2016

Does Better Information Lead to Better Choices? Evidence from Energy-Efficiency Labels

Lucas W. Davis
Gilbert E. Metcalf

Does Better Information Lead to Better Choices? Evidence from Energy-Efficiency Labels

Lucas W. Davis, Gilbert E. Metcalf

Abstract: Information provision is a key element of government energy-efficiency policy, but the information that is provided is often too coarse to allow consumers to make efficient decisions. An important example is the ubiquitous yellow "EnergyGuide" label, which is required by law to be displayed on all major appliances sold in the United States. These labels report energy cost information based on average national usage and energy prices. We conduct an online stated-choice experiment to measure the potential welfare benefits from labels tailored to each household's state of residence. We find that state-specific labels lead to significantly better choices. Consumers choose to invest about the same amount overall in energy efficiency, but the allocation is much better with more investment in high-usage high-price states and less investment in low-usage low-price states.

JEL Codes: D12, H49, Q41, Q48

Keywords: Energy demand, Energy efficiency, EnergyGuide, Inattention, Information provision

INFORMATION PROVISION IS A KEY element of government energy-efficiency policy. An important example is the ubiquitous yellow "EnergyGuide" label, which is required by law to be displayed on all major appliances sold in the United States.

Lucas W. Davis (corresponding author) is at the Haas School of Business, University of California, Berkeley; Energy Institute at Haas; and National Bureau of Economic Research (ldavis@haas.berkeley.edu). Gilbert E. Metcalf is at the Department of Economics, Tufts University, and National Bureau of Economic Research (gmetcalf@tufts.edu). We are grateful to Hunt Allcott, Stefano DellaVigna, Matthew Harding, Sébastien Houde, Kelsey Jack, and seminar participants at Iowa State, Illinois, University of California, Berkeley, Harvard, and the NBER for helpful comments. We also thank Poom Nukulkij at GfK for his work on the experiment. Data collected by Time-sharing Experiments for the Social Sciences, NSF grant 0818839, Jeremy Freese and James Druckman, principal investigators. This RCT was registered in the American Economic Association Registry for randomized control trials under trial number 560. The authors have not received any financial compensation for this project nor do they have any financial relationships that relate to this research.

Received March 30, 2015; Accepted February 9, 2016; Published online July 14, 2016.

JAERE, volume 3, number 3. 2333-5955/2016/0303-0003$10.00 http://dx.doi.org/10.1086/686252

Similarly, new cars and trucks sold in the United States must display information about vehicle fuel efficiency and an estimate of annual gasoline expenditures. Over 40 countries worldwide have some sort of energy-efficiency labeling requirements (CLASP 2014).

This information is intended to help consumers make better decisions. However, in many cases government-mandated labels do not provide accurate information necessary for consumers to make efficient decisions. In particular, most labels report only very coarse information based on national average energy prices and typical national usage. In practice, energy prices and typical usage vary substantially, so the labels provide information that is highly inaccurate for many consumers.

The objective of our project is to evaluate the potential welfare benefits from providing more accurate information. We focus on room air conditioners because they are a particularly lucid example. Within the lower 48 US states we show that annual cooling hours range by a 9:1 ratio, while electricity prices vary by more than a 2:1 ratio. As a result, typical operating costs vary widely, from $28 per year in Washington state, to $316 per year in Florida. Despite these very large differences in operating costs, consumers in all states see the exact same EnergyGuide label.

We designed and implemented an online stated-choice experiment to measure how consumer decisions would change with information tailored to each household's state of residence. We find that better labels indeed lead to better choices. When presented with more accurate information, the average energy efficiency of selected air conditioners stays about the same, but the allocation is much better. Households facing low energy prices and low expected usage invest less in energy efficiency, while households facing high energy prices and high expected usage invest more. This reallocation leads to lower lifetime costs—defined as the sum of purchase price plus present discounted value of energy costs—for both types of households.

The implied aggregate savings are substantial. State-specific labels decrease lifetime cost by an average of $11.60 per air conditioner. While small as a percentage of the average lifetime cost (just under 1%), absolute savings can be large when aggregated over the large number of air conditioners sold each year. US consumers purchase more than 4 million room air conditioners each year, so the implied aggregate cost savings exceed $50 million annually.[1] Moreover, our results suggest that state-specific labels would improve decision making not just for room air conditioners, but for a whole host of residential appliances.

1. Our estimate of the aggregate cost savings assumes that our survey choice alternatives are representative of air conditioners available on the market. As discussed below, we went to considerable effort to try to span efficiency and purchase price ranges relevant for room air conditioners. Our estimates are based on a representative and quite typical air conditioner size (10,000 BTU). Our cost savings estimates should be interpreted in light of this assumption.

We then provide additional analysis and evidence aimed at better understanding the mechanisms underlying our results. We find that immediately after the experiment most participants are unable to correctly answer basic questions about the information they have just seen. Most do not know whether the labels they just saw were based on national or state energy prices, nor do they know how energy prices or appliance usage in their state compares to the national average.

Overall, the evidence points to people taking the information in these labels as given without analyzing it carefully. Daniel Kahneman (2011) has referred to this kind of decision making as WYSIATI: "What You See Is All There Is." The content of the labels changes participants' decisions, so it is not that they are ignoring this information completely. But they appear not to be exerting the additional effort that would be required to understand what this information means nor are they spontaneously transforming this information to take local conditions into account.

Our paper differs from most previous studies of energy efficiency. While there is an extensive theoretical and empirical literature on the economic determinants of investments in energy-efficient capital, there is little that has taken an explicit experimental approach.[2] None of the work to date has focused on the efficiency cost of inaccurate information provided to consumers as this study does.[3] Our paper complements a growing broader literature that shows that customized information can significantly improve education, health, and finance-related choices (see, e.g., Hastings and Weinstein 2008; Bertrand and Morse 2011; Kling et al. 2012; and Hoxby and Turner 2013).

It is worth emphasizing that our evidence comes from a stated-choice experiment. The highly stylized setting allows us to eliminate many of the factors that complicate these decisions in real-world settings. This facilitates analysis and interpretation, but it also may lead participants to focus more on labels than they otherwise would. One approach to validating our results is to look for complementary evidence from actual choices. Examining nationally representative data from air conditioner purchases, we find no evidence of a positive correlation between operating costs and investments in energy efficiency. Although this does not tell us how much choices would change with

2. Studies focusing on consumer choice of energy-efficient capital include Hausman (1979), Dubin and McFadden (1984), Metcalf (1994), Revelt and Train (1998), Metcalf and Hassett (1999), and Davis (2008), among others. See Gillingham, Newell, and Palmer (2009) and Gillingham and Palmer (2014) for recent surveys.

3. Two related studies perform online experiments using the same nationally representative panel that we employ. Newell and Siikamaki (2014) analyze optimal EnergyGuide label design, while Allcott and Taubinsky (2015) measure the effect of information provision on willingness to pay for energy-efficient lightbulbs. Neither study considers the role of inaccurate information provided to consumers.

better information, it provides some corroboration for other results in the paper about the lack of effectiveness of current labels.

The paper proceeds as follows. Section 1 provides background information and makes the case for why better information might matter. Section 2 describes our online experiment. Sections 3 and 4 provide the main results and additional analysis. Section 5 offers concluding comments.

1. BACKGROUND

1.1. Previous Research

Economists have long been interested in how consumers make energy-related decisions. Hausman (1979) and Dubin and McFadden (1984) model durable good purchase decisions as a household production problem with a trade-off between purchase price and operating cost. Following these seminal studies, much of the literature has focused on whether or not consumers undervalue operating cost when making these trade-offs (see, e.g., Metcalf 1994; Metcalf and Hassett 1999). The most recent evidence comes from vehicle purchases and indicates that consumers do not undervalue (Busse, Knittel, and Zettelmeyer 2013) or modestly undervalue operating costs (Allcott and Wozny 2014).

Another recent strand in the literature has aimed at understanding specific behavioral biases in energy-related decisions. Studies by Allcott (2011a, 2013) examine "MPG Illusion," the idea that consumers may not understand the nonlinear relationship between miles per gallon and motor vehicle fuel consumption. Camilleri and Larrick (2014) test whether vehicle preferences are affected by the scale in which fuel economy information is expressed, for example, gallons per 100 miles versus gallons per 1,000 miles. Finally, Allcott and Taubinsky (2015) and Allcott and Sweeney (forthcoming) test for biased beliefs and imperfect information by measuring the effect of information provision on demand for energy-efficient lightbulbs and hot water heaters, respectively.

There are also studies that examine the effect of environmental messaging, such as Energy Star Certification (e.g., Houde 2014b; Newell and Siikamaki 2014) and "normative" letter grades for the energy-efficiency characteristics of products (e.g., Brounen and Kok 2011).[4] The evidence shows that people respond to these nonprice

4. Newell and Siikamaki (2014) is similar to our study in that it uses an online stated-choice experiment to evaluate components of EnergyGuide labels. In addition to comparing choices with and without Energy Star certification, they randomly include or exclude information about carbon dioxide emissions, normative letter grades, and other elements of label design. While they vary the way operating cost information is displayed, they do not vary the operating cost information itself or explore information that is tailored to the participant's local usage or prices.

interventions, although it is not always clear if this is because they trigger "warm glow" responses or because they are indirectly providing information about private costs.

Finally, there is a group of papers that study the effect of peer comparisons. Learning about how your electricity consumption compares to that of your neighbors tends to significantly reduce consumption, both in the short run and long run. See, for example, Ayres, Raseman, and Shih (2009), Allcott (2011b), and Allcott and Rogers (2014).

We see what we are doing as quite different. We are not studying consumers' undervaluation of energy costs, nor are we studying a specific behavioral bias like MPG illusion. Moreover, we have designed our experiment explicitly to exclude any environmental messaging or peer comparisons. Instead, we are focused sharply on the quality of the information that is publicly provided, and we want to ask whether better tailoring this information to consumers' characteristics can lead to more efficient choices.

1.2. US Energy Labeling Requirements

EnergyGuide labels must be displayed on all major appliances sold in the United States. As of 2015, this includes clothes washers, dishwashers, refrigerators, freezers, televisions, water heaters, window air conditioners, central air conditioners, furnaces, boilers, heat pumps, and pool heaters. Collectively, these appliances account for over 60% of residential energy consumption and 13% of total US energy consumption.[5]

Energy-efficiency labels have existed since the first energy crisis in the mid-1970s. France mandated labels for a variety of appliances in 1976, and Japan, Canada, and the United States followed soon after (Wiel and McMahon 2001).[6] The Energy Policy and Conservation Act of 1975 mandated labels for certain appliances beginning in 1980. Changes to the labeling program were made in the Energy Policy Act of 1992, which gave rise to the EnergyGuide labels in their current form.

The Federal Trade Commission (FTC) is charged with enforcing these labeling requirements. The FTC provides templates on its website for manufacturers to use and the Energy Labeling Rule in the Code of Federal Regulations provides samples of acceptable labels (Federal Trade Commission 2014).

Information provision requirements for vehicles are similar. Since 1977, all new cars and trucks sold in the United States must display information about vehicle fuel

---

5. According to US Energy Information Administration (2014a, table A4), space heating, space cooling, water heating, refrigeration, clothes dryers, freezers, clothes washers, and dishwashers accounted for 62% of total residential energy consumption in 2012. These end uses represented in 2012 a total of 12.5 quadrillion Btu compared to 95.0 quadrillion Btu from all sectors and sources in 2012.

6. Wiel and McMahon (2001) discuss the early motivation for energy labels. Thorne and Egan (2002) conduct qualitative interviews with focus groups about alternative graphical elements and other aspects of EnergyGuide label design.

efficiency. Until recently, labels reported estimated city, highway, and combined fuel efficiency in miles per gallon (MPG). Starting with model year 2013, new labels provide additional information, including estimated gallons per 100 miles, annual fuel cost, and 5-year fuel cost savings compared to the average new vehicle. The inclusion of gallons per 100 miles brings the United States in line with the European Union, which reports liters per 100 kilometers.

Fuel economy labels on vehicles suffer from the same problem as do appliance labels in using national energy prices to compute fuel savings and ignoring variation in vehicle miles traveled across the states. Paradoxically, the improvement in fuel economy labels on motor vehicles may exacerbate losses from inaccurate information on the labels. When labels only reported miles per gallon, consumers had to undertake significant mental computations to balance the cost savings from a more fuel efficient vehicle against the higher purchase price (holding other attributes constant). The current labels now report estimated 5-year cost savings for each vehicle relative to the fleet average. Now it is more straightforward to balance cost savings from more efficient vehicles against a higher purchase price. But cost savings can differ significantly given differences in average gasoline prices and driving patterns across states. Whether consumers will make those mental adjustments is not clear.

1.3. Focus on Air Conditioning

More accurate labels could be important for many different appliance types, but in our experiment we focus specifically on room air conditioners. More than 25 million American households own one or more room air conditioners, so this is an appliance that is of large intrinsic interest.[7] It is also a particularly lucid example of an energy-efficiency investment for which consumers face a clear trade-off between purchase price and energy costs, and for which operating costs vary substantially across states. Moreover, most consumers install room air conditioners themselves, thereby avoiding any principal-agent problem that arises when contractors are involved in selecting and installing equipment.

More broadly, residential air conditioning is of large and growing policy interest nationwide because of the high level of energy consumption associated with it. In the United States, there is air conditioning in nearly 100 million homes (87% of homes), and households spend an estimated $22 billion dollars annually on electricity for air conditioning.[8] Table 1 shows that air conditioner usage is pervasive in all parts of

7. US Department of Energy, Residential Energy Consumption Survey 2009, table HC7.1, "Air Conditioning in U.S. Homes."

8. Data from US Department of Energy (2009). See table HC7.1, "Air Conditioning in U.S. Homes" and table CE3.6, "Household Site End-Use Consumption in the U.S."

the country. The lowest share is in the West, where one-third of households have no form of air conditioning. The table also illustrates considerable variation in the shares of central versus room air conditioning among those households with air conditioning with central air conditioning dominating in all regions except the Northeast.

Figure 1 shows annual cooling hours by state from US Department of Energy (2014b).[9] This is the number of hours per year for which a household should expect to use an air conditioner. On average, Americans face 1,265 cooling hours per year, but there is enormous geographic variation. Within the continental United States average annual cooling hours range from 310 in Maine to 2,771 in Florida, almost a 9:1 ratio.

Figure 2 shows average residential electricity prices by state for 2012 from US Department of Energy (2013, table 2.10). The average price is 12.4 cents per kilowatt hour (kWh), but again there is substantial geographic variation. The lowest electricity prices in 2012 were in Louisiana (8.4 cents), while New York had the most expensive prices (17.6 cents), so more than a 2:1 ratio. Figure 2 is only showing variation in prices across states. But there is variation within states across utilities as well. Using data from the 2013 EIA Form 861, we computed the standard deviation of residential electricity prices by utility across the United States. The standard deviation in prices across the country is 3.7 cents per kWh. The standard deviation across states is 5.22 cents per kWh, while the standard deviation within states is only 2.7 cents per kWh. This much lower variation within states suggests the potential for improving information with state-specific labels.

Annual operating cost for a room air conditioner depends on cooling hours and electricity prices according to this simple equation,

$$\begin{aligned}\text{Annual Operating Cost (dollars)} = {} & \text{Annual Cooling Hours} \\ & \times \text{ Electricity Price (dollars per watt hour)} \\ & \times \text{ Size of Air Conditioner (BTUs)} \\ & / \text{ Energy-Efficiency Ratio of Air Conditioner} \\ & \text{ (BTUs per watt).}\end{aligned} \tag{1}$$

The "energy-efficiency ratio," or EER, of an air conditioner is the ratio of the unit's cooling capacity (in BTUs) to its electricity consumption (in watts). The higher the EER, the more energy efficient the air conditioner. Figure 3 shows annual operating costs for a medium-sized (10,000 Btu), medium-efficiency (10.0 EER) room air conditioner by state. Operating costs vary widely across states, from $28 per year in

9. US Department of Energy (2014b) reports annual cooling hours for room air conditioners for 218 US cities. We aggregated to the state level taking a weighted average of cities within each state weighting by population.

Table 1. Air Conditioner Penetration in US Homes (%)

	United States	Northeast	Midwest	South	West
Central air conditioner	62	35	66	82	46
Room air conditioner(s)	24	50	22	15	17
Both central and room air conditioners	1	1	2	1	1
No air conditioner	13	13	9	2	36

Note.—This table describes air conditioner penetration in the United States by region as estimated in the US Energy Information Administration, Residential Energy Consumption Survey (2009). We have excluded a small share of households who report having central or room air conditioners but not using them. Regions are defined using standard Census definitions as Northeast (CT, MA, ME, NH, NJ, NY, PA, RI, VT), Midwest (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI), South (AL, AR, DC, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV), and West (AK, AZ, CA, CO, HI, ID, MT, NM, NV, OR, UT, WA, WY).

Washington to $316 per year in Florida, more than an 11:1 ratio. The geographic pattern reflects variation in both cooling hours and electricity prices.

2. EXPERIMENTAL DESIGN

2.1. Overview

Our experiment was implemented through Time-Sharing Experiments for the Social Sciences (TESS), an NSF-funded program aimed at making it easier for academics to run online experiments. TESS contracts with GfK (formerly Knowledge Networks) a company that administers surveys and experiments using a nationally representative panel that they call the KnowledgePanel. This platform has been widely used by economists (see, e.g., Allcott 2013; Newell and Siikamaki 2014; Allcott and Taubinsky 2015).

The KnowledgePanel is a nationally representative panel of some 55,000 adults selected using random-digit dialing and address-based sampling (GfK 2013). Participants are provided with a computer and free Internet service if they do not already have it. From this panel, GfK constructs samples to respond to surveys and participate in experiments on a wide variety of topics. Samples are constructed to represent the underlying population of interest and upon completion of the survey or experiment, study-specific sample weights are provided to ensure that the observable characteristics of the final sample match the characteristics of the population of interest (GfK, nd). The TESS-funded surveys put limits on sample size and the number of questions. For our experiment, GfK asked 3,744 participants to take the survey, of whom 2,440 completed the experiment (completion rate of 62.5%).

Participants in our experiment were asked to make three hypothetical purchase decisions. Each decision involved selecting one of three room air conditioners that varied by purchase price and expected annual energy cost. Participants were told that

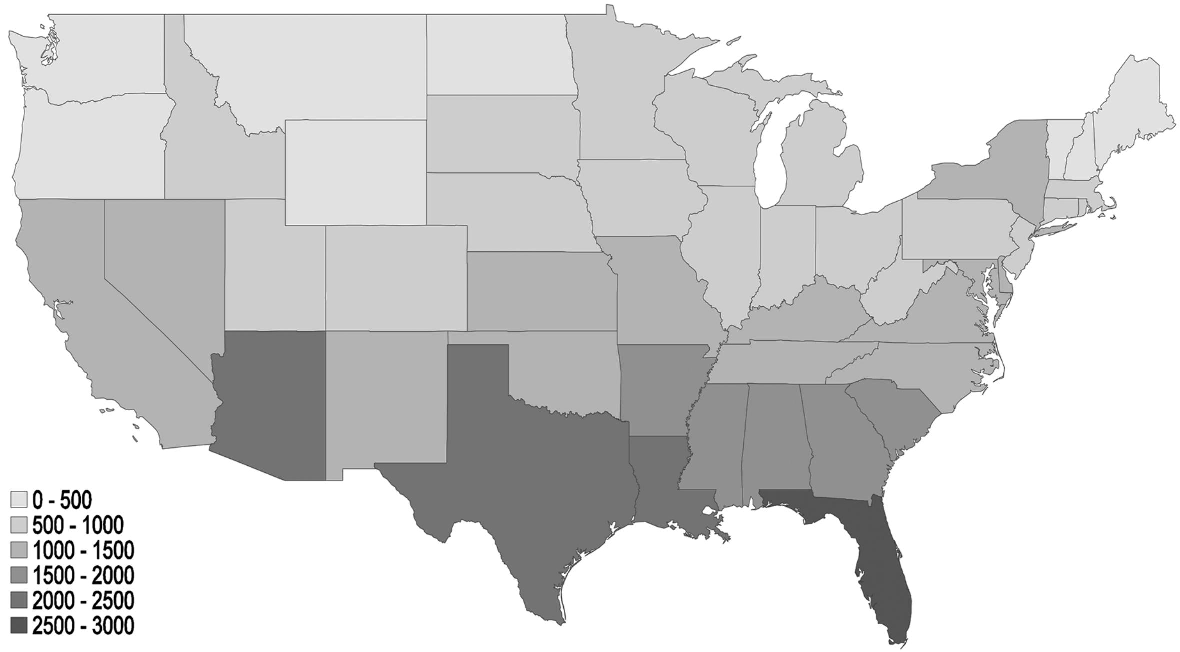

Figure 1. Annual cooling hours by state. A color version of this figure is available online

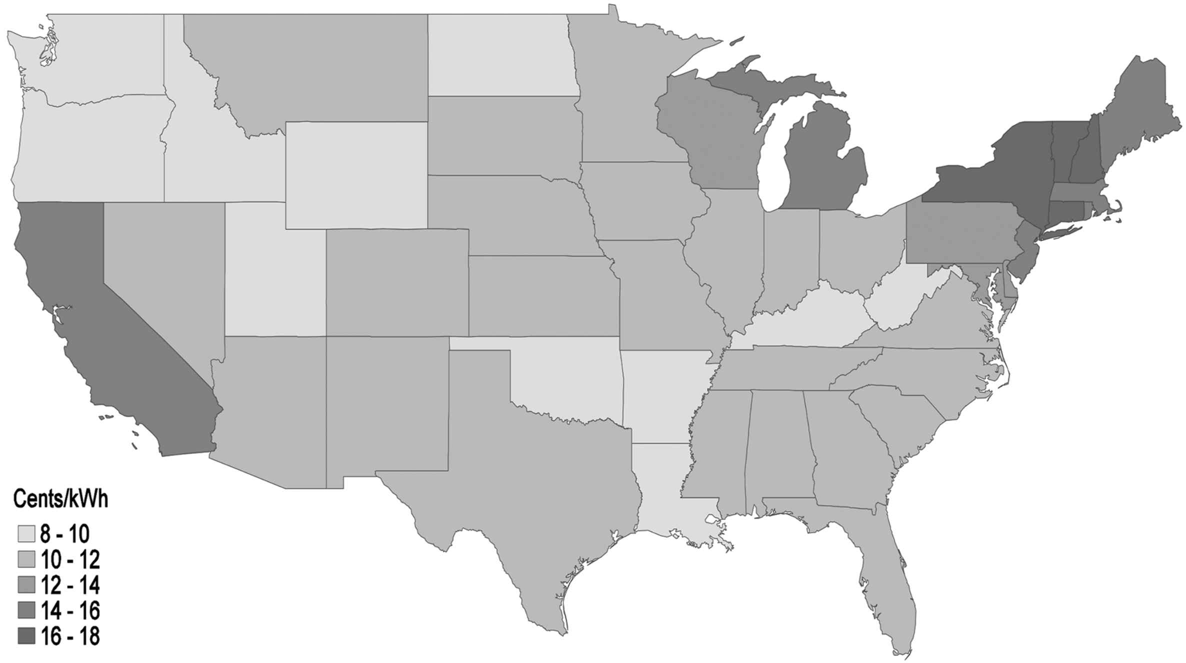

Figure 2. Residential electricity prices by state. A color version of this figure is available online

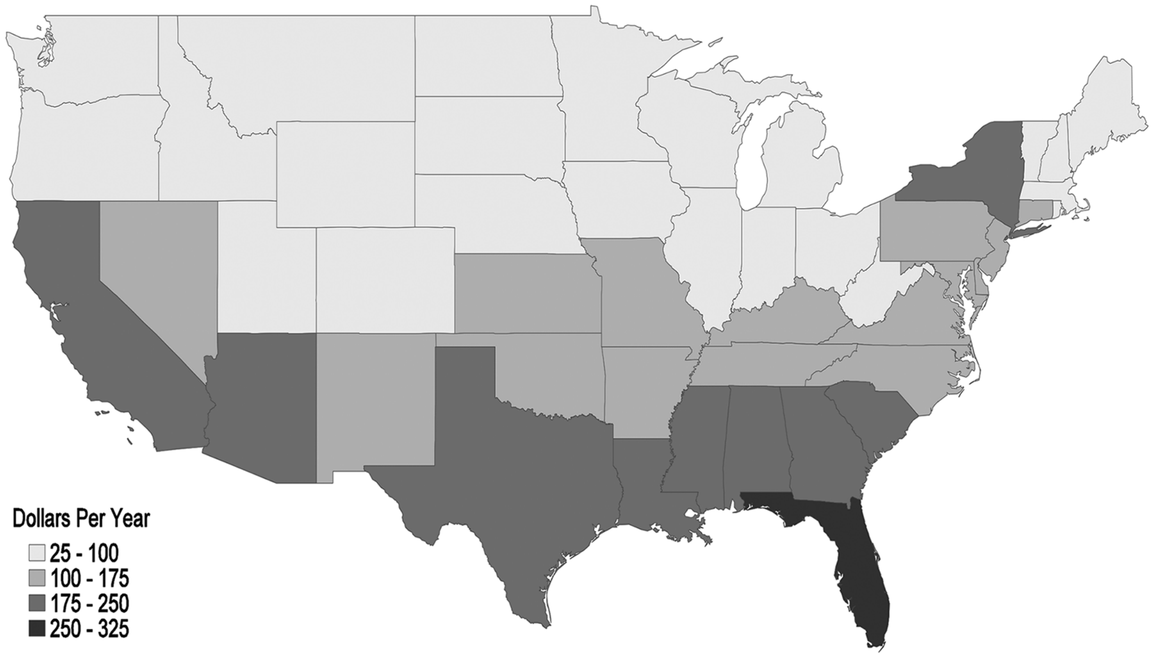

Figure 3. The cost of operating a medium-sized room air conditioner. A color version of this figure is available online

the three air conditioners were otherwise identical except for these features. And, as we explain in the appendix, available online, we designed the choice sets carefully to maximize the precision of our estimates. We designed the experiment as a simple randomized controlled trial with participants randomly assigned to either the control group or the treatment group. During the experiment, the only difference between these two groups was the labels that they were shown. The control group was shown the current EnergyGuide labels, which report operating costs based on national average electricity prices and typical national usage. The treatment group, in contrast, was shown labels that report operating costs based on average electricity prices and usage for the state in which each participant resides.[10] Finally, at the end we asked a short set of questions to elicit how well the participants understood the labels they had just seen and to assess their knowledge about state and national electricity prices and air conditioner usage. GfK also provided us with a rich array of socioeconomic information about the participants collected from previous surveys. See the appendix for the complete survey instrument and list of variables.

2.2. The Treatment

Figure 4 shows examples of the labels we showed participants in the experiment. Participants in the control group saw labels like the one on the left. This is the current EnergyGuide label, and it shows estimated yearly energy cost based on national average electricity costs and usage.[11] Participants in the treatment group saw labels like the one on the right. This particular label is for a participant in Iowa. The estimated yearly energy cost is calculated based on the average residential price of electricity in Iowa ($0.1082 per kWh) and the average usage in Iowa (828 hours per year). These state-specific labels were tailored to the state of residence of each participant.[12] That is, participants in the treatment group from Iowa saw the Iowa label,

10. We pretested the survey with a number of colleagues, coworkers, and others. Going to colleagues worked well because we were able to work sequentially, each time refining the survey instrument before showing to another individual. We were careful to include non-economist coworkers and others to get a broader response.

11. The actual EnergyGuide labels for room air conditioners report estimated annual energy cost based on 750 hours of usage. This has long been used as a rule of thumb, for example, by the Association of Home Appliance Manufacturers, but average usage in the United States is actually significantly higher. We use 1,265 hours of usage per year based on the data that we use to calculate state-specific energy costs from US Department of Energy (2014b). In all other ways, our labels are identical to the current EnergyGuide labels.

12. The KnowledgePanel programmers programmed the experiment so that the appropriate state-specific label was automatically shown to each participant in the treatment group in a seamless fashion so that the survey experience was identical across the control and treatment groups.

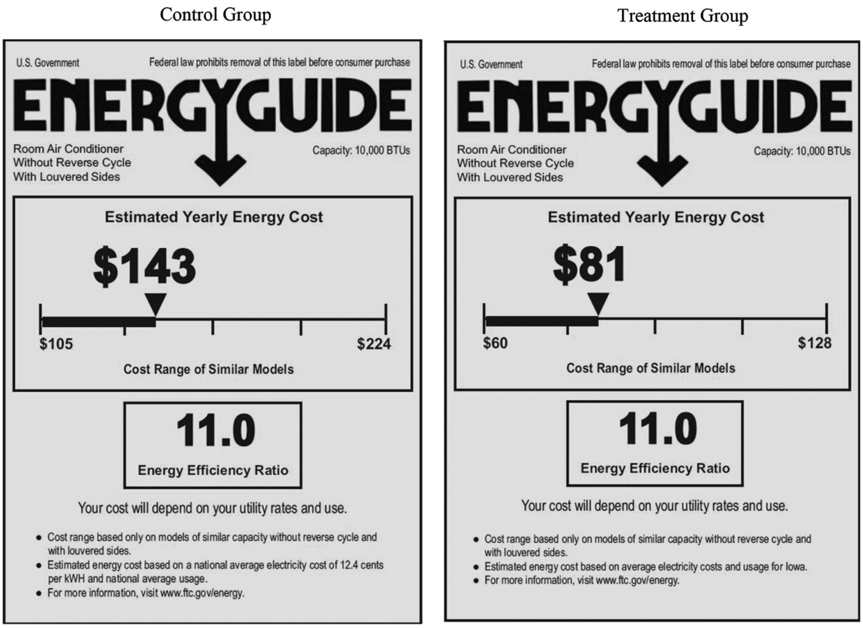

Figure 4. Control and treatment labels. A color version of this figure is available online

and participants in the treatment group from Nevada saw the Nevada label. Moreover, for all state-specific labels, we adjusted the cost range to reflect the relevant range for that particular state. Because energy costs scale linearly, this meant that the slider bar and "triangle" were positioned in the same place in control and treatment labels.

In all cases, our labels are for a medium-sized (10,000 Btu) window unit. In addition to reporting the estimated yearly energy cost in dollars, the label also reports the unit's EER, and further below, the label includes the language "Your cost will depend on your utility rates and use." Finally, the bottom of the label provides three bullets with additional details. The first bullet explains that the cost range is based only on models with similar capacity and characteristics. The second bullet explains how the energy cost was calculated. This is important for our experiment, and we varied the text here depending on treatment status. For the control group, the text reads, "Estimated energy cost based on a national average electricity cost of 12.4 cents per kWh and national average usage." For the treatment group, the text reads, "Estimated energy cost based on average electricity costs and usage for [state name]." Finally, the last bullet points consumers to the FTC website for more information.

2.3. Balance in Sample

Before moving on to results, we test for balance between the control and treatment groups. Since treatment status was randomly assigned, we expect very similar characteristics in the two groups. Table 2 reports mean characteristics for the control and treatment groups as well as *p*-values from tests that the means are equal. We report weighted means using the sampling weights that GfK constructed specifically for our experiment. This socioeconomic information, including political party affiliation, was collected from the individuals in the KnowledgePanel by GfK during previous surveys.[13]

Not surprisingly, given the design of the experiment, we fail to reject equality of means between the two groups for any of the socioeconomic characteristics. The *p*-values of 1.0 for educational status, sex, and race reflect the fact that the experiment-specific sampling weights are balancing on these attributes.[14] The mean characteristics also match national data quite well. For example, the proportion of households with central air conditioners (65.5% and 67.5%) is similar to the national average from the 2009 Residential Energy Consumption Survey reported in table 1 (63%). The fraction of participants with high school and college degrees is also similar to data from the US Census Bureau.

Despite households being randomly assigned to control and treatment groups, the average residential electricity price is slightly higher in the control group and statistically significant at the 10% level. Consequently, average yearly energy costs are also slightly higher in the control group, though this difference is not statistically significant. We attribute these modest differences to sampling variation and in our preferred estimates will control for state fixed effects.

3. RESULTS

We present results in this section as follows. First we provide a simple graphical depiction of our main results. We then turn to a regression framework to quantify the magnitude of the effect controlling for state-fixed effects and other observable characteristics, and we compare treatment effects across subsets of participants. Finally, we use our preferred estimates to calculate aggregate national impacts.

3.1. Graphical Evidence

As a first cut at the data, we compare the average characteristics of the air conditioners selected by the treatment and control groups. We hypothesize, for example, that

13. Political party affiliation is measured by GfK as "strong," "not strong," or "leans." We constructed indicator variables for Democratic and Republican affiliation based on whether each participant indicated "strong" or "not strong" support for a particular party.

14. The unweighted means are also very similar between the control and treatment groups. We also computed *p*-values for equality of means between the two groups with the unweighted data, and we continue to find *p*-values in excess of 10% for the demographic and economic characteristics. In addition we ran a weighted regression of a treatment indicator variable on all the variables in table 2. The *F*-statistic for the joint test that all the estimated coefficients are zero has a *p*-value of 0.75.

Table 2. Testing for Balance in Randomized Sample

	Control (1)	Treatment (2)	*p*-Value (3)
Annual household income (in dollars)	72,817	70,848	.363
High school graduate	.874	.874	1.000
College graduate	.289	.289	1.000
Household size	2.745	2.756	.871
Married	.533	.533	.981
Employed	.582	.564	.408
Age 65 and older	.174	.179	.723
Female	.519	.519	1.000
Nonwhite	.338	.338	1.000
Homeowner	.728	.695	.100
Multiunit property	.250	.256	.718
Household has a central air conditioner	.655	.675	.322
Democratic affiliation	.316	.314	.942
Republican affiliation	.217	.244	.115
Average residential electricity price in the state of residence (cents per kWh)	12.49	12.32	.088
Average annual hours of air conditioning use in the state of residence	1,260	1,265	.840
Annual cost of operating a medium-sized room air conditioner in the state of residence (in dollars)	154.58	153.04	.601

Note.—This table tests for balance between the control and treatment groups. There are 1,231 participants in the control group and 1,209 participants in the treatment group. Columns 1 and 2 report means of the variables listed in the row headings, weighted using sampling weights. Proportion high school graduate, college graduate, employment status, and the other individual characteristics correspond to the individual in each household who participates in the KnowledgePanel, not for the head of household. The annual cost of operating a medium-sized room air conditioner is calculated for a 10,000 Btu unit with an EER of 10.0. Column 3 reports *p*-values from tests that the weighted means in the two groups are equal.

participants living in states with high electricity prices will respond to more accurate labels by choosing more energy-efficient air conditioners (i.e., with a higher EER). The same prediction can be made for participants living in states with a large number of annual cooling hours.

Figure 5 provides an initial attempt to answer our central research question. We divided states into those with low, medium, and high operating costs. Specifically, we ranked states by estimated annual energy cost (average state electricity price multiplied by average state usage) and assigned states to these three categories based on whether the state was in the lower, middle, or upper third of all states. For each group of states, we plot the mean energy efficiency of air conditioners selected by the treatment and control groups. In addition to plotting these means, the figure also in-

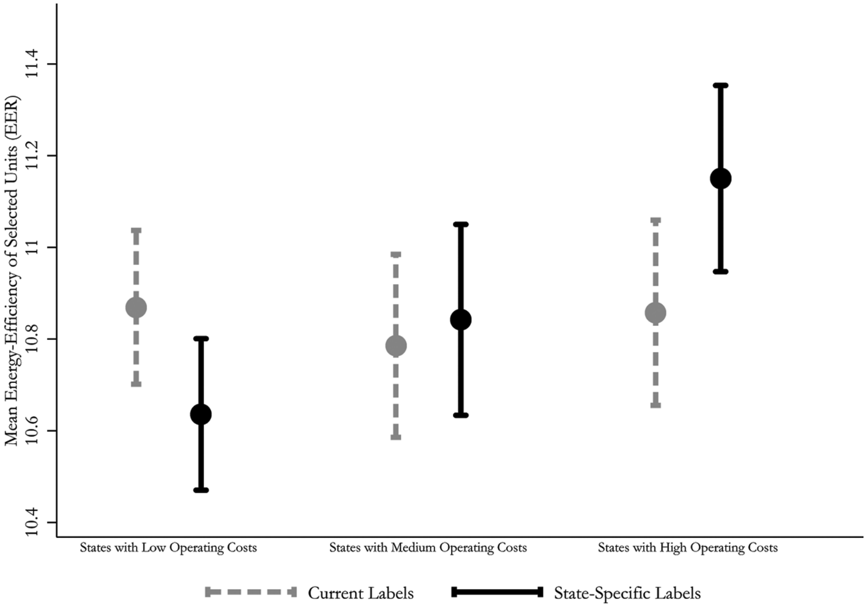

Figure 5. Do better labels lead to better choices? A color version of this figure is available online.

cludes 95% confidence intervals for each group constructed using standard errors clustered by participant.

The results are striking. The participants who see the current EnergyGuide labels choose similar levels of energy efficiency in all three groups of states. This is interesting and perhaps surprising given the large variation in cooling hours and electricity prices across states that we documented earlier. The participants who see state-specific labels choose less energy-efficient air conditioners in low-cost states and more energy-efficient air conditioners in high-cost states. This suggests a more efficient allocation of energy efficiency. The returns to energy efficiency are higher in states with high operating costs because electricity expenditures are a larger share of the total cost of cooling.

While illustrative, this figure does not control for electricity prices and other factors that are imperfectly balanced between the treatment and control groups. Nor does it allow us to quantify the cost of any misallocation of energy efficiency across households. We turn to that analysis next.

3.2. Measuring the Lifetime Cost of Appliance Ownership

With energy-efficiency investments the relevant measure is the lifetime cost of the appliance. Lifetime cost (LTC) is the sum of an appliance's purchase price (PP) and the present discounted value of its annual energy costs (EC) over the appliance's lifetime. Specifically

$$LTC = PP + \frac{EC(1-(1+\rho)^{-T})}{\rho}, \tag{2}$$

where ρ is the consumer's discount rate and T is the expected operating life of the appliance.[15]

Our conjecture is that the group shown state-specific labels will make better choices leading to lower average lifetime cost.[16] When we make these calculations we use a 12-year appliance lifetime and use a discount rate that we estimate from our data.[17] Given the considerable discussion in the energy literature on the relevant discount rate for thinking about energy-efficient capital, we also report results based on other discount rates. But as a starting point, we believe it is reasonable to estimate a discount rate using our data following long-standing practice in the literature. Specifically, we first analyze the data using a discrete choice model, as has been done in previous studies of consumer take-up of energy efficient appliances.[18]

Participants are assumed to choose the appliance that yields the highest level of utility,

$$U_{ij} = \alpha_1 PP_j + \alpha_2 EC_{ij} + \varepsilon_{ij}, \tag{3}$$

where i indexes the participant and j indexes the different air conditioner alternatives. Purchase prices PP_j are the same for all participants regardless of where they live, but annual energy costs EC_{ij} vary across participants.[19] The idiosyncratic term ε_{ij} is assumed to be independent across participants and alternatives and to

---

15. We assume that the best estimate of future electricity prices is the electricity price at time of purchase. This is consistent with US Energy Information Administration (2014a), which predicts a flat 10-year real price trend for US retail electricity prices.

16. Lifetime cost is an appropriate measure of welfare in our context because the air conditioners in our experiment are otherwise undifferentiated. With actual air conditioners, consumers also derive utility from the manufacturer brand, color, ease of use, etc. These other characteristics are easily observable so appliance buyers are presumably already making efficient purchase decisions along these margins, and we would not expect those choices to change materially with changes in EnergyGuide label design.

17. The US Energy Information Administration (2014b) assumes that room air conditioners have a minimum life of 8 years and a maximum life of 16 years. EIA assumes an approximately linear retirement schedule, so the average expected lifetime is 12 years.

18. Hausman (1979) and Dubin and McFadden (1984) are seminal papers in this literature.

19. In particular, we assume that participants make decisions based on the information provided on the label. For the control group, this is based on national average electricity prices and usage, and for the treatment group, this is based on their state's electricity prices

have an extreme value distribution, so the choice probabilities take the well-known conditional logit form.

Table 3 reports estimates and standard errors. Both coefficient estimates are negative as expected. The ratio of the coefficient estimates on purchase price and energy cost is 0.174, indicating that participants are willing to trade-off \$1.00 in purchase price for a \$0.17 change in annual energy costs. This corresponds to a discount rate (ρ) of 13.7% assuming a 12-year lifetime.[20] In the results that follow we report lifetime costs using this discount rate as well as alternative discount rates corresponding to a ratio of coefficients that are 5 percentage points higher and lower. As will become clear, our qualitative results are not affected by the discount rate we choose.

3.3. Regression Estimates

We estimate regressions of the following form,

$$Y_{ijs} = \beta \cdot \text{Treatment}_i + X_i'\gamma + \alpha_s + \varepsilon_{ijs}, \tag{4}$$

where the dependent variable Y_{ijs} is one of our three different measures of cost (purchase price, annual energy cost, or lifetime cost) based on the purchase decisions made by the participants. The subscript indexes participant i, purchase decision j ($j =$ 1, 2, 3), and state s. Energy costs were calculated for all participants using state-specific measures of cooling hours and electricity prices and thus reflect our best estimate of actual operating costs regardless of which labels the participant was shown.[21] Regressions are estimated using all 7,275 choices made by the 2,440 participants in our online experiment. We estimate these models in levels, but we have also estimated specifications in which costs are measured in logs and the results are similar.

The covariate of interest is *Treatment*, an indicator variable equal to 0 if the individual is in the control group and 1 if in the treatment group. Thus, the treatment effect β is the estimated difference in cost between the treatment and control

---

and usage. We have also estimated the model restricting the sample to include the treatment group only, and our estimate of the discount rate is similar.

20. This discount rate is similar to recent estimates in the literature from vehicle purchases, including Busse et al. (2013) and Allcott and Wozny (2014). Newell and Siikamaki (2015) estimate a mean annual discount rate of 19% with large heterogeneity across individuals.

21. These calculations implicitly assume that the price elasticity of demand for cooling is zero (i.e., that there is no "rebound" effect). A richer framework would describe air conditioning as a household production problem in which thermal comfort is traded off against electricity expenditure. Allowing for a nonzero elasticity would increase the lifetime pecuniary cost of an energy-efficient unit, but also provide utility in the form of improved thermal comfort. Because households are choosing usage levels optimally, these two components will be similar in magnitude for small differences in energy efficiency.

Table 3. Conditional Logit Regression Results

Variable	Coefficient Estimate
Purchase price (PP)	−.00223
	(.0004)
Energy cost (EC)	−.01281
	(.0016)
Ratio of the coefficient estimates on PP and EC	.174
	(.013)
Implied discount rate (ρ)	.137
	(.017)

Note.—This table reports coefficients from a conditional logit model estimated using all 7,275 choices made by the 2,440 participants in our online experiment. There are slightly fewer than three choices per participant because a small number of participants failed to finish the experiment. The implied discount rate is calculated using an assumed 12-year appliance lifetime. Observations are weighted using sampling weights. Standard errors, clustered by state, are reported in parentheses. For the ratio we calculate the standard error using the delta method, and for the implied discount rate we calculate the standard error using bootstrap with 1,000 replications. All coefficient estimates are statistically significant at the 1% level.

groups, after controlling for covariates. The vector X includes household income and indicator variables for college graduate, nonwhite, married, age 65 and older, and political affiliation. We also control for state fixed effects (α_s). These controls increase the precision of our estimates and correct for the modest imbalance in observed characteristics between the treatment and control groups observed in table 2. Identification of β comes from within-state comparisons between participants in the treatment and control groups.

Table 4 reports the regression estimates. The treatment group paid on average \$3.44 more in purchase price than the control group, indicating slightly more investment in energy efficiency. We hypothesized that the state-specific labels would improve the allocation of energy-efficiency investments across households, but there was no clear prediction for average purchase prices so this is not particularly surprising. Annual energy cost is \$2.36 lower on average in the treatment group and is statistically significant at the 10% level.

We are most interested in the impact on lifetime cost. The reduction in annual energy cost accumulates over the lifetime of the air conditioner, resulting in lower lifetime costs from state-specific labels. On average, lifetime costs are \$10.12 lower in the treatment group than the control group. This estimate is statistically significant at the 1% level. This reduction in lifetime costs is consistent with figure 5 and

Table 4. Cost Impacts of State-Specific Labels, Regression Estimates

Variables	Purchase Price	Annual Energy Cost	Lifetime Cost
Treatment	3.436	−2.357*	−10.123***
	(4.996)	(1.344)	(3.765)
Household income (×1,000)	.307***	−.081***	−.161***
	(.055)	(.014)	(.040)
College graduate	1.771	−1.738	−8.224*
	(5.812)	(1.532)	(4.226)
Nonwhite	−13.869**	5.532***	17.954***
	(6.187)	(1.740)	(5.004)
Married	16.511***	−3.232**	−2.078
	(5.321)	(1.415)	(3.933)
Age 65 and Over	18.366***	−5.816***	−15.087***
	(6.131)	(1.575)	(4.453)
Democrat	.000	−.413	−2.375
	(6.066)	(1.657)	(4.619)
Republican	−9.026	3.102*	8.817*
	(6.371)	(1.685)	(4.843)
Constant	365.458***	155.148***	1,257.890***
	(6.456)	(1.686)	(4.674)
Observations	7,275	7,275	7,275
R-squared	.045	.781	.916

Note.—This table reports coefficient estimates and standard errors from three separate least squares regressions. The dependent variable varies across regression as indicated in the column headings. Lifetime cost is calculated using a discount rate (ρ) of 13.7%. All regressions include state fixed effects in addition to the covariates listed in the row headings. The sample includes all 7,275 choices made by the 2,440 participants in our online experiment. In all regressions, observations are weighted using sampling weights. Standard errors are clustered by participant.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

indicates a better allocation of energy-efficient air conditioners across states. In terms of magnitude, this $10.12 savings represents a little less than a 1% decrease in total lifetime costs. Some of the other coefficient estimates are also interesting. Lifetime cost is decreasing in household income and education. Also, nonwhite participants pay considerably more in lifetime cost and older participants pay considerably less. Finally, Democrats spend about the same amount in lifetime cost, but there is suggestive evidence that Republicans spend somewhat more.

It is worth noting that the fit of the model differs substantially across dependent variables. In the first column, the R^2 is only 0.045, indicating that these decisions are driven mostly by idiosyncratic factors. The R^2 in the second column is much higher (0.781) because the state fixed effects capture the variation in energy costs driven by electricity prices and usage. And the R^2 in the third column is the highest of all (0.916). Lifetime costs are easier to predict because differences in purchase price offset differences in the present discounted value of energy costs, so that the variation in lifetime cost has more to do with cooling hours and electricity prices than with the energy efficiency of the selected appliances.

Results are similar in specifications where we control for whether each participant has central air conditioning, room air conditioners, or no air conditioning. We also ran regressions on each subgroup separately and find negative coefficients on the treatment variable in all three regressions, but only statistically significant results for survey participants with central air conditioners. The lower statistical significance reflects, in part, the smaller sample sizes and that more than two-thirds of the survey participants have central air conditioning. Finally, we also estimated regressions with interaction effects between treatment and participant characteristics. The interaction terms are imprecisely estimated but suggest that the gains from better labels are larger for college graduates and Democrats. See appendix tables for these regressions.

3.4. The Allocation of Energy Efficiency across Regions

Table 5 reports additional regression estimates. Focusing on cost savings across the entire sample masks important heterogeneity. As suggested by figure 5, participants in low-cost states may respond differently to state-specific labels than participants in high-cost states. The top row corresponds exactly to the regression estimates in table 4 but also includes estimates of lifetime cost corresponding to alternative values of the discount rate (ρ). Estimated savings increase to \$15.60 with a 6.7% discount rate and fall to \$7.09 with a 19.8% discount rate. In all cases, the savings are statistically significant at the 5% level or lower.

For the regressions reported in the second through fourth rows, the sample is split into three parts corresponding to low-, middle-, and high-energy cost states. As we saw initially with figure 5, the impact of state-specific labels varies considerably across groups. Participants in low-cost states spend less up front on air conditioners and incur less overall lifetime cost. With a 13.7% discount rate, lifetime savings are \$6.78, a difference that is statistically significant at the 5% level. Participants in medium-cost states incur about the same amount in overall lifetime cost. For these states, state-specific labels provide information that is very similar to the current EnergyGuide labels, so it makes sense that there would not be large differences in behavior. Finally, participants in high-cost states spend considerably more up front on air conditioners and then incur considerably lower lifetime costs, ranging from \$12.81 to \$41.61 for the discount rates we consider. In all cases the lifetime savings for this group are statistically significant at the 5% level.

Table 5. Cost Impacts of State-Specific Labels, Additional Regression Estimates

			Lifetime Cost		
	Purchase Price	Annual Energy Cost	$\rho = .137$	$\rho = .067$	$\rho = .198$
Entire sample	\$3.44	–\$2.36*	–\$10.12***	–\$15.60**	–\$7.09***
	(5.00)	(1.34)	(3.76)	(6.61)	(2.49)
Low operating cost states	–\$12.49	\$0.99	–\$6.78**	–\$4.48	–\$8.06**
	(7.82)	(1.09)	(2.77)	(2.87)	(3.58)
Medium operating cost states	\$1.50	–\$0.02	\$1.37	\$1.32	\$1.40
	(9.35)	(2.31)	(4.40)	(9.58)	(1.99)
High operating cost states	\$22.86**	–\$7.98**	–\$23.06**	–\$41.61**	–\$12.81**
	(9.02)	(3.23)	(9.98)	(17.39)	(5.97)

Note.—This table reports coefficient estimates and standard errors corresponding to the treatment indicator variable from 20 separate least squares regressions. Positive numbers indicate a higher price or cost for the treatment group. The dependent variable varies across regressions as indicated in the column headings. Lifetime costs are calculated using the discount rates as indicated. All regressions include state fixed effects as well as household income and indicator variables for college graduate, nonwhite, married, age 65 or over, and political party affiliation. For the first row, the sample includes all 7,275 choices made by the 2,440 participants in our online experiment. For the regressions reported in the second through fourth rows, states are divided into three groups (terciles) based on average energy costs (residential electricity prices multiplied by annual hours of air conditioning use), and then regressions are run using participants from each subset of states. In all regressions observations are weighted using sampling weights. Standard errors are clustered by participant.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

3.5. Aggregate Savings Nationwide from State-Specific Labels

Households can make two kinds of mistakes when buying air conditioners with inaccurate information about operating costs. Households in low-cost states (e.g., Massachusetts) may purchase overly energy-efficient air conditioners despite the fact they will operate these air conditioners only a few days a year. In our experiment, participants from low-cost states save nearly $7 on average in lifetime costs with better information. Conversely, households in high-cost states (e.g., Florida) may purchase less energy-efficient air conditioners than is optimal given the expected heavy usage in that state. In our experiment, participants from high-cost states save $23 on average in lifetime costs with better information. Overall, better information leads to private gains of over $10 per air conditioner purchase.

Table 6 reports the aggregate national savings implied by our estimates. That is, the table reports how much consumers would save nationwide from a shift to state-specific EnergyGuide labels. We calculated the average lifetime cost savings across states using a weighted average of the cost savings for low-, medium-, and high-operating-cost states weighted by the distribution of room air conditioners in the United States as reported in the 2009 Residential Energy Consumption Survey.[22] The weighted average lifetime cost savings is $11.60 per unit with a 95% confidence interval ranging from $7.78 to $15.42. Given nationwide annual sales of 4.4 million units, the cost savings for room air conditioners sold in a given year is $51.0 million.[23] Discounting future year savings at 13.7% (and assuming no increase in sales or annual energy costs), we get a present discounted value of savings of $424 million with a 95% confidence interval of $284 to $563 million.

Our findings suggest that state-specific labels would improve purchase decisions not just for room air conditioners but also for many different types of appliances. Central air conditioners, furnaces, and heat pumps are obvious examples because cooling and heating demand varies across states. But appliances like refrigerators, freezers, clothes washers, and dishwashers could also benefit from state-specific labels. As we showed earlier, residential electricity prices vary by more than 2:1 across states, so there

22. We used the distribution of room air conditioners rather than sales of room air conditioners due to the lack of data on the latter.

23. The 95% confidence interval is from $34.22 to $67.85 million. These calculations ignore potential responses by appliance manufacturers and retailers. In the short run, firms might adjust pricing in response to the change in demand for different models. The US appliance market has become more competitive with the recent entry of LG, Samsung, and other international manufacturers, but firms are still able to charge significant markups particularly for high-end models (Houde 2014a; Spurlock 2013). Moreover, in the long run manufacturers might respond to better information by changing the set of appliances offered for sale.

Table 6. Implied Aggregate National Savings from State-Specific Labels

Lifetime cost savings per room air conditioner (weighting by RAC distribution across states)	$11.60
Annual US sales of room air conditioners	$4.4 million
Total cost savings per year	$51.0 million
Total cost savings—all future years (discounted at 13.7%)	$423.5 million

Note.—This table reports the implied aggregate national savings implied by our estimates. Lifetime cost savings per air conditioner come from the full-sample regression estimate corresponding to a discount rate of 13.7%. Annual sales of room air conditioners come from US Department of Energy (2014a). Total cost savings for all room air conditioners is the product of the first and second rows. The final row reports the present discounted value of total cost savings implied by a permanent switch to state-specific labels.

are significant potential efficiency gains from improved information even for products with little predictable cross-state variation in usage.[24]

These estimated benefits need to be compared to the costs of implementing state-specific labels. Requiring manufacturers to ship appliances with state-specific labels would not require any additional appliance testing. The FTC currently maintains label templates that manufacturers download and print. Instead of one template per appliance, the FTC would need to maintain 50 different templates, one for each state, perhaps accessible through a drop-down menu. At the same time it might also make sense to automate the simple calculation required to fill in estimated yearly energy cost. Although these changes with the FTC website would presumably be relatively inexpensive, the more substantive administrative burden would fall on the manufacturers themselves. The challenge for manufacturers is that labels are often attached to appliances even before it is known where they are going to be shipped. Moreover, appliances are frequently rerouted across states. For example, an appliance originally intended for California can end up Nevada. It might make sense to use region-specific labels, rather than state specific, to reduce the amount of relabeling that is required and/or to ship appliances with labels prepared for several different states.[25]

---

24. While we have not addressed the issue of externalities associated with appliance use and the interaction with better labels, we note that carbon pricing, for example, would change—and perhaps increase—the regional variation in electricity prices. See, e.g., Graff Ziven, Kotchen, and Mansur (2014).

25. The US Department of Energy has taken a region-based approach with new minimum efficiency standards for central air conditioners and heat pumps. The United States has been divided into three regions (North, Southwest, and Southeast) and, beginning January 1, 2015, central air conditioners and heat pumps manufactured for the two southern regions must meet a higher minimum efficiency standard. See US Court of Appeals Case 11-1485, April 24, 2014, for details. Interestingly, a regional standard likely decreases the

An alternative deployment option would be add a QR scan code to existing labels that consumers could scan with their smart phones.[26] The phone would then automatically display a label with state-specific or even county-specific annual energy costs. This would require the FTC to maintain a website with data on average annual energy costs that would be queried by the phone's QR scan app. The cost of including a QR scan code on labels would be near zero, and the cost to the FTC of developing the software and maintaining such a system would be relatively low, although whether or not consumers would use the information is unclear. Another related deployment option would be to develop an automated system for online retailers. By law retailers must make EnergyGuide labels available for online shoppers, and an automated system could display labels that are tailored to each consumer's state or county of residence. This customization would be somewhat easier logistically than the physical labels because of the issue of not knowing where appliances are going to be shipped.

4. UNDERLYING MECHANISMS

Having documented substantial treatment effects from the introduction of state-specific EnergyGuide labels, we next turn to an analysis of the underlying mechanisms driving our results. Specifically, we ask three questions: (1) Do participants understand the labels? (2) Do participants know whether their state's annual energy cost from operating an air conditioner is higher or lower than the national average? (3) Do participants take local factors into account when selecting a level of efficiency?

4.1. Do Participants Understand the Labels?

Table 7 shows the responses to two multiple choice questions we asked participants immediately after they made their hypothetical appliance choices. The exact wording of the questions is provided in the table. These questions were aimed at investigating how well participants understood the labels they had just seen. Participants were not able to go back and look again at the labels before answering the questions.

Most participants were not able to correctly answer questions about how yearly operating costs were calculated. Over half the participants were not sure whether the national or state electricity price was used to compute yearly costs, and among those who had an opinion, many incorrectly answered the question. There is no statistical

---

potential benefits from customized labels by eliminating the least energy-efficient models in high operating cost states.

26. The new EPA vehicle mileage labels that went into effect beginning with model year 2013 include a QR scan code providing smart phone access to online information about fuel economy and environmental factors.

Table 7. Testing Knowledge about How Energy Costs Were Calculated

	Participants Shown Current Labels (i.e., Control Group)	Participants Shown State-Specific Labels (i.e., Treatment Group)	*p*-Values for Equality of Proportions across Groups
What electricity price was used to calculate estimated yearly energy cost in the Energy Guide labels you were shown?			
The average electricity price in the United States	**33.6%**	30.8%	.152
The average electricity price in my state.	10.1%	**17.0%**	.000
I'm not sure.	56.3%	52.2%	. . .
Operating costs for an air conditioner depend on the cost of electricity and the number of hours the air conditioner is used. What usage level was used to calculate estimated yearly energy cost in the Energy Guide labels you were shown?			
The average usage level for air conditioners in the United States.	**33.9%**	32.2%	.392
The average usage level for air conditioners in my state.	9.8%	**14.5%**	.001
I'm not sure.	56.2%	53.2%	. . .

Note.—This table reports the results from two qualitative questions we asked at the end of the experiment. The table replicates the exact wording used for the question and the answers, including underlined text as indicated. We have excluded a small number of observations (<1%) in which participants refused to answer the question. The correct answers are highlighted in bold. We calculate all proportions using sampling weights.

difference between the percentage of each group that thought it was the national average price (33.6% versus 30.8%). However, the treatment group was more likely to answer correctly that it was the state price (17.0% versus 10.1%). This difference is statistically significant but indicates that only a relatively small fraction of participants in the treatment group actually realized they were seeing operating costs calculated using state-specific information. The responses are similar for the question about what usage level was used. Again, over half of the participants were not sure whether national or state information was used and again, among those who expressed an opinion, there is a large fraction of incorrect responses.

4.2. Do Participants Know How Their State Compares?

Part of the rationale for the current EnergyGuide labels is that individuals should be able to "translate" the operating cost information to incorporate information about local electricity prices and usage. The labels include the phrase, "Your cost will depend on your utility rates and use." And, at least in theory, an individual could transform the estimated yearly energy cost to a more meaningful measure reflecting local information. This hinges, however, on individuals having some sense of how their local energy prices and usage compare to the national average.

Table 8 shows the responses to two multiple choice questions aimed at evaluating this knowledge. We first asked participants how electricity prices in their state compare to the national average. More than two-thirds of the participants answered that they were not sure and, overall, only 20% of participants were able to correctly answer the question. Participants have a somewhat better understanding of how their air conditioning usage compares to the national average. A larger fraction of participants felt confident in taking a position (60% versus 30%) and, overall, 40% of participants were able to correctly answer the question.[27]

4.3. Do Participants Take Local Factors Into Account?

The evidence from the previous subsections suggests that consumers are not going to be able to mentally adjust the information in the current EnergyGuide labels to account for local factors. Many participants do not fully understand the information they are being shown, nor do they consistently know how electricity prices and usage in their state compare to the national average. In this section, we formalize this conjecture by testing whether state-level electricity prices and usage have any predictive power for purchase decisions.

---

27. We also examined responses separately for the treatment and control groups and the distribution of responses is very similar and not statistically different (p-values .41 and .70). This suggests that participants in the treatment group are not inferring anything about their state's electricity prices or usage based on the labels they are shown.

Table 8. Testing Knowledge about How State Energy Costs Compare to National Average

The national average residential electricity price is 12.4 cents per kilowatt hour (kWh). How does the average residential electricity price in your state compare to the national average?	
My state's electricity prices are higher than the national average.	14.3%
My state's electricity prices are lower than the national average.	16.6%
I'm not sure.	69.2%
Percentage correct	20.2%
How do you think average air conditioning usage in your state compares to the average usage nationally?	
Average usage in my state is probably higher than the national average.	30.6%
Average usage in my state is probably lower than the national average.	28.1%
I'm not sure.	41.3%
Percentage correct	40.4%

Note.—This table reports the results from two questions we asked at the end of the exper-iment. The table replicates the exact wording used for the question and the answers, including underlined text as indicated. We have excluded a small number of observations (<1%) in which participants refused to answer the question. The percentage correct is the fraction of participants who are able to answer the question (i.e., they don't respond "I'm not sure") and are correct in how their local conditions compare to the national average. We calculate all proportions using sampling weights.

Table 9 shows regression estimates from two separate regressions. The dependent variable in both regressions is the energy efficiency of the selected air conditioner (measured in EER). For the control group, neither the electricity price nor usage has a statistically significant effect on energy efficiency. The *p*-value for the joint null hypothesis of no influence is 0.24. Moreover, the sign of the estimated coefficient on price is negative, counter to what theory would suggest. This is pretty surprising and provides no evidence that participants in the control group are mentally adjusting the information provided in the labels to account for local operating costs.

In contrast, for the treatment group, both price and usage are positive and jointly strongly statistically significant. While we cannot reject the null that the coefficient on price is zero at the 5% level, it is statistically significant at the 10% level and the coefficient on usage is significant at the 1% level. A one-unit change in price (one cent) or annual hours (100 hours) is associated with roughly the same increase in annual operating costs ($12.50) when evaluated at mean hours (for the price coefficient) or mean price (for the hours coefficient). The similarity of these estimated coefficients suggests that survey participants respond to the operating cost presented in the state-specific labels.

4.4. Complementary Revealed Preference Evidence

An important question is how any of these results would generalize to actual choices. With good reason, economists have long been skeptical about interpreting results

Table 9. Do Participants Take Local Factors into Account?

	Participants Shown Current Labels (i.e., Control Group)	Participants Shown State-Specific Labels (i.e., Treatment Group)
Electricity price (cents per kWh)	−.036	.041*
	(.025)	(.024)
Annual hours of air conditioning usage (in 100s)	.005	.040***
	(.008)	(.008)
p-value for joint test that price and usage do not influence EER choice	.24	.00
Number of observations	3,670	3,605

Note.—This table reports estimated coefficients and standard errors from two separate regressions. For column 1, the sample is restricted to the 3,670 choices made by participants in the control group, and for column 2, the sample is restricted to the 3,605 choices made by participants in the treatment group. The dependent variable in both regressions is the energy efficiency of the selected air conditioner (measured in EER). In addition to the independent variables listed in the row headings, both regressions include household income and indicator variables for college graduate, nonwhite, married, age 65 or over, and political party affiliation. In both regressions, observations are weighted using sampling weights. Standard errors are clustered by participant.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

from stated-choice experiments (Hausman 2012). Without any real "skin in the game," it is not at all clear that participants in an online experiment are going to make the same choices that they would when faced with real financial consequences. We have attempted to reduce these concerns by focusing on a concrete purchase decision that is designed to look similar to actual decisions that individuals face, but we recognize the limitations inherent with stated choice, and an important priority for future research is to replicate these experiments in the field.

In our context, it is not even possible to make strong statements about the direction of bias. On the one hand, better labels might tend to be less effective than in the real world because there is no actual money at stake, so participants are going to tend to answer these questions quickly and perhaps not read the fine print. On the other hand, our stated-choice setting removes some additional factors like appliance manufacturer and differences in sizes, color, and other design considerations potentially leading participants to focus more on these labels than they would in the real world. It is impossible to know which of these potential biases is more important.

Federal law requires that EnergyGuide labels be displayed on all major appliances sold in the United States. Thus, it would not be straightforward to replicate this online experiment in the field. Strictly speaking, it would be illegal to go into an appliance retailer and replace the current labels with labels providing state-specific information. One possibility would be to supplement the existing labels with additional information of some form. Although this would indeed be interesting, the results of such an experiment would be somewhat difficult to interpret. Such a treatment would inevitably increase attention on operating costs, and it would be difficult to disentangle the impact of that attention from the pure information content.

Another approach to validating our stated-choice experiment is to look for complementary evidence from actual choices. Figure 6 shows the fraction of new central air conditioners sold in each state in 2009 that had an Energy Star rating.[28] What is potentially interesting about this figure is the lack of correlation between these choices and the pattern of operating costs we showed in figure 3. Operating costs are highest throughout the South, from Texas through Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. So if choices are being made efficiently, we would expect to see large investments in energy efficiency in these states. Instead, the states with the highest Energy Star shares are in the Northeast and upper Midwest. The cross-state correlation between the Energy Star share and estimated annual operating costs is −0.23.[29] Thus, the correlation is actually negative, which would imply that Energy Star purchases are biased away from what would be required for efficiency.

As always, however, it is important to interpret cross-sectional comparisons with caution. The high penetration of Energy Star air conditioners in states like Vermont and Massachusetts suggests that other factors, including political ideology, may come into play when households make choices about energy efficiency. Our experiment provides some supportive evidence for this hypothesis. In particular, political party affiliation did seem to matter for air conditioner choices in table 4. While being affiliated with the Democratic Party does not have a statistically significant effect, participants who are affiliated with the Republican Party tend to choose less expensive (i.e., less energy-efficient) air conditioners and thus spend more

28. We would have also been interested in examining this pattern for room air conditioners, but state-level Energy Star shares are not available. These data on central air conditioners come from US Department of Energy (2010) and are derived from a survey that includes about 60% of the retail market.

29. We also estimated regressions with Energy Star penetration as the dependent variable and average operating cost along with average state household income, education, gender, age, and political ideology covariates. Even after controlling for these other factors, operating cost continues to be negatively correlated with Energy Star penetration albeit with a *t*-statistic of −0.97.

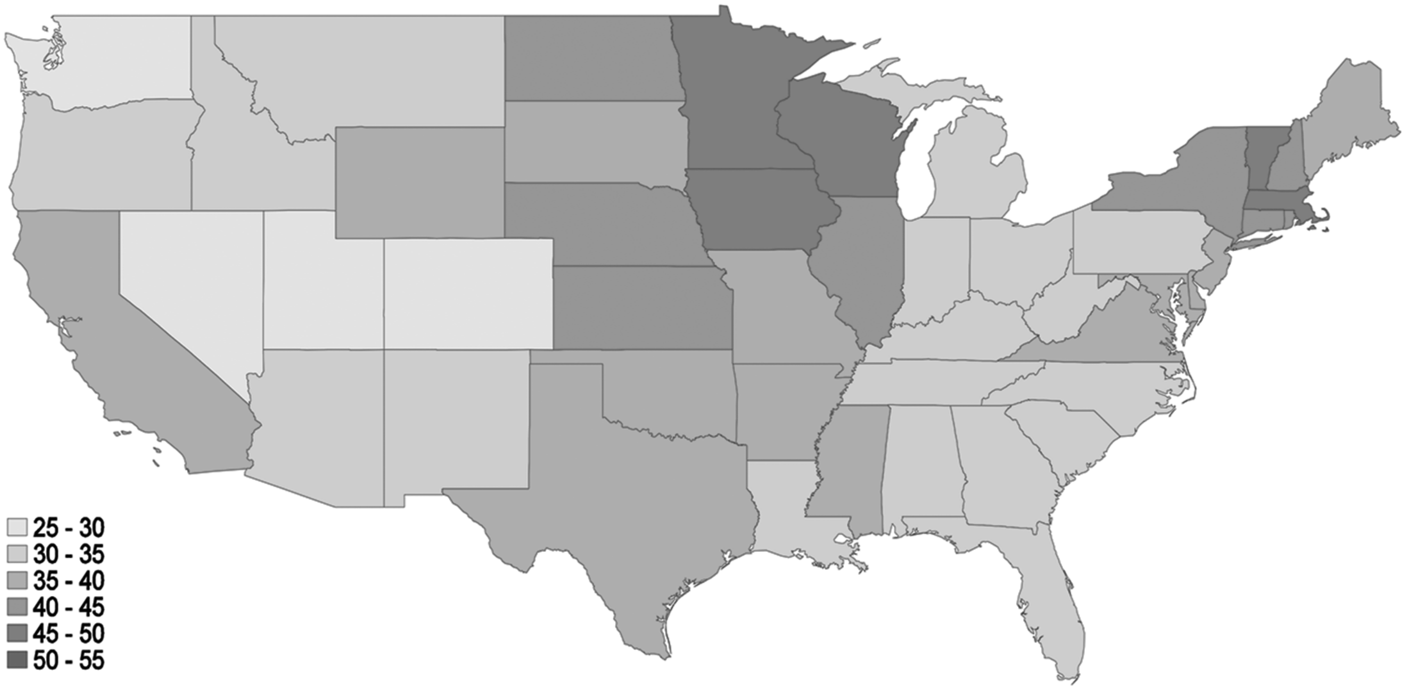

Figure 6. Share of new air conditioners sold in 2009 that are Energy Star. A color version of this figure is available online

in annual operating cost.[30] Political ideology is not the only possible explanation for this geographic pattern of Energy Star adoption. Air conditioning is less common in the North, so it tends to be higher-income households making these purchases, and this compositional effect could provide an alternative explanation.

That said, this apparent lack of positive correlation between appliance choices and operating costs is not without precedent in the existing literature. In related work, Jacobsen (2015) finds using panel data no evidence that electricity prices increase purchases of Energy Star appliances. Similarly, Houde (2014b), using transaction-level data from a major retailer, finds little sensitivity of appliance choices to local electricity prices. These are surprising findings given how much electricity rates vary across states but perhaps make sense given the coarse information provided by current labels and that most consumers appear to have little understanding about how their electricity rates compare to the national average.

Revealed preference cannot tell us how much choices would be improved by better information, but it does provide some real-world corroboration for the evidence in our stated-choice experiment, suggesting that the current labels are not working as well as they could. It may not be enough to simply say, as the current labels do, that "Your cost will depend on your utility rates and use." We may need to provide better information to help consumers connect the dots.

4.5. Discussion and Implications

The state-specific labels changed participants' behavior, so participants are not ignoring these labels completely. But at the same time, participants are not exerting the effort that would be required to understand the information beyond a superficial level. In the labels, the annual operating cost appears in 24-point font, bigger than all other text. Participants in the experiment appear to have read and internalized that one number but then failed to read or internalize anything else. Moreover, there is no evidence of individuals spontaneously incorporating local information when they see only national-average information.

Most participants do not make intertemporal decisions like this regularly. Getting a decision like this exactly right would require real time and cognitive effort, so it makes

30. Previous papers have documented similar correlations between political ideology and adoption of energy-efficient vehicles and buildings (Kahn and Vaughn 2009). One of the potential explanations that has been suggested is that in "green" communities, driving an energy-efficient vehicle or owning an energy-efficient building could be perceived as a symbol of "status" (Kahn 2007). We are not aware of previous attempts to correlate political ideology with air conditioner choices, but these purchases are considerably less visible than vehicles and buildings, suggesting that other more intrinsic explanations may play a role.

sense that participants may try to simplify these decisions, either consciously or unconsciously. One way to simplify the problem is to take the headline operating cost number as given and ignore everything else. Whether this inattention is rational or irrational is unclear. It could be that participants are weighing the potential benefits of becoming perfectly informed against attention and other costs and choosing consciously to be inattentive (Sallee 2014). Or it could be that they have unconsciously switched into an inattentive mode and could switch back at relatively low cost.

Another point that emerges from this analysis is the distinction between information programs and energy conservation programs. While providing state-specific information to households appears to lead to more economically efficient appliance purchases, it does not necessarily mean that aggregate energy use will fall. Additional regression evidence in table 10 shows that, in our experiment, electricity consump-

Table 10. The Impact of State-Specific Labels on Electricity Consumption

	Annual Electricity Consumption (in Kilowatt Hours)
Entire sample	–16.5
	(11.1)
Low operating cost states	10.2
	(9.2)
Medium operating cost states	8.5
	(16.2)
High operating cost states	–64.6**
	(27.0)

Note.—This table reports coefficient estimates and standard errors corresponding to the treatment indicator variable from four separate least squares regressions. The dependent variable in all regressions is the annual electricity consumption in kilowatt hours of the air conditioner selected by the participant based on annual cooling hours in the state where the participant lives. All regressions include state fixed effects as well as household income and indicator variables for college graduate, nonwhite, married, age 65 or over, and political party affiliation. For the first row the sample includes all 7,275 choices made by the 2,440 participants in our online experiment. For the regressions reported in the second through fourth rows, states are divided into three groups (terciles) based on average energy costs (residential electricity prices multiplied by annual hours of air conditioning use), and then regressions are run using participants from each subset of states. In all regressions observations are weighted using sampling weights. Standard errors are clustered by participant.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

tion, in fact, does go down, by an average of 16.5 kilowatt hours per year, driven by significant decreases in consumption high-cost states. However, this need not be the case. In general, providing better information leads energy consumption to decrease in high-cost states but increase in low-cost states. Whether the net change in consumption is positive or negative depends on the type of information provided and characteristics of the households receiving that better information. But—and this is important—better information is efficiency enhancing regardless of the effect on energy use.[31]

5. CONCLUSION

Energy efficiency is critically important both as an element of a portfolio of measures to reduce greenhouse gas emissions to address global climate change (IPCC 2014) and as concerns about local pollutants from the burning of fossil fuels. This paper contributes to our understanding of the role information plays in shaping consumer purchase decisions as well as possible instruments to improve purchase decisions for optimal levels of energy-efficient capital.

We find that better labels lead to better choices. State-specific labels decrease the lifetime cost of air conditioning in both high- and low- operating costs states. In high-cost states like Florida and Texas, consumers invest more in energy efficiency, and this increase in up front spending is outweighed by a substantial decrease in annual energy expenditures. In low-cost states like Maine and Oregon, consumers invest less in energy efficiency, and this decrease in up front spending outweighs a modest increase in annual energy expenditures.

Despite the improved allocation, there remains a puzzle. Although participants respond to the labels, they do so without a precise understanding about how the information was calculated. For example, few participants knew whether the information they had just seen was based on state- or national-level electricity rates, even though this information was available at the bottom of the label. One possible explanation for the puzzle is that participants treat the label as WYSIATI. That is, when they look at the labels they fixate on the main headline summary number in large font while essentially ignoring everything else. If this is correct, it has important implications for label design. Most importantly, it suggests that we should be working hard to make sure that the headline number is as accurate as possible and that we should not assume that households can "translate" information to reflect local or personal variation in prices and usage. This conjecture suggests a fruitful line of future research, both in the lab and in the field.

31. This ignores the fact that the private cost of energy may not match the social cost. For an in-depth analysis of the externalities associated with energy production and consumption, see National Research Council (2009).

Our research has practical significance as well. The implied aggregate cost savings for this appliance category alone exceeds $50 million annually. Moreover, our results suggest that customized information could improve decision making not only for air conditioners, but for many different types of appliances as well. While the usage of most appliances does not vary geographically as much as air conditioning, electricity prices vary by more than 2:1 across states, so there are potentially significant efficiency gains from improved information even for products with little variation in usage.

REFERENCES

Allcott, Hunt. 2011a. Consumers' perceptions and misperceptions of energy costs. *American Economic Review Papers and Proceedings* 101 (3): 98–104.

———. 2011b. Social norms and energy conservation. *Journal of Public Economics* 95 (9–10): 1082–95.

———. 2013. The welfare effects of misperceived product costs: Data and calibrations from the automobile market. *American Economic Journal: Economic Policy* 5 (3): 30–66.

Allcott, Hunt, and Todd Rogers. 2014. The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review* 104 (10): 3003–37.

Allcott, Hunt, and Richard L. Sweeney. Forthcoming. The role of sales agents in information disclosure: Evidence from a field experiment. *Management Science*.

Allcott, Hunt, and Dmitry Taubinsky. 2015. Evaluating behaviorally-motivated policy: Experimental evidence from the lightbulb market. *American Economic Review* 105 (8): 2501–38.

Allcott, Hunt, and Nathan Wozny. 2014. Gasoline prices, fuel economy, and the energy paradox. *Review of Economics and Statistics* 96 (10): 779–95.

Ayres, Ian, Sophie Raseman, and Alice Shih. 2009. Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage. NBER Working paper no. 15386. National Bureau of Economic Research, Cambridge, MA.

Bertrand, Marianne, and Adair Morse. 2011. Information disclosure, cognitive biases, and payday borrowing. *Journal of Finance* 66 (6): 1865–93.

Brounen, Dirk, and Nils Kok. 2011. On the economics of energy labels in the housing market. *Journal of Environmental Economics and Management* 62 (2): 166–79.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer. 2013. Are consumers myopic? Evidence from new and used car purchases. *American Economic Review* 103 (1): 220–56.

Camilleri, Adrian R., and Richard P. Larrick. 2014. Metric and scale design as choice architecture tools. *Journal of Public Policy and Marketing* 33 (1): 108–25.

CLASP (Collaborative Labeling and Appliance Standards Program). 2014. Global S&L database. CLASP 2014 (accessed September 25, 2014). http://www.clasponline.org/en/Tools/Tools/SL_Search.aspx.

Davis, Lucas W. 2008. Durable goods and residential demand for energy and water: Evidence from a field trial. *RAND Journal of Economics* 39 (2): 530–46.

Dubin, Jeffrey A., and Daniel L. McFadden. 1984. An econometric analysis of residential electric appliance holdings and consumption. *Econometrica* 52 (2): 345–62.

Federal Trade Commission. 2014. EnergyGuide labeling: FAQs for appliance manufacturers 2014 (accessed October 9, 2014). http://www.business.ftc.gov/documents/bus-82-energyguide-labels-faqs.

GfK. 2013. KnowledgePanel design summary (accessed September 26, 2014). http://www.gfk.com/Documents/GfK-KnowledgePanel-Design-Summary.pdf.

GfK. nd. GfK methodology. http://www.knowledgenetworks.com/ganp/irbsupport/.

Gillingham, Kenneth, Richard G. Newell, and Karen Palmer. 2009. Energy efficiency economics and policy. *Annual Review of Resource Economics* 1 (1): 597–619.

Gillingham, Kenneth, and Karen Palmer. 2014. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy* 8 (1): 18–38.

Graff Ziven, Joshua, Matthew J. Kotchen, and Erin T. Mansur. 2014. Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. *Journal of Economic Behavior and Organization* 107 (pt. A, November): 248–68.

Hastings, Justine S., and Jeffrey M. Weinstein. 2008. Information, school choice, and academic achievement: Evidence from two experiments. *Quarterly Journal of Economics* 123 (4): 1373–1414.

Hausman, Jerry A. 1979. Individual discount rates and the purchase and utilization of energy-using durables. *Bell Journal of Economics* 10 (1): 33–54.

———. 2012. Contingent valuation: From dubious to hopeless. *Journal of Economic Perspectives* 26 (4): 43–56.

Houde, Sebastien. 2014a. Bunching with the stars: How firms respond to environmental certification. Working paper, University of Maryland, Department of Agricultural and Resource Economics. http://terpconnect.umd.edu/~shoude/index.html.

———. 2014b. How consumers respond to environmental certification and the value of energy information. E2e Project Working paper 007.

Hoxby, Caroline, and Sarah Turner. 2013. Expanding college opportunities for high-achieving, low income students. Stanford Institute for Economic Policy Research Discussion paper, Stanford, CA.

IPCC (Intergovernmental Panel on Climate Change). 2014. Climate change 2014: Mitigation of climate change. Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva.

Jacobsen, Grant. 2015. Do energy prices influence investment in energy efficiency? Evidence from Energy Star appliances. *Journal of Environmental Economics and Management* 74:94–106.

Kahn, Matthew E. 2007. Do greens drive hummers? Environmental ideology as a determinant of consumer choice. *Journal of Environmental Economics and Management* 54:129–45.

Kahn, Matthew E., and Ryan K. Vaughn. 2009. Green market geography: The spatial clustering of hybrid vehicles and LEED registered buildings. *B.E. Journal of Economic Analysis and Policy* 9 (2, article 2): 1–24.

Kahneman, Daniel. 2011. *Thinking fast and slow*. New York: Farrar, Strauss & Giroux.

Kling, Jeffrey R., Sendhil Mullainathan, Eldar Shafir, Lee C. Vermeulen, and Marian V. Wrobel. 2012. Comparison friction: Experimental evidence from Medicare drug plans. *Quarterly Journal of Economics* 127 (1): 199–235.

Metcalf, Gilbert E. 1994. Economics and rational conservation policy. *Energy Policy* 22 (10): 819–25.

Metcalf, Gilbert E., and Kevin A. Hassett. 1999. Measuring the energy savings from home improvement investments: Evidence from monthly billing data. *Review of Economics and Statistics* 81 (3): 516–28.

National Research Council. 2009. *Hidden costs of energy: Unpriced consequences of energy production and use*. Washington, DC: National Academies Press.

Newell, Richard G., and Juha V. Siikamaki. 2014. Nudging energy efficiency behavior: The role of information labels. *Journal of the Association of Environmental and Natural Resource Economists* 1 (4): 555–98.

———. 2015. Individual time preferences and energy efficiency. *American Economic Review: Papers and Proceedings* 105 (5): 196–200.

Revelt, David, and Kenneth Train. 1998. Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Review of Economics and Statistics* 80 (4): 647–57.

Sallee, James M. 2014. Rational inattention and energy efficiency. *Journal of Law and Economics* 57 (3): 781–820.

Spurlock, Anna. 2013. Appliance efficiency standards and price discrimination. Lawrence Berkeley Lab Report LBNL-6283E. Lawrence Berkeley National Laboratory, Berkeley, CA. http://eetd.lbl.gov/publications/appliance-efficiency-standards-and-pr.

Thorne, Jennifer, and Christine Egan. 2002. An evaluation of the Federal Trade Commission's EnergyGuide appliance label. American Council for an Energy Efficient Economy.

US Department of Energy, Energy Information Administration. 2009. Residential energy consumption survey (RECS) 2009. DOE EIA 2009. http://www.eia.gov/consumption/residential/data/2009/ (accessed September 25, 2014).

US Department of Energy. 2010. 2009 unit shipment data collection forms. Energy Star 2010. https://www.energystar.gov/index.cfm?c=partners.unit_shipment_data_archives.

———. 2013. *Electric power annual*. Washington, DC: US Government Printing Office.

———. 2014a. Energy Star unit shipment and market penetration report calendar year 2012 summary (accessed September 25, 2014). https://www.energystar.gov/index.cfm?c=partners.unit_shipment_data_archives .

———. 2014b. Room air conditioner savings calculator 2014 (accessed September 26, 2014). http://www.energystar.gov/buildings/sites/default/uploads/files/RoomAC_Calculator.xls.

US Energy Information Administration. 2014a. *Annual energy outlook 2014*. Washington, DC: US Department of Energy.

———. 2014b. *Assumptions to the annual energy outlook 2014: Residential demand model*. Washington, DC: US Department of Energy.

Wiel, Stephen, and James E. McMahon. 2001. *Energy-efficiency labels and standards*. Washington, DC: Collaborative Labeling and Appliance Standards Program (CLASP).