}$ and $CFL2_{it\text{-}s}$, respectively.

Table 3. Summary statistics

	Abb.	Obs	Mean	Std. Dev.	Min	Max
Monthly variables:						
Electricity consumption (kWh)	*kWh*	50,276	272.53	262.83	0.36	4807.00
Number of CFLs distributed under the program	*CFL1*	50,276	0.71	1.39	0	4
Number of program CFL replaced with another CFL when it burned out	*CFL2*	50,276	0.41	1.01	0	4
Marginal price (Birr per kWh)	*MP*	50,276	0.45	0.21	0.13	1.29
Nordin's difference variable (Birr)	*D*	50,276	-25.46	26.68	-176.55	0
Dummy variables for household assets:						
Iron [1]	*dIRON*	50,276	0.34	0.47	0	1
Hot plate [1]	*dHOTP*	50,276	0.41	0.49	0	1
Water boiler [1]	*dBOIL*	50,276	0.30	0.46	0	1
Household-specific time-invariant variables:						
Household size	*SIZE*	473	4.82	2.27	1	15
Number of rooms	*ROOM*	472	5.71	3.39	1	28
Dummy variable for male household head	*dMALE*	480	0.57	0.50	0	1
Level of education attained by household head	*EDU*	382	3.41	2.62	1	14
Household income (ETB 1,000)	*INCOME*	338	6.53	9.18	0.1	100
Dummy variables for household assets:						
TV	*dTV*	480	0.95	0.23	0	1
Refrigerator	*dREFR*	480	0.81	0.39	0	1
Injera mitad	*dINJERA*	480	0.83	0.38	0	1
Instant water heater	*dWATIN*	480	0.10	0.30	0	1
Bread oven	*dBREAD*	480	0.26	0.44	0	1
Solar lantern	*dSOLANT*	480	0.03	0.18	0	1
Solar home system	*dSOHOME*	480	0.02	0.14	0	1
Petroleum based generator	*dGENER*	480	0.03	0.18	0	1

[1] Time-variant appliance variables over the sample period.

Apart from the demand equations, it is also interesting to examine the impact of the program participation on people's lightbulb choice over time. To this end, the following reduced-form equation is considered:

$$SHRCFL_i = \gamma_1 Treat_i + X_i \delta + \varepsilon_i \qquad (4)$$

where *SHRCFL* is the share of the total CFLs that are in use in each household *i*. This is expected to capture the household's tendency to purchase and use CFLs, as opposed to incandescent lightbulbs, with the size effect controlled.[3] *X* includes a set of household characteristics at the time of survey. Note that this is a cross-sectional analysis. *Treat* is set to one if household *i* benefited from the program, and zero otherwise.

Based on simple average comparison, it is shown that the share of the total CFLs used by program participants is higher than non-participants (Table 4). While 59 percent of the total lightbulbs used by program participants are CFLs, this ratio goes down to 48 percent among program non-participants. The difference is statistically significant. Again, the potential problem is self-selection bias associated with *Treat*. Basic demographics, such as age of household head, seem to be comparable between the two groups. But there are clear differences in economic characteristics. For example, program participants are clearly poorer. Statistically, the difference in income is significantly different from zero. Program participants are more likely to be home renters. The number of rooms is also smaller in the program participants' houses and apartments. These observed differences are included in *X*. However, there may remain other unobserved household characteristics that affect both the household's choice of CFL use and program participation.

Table 4. Two-sample t-tests

	Abb.	*Treat*=1		*Treat*=0		Difference		
		Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	
Share of CFLs out of all bulbs	*SHRCFL*	0.59	(0.02)	0.48	(0.02)	0.11	(0.03)	***
Product life of distributed CFL (month)	*DUR*	10.67	(0.49)					
Household size	*SIZE*	4.86	(0.15)	4.88	(0.14)	-0.03	(0.21)	
Age of household head	*AGE*	53.77	(0.97)	52.00	(0.97)	1.77	(1.37)	
Dummy variable for male household head	*dMALE*	0.54	(0.03)	0.58	(0.03)	-0.04	(0.04)	
Level of education attained by household head	*EDU*	2.17	(0.11)	2.80	(0.12)	-0.63	(0.16)	***
Dummy variable for government employees	*dGOV*	0.15	(0.02)	0.14	(0.02)	0.01	(0.03)	
Dummy variable for self-employees	*dSELF*	0.36	(0.03)	0.41	(0.03)	-0.05	(0.04)	
Household income (ETB 1,000)	*INCOME*	4.56	(0.61)	8.49	(0.70)	-3.93	(0.92)	***
Dummy variable for homeowners	*dOWN*	0.52	(0.03)	0.65	(0.03)	-0.13	(0.04)	***
Number of rooms	*ROOM*	4.99	(0.18)	6.43	(0.23)	-1.44	(0.30)	***
Instrumental variables:								
Dummy variable for HH living within 10 minute walking distance from an electric shop	*dSHOP*	0.103	(0.019)	0.007	(0.005)	0.096	(0.019)	***
Number of other CFL program beneficiaries within 200m distance	*NEIGH*	5.586	(0.270)	3.261	(0.241)	2.324	(0.361)	***

*** p<0.01

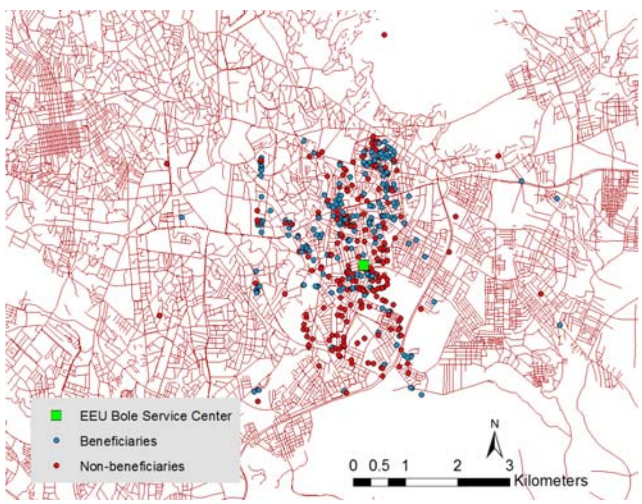
[3] As discussed, program participants are relatively low-income households, whose houses and apartments have fewer rooms. Thus, the share of CFLs in use is a better indicator than the absolute number of CFLs. It is clear that the average number of CFLs used by program participants are systematically smaller than that among program non-participants.

Two instrumental variables are constructed to deal with this problem:[4] Dummy variable for households who live within 10 minute walking distance from an electric shop where people can buy a lightbulb (denoted by *dSHOP*), and the number of neighboring households who benefited from the program (*NEIGH*). These are calculated based on spatial data collected from the household survey (Figure 6). If people live near an electric shop, they may be likely to purchase more CFLs. Recall that one of the most important weakness of CFL is market unavailability of CFL lamps.

If there are more neighbors who benefited from the free distribution program, the probability of a household's participating in the program is also likely to be high, because of "information externalities." The survey indicates that the program itself is an important source of information about CFLs. The majority of people responded that they learned about CFLs from EEU, followed by mass-media (Figure 7). To measure this effect, the number of neighboring households who live in 200 meters and participated in the program is calculated in the sample data.

The instrumental variable (IV) estimator can provide an unbiased effect of the program participation, γ. The validity of the instruments needs to be verified by the conventional exogeneity and over-identifying restriction tests.

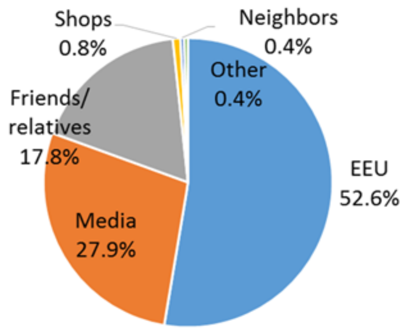
Figure 6. Locations of program beneficiaries and non-beneficiaries



Sources: Authors' survey data.

[4] These are different from the above instruments created in the demand equation context.

Figure 7. Primary information source of CFLs



Sources: Authors' survey data.

IV. Main Results and Policy Implications

The fixed- and random-effects IV regressions are performed with both individual- and time-specific effects included. While the former is consistent or unbiased, the latter is most efficient if unobservable household characteristics are not correlated with other household characteristics that we observe. The results are very similar (Table 5). But according to the traditional Hausman test, the null hypothesis that the individual-specific errors are not correlated with the regressors can be rejected. The Hausman test statistic, which indicates validity of using the random-effect model, is 489.25, which is well above the conventional threshold (e.g., a chi-squared statistic of 135.48 at the 5 percent confidence level). Thus, the fixed-effects model is preferred to the random-effect model.

In the fixed-effects model, the coefficients of *CFL1* and *CFL2* are both negative and significant, indicating the substantial energy conservation impacts of the CFL program. Not surprisingly, CFLs distributed under the program reduced households' electricity consumption. The estimated coefficient of *CFL1* indicates how much energy could be saved by installing one more CFL under the program. It is estimated at -13.5, meaning that 13.5 kWh could be saved by one unit of CFL bulb distributed under the program. Similarly, the coefficient of *CFL2* is also negative at -16.0, meaning that additional CFLs installed when the program CFLs burned out also contributed to energy conservation. Thus, we found both direct and long-term effects of the program. Numerically, the coefficients look different, however, there is no statistically significant difference. The test that they are the same cannot be rejected with a chi-squared test statistic of 0.37.

These are the intent-to-treat (ITT) estimates because the program participation is voluntary, not mandatory. If the conventional formula is used, the treatment-on-the-treated (TOT) estimate may range from 50 to 60 kWh. However, this interpretation may be complex when the fact that non-beneficiaries are also using CFL bulbs is considered. See the following section for more discussion.

Beside the CFL effects, the marginal price has a negative impact on the electricity consumption, as predicted in theory. The coefficient of *MP* indicates how much energy consumption could be reduced by increasing marginal block rates. It is estimated at -730.7, which can be translated into a price elasticity of -1.20 when evaluated at sample means, as shown at the bottom of the table. Thus, the elasticity is relatively high: A 10 percent of price increase would result in reducing the electricity demand by 12 percent. The income elasticity can be computed based on the coefficient of *D*, since the Nordin's *D* has the same implication as negative income. The elasticity is 1.08, which is also significant. Thus, as expected, the electricity demand increases with household income. Among the three home appliances, only the water boiler is found as a major demand factor in Ethiopia. If a household owns a water boiler, the electricity demand is increased by about 59kWh per month.

Table 5. Fixed- and random-effects IV estimation

	Fixed effects model			Random effects model		
	Coef.	Std.Err.		Coef.	Std.Err.	
MP	-730.73	(48.22)	***	-715.07	(47.20)	***
D	-11.54	(0.36)	***	-11.56	(0.35)	***
CFL1	-13.51	(2.51)	***	-12.46	(2.36)	***
CFL2	-16.00	(4.77)	***	-14.78	(4.35)	
dIRON	11.16	(16.20)		5.69	(11.55)	
dHOTP	-8.11	(9.01)		-8.55	(8.33)	
dBOIL	59.48	(22.21)	***	48.24	(13.71)	***
Constant	339.91	(32.92)	***	328.69	(32.69)	***
Obs.	50,276			50,276		
Number of groups	504			504		
R-squared:						
Within	0.248			0.367		
Between	0.880			0.887		
Overall	0.640			0.641		
Wald chi2	3272.27	***		6647.83	***	
Fixed effects:						
Individual	Yes			Yes		
Time	Year-month			Year-month		
Imputed elasticity:						
MP	-1.204	(0.079)	***	-1.178	(0.078)	***
D	1.078	(0.034)	***	1.080	(0.033)	***

The dependent variable is *KWH*. The clustered standard errors, which allow for intragroup correlation, are shown in parentheses. *, ** and *** indicate the statistical significance at the 10, 5 and 1 percent, respectively.

It is of particular interest to examine how time-invariant household characteristics are related to the electricity demand, although the fixed-effects specification seems to better fit our data, as discussed above. The random-effects IV regression is performed without fixed-effects included. The results are broadly consistent with the above. The CFL effects are both significant (Table 6). In addition to water boilers, the use of a refrigerator is a statistically significant demand factor. It is also found that electricity can be saved if a solar lantern is used, holding everything else constant.

In our data, income data are relatively limited. About 140 households did not answer the question of household income. But the estimation results look unchanged regardless of whether the income variable is included or not. The first model in the table includes the income variable, and the second model does not. The coefficients are broadly consistent with one another.

Table 6. Random-effects IV estimation without individual-specific fixed effects

	Random effect model			Random effect model		
	Coef.	Std.Err.		Coef.	Std.Err.	
MP	-723.62	(51.20)	***	-724.96	(47.47)	***
D	-11.58	(0.42)	***	-11.66	(0.37)	***
CFL1	-14.00	(2.03)	***	-14.41	(1.86)	***
CFL2	-14.81	(4.21)	***	-16.27	(3.99)	***
ln*SIZE*	10.90	(9.72)		12.85	(8.09)	
ln*ROOM*	1.18	(10.35)		0.67	(8.24)	
dMALE	4.13	(6.66)		4.75	(5.42)	
ln*EDU*	-2.14	(1.40)		-2.70	(1.19)	**
ln*INCOME*	-5.84	(6.22)				
dIRON	2.52	(15.06)		6.35	(12.02)	
dHOTP	11.29	(9.55)		-1.84	(8.07)	
dBOIL	50.14	(21.98)	**	37.38	(15.29)	**
dTV	18.58	(17.13)		6.83	(14.98)	
dREFR	16.78	(7.90)	**	11.48	(7.11)	*
dINJERA	12.68	(10.78)		10.18	(8.09)	
dWATIN	33.67	(23.86)		25.21	(18.15)	
dBREAD	3.31	(9.80)		10.73	(8.43)	
dSOLANT	-34.68	(20.16)	*	-27.09	(12.46)	**
dSOHOME	-46.61	(43.73)		-29.45	(30.25)	
dGENER	8.49	(37.85)		20.75	(34.24)	
T	-0.03	(0.26)		0.20	(0.22)	
Constant	284.02	(59.35)	***	243.90	(30.18)	***
Obs.	34,817			48,677		
Number of groups	347			488		
R-squared:						
Within	0.385			0.372		
Between	0.879			0.893		
Overall	0.658			0.652		
Wald chi2	3744.8	***		4456.78	***	
Fixed effects:						
Individual	No			No		
Time	Monthly			Monthly		
Imputed elasticity:						
MP	-1.246	(0.088)	***	-1.204	(0.079)	***
D	1.077	(0.039)	***	1.090	(0.034)	***

The dependent variable is KWH. The clustered standard errors, which allow for intragroup correlation, are shown in parentheses. *, ** and *** indicate the statistical significance at the 10, 5 and 1 percent, respectively.

The above estimation results indicate that systematic differences exist in electricity consumption patterns between the poor and the rich. To examine this formally, the data are divided into two subgroups based on household income. The selected threshold is 3,700 Ethiopian birr. The results are broadly the same as above (Table 7). However, there are several noticeable differences between the two groups. The implied price elasticity for relatively low-income households is estimated at about -1.8, which is higher than the elasticity for the relatively high-income group (i.e., -0.9). Thus, relatively low-income households are more sensitive to pricing.

The income elasticity is also high at about 1.2 for low-income households. This can be interpreted to mean that the demand for electricity would likely increase more than proportionally with household income. The current level of electricity consumption for these households is still minimal. As household income increases, people would likely purchase more and more home appliances and use more electricity.

Regarding the CFL effects, the coefficients of *CFL1* are always significant regardless of income level. Thus, the impact of distributing CFLs under the program is unambiguous. However, the coefficient of *CFL2* is only significant for the low-income group. The coefficient for the high-income group is still negative but not statistically significant. This indicates that the long-term effect of the program is particularly strong among relatively low-income households. This is consistent with the view that energy-efficient products can pay for themselves and the above estimation result that low-income households are more price-elastic. Therefore, poor people are keener to continue using CFL bulbs even after the program.

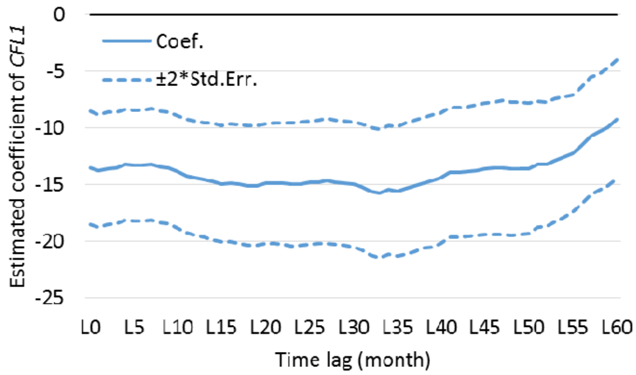
Related to the above, sustainability of the program effect is examined by taking advantage of the panel feature. Equation (2) with the lagged CFL variables is estimated by the fixed-effects IV regression. Figure 8 shows the coefficients estimated with different lags. The program effect is broadly sustained at least for four years after the program. Then, the program effect seems to taper off, possibly because some of the program beneficiaries do not use CFLs any longer. But the impact still exists. The estimated effect is statistically significantly different from zero.

Table 7. Comparison between the poor and the rich: Fixed- and random-effects IV estimation

	Household income < Birr 3,700						Household income > Birr 3,700					
	Fixed effect model			Random effect model			Fixed effect model			Random effect model		
	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
MP	-857.37	(81.55)	***	-865.27	(89.56)	***	-601.53	(76.90)	***	-586.49	(75.61)	***
D	-12.86	(0.83)	***	-13.27	(0.92)	***	-10.49	(0.48)	***	-10.54	(0.48)	***
CFL1	-9.92	(4.33)	**	-12.28	(2.43)	***	-11.48	(4.10)	***	-13.16	(3.48)	***
CFL2	-12.17	(5.09)	**	-14.25	(3.74)	***	-1.97	(10.79)		-4.46	(9.80)	
ln*SIZE*				8.45	(6.35)					11.99	(16.86)	
ln*ROOM*				11.67	(7.82)					-4.15	(17.67)	
dMALE				-3.64	(5.80)					4.46	(9.50)	
ln*EDU*				-3.03	(1.37)	**				1.09	(2.43)	
ln*INCOME*				6.92	(6.34)					14.64	(15.85)	
dIRON	26.15	(28.40)		11.30	(19.95)		-15.51	(21.46)		-18.13	(18.25)	
dHOTP	14.47	(12.53)		24.14	(11.31)	**	-6.42	(14.93)		-3.19	(15.02)	
dBOIL	33.97	(42.89)		7.07	(27.57)		83.88	(33.74)	**	60.01	(27.29)	**
dTV				18.77	(16.98)					29.72	(74.06)	
dREFR				17.37	(8.23)	**				0.15	(27.70)	
dINJERA				4.22	(13.14)					27.17	(13.84)	**
dWATIN				-34.49	(48.91)					36.73	(23.78)	
dBREAD				2.92	(12.08)					16.15	(13.36)	
dSOLANT				-23.45	(18.26)					-38.83	(24.48)	
dSOHOME				-246.32	(47.25)	***				-7.51	(39.47)	
dGENER				124.35	(92.76)					-20.16	(29.17)	
T				-1.10	(0.42)	***				1.02	(0.42)	**
Constant	459.49	(49.10)	***	281.78	(75.67)	***	229.35	(59.02)	***	3.69	(168.24)	
Obs.	17,648			17,443			17,784			17,374		
Number of groups	176			174			177			173		
R-squared:												
Within	0.333			0.426			0.283			0.373		
Between	0.875			0.911			0.845			0.869		
Overall	0.674			0.678			0.624			0.635		
Wald chi2	7576.78 ***			902.91 ***			4604.92 ***			2573.21 ***		
Fixed effects:												
Individual	Yes			Yes			Yes			Yes		
Time	Year-month			Monthly			Year-month			Monthly		
Imputed elasticity:												
MP	-1.805	(0.172)	***	-1.821	(0.189)	***	-0.891	(0.114)	***	-0.868	(0.112)	***
D	1.163	(0.075)	***	1.200	(0.083)	***	0.994	(0.045)	***	0.999	(0.045)	***

The dependent variable is KWH. The clustered standard errors, which allow for intragroup correlation, are shown in parentheses. *, ** and *** indicate the statistical significance at the 10, 5 and 1 percent, respectively.

Figure 8. Estimated coefficient of CFL effect by fixed-effects IV regression



To investigate further into the reason why some people choose CFLs and others do not, Equation (4) is estimated by OLS and IV regression. Clearly, the coefficient of *Treat* is significantly positive regardless of the estimation model (Table 8). Formally, the exogeneity test cannot reject the hypothesis that program participation is exogenous. Therefore, the IV estimation is consistent, but the OLS model is efficient.

In the latter, the coefficient of *Treat* is estimated at 0.089, which is statistically significant. Even without the income variable, the coefficient is similar (0.100). It means that CFL program participants are more likely to use CFL bulbs, holding everything else constant. This can be interpreted as the learning effect of the program, and this is likely to be one of the most important reasons for the sustained program effect as shown above.

Unlike the literature, there is no evidence that home renters are less likely to adopt energy-efficient products because of their myopic view. The coefficient of *dOWN* is positive but not significant. An interesting finding is that the tendency to use more CFLs increases with the level of education attained by the household head. This may be consistent with the literature supportive of the importance of information to diffuse energy-efficient products in general. In addition, the evidence seems to show that female headed households are using more CFLs, although this effect is not significant when the income variable is included. Thus, the negative coefficient of *dMALE* may partly capture the fact that the income level of female headed households is lower than that of male headed households.

Table 9 shows the first-stage regression results associated with the IV models. As expected, both *dSHOP* and *NEIGH* have positive and significant effects on people's program participation. People are more likely to participate in the program when there are other neighbors who also participate in the program. This is understood as the effect of spread of information among neighbors and consistent with the survey result that many people learned about CFLs from the program itself, that is, the EEU. This confirms the advantage of the CFL distribution program to raise people's awareness and adoption of energy-efficient products.

In addition, as expected, if people live near an electric shop, they may have a better chance to know about energy-efficient products and purchase them more frequently. The supply side development is therefore important. If there is no shop where CFLs are available, people would likely go back to using an incandescent lamp. One of the most important weaknesses that people pointed out in the survey is the difficulty to find CFLs in a market.

As discussed above, lower-income households are more likely to participate in the program. This is captured by the coefficient of *INCOME*, which is significantly negative. All the evidence is consistent: The program benefitted relatively low-income households, and they are keen about electricity spending and tend to continue using CFLs even if the distributed bulbs burn out. Thus, the measured program effect is sustained at least four years after the program.

Table 8. OLS and IV estimation for household's CFL share

	OLS		IV		OLS		IV	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Treat	0.089	(0.040) **	0.194	(0.116) *	0.100	(0.034) ***	0.207	(0.098) **
ln*KWH*	0.013	(0.028)	0.016	(0.027)	0.005	(0.022)	0.013	(0.023)
ln*SIZE*	0.018	(0.039)	0.015	(0.038)	0.014	(0.036)	0.011	(0.035)
ln*AGE*	0.113	(0.060) *	0.102	(0.060) *	0.074	(0.047)	0.069	(0.046)
dMALE	-0.041	(0.041)	-0.042	(0.040)	-0.064	(0.035) *	-0.071	(0.035) **
ln*EDU*	0.027	(0.011) **	0.027	(0.011) **	0.023	(0.009) ***	0.027	(0.009) ***
ln*INCOME*	-0.022	(0.027)	-0.008	(0.030)				
dGOV	0.019	(0.061)	0.012	(0.060)	-0.022	(0.053)	-0.027	(0.052)
dSELF	-0.005	(0.044)	0.002	(0.043)	-0.017	(0.038)	-0.009	(0.037)
dOWN	0.016	(0.043)	0.019	(0.043)	0.024	(0.038)	0.027	(0.038)
ln*ROOM*	-0.021	(0.043)	-0.010	(0.042)	-0.049	(0.038)	-0.034	(0.038)
dIRON	-0.105	(0.073)	-0.104	(0.071)	-0.098	(0.060) *	-0.094	(0.059)
dHOTP	0.120	(0.073) *	0.151	(0.077) **	0.137	(0.063) **	0.156	(0.063) **
dBOIL	0.086	(0.062)	0.106	(0.060) *	0.112	(0.053) **	0.124	(0.051) **
dTV	0.047	(0.113)	0.034	(0.120)	0.032	(0.123)	0.035	(0.119)
dREFR	-0.155	(0.098)	-0.142	(0.092)	-0.106	(0.086)	-0.104	(0.084)
dINJERA	-0.041	(0.129)	-0.125	(0.132)	-0.040	(0.087)	-0.095	(0.089)
dWATIN	-0.034	(0.071)	-0.042	(0.072)	-0.026	(0.057)	-0.040	(0.058)
dBREAD	0.097	(0.083)	0.072	(0.084)	0.036	(0.062)	0.023	(0.064)
constant	0.154	(0.356)	0.046	(0.364)	0.208	(0.263)	0.126	(0.268)
Obs.	339		338		472		469	
R-squared:	0.072		0.053		0.058		0.040	
F-statistics	1.64 **				1.89 **			
Wald chi2			30.22 **				29.28 **	
Exogeneity test C stat.			0.949				1.415	
Overidentifying restriction Hansen's J stat.			1.799				1.291	

The dependent variable is the share of CFLs out of total bulbs. Robust standard errors are shown in parentheses. *, ** and *** indicate the statistical significance at the 10, 5 and 1 percent, respectively.

Table 9. First stage regression for IV estimation

	Coef.	Std.Err.		Coef.	Std.Err.	
dSHOP	0.464	(0.064)	***	0.464	(0.057)	***
ln*NEIGH*	0.037	(0.011)	***	0.042	(0.009)	***
ln*KWH*	-0.007	(0.037)		-0.052	(0.031)	*
ln*SIZE*	0.023	(0.054)		0.004	(0.044)	
ln*AGE*	0.049	(0.088)		0.012	(0.071)	
dMALE	-0.010	(0.057)		0.029	(0.047)	
ln*EDU*	-0.003	(0.015)		-0.028	(0.012)	**
ln*INCOME*	-0.102	(0.033)	***			
dGOV	0.052	(0.077)		0.002	(0.068)	
dSELF	-0.020	(0.060)		-0.026	(0.050)	
dOWN	-0.074	(0.059)		-0.061	(0.053)	
ln*ROOM*	-0.007	(0.062)		-0.051	(0.054)	
dIRON	-0.104	(0.111)		-0.099	(0.087)	
dHOTP	-0.180	(0.094)	*	-0.110	(0.087)	
dBOIL	-0.065	(0.097)		-0.059	(0.079)	
dTV	0.260	(0.199)		-0.002	(0.189)	
dREFR	-0.076	(0.135)		0.066	(0.133)	
dINJERA	0.235	(0.131)	*	0.192	(0.100)	*
dWATIN	0.007	(0.091)		-0.019	(0.070)	
dBREAD	0.193	(0.103)	*	0.196	(0.078)	**
constant	0.946	(0.512)	*	0.755	(0.407)	*
Obs.	338			469		
R-squared:	0.220			0.197		
F-statistics	10.50	**		12.68	***	

The dependent variable is the dummy variable for CFL program participation, *Treat*. Robust standard errors are shown in parentheses. *, ** and *** indicate the statistical significance at the 10, 5 and 1 percent, respectively.

Finally, the effect of CFL bulb life is examined. The people's preferences to CFLs may depend on their past experiences. Since the household survey asked the actual product life of the distributed CFL bulbs (denoted by *DUR*), this is interacted with our treatment variable, *Treat*. In this specification, therefore, the program effect is not only measured by the participation but also the duration of exposure to the program.

The estimation result confirms that the share of CFL bulbs in a house is higher when a household benefited from the program and the distributed CFLs lasted longer. The coefficient in the OLS model is estimated at 0.007, which is significant (Table 10). The other coefficients are broadly in line with the previous evidence.

Table 10. Effect of CFL bulb life on household's CFL share

	OLS			IV		
	Coef.	Std.Err.		Coef.	Std.Err.	
*Treat*DUR*	0.007	(0.002)	***	0.015	(0.007)	**
ln*KWH*	0.001	(0.022)		0.006	(0.022)	
ln*SIZE*	0.019	(0.036)		0.023	(0.036)	
ln*AGE*	0.073	(0.047)		0.067	(0.046)	
dMALE	-0.063	(0.035)	*	-0.072	(0.035)	**
ln*EDU*	0.022	(0.009)	**	0.025	(0.009)	***
dGOV	-0.021	(0.054)		-0.020	(0.053)	
dSELF	-0.018	(0.038)		-0.007	(0.037)	
dOWN	0.033	(0.038)		0.046	(0.040)	
ln*ROOM*	-0.059	(0.038)		-0.055	(0.038)	
dIRON	-0.104	(0.060)	*	-0.105	(0.059)	*
dHOTP	0.126	(0.064)	**	0.133	(0.064)	**
dBOIL	0.117	(0.054)	**	0.134	(0.053)	**
dTV	0.020	(0.121)		0.009	(0.115)	
dREFR	-0.100	(0.088)		-0.096	(0.088)	
dINJERA	-0.025	(0.085)		-0.062	(0.086)	
dWATIN	-0.037	(0.057)		-0.060	(0.057)	
dBREAD	0.048	(0.061)		0.045	(0.061)	
constant	0.265	(0.263)		0.242	(0.256)	
Obs.	472			469		
R-squared:	0.055			0.037		
F-statistics	1.83	**				
Wald chi2				28.73	*	
Exogeneity test C stat.				1.326		
Overidentifying restriction Hansen's J stat.				1.983		

The dependent variable is the share of CFLs out of total bulbs. Robust standard errors are shown in parentheses. *, ** and *** indicate the statistical significance at the 10, 5 and 1 percent, respectively.

V. Robustness

One may be concerned that the identification strategy of the above analysis is weak, though the instruments used are valid from a statistical point of view. To check the robustness of the main estimation results, a propensity score matching technique is used, which ensures comparability between the two groups: program beneficiaries and non-beneficiaries. As indicated, there seem to be systematic differences between them. In addition to the household characteristics that are used above, the Customer Contract Number is used as another external variable. This is artificially assigned by the utility and considered to be relevant to the household's willingness to participate in the CFL program. Households with larger customer numbers are perhaps relatively new customers, who may be relatively poor and need more lightbulbs. Old customers may already have sufficient lightbulbs.

As expected, the Contract Number is positively correlated with the participation in the CFL program. It was found that 912 observations were out of the common support and thus excluded from our sample. Then, the fixed-effects IV model is applied (Table 11). The result is broadly the same as the main results in the previous section.

Another concern may be that non-beneficiaries could also purchase and possess CFLs regardless of the program. It is important to recall that the intervention to be evaluated is the free CFL distribution under the first phase of the program. Both treatment and control households have CFLs. As shown in the previous section, the former possess relatively more CFLs than the latter. Still, it may be of particular concern that the second and third phases of the CFL program were implemented in July 2011 and January 2012, respectively.

To address this issue, the fixed-effects model is estimated with the limited sample up to June 2011. As shown in the second column model of the table, the main results are similar but the magnitude of the coefficients is different. The CFL effects still exist but are smaller, simply because the impacts are small in the short run, or because the previous estimates were overestimated: Non-beneficiaries are also using CFLs.

Table 11. Fixed-effects IV panel estimation with limited sample data

	With score matching			With the sample before 2nd phase		
	Coef.	Std.Err.		Coef.	Std.Err.	
MP	-728.14	(48.83)	***	-279.18	(26.70)	***
D	-11.52	(0.36)	***	-6.73	(0.21)	***
CFL1	-13.37	(2.53)	***	-5.75	(1.19)	***
CFL2	-15.75	(4.83)	***	-5.98	(2.39)	**
dIRON	10.57	(16.21)		-1.93	(9.22)	
dHOTP	-8.61	(9.12)		-3.39	(8.52)	
dBOIL	59.04	(22.21)	***	29.87	(14.67)	**
Constant	337.27	(33.42)	***	159.27	(19.25)	***
Obs.	49,458			25,652		
Number of groups	496			496.00		
R-squared:						
Within	0.248			0.347		
Between	0.881			0.917		
Overall	0.639			0.748		
Wald chi2	3228.6	***		2591.84	***	
Fixed effects:						
Individual	Yes			Yes		
Time	Year-month			Year-month		

The dependent variable is *KWH*. The clustered standard errors, which allow for intragroup correlation, are shown in parentheses. *, ** and *** indicate the statistical significance at the 10, 5 and 1 percent, respectively.

VI. Conclusion

Energy-efficient products generally offer an inexpensive, win-win proposition. While end users can reduce their energy costs, power utilities can avoid costly new investments in developing their generation capacity. Moreover, energy efficiency can contribute to mitigating global warming. Like other countries, Ethiopia has been implementing a series of energy-efficiency programs at the end user level to manage the rapidly increasing demand for electricity.

With detailed household-level data collected, this paper examined the sustainability of the residential use of CFL bulbs after the free CFL distribution program in Ethiopia. The evidence from the panel analysis shows that the direct program effect was sustained at least four years after the program. Then, the effect of the distributed CFLs may taper off. But some of the program beneficiaries reinstalled new CFLs when the program CFLs burned out. In the sample data, about 70 percent were replaced with CFLs again. But the rest were replaced with incandescent lightbulbs, because they are cheaper and their perceived quality is better.

The effect of replacing the program CFLs with new CFLs is found statistically significant. Of particular note, this effect is especially significant among relatively low-income households. It is also shown that their electricity demand is more price-elastic. Thus, it can be concluded that the program effect is sustained particularly because low-income households are convinced that CFL bulbs are more cost-effective in the long run, as theory predicts.

The evidence from the IV estimation of the share of CFL bulbs in a house is also consistent with the above. After the selection bias is controlled, program beneficiaries are found to use more CFL bulbs than non-beneficiaries. The poor are more likely to use CFLs. All the indications are that the effect of the CFL program is sustained particularly among the poor. It is also found that the use of CFLs depends on people’s experiences. It is therefore important to ensure that the local markets provide good quality energy-efficient products.

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