Division of Economics and Business
Working Paper Series

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Working Paper 2020-07
http://econbus-papers.mines.edu/working-papers/wp202007.pdf

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November 2020

Colorado School of Mines
Division of Economics and Business
Working Paper No. **2020-07**
November 2020

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Heterogeneity in the Rebound Effect: Evidence from Efficient Lighting Subsidies

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ABSTRACT
This paper quantifies heterogeneity in rebound effects from policy-induced energy efficiency improvements by income and home size. We do so in a relatively understudied context: residential lighting. This context allows us to separately estimate effects for energy services (lighting hours) and electricity consumption. We identify the effect of household-level subsidy uptake using instrumental variables for program awareness and coarsened exact matching. We find that rebound effects are larger for households with lower incomes and smaller homes. We also show that the rebound effect is not large enough to "backfire" and all income and size subsamples exhibit net energy savings.

JEL **classifications: D12, H31, L68, Q41**
Keywords: rebound effect, heterogeneity, energy efficiency policy.

1 Introduction

Energy efficiency is associated with private benefits such as lower energy bills for consumers and lower excess capacity for electricity producers, as well as social benefits such as reduced pollution emissions. Energy efficiency subsidies are often used to address market failures, such as pollution externalities or investment inefficiencies driven by factors such as incomplete information (see, e.g., Allcott and Greenstone (2012)). Energy efficiency subsidies are also used as safety net programs in order to improve the energy security of low income households (Fowlie et al., 2018). However, a "rebound effect" often occurs when expected savings from energy efficiency improvements are not fully realized. The reduced operating costs from energy efficiency may increase utilization rates of existing energy-using durable goods, or increase investment in new durable goods. Because energy efficiency subsidies have both economic efficiency and distributional implications, it is important to understand how this rebound effect varies across the income distribution.

The purpose of this study is to explore heterogeneity in the direct rebound effect from policy-induced energy efficiency improvements. We estimate the rebound effect from energy efficiency subsidies for different income and home-size categories. A vast literature has examined the economic efficiency of energy efficiency subsidies and quantified the rebound effect in a variety of contexts, as we discuss in detail in section 2. However, heterogeneous treatment effects from energy efficiency subsidy policies are not as well-understood. We conduct our investigation in a context for which there are very few detailed econometric studies: residential lighting. This context allows us to separately estimate effects on energy services utilization (i.e., hours of lighting use) versus electricity consumption.

Heterogeneous responses to energy efficiency subsidies may arise for several reasons. Low-income consumers usually spend a higher share of their income on energy, so energy efficiency policies may induce a proportionately larger behavioral response in comparison to high-income consumers. Higher-income households, however, have larger energy bills and may be more price elastic. High income households may also face lower non-pecuniary costs of program participation, such as fewer time constraints to investigate participation requirements and fill out rebate paperwork. On the other hand, barriers to adoption of energy efficient technologies may be higher for low-income households because of credit constraints, lack of knowledge or attention, or scale.[1] As with many energy efficiency technologies, the higher upfront

[1] For example, Mills and Schleich (2010) investigate barriers to households' uptake of energy efficient lightbulbs (i.e. CFLs) and to the subsequent usage intensity using a Double-Hurdle model.

cost of efficient light bulbs may discourage their adoption. This is especially likely among households with lower baseline lighting usage over which to distribute those fixed costs, such as smaller homes (Frondel and Lohmann, 2011), or households with tighter budget constraints. Because such barriers apply heterogeneously across households, policies that eliminate or reduce these barriers may have a heterogeneous impacts. Quantifying these responses is important for policy makers and economists because of their associated distributional implications.

In order to identify the rebound effect of energy efficiency subsidy policies in different income and home size categories, we apply an instrumental variables (IV) strategy along with a coarsened exact matching (CEM) algorithm to household-level data from the 2009 Residential Electricity Consumption Survey (RECS). Households report in RECS whether they received assistance from an energy efficiency program. Program participation is voluntary and endogenous to household level unobservables such as preferences and information (Alberini and Towe, 2015). In order to address self-selection in participation we construct several instrumental variables. First, we calculate the number of energy efficiency incentives available in the same state as the observed household, but in the previous survey year, as a "policy availability" instrument. Second, as a "policy intensity" instrument, for each household we calculate the number of other households in RECS in the same region but in the previous year who received energy efficiency assistance for lighting. We also use the state-level legislative election returns as an additional instrument to capture state-specific factors (e.g. environmentally friendly states) influencing program participation.[2] We also apply CEM to covariates such as household size, employment status, and household use of energy audits, and estimate our IV regressions on the matched subsample. We then estimate the impacts of program uptake on demand for energy services – specifically lighting hours and electricity consumption – within different income and home-size categories.

We find that program uptake causes a statistically significant direct rebound effect, as measured by an increase in total hours of lighting usage across all bulbs in the home. The rebound effect is proportionately largest for consumers who have low incomes or small homes. This suggests that barriers to energy efficiency adoption apply heterogeneously across the income and wealth distribution. Our findings further suggest that the policy objectives of externality reduction and redistribution may be at odds with each other; rebound effects that are declining in wealth imply an equity-

Their simulations show that barriers are higher for low-income households

[2]We thank an anonymous referee for the suggestion to use election returns. Results are robust to using different subsets of these instruments.

efficiency trade-off for policies targeted at less wealthy households. Although we do find that the high-income group has the second-largest rebound effect among income categories, our estimated rebound effects are monotonically declining across home size categories. Additionally, we examine the existence of a backfire rebound effect, which would occur if the rebound effect were so large that it more than offsets all of the expected reduction in energy use. In order to assess the existence of a backfire effect, we construct a proxy variable for electricity consumption in lighting as the outcome variable in our regressions. We find that policy participation has a negative net impact on electricity use for lighting both on average and also at each income and home-size group, which implies that there is no backfire effect. Succinctly, there is an increase in hours of use, but there is a decrease in total electricity consumed, resulting in net energy savings. It is beyond the scope of this study to calculate the cost effectiveness of these policy-induced improvements, which has been investigated at length in other studies and which we describe in the next section.

The remainder of this article is organized as follows. Section 2 discusses our contribution in the context of the larger energy efficiency and rebound effect literature. Section 3 provides a brief theoretical motivation for this study. The empirical methods and data are presented in Section 4, followed by the results in Section 5. Section 6 explores some policy implications and finally, Section 7 concludes.

2 Literature Review

Although energy efficiency subsidies are often used to reduce energy use externalities or as a form of redistribution, they typically do not achieve the efficient level of consumption (Borenstein and Davis, 2016). One reason energy reduction goals might not be fully accomplished is the rebound effect.[3] The "total rebound effect" can be divided into "direct" and "indirect" rebound effects. The direct rebound effect refers to increased utilization rates of energy-using goods following an energy efficiency improvement that reduces operating costs. The indirect rebound effect refers to the increase in consumption of other goods that also require energy inputs. This arises because the reduced operating costs from the initial energy efficiency improvement relax the consumer's budget constraint, leading to an expansion in consumption of other goods. Both types of rebound effects cause realized energy savings to be less than those expected ex-ante (Graff Zivin and Novan, 2016).

[3] There are of course other reasons that subsidies may not be efficient; see, for example, Boomhower and Davis (2014) and Gilbert et al. (2019) on the non-additionality of subsidy uptake, and Allcott et al. (2015) on whether subsidies are poorly targeted.

There is a vast literature that characterizes and quantifies different forms of rebound effects (i.e. direct, indirect, and total economy-wide rebound effects). The indirect rebound effect can be measured by employing methods such as input-output analysis (Thomas and Azevedo, 2013) and demand system analysis e.g. Almost Ideal Demand System (AIDS) models (Deaton and Muellbauer, 1980; Brännlund et al., 2007). Economy-wide impacts of energy efficiency improvements are usually analyzed by employing general equilibrium modeling (Yu et al., 2015). In this paper, however, we focus on direct rebound effects.

The direct rebound effect is often measured using experimental, quasi-experimental, or econometric approaches with observational data. Dealing with selection bias is an important challenge with these approaches because market participants self-select into energy efficiency uptake (González, 2010; Meyer, 1995; Hartman, 1988). For example, information failures are influential in determining whether consumers participate in an energy efficiency program (Murray and Mills, 2011; Ramos et al., 2015). More recent literature focuses on quasi-experimental methods or randomized control trials to measure the direct rebound effect, typically measuring energy demand from a sample of consumers with and without an energy efficiency improvement and leveraging some source of exogenous variation in the improvement (Gillingham et al., 2016; Frondel et al., 2008). These methods have been applied in a variety of sectors with different durable goods such as passenger vehicles (Greene et al., 1999; Wang et al., 2012; Allcott and Wozny, 2012; Borger et al., 2016; Linn, 2016), residential weatherization (Fowlie et al., 2018), and various types of appliances such as clothes washing machines (Davis, 2008), air conditioners and refrigerators (Davis et al., 2014; Jin, 2007), and space heating (Haas and Biermayr, 2000). For example, Fowlie et al. (2015) show that increasing the level of information significantly affects energy efficiency program participation, so they randomize the provision of information in a field experiment with weatherization assistance. Our paper also leverages variation in program information through an instrumental variables strategy. Our policy availability, policy intensity, and political party vote share instruments for program participation capture the effects of information availability and environmental preferences on the participation decision. We also extend this literature by applying causal inference tools to a relatively understudied good – residential lighting – as well as by estimating heterogeneous treatment effects and distinguishing between lighting energy demand versus lighting utilization rates.

Quantifying heterogeneity in the rebound effect is important for understanding the trade-off between equity and economic efficiency in energy efficiency programs, especially if redistribution is a policy objective. For example, Borenstein (2012) shows that while increasing-block pricing has distributional benefits for low-income groups, it is neither economically optimal nor even the most efficient method of achieving a given amount of redistribution. Energy efficiency subsidies reduce the up-front cost of energy-efficient goods which helps low-income consumers relatively more. These subsidies result in income redistribution (Tullock, 2013) even when the up-front cost exceeds the expected present value of energy saving, as Fowlie et al. (2018) show has occurred with weatherization assistance. Even if redistribution is not a policy objective, however, heterogeneity in the rebound effect may have distributional consequences and may occur because of preexisting income inequality.

Heterogeneity in the rebound effect may occur along different dimensions such as consumer income (Guertin et al., 2003; Milne and Boardman, 2000), energy use intensity (Frondel et al., 2012), location, or durable good attributes such as vehicle fuel efficiency (Gillingham et al., 2015; Su, 2012; Winebrake et al., 2012). Gillingham et al. (2015), for example, show that gasoline price elasticity of driving depends on the fuel economy and age of the vehicle. Frondel et al. (2012) show that households with low vehicle mileage are expected to be less fuel price elastic so the rebound effect would be lower for them; in our context this suggest that the rebound effect could be larger for high-income consumers with larger energy bills. However, greater rebound effects for low-income households were found by Milne and Boardman (2000) for residential heating, by (Chitnis et al., 2014) for multiple broad categories of goods, and by Guertin et al. (2003) in a demand system of household energy end-uses which includes lighting and appliances. None of these studies uses quasi-experimental causal inference tools. Milne and Boardman (2000) synthesize a set of non-experimental case studies implemented over a two-decade span. (Chitnis et al., 2014) combine Engle curve estimation for broad goods categories with engineering calculations for energy use. Guertin et al. (2003) estimates the rebound effect for appliances and lighting as a bundle, although their study is quite different from ours. They estimate price and income elasticities in a demand system for several energy end uses, rather than estimating the policy-induced rebound effect or focusing on lighting specifically. Their study uses engineering calculations to decompose billing data into space heating and water heating, with lighting and appliance use attributed to a residual and bundled as a single variable. Their approach also does not isolate any source of exogenous variation in energy efficient technology uptake. Our study, by contrast, estimates the heterogeneous rebound effect of subsidy policy uptake for lighting specifically with a survey-based measure of lighting utilization. Although we do not estimate the size of the rebound effect directly, our results show that energy efficiency subsidies for lighting cause low-income and small-home groups to have the greatest increase in lighting utilization, which implies a larger direct rebound effect for these groups even as total lighting electricity use falls.

Quantifying the size of of these rebound effects is important for evaluating energy efficiency policies in terms of both energy savings and welfare (Gillingham et al., 2016). In this paper, we test for the existence of a direct rebound effect from energy efficiency subsidy programs rather than estimating the magnitude of the rebound effect as an output of the econometric model. However, we perform a rough back-of-the-envelope calculation to compare the magnitude of our estimates with other studies that directly estimate the size of the rebound effect. Establishing the existence of rebound effects does not mean that energy efficiency programs are not useful. The rebound effect is important to be aware of in strategic energy planning, and our results confirm the conclusion in Gillingham et al. (2013) that there is little evidence for the backfire case. There are still net energy savings, but we cannot say whether they have been achieved through a cost effective mechanism.

2.1 Energy Efficiency in Lighting

Consumer behavior in adopting and using energy efficient lighting has been associated with two main questions. First, what motivates consumers to adopt energy efficient light bulbs? Second, how much will consumption change after technology adoption?

Compact fluorescent lightbulbs (CFLs), and more recently light-emitting diodes (LEDs), are the most common types of energy efficient light bulbs. These bulbs use less energy than a comparable incandescent light bulb with the same amount of lumens or brightness, and they have a longer life span. Adoption of energy efficient bulbs has been stymied by several barriers such as higher up front costs, lower lighting quality and/or a warm-up period before achieving full brightness (Wall and Crosbie, 2009; Frondel and Lohmann, 2011). A well-known experiment by Allcott and Taubinsky (2015) shows that the salience of costs and benefits is an important factor in adoption of efficient light bulbs.

These bulbs have the potential to significantly lower the operating cost of lighting by requiring less electricity to provide the same amount of lighting energy services. Total energy savings in the United States from using these energy efficient light bulbs between 2010 and 2030 have been predicted to be around 2,700 terawatt hours (TWh), or approximately $250 billion at 2012 energy prices (Navigant Consulting, 2012). If there are no behavioral changes, these expected cost savings over time outweigh the higher up front prices of these light bulbs, even without factoring in the external social benefits from pollution abatement (Navigant Consulting, 2012).

Rebound effects may change these calculations, however. For example, innovations in lighting technology have lead to increased use of lighting for indoor and outdoor decorating could raise the number of bulbs in use (Bladh and Krantz, 2008). Fouquet et al. (2012) estimate the rebound effect for lighting using aggregate time series data over 200 years in Britain and show that although the rebound effect has decreased over time, it is still not negligible and remains at around 5 percent. Using engineering methods and employing a household survey in Germany, Schleich et al. (2014) calculated the expected direct rebound effects for an average bulb at about 6%. However, their study does not use econometric methods to control for potential confounders or to identify a causal effect. In a study from Pakistan, Chun and Jiang (2013) show that the lower operating cost of energy efficient light-bulbs reduces potential energy savings by 23% to 35% due to increased brightness and extended hours of use. By comparison, our study combines the hours of lighting use with the number of light-bulbs used as a measure of total lighting services consumed in the household, although we do not separately measure changes in effective use associated with brightness or light quality. Chitnis et al. (2013) also estimate the rebound in lighting, but they do so by estimating expenditure elasticities for broad categories of goods and then use engineering calculations to derive the rebound effect for subclasses of end-uses like lighting. Our study by contrast uses quasi-experimental econometric methods with direct measures of lighting services, disentangling lighting use intensity via the number of light bulbs used and their burning time.

3 Theoretical motivation

In order to show the intuition behind the potential rebound effect caused by energy efficiency subsidies, we start with a simple utility maximization problem by a representative household. The household's goal is to maximize its utility subject to its budget constraint, where the household's utility is a function of lighting energy services (S) and a numeraire for all other goods (X).

$$U = f(S, X)$$

Lighting energy services increase by using either more electricity for a given light bulb or a more effective capital stock, i.e., energy efficient light bulbs, for a given amount of electricity. A policy-induced adoption of more energy efficient light bulbs which increases S also implies the existence of a rebound effect. This is illustrated in Figures 1 and 2. The red budget line shows the case with standard light bulbs and no energy efficiency subsidy. The green budget line shows the case where the household adopts energy efficient light bulbs which are more expensive to buy but cheaper to use. The higher fixed cost shifts the budget line down compared to the initial red line, but the reduced cost of energy services makes the budget line flatter. The indifference curve U_0 shows the initial utility for a household that would not buy energy efficient bulbs without receiving financial assistance from a subsidy, since the utility will be lower on the green budget line. In order for a household to buy energy efficient light bulbs without subsidies, the initial utility would need to be tangent with the green budget line towards the bottom right corner of the graph.

If the household receives financial assistance for energy efficient lighting, the green budget line shifts up to the dashed black budget line as depicted in Figure 2. This figure illustrates the case when the subsidy is such that the household is indifferent between adopting versus not adopting energy efficient light bulbs. For one additional dollar of subsidy, the household will strictly prefer to adopt the efficient light bulbs. After taking the subsidy and adopting the efficient light bulbs, the household's indifference curve would be tangent to the black dashed budget line, and lighting energy services consumption would increase relative to the tangency with the red budget line, as well as relative to any tangency with the green budget line (not pictured). We know that this is a rebound effect because both the green and black dashed budget lines represent the same energy efficient light bulb technology with and without a subsidy. An expansion in energy services from the outward shift in the budget line from the green to the black dashed line therefore must be accounted for by an increase in the utilization rate rather than a change in the energy efficiency of the capital stock. Our empirical exercise quantifies this rebound effect as a result of policy uptake for different income and home-size categories.

4 Empirical Approach

4.1 Methodology

To analyze the potential heterogeneous rebound effect in lighting, we regress total hours of lighting consumption on a treatment dummy for lighting subsidy uptake and a vector of control variables. Subsidy assistance can take the form of manufacturer or retailer rebates, utility or energy supplier rebates, and/or weatherization assistance. We are not able to observe the form of the assistance in RECS, so we use a single dummy for household subsidy uptake. Participating in these subsidy programs may be endogenous to household-level unobservables such as preferences and information that affect the hours of lighting use. We therefore use an instrumental variables strategy that leverages variation in awareness and availability of the programs, applied to a subsample constructed through Coarsened Exact Matching (CEM).

We consider heterogeneity by choosing sub-samples based on income level and home size. Our regression equations for the full sample and the income and home-size subsamples take the form

$$y_i = \beta_0 + \beta_1 treat_i + \alpha' X_i + \epsilon_i, \tag{1}$$

where the outcome variable is the log of total hours of lighting use during a summer day, $treat_i$ is the treatment dummy for subsidy assistance for energy efficient lighting, and X_i is a vector of control variables including the electricity price, income level, home ownership status, an energy bill payment dummy, state or reportable domain dummy variables, home size, and number of household members. All variables other than the binary variables are in log form.

In order to assess the existence of a backfire rebound effect, we estimate equation (1) with a proxy for electricity used in lighting as the dependent variable rather than hours of lighting use. We calculate this by multiplying the hours of energy efficient and inefficient light bulb use by the number of each bulb type in the household and the average electricity use of an energy efficient and inefficient light-bulb, and then adding them together.

4.1.1 Instrumental Variables

We use three instrumental variables for subsidy uptake: "policy availability", "policy intensity", and legislative party strength. Policy availability and policy intensity are the number of other lighting subsidy policies available, and the number of other households reporting subsidy uptake in RECS, in a given region in a previous year, respectively. The intuition behind this approach is that in areas with more energy efficiency subsidies historically and more recent adopters of those policies, any individual household is more likely to be aware of the policies – and more likely to find a policy that fits their needs – and therefore more likely to adopt the policy. In addition, with a greater number of recent adopters in the same region for a given number of programs, there may be fewer subsidy resources available for later adopters.[4] We

[4] This approach is similar to that of Si et al. (2018) for estimating the effect of energy efficiency policies in Chinese provinces, although their analysis is at the province level rather than household level.

also use legislative party strength as an additional instrument to control for states that have many environmentally conscious consumers.

The first two instrumental variables are time lagged. Our main assumption is that the time lagged instruments have no impact on a household's lighting use except through their impact on the household's current policy adoption, conditional on the control variables. This assumption is reasonable, because variables such as household size, income, home size, and home ownership control for unobservable factors such as preferences and needs that may be correlated across households. Therefore, conditional on control variables, the time lag of policy adoption by other households and the time lag of available incentives should not affect the lighting use by household i, except through their impact on the household's current policy adoption.

4.1.2 Coarsened Exact Matching

In addition to using the IV estimator, we use the CEM algorithm as another identification strategy to control for a set of pre-treatment variables and address the selection-bias issue. The algorithm is used to match each adopter of energy efficiency assistance to similar non-adopters and drop non-matched observations. This method is preferred to other types of matching methods due to some features such as requiring fewer assumptions, reducing the degree of model dependence, and reducing the estimation error of the causal impact (Blackwell et al., 2009). It also reduces any potential imbalance between treated and control groups (Iacus et al., 2012). The matching is done using covariates such as household size, employment status, and a binary variable for receiving subsidy assistance for a home energy audit.

4.2 Data

We primarily rely on cross sectional data from the 2009 Residential Electricity Consumption Survey (RECS). The U.S Energy Information Administration (EIA) administered this survey to a stratified random sample of 12,083 households in the United States in 2009. The sampling process first randomly selects a group of counties, then randomly selects a group of Census blocks from within each chosen county, followed by a random sample of occupied primary residences from within the chosen Census blocks. Within the publicly available data, however, geographic information on individual households is given as a "reportable domain" which is either a state or a group of states. Twenty-one states and six state groups are reported, to make 27 reportable domains.

The survey collects detailed information about energy-related durable goods and energy consumption behaviors, such as lighting, appliances, electronics, space heating, air conditioning, water heating, energy program participation, energy bills, energy suppliers, housing unit characteristics, and household characteristics. Important for our study, households report the number of total light bulbs, and the number of energy efficient light-bulbs, that were turned on for either one to four hours, four to 12 hours, or more than 12 hours during a summer day. We use the information on the number of light bulbs in each of these time bins to calculate the outcome variables of "Hours of lighting use" and "Electricity used for lighting" for our regression analysis.

We calculate "Hours of lighting use" by multiplying the number of lightbulbs in each time bin by the number of hours associated with that bin according to the formula

$$y_i = \sum_j h_j N_{ij}, \tag{2}$$

where $h_j \in \{2.5, 8, 12\}$ is the approximate number of hours in each bin and N_{ij} is the number of light bulbs that household i reports as turned on for the number of hours in bin j.

We also construct a proxy variable for "Electricity used for lighting" in order to investigate the backfire hypothesis. In order to do so, we use equation (2) to calculate hours of lighting from energy efficient bulbs, y_{ie} (where N_{ij} in equation (2) would refer to the number of energy efficient bulbs, rather than total light bulbs, turned on for j hours). We then calculate hours of lighting use for conventional or "inefficient" bulbs as

$$y_{in} = y_i - y_{ie}.$$

The "Electricity used for lighting" variable is then calculated according to

$$KWh_i = \beta_1 y_{in} + \beta_2 y_{ie}, \tag{3}$$

where the β_1 and β_2 coefficients are approximate KW ratings of standard energy inefficient and energy efficient light bulbs, respectively. These are 0.060 for a 60 watt incandescent bulb, and 0.014 for a 14-watt efficient replacement bulb.

A summary of all variables used in this paper is shown in Table 1. Assistance for energy efficient light-bulbs, our treatment variable, is a binary variable equal to one if the household reports receiving financial assistance from an energy efficiency subsidy program, and is equal to zero otherwise. Not quite four percent of the sample households received monetary assistance from an energy efficiency subsidy program.

In order to construct our policy availability instrumental variable, we used information from the Database of State Incentives for Renewables and Efficiency (DSIRE) along with additional data from RECS. To create this variable, we simply summed the number of residential energy efficiency programs for lighting available in the reportable domain where each household lives, with a one-year lag. Households provide RECS with the year they most recently received subsidy assistance. To operationalize the one-year lag, for households that adopt subsidy assistance we use the year before they did so, and for households that did not receive lighting subsidy assistance we use the year 2008, one year before the survey.

The second instrument, policy intensity, is a measure of the number of people who received assistance from energy efficiency subsidies in the same reportable domain as household i, again with a one-year lag. In order to calculate this, we summed the number of other RECS respondents with a positive treatment dummy as of the year before household i received subsidy assistance (for treated households), or as of 2008 (for nontreated households).

In our preferred estimates we also weight these instruments by the population of the reportable domain in order to create a per capita measure. It is likely that "n" programs in California implies a different availability of subsidies – and different information about subsidy availability – to the average household than "n" programs in Wyoming. Likewise, a given number of other households taking subsidies in New York implies a different spread of information, and a different depletion rate of subsidy program resources, than the same number of households taking subsidies in Montana. The population-weighted instruments reflect these differences.

In addition, the third instrument is the state-level or reportable domain-level legislative election returns in the form of the percent of the two-party vote going to Republicans, taken from the data provided by Klarner (2018).

We also include additional control variables from the RECS data such as annual income (USD), home size (sqft), state or reportable domain average electricity price, household size (i.e., the number of household members), a dummy for female respondent, an electricity bill payment dummy equal to one if the household pays the electricity bills and zero otherwise, and a home ownership dummy.

In order to evaluate the quality of matching, a summary of the CEM matching as well as the level of imbalance between treated and control groups before and after the matching are shown in Table 2. The global imbalance, which was first introduced by Iacus et al. (2008), is shown by the multivariate L_1 statistics. The goal is to reduce this global imbalance which is the difference between the multivariate empirical distribution of the pre-treatment covariates for the treated $p(X|T = 1)$ and matched control $p(\tilde{X}|T = 0)$ groups (Iacus et al., 2008). The matching results demonstrate that the level of imbalance decreases, after the matching, compared to the unmatched data. We therefore apply our instrumental variables strategy to the matched data in our preferred regression specifications.

The results of the first stage regressions for the full sample and the matched sample are reported in Table 3. The first two columns report first-stage results with non-population-weighted policy instruments, with the full sample and the CEM sample, respectively. The third and fourth columns report these results with population-weighted policy instruments. Table 3 shows that the policy availability and state legislative instrumental variables (IVs) have a positive significant impact on uptake of subsidy assistance, but that the policy intensity variable has a negative effect. If more other households in a region have taken advantage of the subsidy program, there may be fewer subsidy dollars available leading to reduced uptake later. All four columns demonstrate that the impact of all three instruments on the endogenous subsidy assistance variable are statistically significant, conditional on all other explanatory variables. In order to confirm that these are not weak instruments conditional, we report the Montiel-Pflueger robust weak instrument test (Olea and Pflueger, 2013) for all instrumental variable regressions in the second stage tables in the next section. This test statistic is preferred to the regular non-robust first stage F test because it uses a correction factor for heteroskedasticity (Andrews and Stock, 2018).

It is also interesting to note that income level and home size do not have a statistically significant effect on uptake of subsidy assistance, which implies that the major policy adopters are not necessarily the low-income or low-wealth households. Figure 3 also shows that the income distribution for policy participants is similar to non-participants. The spike on the right tail of each distribution mainly stems from the top-censored income question for confidentiality purposes. The figure implies that although policy adoption might have heterogeneous impacts on energy services consumption at different income level groups, policy adoption, however, is not dependent on income level.

5 Results

5.1 Rebound Effect in Lighting Hours: Full and CEM Samples

The OLS and IV results for lighting hours, for the full sample and the matched sample, are shown in Table 4. The first and second columns report OLS results for the full and CEM samples, respectively, while the middle two columns report unweighted IV results for the full and CEM samples, and the final two columns report IV results with the policy availability and policy intensity instruments weighted by population. In all IV results, the Montiel-Pflueger robust F-statistic is far above 10. The coefficient on subsidy assistance is positive and statistically significant in all specifications. This coefficient is about three times as large in the IV results as in the OLS results, however, increasing from between 0.12 and 0.16 to between 0.42 to 0.50.

The coefficients on the additional explanatory variables are approximately the same magnitude across specifications, and have the expected signs. The home size and income coefficients are positive and statistically significant. Using our preferred specification in the final column with population-weighted IVs and the CEM sample, these coefficients imply an income elasticity of lighting hours of about 0.10 and a home size elasticity of about 0.16. Conditional on income, however, employment status does not explain lighting hours. Conditional on home size, larger households use significantly more lighting hours with an elasticity of 0.21. The electricity price coefficient is not distinguishable from zero but the household electricity bill payment dummy is negative and statistically significant, with a semi-elasticity of about -0.12. Consistent with Ito (2014), this suggests that households are responsive to their bill but not the marginal price. We also find that home owners may use slightly more hours of lighting while female-headed households use significantly less.

5.2 Heterogeneity in the Rebound Effect: Income and Home Size

For the findings on heterogeneity in the rebound effect, Table 5 reports the IV results for three income quantiles using the population-weighted policy instruments. The first two columns report results without and then with CEM matching for the low-income group, whereas the next two columns represent the middle-income group and the last two columns are the high-income group. Table 6 reports the analogous results for three home size quantiles.[5]

The results for income quantiles in Table 5 show that, while the impact of subsidy assistance on hours of lighting use is positive for all income groups, the size of the impact is largest for the low-income households who increase hours of lighting use by 60 percent. However, the second largest rebound effect occurs among the high-income group, who increase hours of lighting use by 49 percent. As discussed earlier, if energy expenditures are a larger share of income and the subsidy has a proportionately larger effect on the budget constraint of lower-income households then we should observe a larger rebound effect for this group. However, one reason for the rebound effect is a change in relative prices for operating durable goods so we should see larger rebound effects among price-responsive consumers. These pattern are reflected in Table 5. The low-income quantile is the only subgroup with a statistically significant and negative effect of the electricity bill payment dummy, which supports the interpretation that this group's budget constraint is meaningfully affected by energy bills. The high-income quantile, by contrast, is the only group with a statistically significantly negative electricity price elasticity of lighting use. Marginal changes in income within income quantile are also largest among the high-income group, suggesting heterogeneity within quantile. However, the home size and household size coefficients are fairly stable across income groups which suggests that the effect of an additional room or an additional occupant on lighting use does not depend on income.

Our main result is very similar for home-size quantiles reported in Table 6, in that the rebound effect is positive and significant among all groups, and largest among households with smaller dwellings. However, the rebound effect does not increase again in the large-home-size quantile as it did with income; the rebound effect for medium and large homes is about the same size. Although home size may partially capture household wealth, it also captures the physical constraints to adding more energy-consuming durable goods like light fixtures. Within home size group, marginal changes in home size have the largest effect on total lighting usage in the largest home-size group, followed by the smallest home-size group. The income and household size coefficients are fairly stable across home size groups, although the household size effect is smallest for small homes which suggests that an additional occupant requires less additional lighting in a smaller dwelling. Home ownership is now statistically significant and positive among the largest home size group, in which there is likely the greatest incentive and most space to add more lighting

[5] Results are robust to using unweighted IVs. Results from these specifications are available upon request.

fixtures.

Our main conclusion from these sets of empirical results is that low-income households and smaller homes exhibit the greatest policy-induced rebound effect for lighting, in that they keep more light bulbs running longer after receiving energy efficiency subsidy assistance. We detect this effect even though income and home size are not the drivers of uptake of subsidy assistance, as demonstrated in our first-stage results.

5.3 Backfire and Electricity Use

Given that we find statistically significant, positive, and heterogeneous rebound effects, we now investigate whether these rebound effects are large enough to "backfire" and cause a net increase in electricity use. We report results from a similar set of regressions with electricity use in lighting as the outcome variable. Table 7 reports results for OLS, unweighted IV, and weighted IV specifications using the full sample and the CEM sample. We find that in all specifications that energy efficiency subsidy assistance causes a net reduction in electricity use in lighting, and that the magnitude of this effect is larger in the IV regressions. Although there is a policy-induced rebound effect, it does not completely offset the average electricity use reduction. We also find a statistically significant negative electricity price elasticity in the CEM sample. In combination with the previous results that electricity prices do not, on average, affect the total hours of lighting use across all light bulbs, this result suggests that electricity prices may affect the type of bulb used. Additional control variable coefficients are consistent with the results for lighting hours used.

Results for the income quantiles are reported in Table 8. Again, we find that the subsidy assistance coefficient is negative and significant across all subgroups, meaning that there is no backfire effect in any income group. We further find that the lighting electricity use reductions are largest among middle-income households who had the lowest rebound effect. Table 9 reports results for home-size quantiles. Here we also find that subsidy assistance causes net reductions in electricity use for lighting in all size categories. However, the energy reductions are greatest for small homes that also had the largest rebound effect. This could occur if these households are both replacing a larger share of their light bulbs and leaving them on longer. Results for control variables in both tables are otherwise similar to those reported earlier for hours of lighting use.

5.4 How Big Are the Results?

In this section, we use our estimation results in a rough back-of-the-envelope calculation in order to compare the implied size of the rebound effect that we find to estimates from previous literature. It is important to emphasize that our econometric specifications do not directly uncover a rebound effect, and our back-of-the-envelope calculation should only give a rough sense for comparison. For example, a typical CFL, which was the standard energy efficient bulb in 2009, uses about 1/4 of the energy of an incandescent light bulb (e.g., a 60 watt bulb uses 15 watts). Using the secant method as a rough approximation, we expect to have $(60 - 15)/37.5 = 1.2$ or 120% decline in operating costs when switching from incandescents to CFLs. Consider our preferred result from the last column of Table 4 as the average effect across quantiles. The coefficient on subsidy assistance of 0.50 implies a 65% approximate increase in total hours ($e^{0.5} - 1$). So a rough estimate of the "light bulb operating price elasticity of lighting hours" is $-\frac{0.65}{1.2} = -0.54$. In an experiment with energy efficient washing machines, Davis (2008) find a price elasticity of clothes washing of about -0.06 which is considerably smaller. However, the margins of adjustment with lighting are much greater than with washing machines because households rarely install extra washing machines or leave them running when not in use.

Our estimates could capture either longer burn time, or greater quantity of lightbulbs that are left on, or both. In order to check the size of the rebound effect in terms of burn time per light bulb, we divide the hours that light bulbs are left on by the number of light bulbs to get an average burn time per light bulb. We then re-estimate our model with the log of average burn time per light bulb as the dependent variable, reported Table 10. The outcome variable is calculated by dividing total burn time by energy efficient and energy inefficient light bulbs by their associated light bulb quantity separately, and then calculating the average per-lightbulb burn time using the average electricity use by each type of light bulb. The subsidy assistance coefficients are smaller in magnitude than those reported for total lighting hours. The coefficient of 0.11 in column (2) using the CEM sample for example, roughly implies a 17% increase in average burn time ($e^{0.11} - 1$) and a price elasticity of average burn time of $-\frac{0.17}{1.2} = -0.14$. Some portion of our estimated rebound effects are therefore very likely to be coming from the addition of new light fixtures in the home.

6 Policy Implication

As a form of income redistribution, energy efficiency subsidies create welfare gains for low-income groups, but they are economically inefficient because they subsidize households in a constrained way. Therefore, they probably are not the first-best policy option to reduce energy use. For example, a low-income household who has an inefficient air conditioner (AC), receives energy efficiency subsidy to get an energy efficient AC unit. The new energy efficient AC unit saves energy and money, which could allow the household to enjoy more energy services by running the unit for longer periods of time or more intensively to improve temperature comfort; this is the direct rebound effect, and will create a welfare gain. The subsidy program, however, does not give that much flexibility to the household to be used for other needs, and equivalent welfare gains could be achieved at lower program costs.

The welfare gain described in the previous paragraph is depicted in Figure 4. The figure shows a household who would not buy an energy efficient light-bulb without subsidy assistance. The status quo utility U_0 at the point labeled 1, without subsidies or energy efficient bulbs, is greater than the utility U_1 at point 2 on the green budget line following unsubsidized adoption of efficient bulbs. As shown before, a subsidy that leaves the household just as well off after adoption as before, i.e., back at u_0, creates a rebound effect by increasing lighting energy services from point 1 to point 3. We find empirically that this effect is largest for low-income households. And we also find empirically that point 3 entails lower electricity use but more bulbs and burn time than point 1. Although the household can be made better off if the subsidy shifts the budget line past U_0, these subsidies constrain how the household uses the funds, so that they do not have complete flexibility in improving their own utility for a given subsidy dollar.

One potential alternative policy is to use energy taxes and rebate some of the tax revenue to low-income groups in the form of cash transfers. This policy could more efficiently accomplish the dual goals of redistribution and reducing electricity use, and use fewer government or utility funds, but its impact on total welfare is ambiguous. A cash transfer that is welfare-equivalent to the energy efficiency subsidy for low-income groups is depicted by the blue budget line in Figure 4. The energy tax makes lighting services more expensive, but the cash transfer shifts the budget line out. The household uses fewer energy services at point 4 compared to the welfare-equivalent subsidy outcome at point 3, and spends the cash transfer on other goods. However, the welfare gains from additional cash transfers would need to be compared to the welfare losses for high-income households who now face higher electricity prices after the tax but do not receive a compensating cash transfer. If an electric utility company without taxation powers implements the policy rather than a government, it could instead raise electricity prices for everyone and construct rebates based on income. This type of tradeoff is discussed in Borenstein (2012). Future work is required to compare these two types of policies along two dimensions. First, what is the cheapest way for the government or utility companies to reduce energy use and not leave all households worse off? Second, what is the most efficient way for the government or utility companies to reduce energy use and not leave low-income groups worse off? These two questions could be answered through calibrated partial or general equilibrium modelling that is an interesting area for ongoing research.

7 Conclusion

We investigate heterogeneity in the rebound effects of energy efficiency subsidies in the context of residential lighting. Using detailed household-level survey data from RECS, we estimate the effect of receiving subsidy assistance for energy efficiency upgrades on the total hours of lighting use across all light bulbs in the home, as well as the effect on electricity consumption from lighting and on hours of use per light bulb. We instrument for subsidy uptake using variables that capture the availability of subsidy policies in the household's region, the intensity of use of those subsidy policies by other households in the region, and by the two-party vote share in recent elections. We also used a matched comparison sample constructed from the CEM algorithm.

We show that despite having no significant impact on subsidy assistance uptake, income and home size are sources of heterogeneity in the size of the rebound effect. Households in the lowest income and home size quantile exhibit the largest direct rebound effects, defined as an increase in total hours of lighting use in response to participation in an energy efficiency subsidy program. This rebound effect is partially from changes in the number of light bulbs and partially from changes in the average time bulbs are left running. We also show that these rebound effects are not so large that they completely offset electricity use reductions from the more energy efficient light bulbs.

Although we do not estimate the rebound effect directly in terms of a price elasticity of usage intensity for energy consuming durable goods like light bulbs, we use our estimates to construct a rough back-of-the-envelope calculation. We find that our rebound effect estimates are somewhat larger than those for other appliances, which is reasonable considering that increasing the number of light bulbs and leaving them running longer is easier for lighting than for larger household appliances.

The associated rebound effect is likely to improve welfare for low-income households due to the increase in energy services. We argue that equivalent welfare gains at lower policy cost could be achieved with alternative policies. For example, energy taxes combined with cash transfers to the lowest income group could be calculated such that they are welfare-neutral for the low income households. However, high income households may experience welfare loss under this policy. Future work might benefit from employing calibrated general or partial equilibrium modeling to compare these two types of policies by answering two broad questions. First, what is the cheapest way for the program sponsor to reduce energy use and not leave all households worse off? Second, what is the most efficient way for the program sponsor to reduce energy use and not leave low-income groups worse off?

Figures and Tables

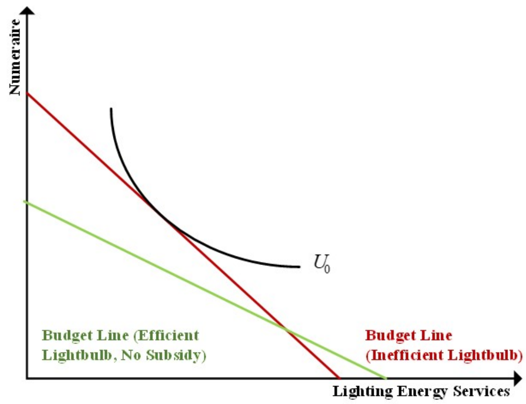


Figure 1: Energy Efficiency Without Assistance

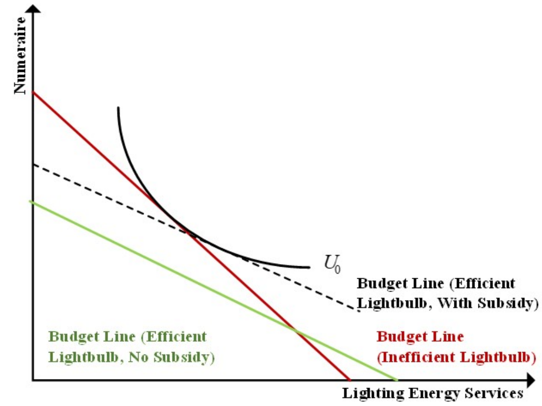
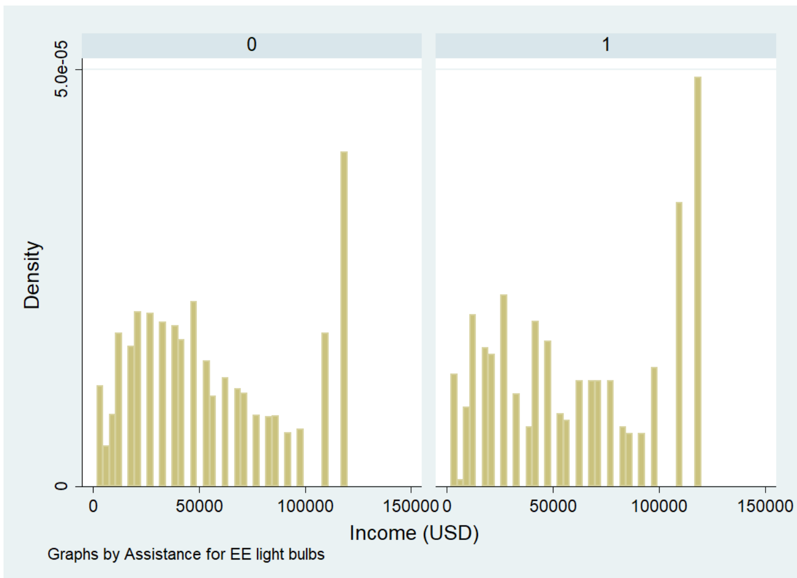


Figure 2: Energy Efficiency With Assistance

Figure 3: Income Distribution by Policy Participation



Note: The figure shows a comparison of income distributions for policy participants (right panel) versus nonparticipants (left panel) which implies that policy participation is not dependent on the income level.

Figure 4: Policy Alternative

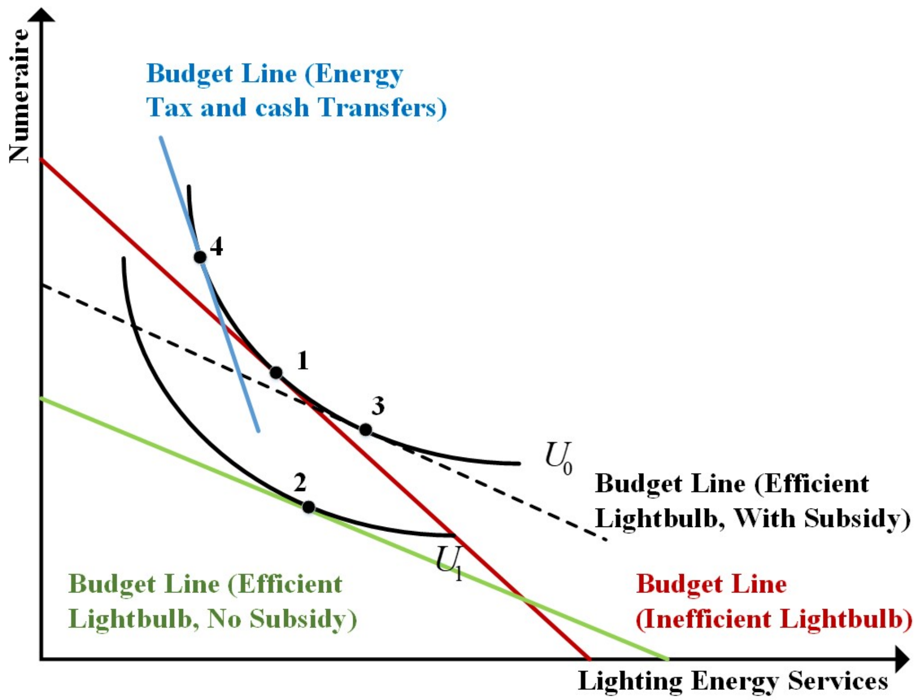


Table 1: Summary Statistics

VARIABLES	N	Mean	Std. Dev.	Min	Max
Hours of lighting use	11,042	27.35	28.77	2.500	505
Hours of efficient lightbulb use	11,042	14.02	20.98	0	362.5
Electricity used for lighting	11,042	0.996	1.335	0.0350	30.30
Assistance for EE light bulbs	11,042	0.0389	0.193	0	1
Policy availability	11,042	2.290	6.765	0	76
Policy intensity	11,042	11.54	12.20	0	50
Weighted policy availability	11,042	0.246	0.678	0	12.54
Weighted policy intensity	11,042	2.839	5.482	0	21.64
Republicans share of the 2-party vote	11,042	44.29	9.380	13.74	61.48
Income (USD)	11,042	55,803	36,532	2,000	120,000
Home size (sqft)	11,042	2,204	1,469	100	16,122
State electricity price (cents/kwh)	10,629	12.37	2.737	8.450	17.50
Electricity bill payment	11,042	0.946	0.226	0	1
Employment status	11,042	0.626	0.484	0	1
Household size	11,042	2.678	1.514	1	14
Female	11,042	0.527	0.499	0	1
Home ownership	11,042	0.682	0.466	0	1

Table 2: Coarsened Exact Matching

Number of strata: 293
Number of matched strata: 123

	0	1
All	10,613	429
Matched	9747	406
Unmatched	866	23

Imbalance (L1 distance)	Before matching	After matching
Household size	0.054	0.003
Employment status	0.027	7.1e-15
Energy audit assistance	0.085	6.0e-16
Hours of lighting use	0.107	0.098
Multivariate L1 distance	**0.308**	**0.232**

Note: The table shows the number of matched and unmatched observations for treated and untreated groups. Additionally, the level of univariate and multivariate imbalances decreases after the matching.

Table 3: First Stage Regression: Assistance for Energy Efficient Lighting

VARIABLES	(1)	(2)	(3)	(4)
Policy intensity	-0.0009***	-0.0009***		
	(0.0002)	(0.0002)		
Policy availability	0.0164***	0.0164***		
	(0.0005)	(0.0005)		
Weighted policy intensity			-0.0059***	-0.0060***
			(0.0005)	(0.0005)
Weighted policy availability			0.1476***	0.1487***
			(0.0104)	(0.0109)
Republicans share of the 2-party vote	0.0014***	0.0015***	0.0007**	0.0008**
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Log of state electricity price	0.0186	0.0221	-0.0092	-0.0047
	(0.0150)	(0.0148)	(0.0147)	(0.0145)
Log of home size	0.0007	0.0019	-0.0028	-0.0019
	(0.0032)	(0.0034)	(0.0033)	(0.0036)
Log of income	-0.0032	-0.0028	-0.0011	-0.0010
	(0.0021)	(0.0022)	(0.0021)	(0.0023)
Female	-0.0039	-0.0051	-0.0036	-0.0043
	(0.0032)	(0.0034)	(0.0033)	(0.0035)
Employment status	-0.0038	-0.0048	-0.0074**	-0.0086**
	(0.0036)	(0.0039)	(0.0037)	(0.0039)
Log of household size	-0.0025	0.0010	-0.0003	0.0050
	(0.0030)	(0.0034)	(0.0030)	(0.0035)
Home ownership	0.0133***	0.0115***	0.0143***	0.0128***
	(0.0041)	(0.0043)	(0.0042)	(0.0045)
Electricity bill payment	-0.0029	0.0007	-0.0094	-0.0055
	(0.0071)	(0.0068)	(0.0074)	(0.0073)
Observations	10,629	9,766	10,629	9,766
CEM matching	No	Yes	No	Yes
Census division dummy	Yes	Yes	Yes	Yes

Notes: This table reports the first stage regressions for household uptake of subsidy assistance. The instrumental variables are Policy intensity, Policy availability, and Republican share of the 2-party vote. The first and third columns use the full sample while the second and fourth columns use the CEM sample. In the first two columns, Policy intensity and Policy availability are not population-weighted, while in the second two columns they are. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Hours of Lighting Use

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Assistance for EE light bulbs	0.12**	0.16***	0.42***	0.46***	0.43***	0.50***
	(0.05)	(0.05)	(0.10)	(0.11)	(0.10)	(0.10)
Log of state electricity price	0.03	-0.02	0.03	-0.02	0.03	-0.02
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Log of home size	0.20***	0.16***	0.20***	0.16***	0.20***	0.16***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log of income	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female	-0.13***	-0.11***	-0.13***	-0.11***	-0.13***	-0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Employment status	0.02	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log of household size	0.20***	0.22***	0.20***	0.21***	0.20***	0.21***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Home ownership	0.04*	0.06**	0.04	0.06**	0.04	0.06**
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Electricity bill payment	-0.15***	-0.12***	-0.15***	-0.12***	-0.15***	-0.12***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	10,629	9,766	10,629	9,766	10,629	9,766
Instrumental variable	No	No	Yes	Yes	Yes	Yes
CEM matching	No	Yes	No	Yes	No	Yes
Weighted IV	-	-	No	No	Yes	Yes
Census division dummy	Yes	Yes	Yes	Yes	Yes	Yes
F_eff			589.6	559.8	177.9	164.5

Notes: This table compares specifications for the rebound effect using the full sample and the CEM sample. The dependent variable is the log of total hours of lighting use. Columns (1), (3), and (5) use the full sample while columns (2), (4), and (6) use the CEM sample. Columns (1) and (2) use OLS, (3) and (4) use unweighted IVs, and (5) and (6) use weighted IVs. Column (6) is our preferred specification. F_eff is the F statistic from the Montiel-Pflueger robust weak instrument test. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Hours of Lighting Use, Heterogeneity by Income Group

	Low-income		Medium-income		High-income	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Assistance for EE light bulbs	0.53***	0.60***	0.25	0.33*	0.44***	0.49***
	(0.19)	(0.18)	(0.20)	(0.18)	(0.15)	(0.15)
Log of state electricity price	0.18	0.18	0.04	-0.00	-0.20	-0.34**
	(0.16)	(0.17)	(0.18)	(0.18)	(0.17)	(0.17)
Log of home size	0.17***	0.15***	0.11***	0.09**	0.23***	0.14***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Log of income	0.00	-0.00	0.18**	0.21**	0.39***	0.34***
	(0.02)	(0.02)	(0.09)	(0.09)	(0.09)	(0.10)
Female	-0.07**	-0.07**	-0.13***	-0.12***	-0.18***	-0.14***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Employment status	0.03	0.02	-0.02	0.00	0.01	-0.01
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Log of household size	0.18***	0.18***	0.22***	0.22***	0.21***	0.24***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Home ownership	0.00	0.01	0.07*	0.10**	0.09*	0.10*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Electricity bill payment	-0.14**	-0.12**	0.00	-0.02	-0.19	-0.13
	(0.06)	(0.06)	(0.09)	(0.09)	(0.12)	(0.12)
Observations	3,818	3,543	3,398	3,136	3,413	3,087
CEM matching	No	Yes	No	Yes	No	Yes
Weighted IV	Yes	Yes	Yes	Yes	Yes	Yes
Census division dummy	Yes	Yes	Yes	Yes	Yes	Yes
F_eff	79.03	70.85	117.4	103.6	71.22	68.84

Notes: This table compares IV estimates of the rebound effect by income group. The dependent variable is the log of hours of lighting use. Instruments are the Republican share of the two-party vote, and population-weighted policy availability and policy intensity. F_eff is the F statistic from the Montiel-Pflueger robust weak instrument test. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Hours of Lighting Use, Heterogeneity by Home Size

	Small home		Medium home		Large home	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Assistance for EE light bulbs	0.64***	0.61***	0.39**	0.48***	0.37**	0.48***
	(0.18)	(0.18)	(0.15)	(0.14)	(0.18)	(0.17)
Log of state electricity price	-0.15	-0.21	0.18	0.09	0.05	0.01
	(0.17)	(0.17)	(0.17)	(0.17)	(0.18)	(0.18)
Log of home size	0.20***	0.19***	0.08	0.01	0.40***	0.30***
	(0.05)	(0.05)	(0.09)	(0.10)	(0.06)	(0.06)
Log of income	0.07***	0.07***	0.15***	0.14***	0.10***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female	-0.09***	-0.09***	-0.07**	-0.07**	-0.21***	-0.17***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Employment status	-0.01	-0.00	-0.01	0.02	0.07*	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Log of household size	0.16***	0.16***	0.22***	0.24***	0.23***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Home ownership	-0.00	0.01	0.05	0.08*	0.23***	0.23***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.08)
Electricity bill payment	-0.08*	-0.08	-0.11	-0.12	-0.20	-0.04
	(0.05)	(0.05)	(0.10)	(0.11)	(0.21)	(0.21)
Observations	3,520	3,308	3,527	3,244	3,582	3,214
CEM matching	No	Yes	No	Yes	No	Yes
Weighted IV	Yes	Yes	Yes	Yes	Yes	Yes
Census division dummy	Yes	Yes	Yes	Yes	Yes	Yes
F_eff	41.96	40.91	41.42	39.33	101.6	90.49

Notes: This table compares IV estimates of the rebound effect by home size group. The dependent variable is the log of hours of lighting use. Instruments are the Republican share of the two-party vote, and population-weighted policy availability and policy intensity. F_eff is the F statistic from the Montiel-Pflueger robust weak instrument test. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Electricity Use for Lighting

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Assistance for EE light bulbs	-0.20***	-0.15***	-0.67***	-0.57***	-0.93***	-0.83***
	(0.06)	(0.06)	(0.14)	(0.14)	(0.14)	(0.14)
Log of state electricity price	-0.19	-0.26**	-0.19	-0.26**	-0.19	-0.26**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Log of home size	0.22***	0.17***	0.22***	0.17***	0.22***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log of income	0.09***	0.09***	0.09***	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female	-0.11***	-0.10***	-0.12***	-0.10***	-0.12***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Employment status	0.02	0.03	0.02	0.03	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Log of household size	0.16***	0.17***	0.16***	0.18***	0.16***	0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Home ownership	-0.08**	-0.06*	-0.07**	-0.05	-0.06**	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Electricity bill payment	-0.17***	-0.14***	-0.17***	-0.14***	-0.17***	-0.14***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	10,629	9,766	10,629	9,766	10,629	9,766
Instrumental variable	No	No	Yes	Yes	Yes	Yes
CEM matching	No	Yes	No	Yes	No	Yes
Weighted IV	-	-	No	No	Yes	Yes
Census division dummy	Yes	Yes	Yes	Yes	Yes	Yes
F_eff			589.6	559.8	177.9	164.5

Notes: This table compares specifications for the backfire effect using the full sample and the CEM sample. The dependent variable is the log of electricity use for lighting. Columns (1), (3), and (5) use the full sample while columns (2), (4), and (6) use the CEM sample. Columns (1) and (2) use OLS, (3) and (4) use unweighted IVs, and (5) and (6) use weighted IVs. Column (6) is our preferred specification. F_eff is the F statistic from the Montiel-Pflueger robust weak instrument test. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Electricity Use for Lighting, Heterogeneity by Income Group

	Low-income		Medium-income		High-income	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Assistance for EE light bulbs	-1.00***	-0.92***	-1.66***	-1.54***	-0.56***	-0.46**
	(0.24)	(0.26)	(0.35)	(0.35)	(0.17)	(0.18)
Log of state electricity price	-0.17	-0.15	-0.13	-0.21	-0.35	-0.52**
	(0.20)	(0.20)	(0.22)	(0.22)	(0.21)	(0.22)
Log of home size	0.14***	0.12***	0.13***	0.11**	0.25***	0.16***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Log of income	-0.05*	-0.05*	0.21*	0.24**	0.57***	0.52***
	(0.03)	(0.03)	(0.11)	(0.11)	(0.12)	(0.12)
Female	-0.05	-0.06	-0.12***	-0.11***	-0.17***	-0.13***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Employment status	0.02	0.02	-0.04	-0.02	0.03	0.03
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Log of household size	0.16***	0.16***	0.15***	0.15***	0.17***	0.21***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Home ownership	-0.09*	-0.08*	-0.04	-0.01	0.00	0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
Electricity bill payment	-0.14**	-0.12*	-0.01	-0.04	-0.25	-0.17
	(0.07)	(0.07)	(0.11)	(0.11)	(0.17)	(0.18)
Observations	3,818	3,543	3,398	3,136	3,413	3,087
CEM matching	No	Yes	No	Yes	No	Yes
Weighted IV	Yes	Yes	Yes	Yes	Yes	Yes
Census division dummy	Yes	Yes	Yes	Yes	Yes	Yes
F_eff	79.03	70.85	117.4	103.6	71.22	68.84

Notes: This table compares IV estimates of the backfire effect by income group. The dependent variable is the log of electricity use for lighting. Instruments are the Republican share of the two-party vote, and population-weighted policy availability and policy intensity. F_eff is the F statistic from the Montiel-Pflueger robust weak instrument test. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Electricity Use for Lighting, Heterogeneity by Home Size

	Small home		Medium home		Large home	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Assistance for EE light bulbs	-1.38***	-1.31***	-0.88***	-0.80***	-0.78***	-0.62***
	(0.26)	(0.25)	(0.23)	(0.23)	(0.21)	(0.21)
Log of state electricity price	-0.32	-0.35*	-0.23	-0.33	0.01	-0.05
	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)	(0.22)
Log of home size	0.18***	0.18***	0.04	0.00	0.47***	0.36***
	(0.07)	(0.07)	(0.12)	(0.12)	(0.07)	(0.07)
Log of income	0.05*	0.05*	0.14***	0.12***	0.11***	0.10***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Female	-0.08**	-0.08*	-0.05	-0.05	-0.22***	-0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Employment status	-0.02	-0.01	-0.02	0.02	0.09**	0.07
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Log of household size	0.13***	0.13***	0.17***	0.19***	0.20***	0.22***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Home ownership	-0.05	-0.05	-0.08	-0.05	0.17**	0.18**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.09)	(0.09)
Electricity bill payment	-0.09	-0.09	-0.15	-0.14	-0.25	-0.06
	(0.06)	(0.06)	(0.13)	(0.14)	(0.24)	(0.25)
Observations	3,520	3,308	3,527	3,244	3,582	3,214
CEM matching	No	Yes	No	Yes	No	Yes
Weighted IV	Yes	Yes	Yes	Yes	Yes	Yes
Census division dummy	Yes	Yes	Yes	Yes	Yes	Yes
F_eff	41.96	40.91	41.42	39.33	101.6	90.49

Notes: This table compares IV estimates of the backfire effect by home size group. The dependent variable is the log of electricity use for lighting. Instruments are the Republican share of the two-party vote, and population-weighted policy availability and policy intensity. F_eff is the F statistic from the Montiel-Pflueger robust weak instrument test. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Average Lighting Hours Per Light Bulb

VARIABLES	(1) log(hours)	(2) log(hours)
Assistance for EE light bulbs	0.08*	0.11**
	(0.04)	(0.04)
Log of state electricity price	0.01	-0.01
	(0.04)	(0.05)
Log of home size	0.00	-0.01
	(0.01)	(0.01)
Log of income	0.01	0.01
	(0.01)	(0.01)
Female	-0.01	-0.01
	(0.01)	(0.01)
Employment status	-0.04***	-0.04***
	(0.01)	(0.01)
Log of household size	0.01	0.01
	(0.01)	(0.01)
Home ownership	0.01	0.01
	(0.01)	(0.01)
Electricity bill payment	-0.06***	-0.05**
	(0.02)	(0.02)
Observations	10,629	9,766
Instrumental variable	Yes	Yes
CEM matching	No	Yes
Weighted IV	Yes	Yes
Census division dummy	Yes	Yes
F_eff	177.9	164.5

Notes: This table reports estimates of the rebound effect in terms of average hours per light bulb rather than total hours of lighting use. The dependent variable is the log of hours per light bulb. Instruments are the Republican share of the two-party vote, and population-weighted policy availability and policy intensity. F_eff is the F statistic from the Montiel-Pflueger robust weak instrument test. Robust standard errors are reported on parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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