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DOES BETTER INFORMATION LEAD TO BETTER CHOICES? EVIDENCE FROM ENERGY-EFFICIENCY LABELS

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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 randomized controlled trial to measure the potential benefits from providing more accurate information. We find that state-specific labels lead to significantly better choices. Consumers 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. The implied aggregate cost savings are larger than any reasonable estimate of the cost of implementing state-specific labels.

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1. Introduction

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. 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 labelling 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 designed and implemented an online randomized controlled trial 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 appliances stays about the same, but the *allocation* is much better. That is, households facing low energy prices and low expected usage tend to invest less in energy-efficiency, while those facing high energy prices and high expected usage tend to invest more.

The implied aggregate savings are substantial. With energy-efficiency investments the relevant measure is “lifetime cost,” calculated as purchase price plus the present discounted value of energy costs over the life of the appliance. We find that state-specific labels decrease lifetime cost by an average of $10 per appliance, with much larger savings in high-cost states. The implied aggregate cost savings are larger than any reasonable estimate of the cost of implementing state-specific labels.

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.

This behavior may well be perfectly rationale. Understanding this information and “translating” it to make it relevant for a consumer's own state of residence requires time and cognitive effort. These are real economic costs, and the benefits of becoming informed are relatively modest, so “rational inattention” may be optimal for many consumers (see Sallee, forthcoming, and references therein).

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. None of the work to date has focused on the efficiency cost of inaccurate information provided to consumers as this study does.[1,2]

It is worth emphasizing, however, that our evidence comes from a stated-choice experiment. The highly-stylized setting allows us to eliminate many of the factors that

[1] 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.

[2] Two related studies perform online experiments using the same nationally-representative panel that we employ. Newell and Siikamaki (2013) analyze optimal EnergyGuide label design while Allcott and Taubinsky (2013) conduct experiments on the importance of attentional biases in leading to sub-optimal energy efficiency investments. Neither of these studies considers the role of inaccurate information as does our study.

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 data from appliance purchases, we find a zero (or even negative) correlation between operating costs and investments in energy-efficiency. Although this doesn't tell us how much choices would change with better information, it corroborates other results in the paper about the lack of effectiveness of current labels.

The paper proceeds as follows. Section 2 provides background information, and makes the case for why better information might matter. Section 3 describes our online experiment. Sections 4 and 5 provide the main results and additional analysis. Section 6 offers concluding comments.

2. Background

A. Previous Research

Early research on energy labeling focused on the role of labels in improving consumer information and in providing incentives to manufacturers to improve energy efficiency in product choices.[3] More recently, interest in information provision has surged over the last couple of years with much of the focus aimed at trying to understand potential behavioral biases like MPG illusion, inattention, and myopia. This work is motivated by the idea of the "energy-efficiency gap." Going back to Hausman (1979) and Dubin and McFadden (1984), and then with intensified focus since McKinsey & Company and The Conference Board (2007), there is a widespread perception that consumers make systematic mistakes when making energy-related decisions that lead them to underinvest in energy-efficiency. Papers include Allcott (2013) focusing on consumer misunderstanding of the non-linear relation between miles per gallon ratings

[3] Wiel and McMahon (2001) discuss the early motivation for energy labels and provide a summary of the early findings on the effectiveness of labeling programs at reducing energy consumption. Thorne and Egan (2002) conduct qualitative interviews with focus groups about alternative graphical elements and other aspects of EnergyGuide label design.

and motor vehicle fuel consumption, Allcott and Taubinsky (2013) who look at the role of product bans as a policy response to address informational or attentional bias, Sallee (forthcoming) who considers rational inattention to small costs and implications for information provision, and Heutel (2011) who focuses on time inconsistent preferences.

There are also studies that examine the effect of environmental messaging like Energy Star Certification (e.g. Newell and Siikamaki (2013), Houde (2014b)) 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 "nudges," though 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 studies that have received a great deal of attention on peer comparisons in energy use. Mostly focusing on Opower, these studies have found that learning about how your electricity consumption compares to your neighbors tends to reduce consumption, both in the short-run and long-run. See, for example, Ayres, Raseman and Shih (2009), Allcott (2011b), and Allcott and Rogers (forthcoming).

We see what we are doing as quite different. We are not viewing this through a behavioral lens but rather as a classic example of decision-making under imperfect information. The stakes are substantial but not enormous, so consumers are "rationally inattentive." In this setting, there can be substantial welfare gains from improved information provision. But they need not move people toward more energy-efficient choices.

Our paper focuses sharply on the quality of the information that is provided and asks whether better tailoring information to consumers' characteristics can lead to more efficient choices. An important feature of the experiment is that the *amount* of information is exactly the same for the treatment and control groups. In related work, Allcott and Taubinsky (2013) and Allcott and Sweeney (2014) conduct field experiments

[4] Newell and Siikami (2013) 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. They do not, however, vary the operating cost information itself or explore information that is tailored to the participant's local usage or prices.

in which the treatment group receives information about the potential benefits from energy-efficiency, while the control group receives nothing or an equivalent-length intervention with irrelevant information. These studies are extremely interesting but it can be difficult to know whether the observed changes in behavior are driven by the information provision *per se*, or by the fact that the intervention focuses consumers' attention on the issue.

B. U.S. Energy Labeling Requirements

EnergyGuide labels must be displayed on all major appliances sold in the United States. As of 2014, 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 U.S. 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). 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. Appliance manufacturers must submit data to the FTC disclosing appliance annual energy costs. While FTC approval of manufacturer labels is not required, the labels must accord with strict guidelines outlining exactly what the labels must look like. 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).

[5] According to U.S. DOE (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.

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 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 five year fuel cost savings compared 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) and addresses a potential cognitive bias in MPG ratings. Fuel savings are not linear in MPG. A five mile-per-gallon fuel economy improvement reduces fuel consumption by a factor of over six times when moving from ten to fifteen miles per gallon versus thirty to thirty-five miles per gallon.[6] Despite this non-linearity, consumers appear to make decisions on the basis of a linear relationship between MPG ratings and fuel consumption, a mistake termed the "MPG Illusion." Allcott (2011b, (2013) provides evidence on the extent of the MPG Illusion but argues that the welfare losses arising from this illusion are modest.[7]

Setting MPG Illusion aside, 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 five 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 higher purchase price. But cost savings can differ significantly given differences in average gasoline prices and driving patterns

[6] Moving from ten to fifteen miles per gallon reduces fuel consumption by about 33 gallons per 1000 miles while moving from thirty to thirty-five MPG reduces consumption by about 5 gallons per 1000 miles.

[7] In related work, Camilleri and Larrick (2014) use an online experiment to test whether vehicle preferences are affected by the *scale* on which fuel economy information is expressed (e.g. the cost of gasoline per 100 miles, per 15,000 miles or per 100,000 miles), finding that participants select more fuel-efficient options when cost is expressed per 100,000 miles.

across states. Whether consumers will make those mental adjustments is not clear.

C. Focus on Air Conditioning

More accurate labels could be important for many different appliance types. We focus in our experiment specifically on room air conditioners. More than 25 million American households own one or more room air conditioners so this is a source of energy consumption that is of large intrinsic interest.[8] It is also a particularly lucid example of an energy-efficiency investment for which consumers face a clear tradeoff 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.[9] Table 1 shows that air conditioner usage is pervasive in all parts of 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 U.S. Department of Energy (2014).[10] 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

[8] U.S. Department of Energy, Residential Energy Consumption Survey 2009. See Table HC7.1 "Air Conditioning in U.S. Homes".

[9] Data from U.S. 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.".

[10] Data in the calculator are taken from an uncited 2002 EPA study and are reported at the city level. We aggregated to the state level taking a weighted average of cities within a state weighting by population.

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 U.S. Department of Energy (2013a), Table 2.10. The average price is 12.4 cents per kilowatt hour, but again there is substantial geographic variation. The lowest electricity prices in 2012 were found in Louisiana (8.4 cents), while New York had the most expensive prices (17.6 cents), so more than a 2:1 ratio.

The cost of operating an air conditioner depends on both cooling hours and electricity prices. Figure 3 shows annual average energy costs for a medium-sized (10,000 Btu), medium-efficiency (10.0 EER) room air conditioner. The geographic pattern reflects variation in both cooling hours and electricity prices. Operating costs range from $28 per year in Washington to $316 per year in Florida, more than an 11:1 ratio.

3. Experimental Design

A. 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 which they call the KnowledgePanel. This platform has been widely used by economists, see, e.g., Allcott (2013), Allcott and Taubinsky (2013), and Newell and Siikamaki (2013).

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 percent).

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 the three air conditioners were otherwise identical except for these features. And, as we explain in the appendix, 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 which 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 which report operating cost based on average electricity prices and usage for the state in which each participant resides. 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 socio-economic information about the participants collected from previous surveys. See the appendix for the complete survey instrument and list of variables.

B. 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

[11] The actual EnergyGuide labels for room air conditioners report estimated annual energy cost based on

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, 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 "Energy Efficiency Ratio" (EER). Although not explained in the label, the EER is the ratio of cooling capacity (in Btu's) to electricity consumption (in watts), and is a direct measure of energy-efficiency. Below the EER, the label includes the language "Your cost will depend on your utility rates and use."

Then the bottom of the label provides 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.

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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 1265 hours of usage per year based on the data that we use to calculate state-specific energy costs from U.S. Department of Energy (2014). 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.

C. 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 were constructed specifically for our experiment. This socio-economic 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 percent) is similar to the national average from the 2009 Residential Energy Consumption Survey reported in Table 1 (63 percent). The fraction of participants with high school and college degrees is also similar to data from the U.S. 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 percent 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.

[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 percent 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.

4. 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.

A. 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 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 includes 95 percent 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 enormous 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.

B. 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

$$LTC = PP + \frac{EC(1-(1+\rho)^{-T})}{\rho} \equiv PP + \frac{EC}{\tilde{\rho}} \quad (1)$$

where ρ is the consumer's discount rate, $\tilde{\rho}$ is the discount rate adjusted for appliance life, 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. When we make these calculations we use a twelve-year appliance lifetime and use a discount rate which we estimate from our data.[16] 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 standard conditional logit model as has been done in previous

[15] We assume that the best estimate of future electricity prices is the electricity price at time of purchase. This is consistent with estimates from U.S. Energy Information Administration (2014a) which shows a flat ten year real price trend for predicted retail electricity prices.

[16] The U.S. Energy Information Administration (2014b) assumes 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.

studies of consumer take-up of energy efficient appliances.[17] This allows us to estimate an average discount rate for the sample, a necessary input for calculating expected lifetime appliance cost using equation (1) above.

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

$$U_{ij} = \alpha_1 PP_j + \alpha_2 EC_{ij} + \varepsilon_{ij}, \tag{2}$$

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} depend on both the energy-efficiency of the appliance and on the usage and electricity prices in the state where the participant lives. The idiosyncratic term ε_{ij} is assumed to be independent across participants and alternatives and have an extreme value distribution so the choice probabilities take the well-known conditional logit form.

Our estimate of $\tilde{\rho}$ is given by the ratio of estimated coefficients on purchase price and energy costs:[18]

$$\hat{\tilde{\rho}} = \frac{\hat{\alpha}_1}{\hat{\alpha}_2}. \tag{3}$$

Table 3 shows results from the regression. Our estimate of $\hat{\rho}$ from this regression is 17.4 percent. This corresponds to an underlying discount rate (ρ) of 13.7 percent assuming a 12-year lifetime.[19] In the results which follow we report lifetime costs using this discount rate as well as a value of $\tilde{\rho}$ both five percentage points lower and higher.[20] As will become clear, our qualitative results are not affected by the discount rate we choose, but the magnitude of the measured cost savings from state-specific labels is sensitive to the discount rate.

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[17] Hausman (1979) and Dubin and McFadden (1984) are seminal papers in this literature.

[18] We assume participants make decisions based on the annual energy cost information provided on the label. Note that for the control group, this is an energy cost based on national usage and electricity prices. Our estimate of the discount rate is similar if we instead restrict the sample to include the treatment group only.

[19] This is similar to recent estimates in the literature from vehicle purchases including Busse, Knittel and Zettelmeyer (2013) and Allcott and Wozny (forthcoming).

[20] These correspond to underlying discount rates, ρ, of 6.7 percent and 19.8 percent respectively.

C. Regression Estimates

We estimate regressions of the following form,

$$Y_{ijs} = \beta \cdot Treatment_i + \boldsymbol{X}'_i\gamma + \alpha_s + \varepsilon_{ijs} \tag{4}$$

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 groups, after controlling for covariates. The vector $\boldsymbol{X}$ includes household income and indicator variables for college graduate, non-white, 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

[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 non-zero 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.

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 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 percent 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 significantly 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 indicates a better allocation of energy-efficient air conditioners across states.

Some of the other coefficient estimates are also interesting. Lifetime cost is decreasing in household income, consistent with energy-efficiency being a normal good. Also, non-white 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.

D. 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, it may well be that participants in low-cost states 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 adjusted discount rate ($\tilde{\rho}$). Estimated savings increase to $15.60 with a 12.4 percent adjusted discount rate and fall to $7.09 with a 22.4 percent adjusted discount rate. In all cases, the savings are statistically significant at the 5 percent 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 upfront on air conditioners, and incur less overall lifetime cost. With a 17.4% adjusted discount rate, lifetime savings are $6.78, a difference that is statistically significant at the 5 percent 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 upfront 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 percent level.

E. 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. At a per-unit savings of $10.12 and nationwide annual sales of 4.4 million units, the cost savings for room air conditioners sold in a given year is $44.5 million.[22] Discounting future year savings at 13.7 percent (and assuming no increase in sales or annual energy costs), we get a present discounted value of savings of $370 million.

These benefits exceed any reasonable estimate of the cost of implementing state-specific labels. There are a couple of different options for deployment. The most expensive would be to require manufacturers to ship appliances with state-specific labels. Although this would not require any additional appliance testing, there would be non-negligible administrative costs from such a change. The FTC currently maintains label templates that manufacturers can download. 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.

None of this would cost very much or add much administrative burden. However, 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

[22] 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 U.S. 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 (2014)). Moreover, in the long-run manufacturers might respond to better information by changing the set of appliances offered for sale.

labels prepared for several different states.[23] We recognize that moving to state-specific labels would impose some real costs on manufacturers but think it is important that these costs be compared to the estimated benefits.

An alternative deployment option would be add a QR scan code to existing labels which consumers could scan with their smart phones.[24] The phone would know the user's location and automatically display a label with state-specific or even county-specific annual energy costs. This approach 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 almost certainly be small compared the benefits from improved information.

Note also that we have only focused on room air conditioners. State-specific labels would improve purchase decisions for all 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 are significant potential efficiency gains from improved information even for products with little predictable cross-state variation in usage.[25]

5. Underlying Mechanisms

Having documented substantial treatment effects from the introduction of state-

[23] The U.S. Department of Energy has taken a region-based approach with new minimum efficiency *standards* for air conditioners and heat pumps. The United States has been divided into three regions (North, Southwest, and Southeast) and, beginning January 1, 2015, air conditioners and heat pumps manufactured for the two Southern regions must meet a higher minimum efficiency standard. See U.S. Court of Appeals Case # 11-1485, April 24, 2014 for details.

[24] 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.

[25] 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, for example, Graff Ziven, Kotchen and Mansur (2014).

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

A. Do People 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.

Overall, participants demonstrate a remarkably poor level of label comprehension. 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.[26] There is no statistical difference between the percentage of each group that thought it was the national average price (33.6 versus 30.8 percent). However, the treatment group was more likely to answer correctly that it was the state price (17.0 versus 10.1 percent). This difference is highly 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.

B. Do People Know How Their State Compares?

[26] Allcott (2011a) provides related evidence from vehicle purchase decisions. When purchasing a vehicle, 40% of respondents report not thinking “at all” about fuel costs, and an additional 35% report thinking “some” about fuel costs but not making any calculations.

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 percent versus 30 percent) and, overall, 40% of participants were able to correctly answer the question.[27]

C. Do People 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. Participants overall 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.

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

[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 0.41 and 0.70).

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 able to mentally adjust 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 percent level, it is statistically significant at the 10 percent level and the coefficient on usage is significant at the 1 percent level. This is what we would expect given the savings documented in Tables 4 and 5. Importantly this evidence does not support the hypothesis that participants are making any mental adjustments. It seems more likely, given the lack of label comprehension in Table 7 that participants are simply responding to the operating cost presented in the state-specific labels.

D. 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 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.

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 is not at all straightforward how 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 has an Energy Star rating.[28] What is striking 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 state average residential electricity prices is 0.41. But the correlation with average usage is -0.33 and the correlation with estimated annual energy cost (electricity price multiplied by usage) is -0.23.[29] Saturation of Energy Star air conditioners appears to be systematically biased away from what would be required for efficiency.

[28] In order to obtain an Energy Star rating (and so display the Energy Star logo) product manufacturers must meet design criteria that contribute to significant energy savings without sacrificing product quality, features, and performance. Unit shipment data are from U.S. Department of Energy (2010) and come from sales data that represent roughly 60 percent of the retail market. The shares in Figure 6 should therefore be seen as indicative only.
[29] In related work, Jacobsen (2014) finds using panel data no evidence that electricity prices increase purchases of *Energy Star* appliances, and Houde (2014b) finds using transaction-level data from a major retailer relatively little sensitivity of appliance choices to local electricity prices.

That states like Vermont and Massachusetts have a high penetration of Energy Star air conditioners 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 lifetime costs in Table 4. While being affiliated with the Democratic Party does not have a statistically significant effect, affiliation with the Republican Party increases lifetime costs by $9.[30] As always, however, it is important to interpret cross-sectional comparisons with caution. Political ideology is not the only factor that could explain 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.

Nonetheless, this pronounced lack of correlation between operating costs and choices provides some real-world corroboration for the evidence from our stated-choice experiment. Revealed preference cannot tell us how much choices would be improved by better information, but it does provide suggestive evidence 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.

[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.

E. Discussion and Implications

The state-specific labels changed participants' behavior, so it is not as if they are ignoring these labels completely. But they are not exerting the effort that would be required to understand the information beyond a superficial level. In the EnergyGuide labels the annual operating cost appears in 24-point font, much 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.

We are not trying to suggest that this behavior is a "mistake". Analyzing this information carefully and translating the information on the current EnergyGuide labels into information relevant for a consumer's own state of residence requires real time and cognitive effort. These costs are significant and the benefits are relatively modest, so "rational inattention" makes sense for many consumers. In this context there can be large gains from improving the government-mandated information. While each individual's benefit from customized information is low, aggregate benefits are quite high, especially when compared with the cost of providing that information.

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. Table 10 shows that, in our experiment, electricity consumption, 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]

6. 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 as well as concerns about local pollutants from the burning of fossil fuels in electric generating plants. 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. Our experiment differs from previous studies in focusing on the role that inaccurate information plays in misdirecting consumers away from optimal choices.

Our results are consistent with an emerging view of consumers as "rationally inattentive" when it comes to making energy-related decisions. They respond to the information that is provided but with a poor understanding about where this information is coming from or what it means. Remaining imperfectly informed may well be optimal given the relatively small stakes involved, but if consumers are rationally inattentive, this elevates the role of information provision. It matters what information is provided and how it is provided. This also raises difficult public policy questions. If we can influence decision-making through information, should we be "nudging" people toward choices that reduce externalities?

The research has practical significance as well. The implied aggregate cost savings are larger than any reasonable estimate of the cost of implementing state-specific labels. The lowest-cost deployment approach would be to add QR scan codes to EnergyGuide labels – just as they have been for the new EPA fuel economy labels – that would allow consumers to pull up state-specific labels with their smart phones based on the location of the phone. This could be done not only for air conditioners, but for all appliances. While the usage of many appliances does not vary geographically as much as

[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).

air conditioning, electricity prices vary by more than 2:1 across states, so there are significant potential efficiency gains from improved information even for products with little variation in usage.

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Table 1. Air Conditioner Penetration in U.S. Homes

	US	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 U.S. 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).

Table 2. Testing for Balance in Randomized Sample

	Control	Treatment	p-value
	(1)	(2)	(3)
Annual Household Income (in dollars)	72,817	70,848	0.363
High School Graduate	0.874	0.874	1.000
College Graduate	0.289	0.289	1.000
Household Size	2.745	2.756	0.871
Married	0.533	0.533	0.981
Employed	0.582	0.564	0.408
Age 65 and older	0.174	0.179	0.723
Female	0.519	0.519	1.000
Nonwhite	0.338	0.338	1.000
Homeowner	0.728	0.695	0.100
Multiunit Property	0.250	0.256	0.718
Household has a Central Air Conditioner	0.655	0.675	0.322
Democratic Affiliation	0.316	0.314	0.942
Republican Affiliation	0.217	0.244	0.115
Average Residential Electricity Price in the State of Residence (cents per kWh)	12.49	12.32	0.088
Average Annual Hours of Air Conditioning Use in the State of Residence	1,260	1,265	0.840
Annual Cost of Operating a Medium-Sized Room Air Conditioner in the State of Residence (in dollars)	154.58	153.04	0.601

Note: This table tests for balance between the control and treatment groups. There are 1231 participants in the control group and 1209 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.

Table 3. Conditional Logit Regression Results

Variable	Coefficient Estimate
Purchase Price (PP)	-0.00223 (0.0004)
Energy cost (EC)	-0.01281 (0.0016)
Implied Discount Rate ($\tilde{\rho}$)	0.174 (0.013)

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 less than 3 choices per participant because a small number of participants failed to finish the experiment. As described in the text, the implied discount rate is calculated as the ratio of the two coefficients. Observations are weighted using sampling weights. Standard errors, clustered by state, are reported in parentheses. All coefficient estimates are statistically significant at the 1 percent level.

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

VARIABLES	(1) Purchase Price	(2) Annual Energy Cost	(3) Lifetime Cost
Treatment	3.436	-2.357*	-10.123***
	(4.996)	(1.344)	(3.765)
Household Income (x1000)	0.307***	-0.081***	-0.161***
	(0.055)	(0.014)	(0.040)
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	0.000	-0.413	-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	0.045	0.781	0.916

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 the adjusted discount rate ($\tilde{\rho}$) of 17.4 percent. 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<0.01, ** p<0.05, * p<0.1

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

			Lifetime Cost		
	Purchase Price	Annual Energy Cost	$\tilde{\rho}$ =.174	$\tilde{\rho}$ =.124	$\tilde{\rho}$ =.224
	(1)	(2)	(3)	(4)	(5)
Entire Sample	$3.44 (5.00)	-$2.36* (1.34)	-$10.12*** (3.76)	-$15.60** (6.61)	-$7.09*** (2.49)
Low Energy Cost States	-$12.49 (7.82)	$0.99 (1.09)	-$6.78** (2.77)	-$4.48 (2.87)	-$8.06** (3.58)
Middle Energy Cost States	$1.50 (9.35)	-$0.02 (2.31)	$1.37 (4.40)	$1.32 (9.58)	$1.40 (1.99)
High Energy Cost States	$22.86** (9.02)	-$7.98** (3.23)	-$23.06** (9.98)	-$41.61** (17.39)	-$12.81** (5.97)

Note: This table reports coefficient estimates and standard errors corresponding to the treatment indicator variable from twenty 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 adjusted discount rates ($\tilde{\rho}$) of 17.4, 12.4, and 22.4 percent as indicated. All regressions include state fixed effects as well as household income and indicator variables for college graduate, non-white, 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.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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

Lifetime Cost Savings per Room Air Conditioner	$10.12
Annual Sales of Room Air Conditioners	4.4 million
Total Cost Savings per Year	$44.5 million
Total Cost Savings – All Future Years (discounted at 13.7 percent)	$369.5 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% (appliance lifetime adjusted discount rate of 17.4%). Annual sales of room air conditioners come from U.S. Department of Energy (2013b). 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.

Table 7. Testing Label Comprehension

	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
	(1)	(2)	(3)
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%	0.152
The average electricity price in my state.	10.1%	**17.0%**	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%	0.392
The average usage level for air conditioners in my state.	9.8%	**14.5%**	0.001
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.			

Table 8: Testing Knowledge About Energy Costs

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 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 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. Do Participants Take Local Factors Into Account?

	Participants Shown Current Labels (i.e. Control Group)	Participants Shown State-Specific Labels (i.e. Treatment Group)
	(1)	(2)
Electricity Price (cents per kWh)	-0.036 (0.025)	0.041* (0.024)
Annual Hours of Air Conditioning Usage (in 100s)	0.0050 (0.0085)	0.0398*** (0.0085)
p-value for joint test that price and usage do not influence EER choice	0.245	0.000
Number of Observations	3670	3605

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, non-white, married, age 65 or over, and political party affiliation. In both regressions observations are weighted using sampling weights. Standard errors are clustered by participant.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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

	Annual Electricity Consumption (in kilowatt hours)
Entire Sample	-16.5 (11.1)
Low Energy Cost States	10.2 (9.2)
Middle Energy Cost States	8.5 (16.2)
High Energy 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, non-white, 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<0.01, ** p<0.05, * p<0.1

Figure 1: Annual Cooling Hours by State

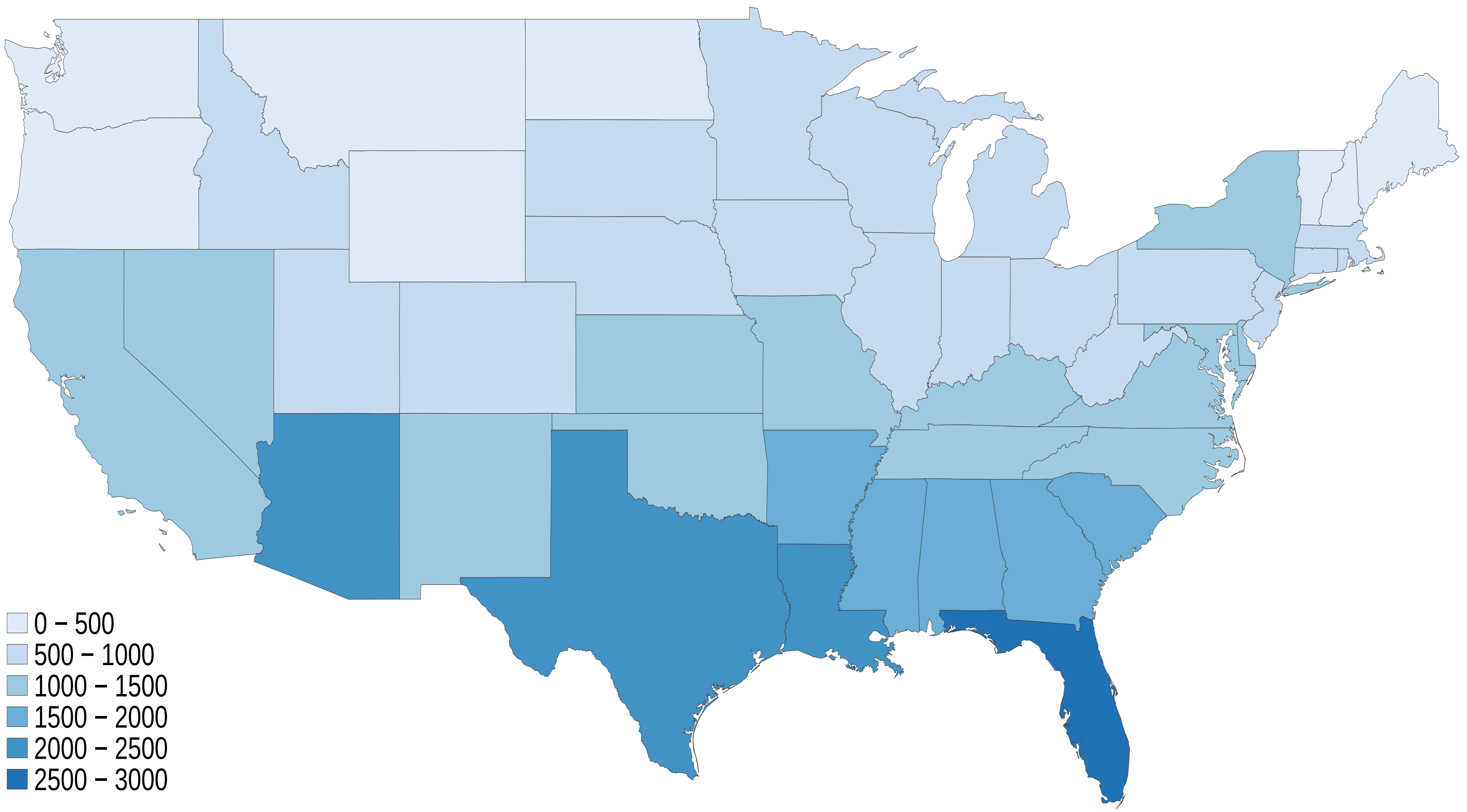


Figure 2: Residential Electricity Prices by State

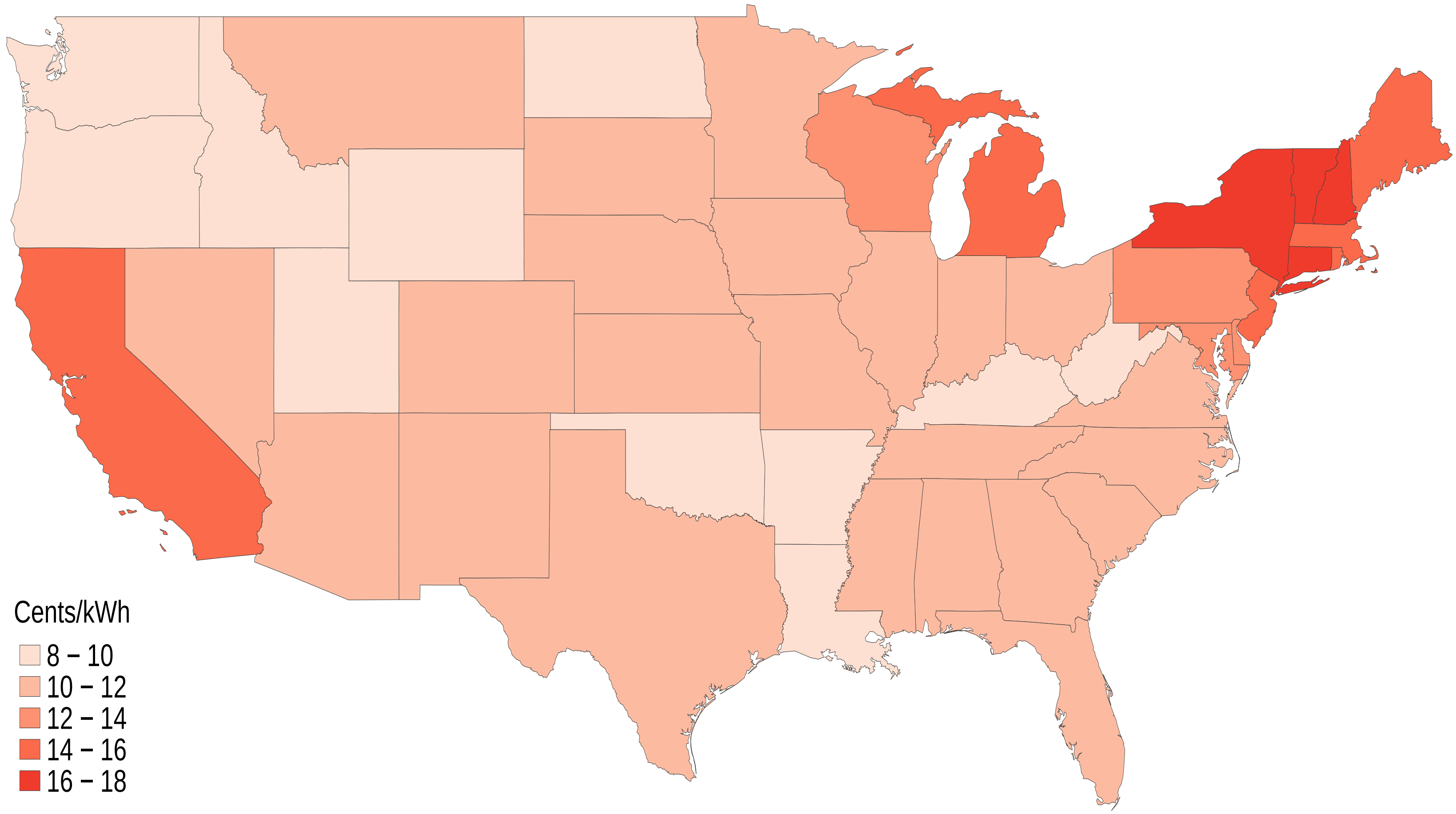


Figure 3: The Cost of Operating a Medium-Sized Room Air Conditioner

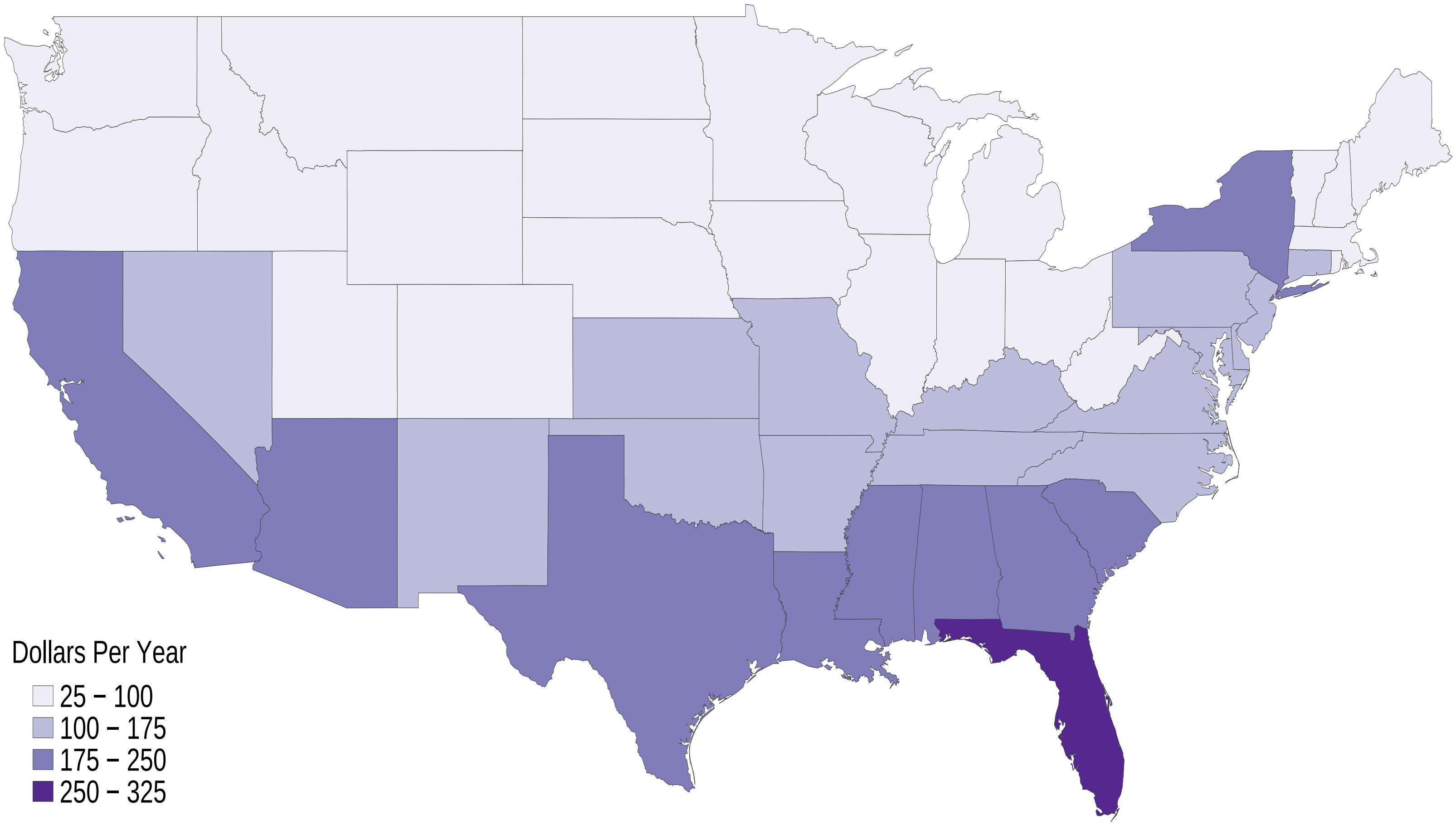
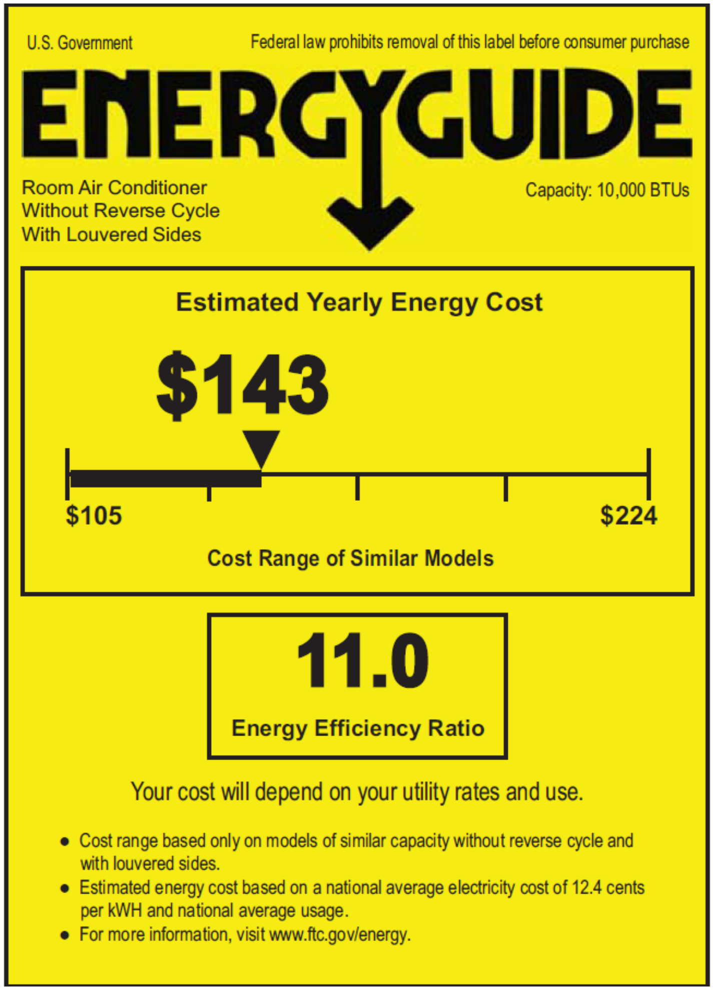


Figure 4: Control and Treatment Labels

Control Group



Treatment Group

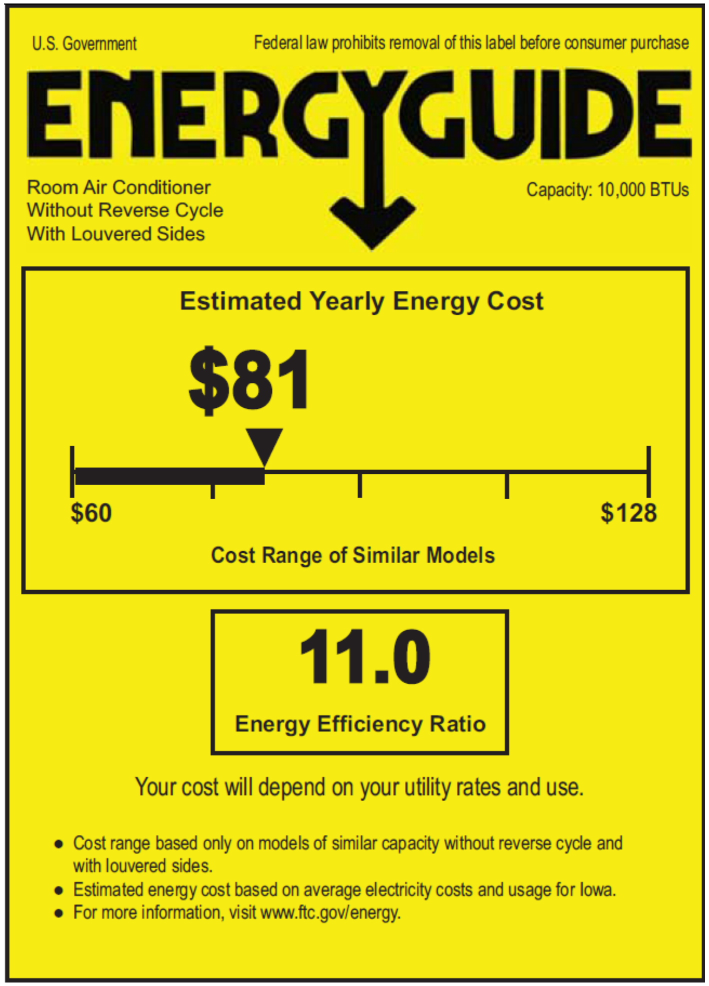


Figure 5. Do Better Labels Lead to Better Choices?

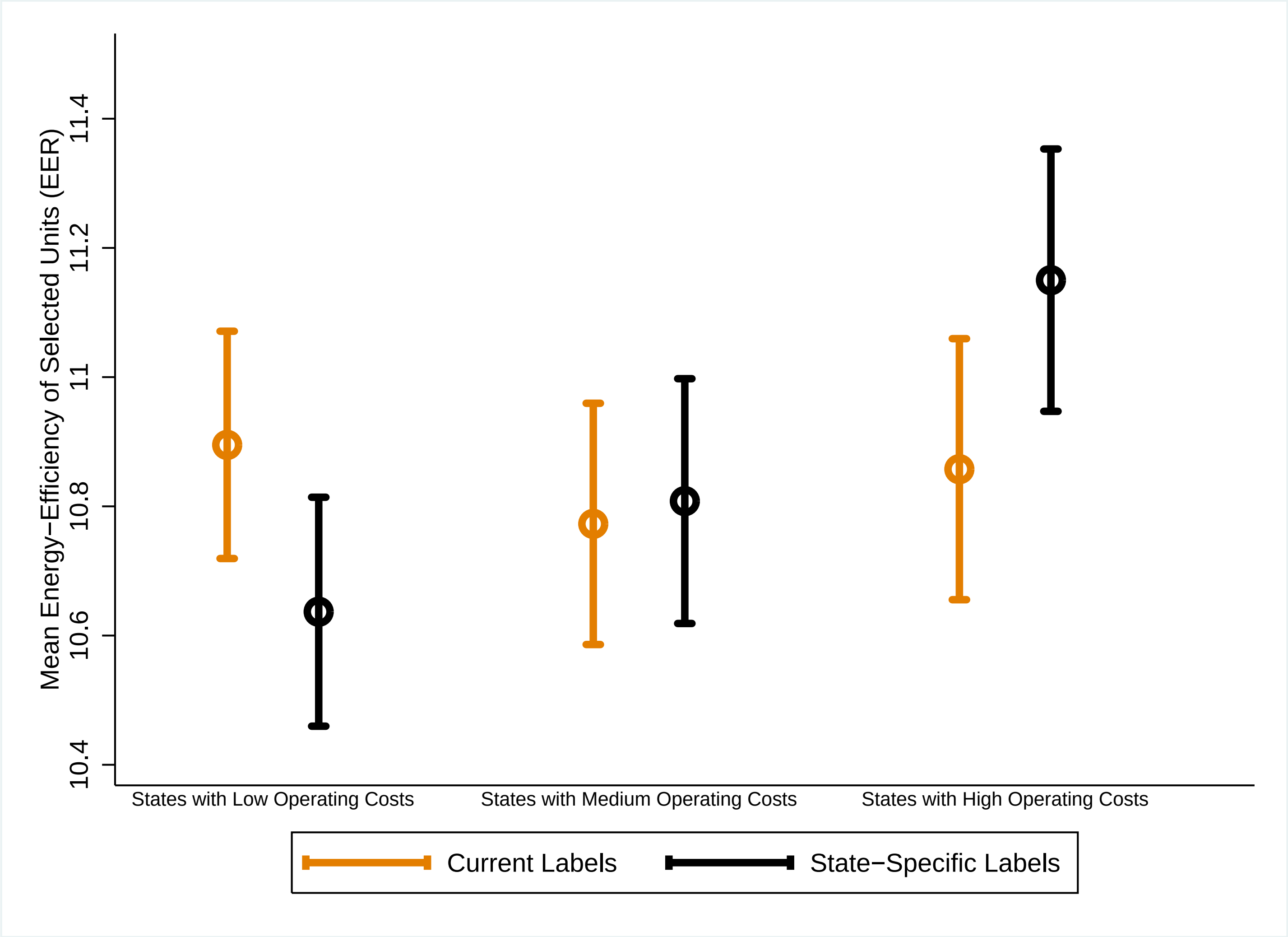
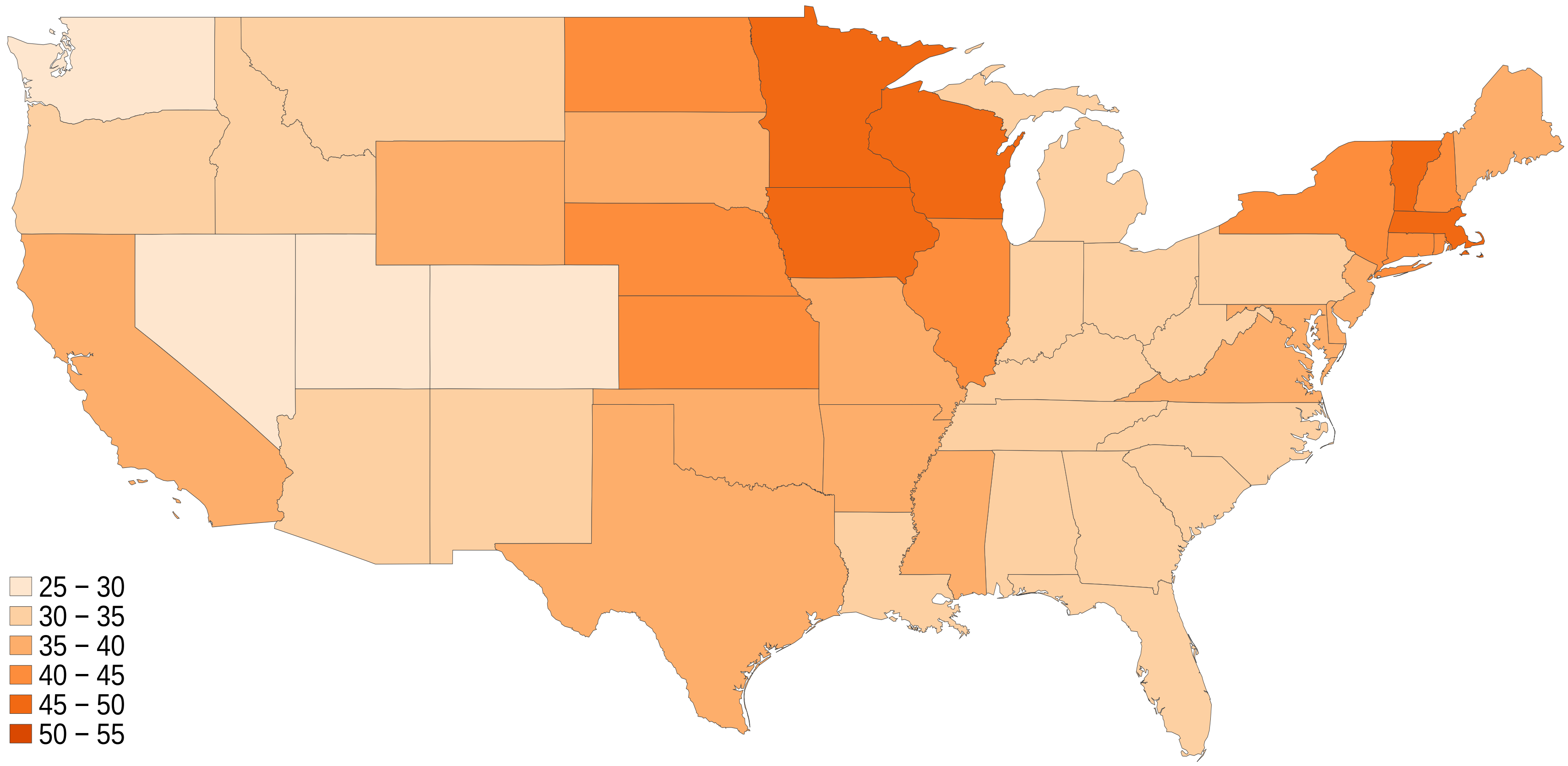


Figure 6. Share of New Air Conditioners Sold in 2009 that are *Energy Star*



Appendix I: Additional Information About the Experiment

The experiment ran from July 16 to August 1, 2014. Participants in the experiment were not allowed to go back to earlier questions upon moving forward to the next screen in the experiment. If they did not answer a question, they were prompted once to answer and then they were allowed to proceed. Less than one percent of responses were blank.

A1 – Complete Survey Instrument

[Screen 1]

Q1. What type of air conditioning equipment do you have in your dwelling?

I have a central air conditioning system. 1
I have a room air conditioning unit (or units). 2
I don't have air conditioning in my dwelling. 3

[Screen 2]

Imagine that a room has been added to your house that is not cooled by your central air conditioner.[32] You have decided to purchase a room air conditioner for this room.

The next screen will describe three different air conditioners. For each option you will be shown an Energy Guide label which provides information about operating costs. The purchase price is also provided for each option. You will be asked to select your preferred air conditioner.

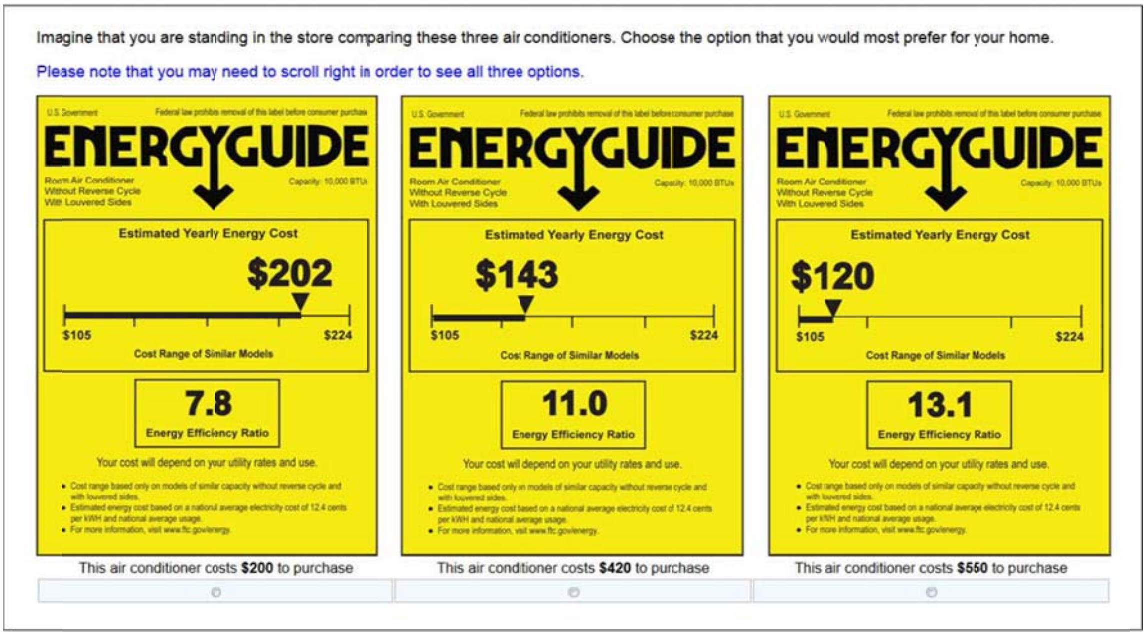
Assume that all characteristics other than purchase and operating cost of the three options are identical and that the air conditioner has been properly sized for this room. Feel free to use a calculator and/or scratch pad to assist you in evaluating the options.

[Screens 3-5]

Q2 – Q4.

Note: The screen shot below is a representative set of room air conditioner choices among which the participant were asked to choose.

[32] If the participant does not have central air, the first sentence reads "Imagine a room in your house that is not currently air conditioned."



[Screen 6]

Q5. 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. 1
The average electricity price in my state. 2
I'm not sure. 3

[Screen 7]

Q6. 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. 1
My state's electricity prices are lower than the national average. 2
I'm not sure. 3

[Screen 8]

Q7. 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. 1

The average usage level for air conditioners in my state. 2
I'm not sure. 3

[Screen 9]

Q8. 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. 1
Average usage in my state is probably lower than the national average. 2
I'm not sure. 3

[Screen 10]

Q9. How do you think air conditioning usage in your home compares to the average usage in your state?

Usage in my home is probably higher than the state average. 1
Usage in my home is probably lower than the state average. 2
Usage in my home is probably very close to the state average. 3

End of Experiment

A2 –Sampling Design

1. Sample designed to match key benchmarks
   - **Gender:** Male or Female
   - **Age:** 18–29, 30–44, 45–59, and 60+
   - **Race/Ethnicity:** Hispanic and non-Hispanic White, Black, Other, and 2+ Races
   - **Education:** Less than High School, High School, Some College, Bachelor and beyond
   - **Census Region:** Northeast, Midwest, South, and West
   - **Household Income:** $0-$10K, $10K-<$25K, $25K-<$50K, $50K-<$75K, $75K-<$100K, and $100K+
   - **Home Ownership:** Own or Rent/Other
   - **Metropolitan Area:** Yes or No
   - **Home Internet Access:** Yes or No

2. Study specific final weights computed to adjust for experiment-specific nonresponse along the following dimensions
   - gender

- race/ethnicity
- education
- census region
- household income
- home internet service

A3 – Appliance Choice Questions

Each participant in the experiment was shown a screen with three room air conditioner choices and asked to select their most preferred model. The choices ranged from least to most expensive. More energy-efficient air conditioners were more expensive. After selecting their preferred model, they were asked to make two additional purchase decisions in an identical manner to their first selection decision. The design matrix for the three sets of choices was as follows:

Table A1. Purchase Prices for Air Conditioner Choices

	Energy Efficiency Rating (EER)		
	7.8	*11.0*	*13.1*
Decision 1	$200	$420	$550
Decision 2	$200	$505	$600
Decision 3	$200	$335	$440

That is, the energy-efficiency rating of the three choices was the same for all participants and all decisions. We varied the purchase prices across decisions as indicated above. For all three questions, participants were shown labels that calculated energy costs as a function of the EER rating (7.8, 11.0, or 13.1) and either average national usage and electricity prices (control group) or average state usage and electricity prices. Annual energy costs (EC) are given by the following formula:

(A1)
$$EC = \frac{BTU}{EER} hours \cdot price$$

where *BTU* is the rated size of the air conditioner (10,000 BTU's for our experiment).

We selected these EER values to reflect typical levels for room air conditioners in the market for sale in 2014. Then we selected the purchase prices based on simulation evidence to maximize the precision of our estimates. In particular, we constructed synthetic nationally-representative data, and then for an assumed distribution of discount rates simulated choices using draws from an extreme value distribution. We included both a treatment group and a control group and assumed both would take the information in the labels at face value. Then with the generated "data," we estimated the discount rate and examined the distribution of choices across states as in Figure 5 from the paper. The purchase prices above were those that minimized the standard error of the estimated discount rate and provided a good mix of choices across states for both the treatment and control groups.