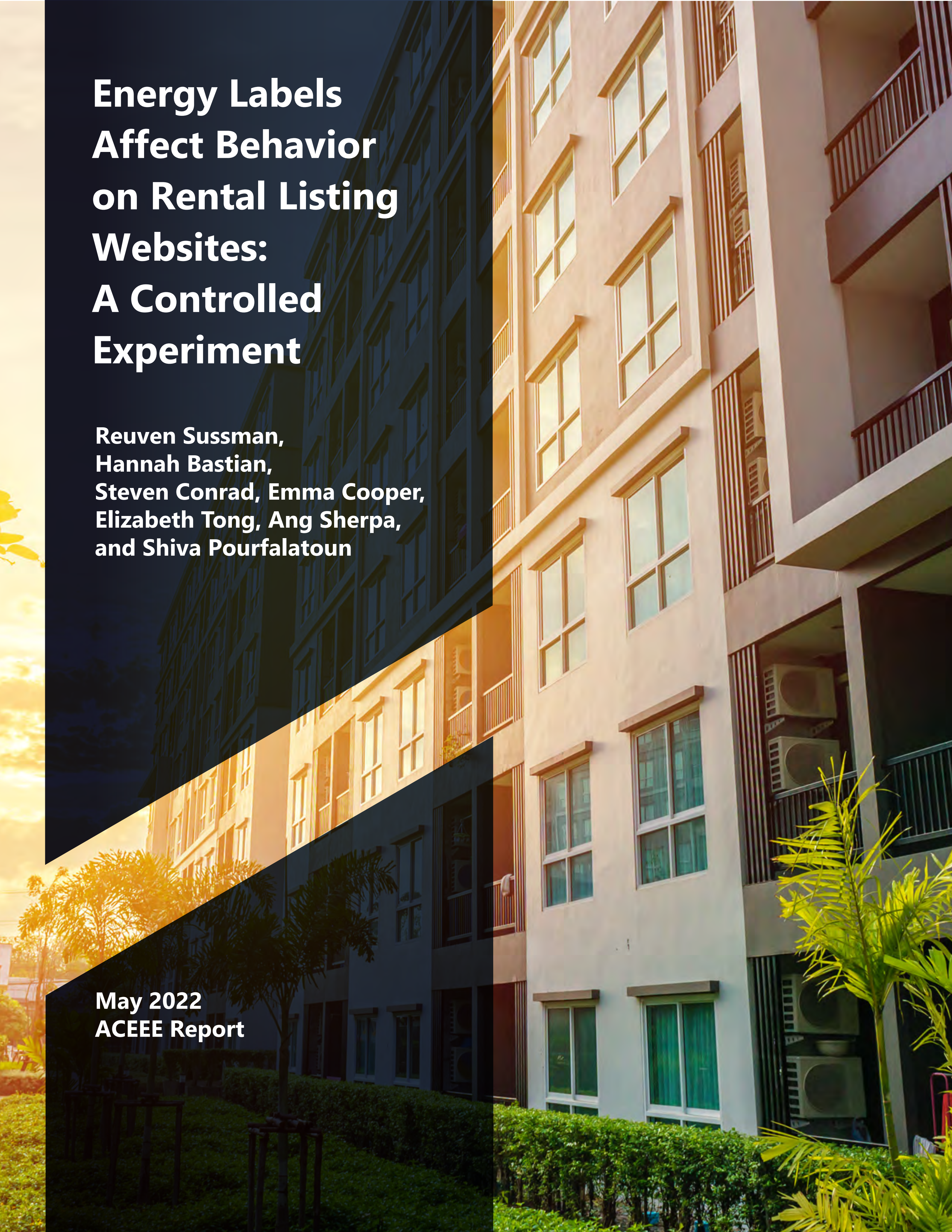

Energy Labels Affect Behavior on Rental Listing Websites: A Controlled Experiment

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ACEEE Report

Contents

About ACEEE

The **American Council for an Energy-Efficient Economy** (ACEEE), a nonprofit research organization, develops policies to reduce energy waste and combat climate change. Its independent analysis advances investments, programs, and behaviors that use energy more effectively and help build an equitable clean energy future.

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Executive Summary

KEY FINDINGS

- Energy labels on rental listings change renters' property preferences. On a mock rental listings website, the presence of energy labels on listings encouraged a nationally representative sample of renters to select the most efficient listings 21% more often and, coincidentally, the least efficient option 21% less often than when energy efficiency information was hidden.
- Energy efficiency labels that provide additional context information (i.e., how one home compares to others or to a maximum score) are better for influencing renter behavior than those offering less context information. When labels show the efficiency of homes (houses and apartments) compared to the efficiency of similar homes, they are more persuasive than when they do not. For example, placing estimated energy costs for a home along a scale of minimum and maximum costs affects decisions more than presenting energy costs without a continuum.
- Presenting efficiency information for only the most efficient homes (as is typical for voluntary programs) did not encourage renters to choose more efficient homes in our simulation. For this reason, voluntary labeling programs for real estate listings should not be local policymakers' preferred solution. However, voluntary programs may work well as stepping-stones toward longer-term goals of mandatory assessment and labeling of all homes at time of listing.
- Renters looking for apartments (as opposed to detached homes), renters in the hottest and coolest climates, and young renters (under 45), were willing to increase rent by the highest percentage in exchange for increases in energy score. Renter income was not a factor in this simulation, even for renters qualified as low income or as having a high energy burden.

When renters search for homes, they rarely know the energy costs they will have to pay in their new residence. This lack of information can hurt them financially once they move in, and it hampers their ability to plan budgets. Landlords, however, experience no repercussions for having inefficient homes—and rarely have incentives to upgrade their rental units. Being overburdened by energy costs can lead renters to cut back in other critical areas, such as monthly spending on food and medicine. More than 40% of renters end up having to occasionally reduce monthly spending on food and medicine to pay their energy bills (JCHS 2022). If energy efficiency or energy cost information was present in rental listings, would it change renters' decisions about where to live? In this study, we sought to explore this question. In addition to better understanding how much renters value energy efficiency when looking for potential rentals, we sought to determine how their decisions would change if rental listings included energy information.

To find a place to live, many renters rely on rental listing websites such as Zillow, Craigslist, and apartments.com. We created a mock rental listings website, replicating real-world conditions, to conduct a tightly controlled discrete choice experiment (DCE) to evaluate the impact of energy information labels on renters' choices. Using a panel research firm, we recruited a large nationally representative sample of current renters to visit the mock website and choose the rental units they most preferred as if they were searching for their next home. Although participants were aware that the website was not real, we asked them to choose their preferred properties as though they were examining actual rental listing search results. They examined six sets of "search results" that related to their specified home preferences. The search results included energy efficiency information but varied in how that information was presented (or, in the control condition, if it was presented at all). Based on each participant's choices, we calculated how often participants selected the most and least efficient listings, and how much participants were willing to pay (in increased monthly rent) for an increase in energy efficiency score.

Do Renters Click on More Efficient Listings?

Yes. The presence of energy labels changed the decisions renters made on our simulated rental listing website. Participants clicked on the most efficient homes (selecting them as their favorite in the set) 21% more frequently, and the least efficient homes 21% less frequently when listings included energy information labels than when they did not. These findings suggest that the presence of energy labels can change the decisions renters make on rental listing websites.

Which Labels Are the Most Effective?

Labels that provide good context information—such as how one home compares to others or to a maximum score—are most effective for encouraging renters to favorite efficient homes. For example, labels in table ES1 that show energy costs along a continuum of minimum and maximum energy costs are more effective than labels that show energy costs without a continuum. These findings suggest that renters need key context information to understand energy information labels.

Table ES1. Energy costs presented with and without a continuum

Energy costs without a continuum	Energy costs along a continuum
$1,239 / month **2** bedrooms | **1.5** bathrooms | **1075** square feet Monthly energy bills: **$155**	**$1,239** / month **2** bedrooms | **1.5** bathrooms | **1075** square feet **Monthly Energy Bills** $ 88 100 112 126 146 $155 178 193 213 234

Similarly, in our simulation, voluntary energy efficiency labels (which present efficiency information only for the most efficient rental options) did not significantly influence renters' choices.[1] Previous research in psychology suggests that this may be because when labels are attached only to the most efficient listings, renters cannot easily compare listings to one another (i.e., the richness of the context information is reduced) and this reduces the label's effectiveness.

Which Renters Value Energy Efficiency the Most?

We found that certain demographic groups showed the highest interest in energy efficiency. Renters looking for apartments (as opposed to detached homes), renters in the hottest and coolest climates, and young renters (those under 45) were willing to increase their rent by the highest percentage in exchange for improvements in energy score. In contrast, income and education levels did not appear to impact behavior, even among those who qualified as low income or as having a high energy burden.

Recommendations for Policymakers

We recommend that local policymakers implement policies requiring landlords to share energy information with renters at the time of listing (i.e., in rental listings on rental websites). Because renters value this information, landlords should be motivated to improve the efficiency of their residential units, which would help improve the energy performance of existing U.S. rental housing (EIA 2018). Information transparency between landlords and tenants improves decision making and is a relatively inexpensive way to encourage rental markets to possibly correct themselves. We further suggest that policymakers choose labels providing context information, and that they use voluntary labeling schemes primarily as precursors to energy assessment and labeling mandates for all homes. Voluntary labeling policies are important first steps toward enacting labeling mandates because they are generally amenable to constituents (voters) and stakeholders (e.g., landlords, renters, real

[1] Renters in the control condition (in which energy efficiency information was hidden for all options) favorited the most efficient homes an average of 1.96 times (out of six). In the voluntary label condition (in which only the most efficient homes were labeled), renters favorited the most efficient homes an average of 2.14 times out of six. This slight increase was not statistically significant ($p > .05$) and therefore may have been due to chance. Similarly, renters in the voluntary label condition favorited the least efficient homes slightly less than those in the control condition (an average of 1.79 times versus 1.89 times), but this difference was also not statistically significant ($p > .05$). A lack of statistical significance does not necessarily mean that voluntary labels are completely ineffective; they may have a small effect that might be detectable in a larger sample size. Moreover, because voluntary labels (e.g., ENERGY STAR labels) are often effective for purchasing other products, this finding deserves further examination and follow-up research.

estate agents, and assessors). However, policymakers should ultimately seek to move to mandatory across-the-board labels if possible.

Introduction

The residential sector is an important target area for carbon reductions and climate change mitigation. In 2020, residential buildings accounted for approximately 22% of energy consumption and 20% of carbon emissions in the United States (EIA 2021a, 2021b). ACEEE's *Halfway There* report outlines a pathway through which we can cut U.S. energy consumption and emissions in half by 2050. In this pathway, building efficiency accounted for 40% of energy savings and 33% of greenhouse gas emissions reductions (Ungar and Nadel 2019).

Improving the efficiency of rental properties will be essential to meeting energy and emissions saving goals in a fair and equitable way. Rental units make up a significant proportion of America's housing stock (approximately 90% of apartment units and 20% of single-family houses) (EIA 2018). They also consume 15% more energy per square foot than owner-occupied homes (EIA 2018) and are more likely to be occupied by low-income individuals and members of racial and ethnic minority groups (Desilver 2021).

Rental properties can be an especially difficult target for policymakers. One of the greatest energy efficiency challenges in this sector is the split-incentive problem: Renters cannot install permanent efficiency upgrades in their homes without landlord permission, while landlords have little incentive to install efficiency upgrades if they do not pay for utilities because they cannot earn back their investment through energy bill savings.

Another challenge is that landlords and prospective renters have asymmetric knowledge of the property in question. Landlords rarely provide renters with information about the energy performance of a building or rental unit when listing or leasing the unit, let alone offer such information in a way that makes it easy for tenants to compare the energy costs of different units. Moreover, multifamily building owners who are not responsible for energy bills may not have access to the energy cost information for their individual units. Similarly, multifamily building owners of master-metered buildings (which do not have unit-level sub-meters) will have access only to energy cost data for the whole building and thus can only estimate the energy cost of individual units. Without energy performance information, renters cannot factor energy efficiency into their decision-making process. Ultimately, this lack of information also prevents the rental market from accurately accounting for the value of energy efficiency (Melvin 2018).

One potential solution for minimizing the impact of these two barriers is to implement policies that require landlords to disclose energy information in rental listings. Several U.S. cities and European Union countries have implemented information disclosure policies to help minimize the information asymmetry between landlords and renters. If including energy information in rental listings influences renters to choose more efficient homes, then landlords may be incentivized to improve their properties' energy efficiency, with the ultimate goal of higher rents and lower vacancy rates. Our project aims to (1) determine whether renters choose more efficient homes and apartments when they have energy label information, (2) quantify how much renters would be willing to increase their rent for a more efficient home or apartment, and (3) identify which energy information has the greatest impact on renter decisions.

Landlords should also be motivated to reduce renter energy costs because high energy costs for renters can impact owners in several ways. They can lead to higher delinquency rates, lower tenant satisfaction, higher turnover costs, and ultimately, lower valuation. Moreover, by reducing the amount renters pay to external third parties (e.g., energy utilities), landlords might increase their "wallet share" of tenants' spending, which is a target metric often used in other industries.

Beyond influencing landlords, energy labels on rental listings may also have important effects on renters. Given that renters typically have higher energy burdens than homeowners (i.e., renters spend a higher proportion of their income on energy costs) (Drehobl et al. 2020) and are more likely to experience energy insecurity and rely on government-funded energy assistance (NEADA 2019), getting a preview of the energy bills in their new home is particularly important. Typically, renters have lower incomes than owners and many have experienced particularly negative financial impacts from the COVID-19 pandemic (JCHS 2022).

Moreover, renters are more likely to live in older homes with a higher likelihood of health and safety problems (e.g., mold). Energy efficiency scores could serve as a proxy for renters to estimate the comfort and healthiness of a given home because energy upgrades have the potential to address some of these issues (Hayes and Denson 2019). As multifamily buildings are renovated and potentially electrified (e.g., moving from a whole-building central heating system to in-unit heat pumps), renters may become more likely to pay their share of heating bills (as opposed to those costs being included in rent) and thus, energy information could become an even more important data point when searching for a home.

Energy labels on rental listings may have the benefit of helping renters make better rental decisions, and this, in turn, may push landlords to improve the efficiency of their buildings. However, research investigating this causal link is rare for rental properties.

AN EXPERIMENTAL APPROACH

A 2020 ACEEE study concluded that including energy efficiency information changes homebuyer decisions—that is, it increases the likelihood of homebuyers clicking on efficient listings (and not clicking on inefficient listings) (Sussman et al. 2020). It also included a calculation of the monetary value homebuyers placed on energy efficiency (the willingness to pay in terms of increase purchase price for a one-unit increase in Home Energy Score[2])

[2] Home Energy Score is an energy efficiency score (from 1 to 10, with 10 being best) based on the home's envelope (foundation, roof/attic, walls, insulation, windows) and heating, cooling, and hot-water systems. It

and noted that this value fluctuated based on how energy efficiency was labeled. Specifically, labels with clear context information (i.e., how a given home compares to others) raised homebuyers' willingness to pay for energy-efficient homes the most and best encouraged them to select energy-efficient options (Sussman et al. 2021).

This project builds on the 2020 experiment, using similar methodology to examine energy efficiency labels for rental properties. Research of this type has been conducted before, but with restricted populations and without a design that replicates real-world experiences (i.e., browsing a rental listing website). For example, an Irish study with students from one university used a discrete choice experiment (DCE) with hypothetical one-bedroom apartments that included energy efficiency among other attributes (Carroll et al. 2019). The study found that energy efficiency was a significant factor in students' decisions. Another study, conducted in Barcelona (Marmolejo-Duarte and Bravi 2017), examined the decisions of renters and buyers through a choice experiment and found that buildings with energy ratings of "A" (most efficient) were preferable to those with ratings of "E" (least efficient). In addition to being situated in Europe and focused on specific populations, these two experiments did not test the effectiveness of different labels in a real-life decision scenario. We also found other behavioral experiments on rental units, but they did not examine energy efficiency as an attribute in decision making (Edwards 2019; Liao, Farber, and Ewing 2013; Verhetsel et al. 2017).

Research Questions

The purpose of our research was to evaluate how energy efficiency information impacts renter behavior when looking for housing on rental listing websites. We asked the following research questions:

1. Do renters click on more efficient homes when rental listings contain energy efficiency information?
2. Which energy efficiency labeling approaches most increase willingness to pay for energy efficiency?
3. Which renter demographics value energy efficiency the most?
4. How do findings about renters compare to our previous research findings about homebuyers?

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provides a total energy use estimate, as well as estimates by fuel type assuming standard operating conditions and occupant behavior. It also provides an energy cost estimate, and it can include a list of cost-effective energy improvement recommendations as well as a "Score with Improvements" assuming all of the listed recommendations are made.

Method

DISCRETE CHOICE EXPERIMENTS

DCEs are a type of experimental method that allows researchers to assess participants' preferences when given a carefully designed set of choices. In DCEs, researchers create controlled sets of choices that require participants to make tradeoffs between the choice options in each set. Based on the participants' decisions, researchers can infer the relative value of each choice. For example, an experiment to determine how consumers value energy efficiency when appliance shopping might use choice sets that ask participants to choose products with varying levels of efficiency ratings, reliability ratings, and prices. Some options may have high efficiency and reliability, but also high prices, while others may have low efficiency, low reliability, and low prices, and still others may have different combinations of those attributes. Using the participants' choices, the researchers can infer how much the participants value energy efficiency relative to other attributes (in this case, price and reliability).

DCEs have three key design features: attributes, attribute levels, and choice sets. *Attributes* are the key characteristics of the product or idea that the researchers are testing. In the example above, the attributes of home appliances were price, reliability ratings, and efficiency ratings. Each attribute has multiple *levels* (e.g., high, moderate, and low). The choice options are constructed with unique combinations of levels of each attribute. These options are combined into *choice sets* of (usually) two to four options each. Each participant is presented with several choice sets in succession and, for each one, decides which option they prefer within the set.

DCEs are well suited for learning about renter energy efficiency preferences because they offer several advantages over other methods. First and foremost, our previous research demonstrated that a DCE could produce statistically significant findings about how energy efficiency information can influence people's behavior when looking for homes on real estate websites. Second, in this study, the DCE reduced the influence of various biases by using specific measurable choice options rather than open-ended questions or self-reports. The DCE also allowed us to calculate how much people were willing to pay in increased rent for rental unit attributes (including energy efficiency) and what tradeoffs they would make among the attributes. Unlike the real-world research on rental listings, using a DCE also allowed us to carefully control all non-energy-related attributes.

THE CURRENT STUDY

For this study, we designed our DCE to look like a simplified rental listing website named *RentDragon* and asked participants to imagine they were using the website to search for an actual property to rent.[3] We instructed them to specify key characteristics for their rental search, including location, desired property type (house or apartment), preferred number of bedrooms, and preferred monthly rent. These specifications are commonly asked on the first pages of rental listing websites.[4] Figures 1 and 2 show the filter pages of our experiment.

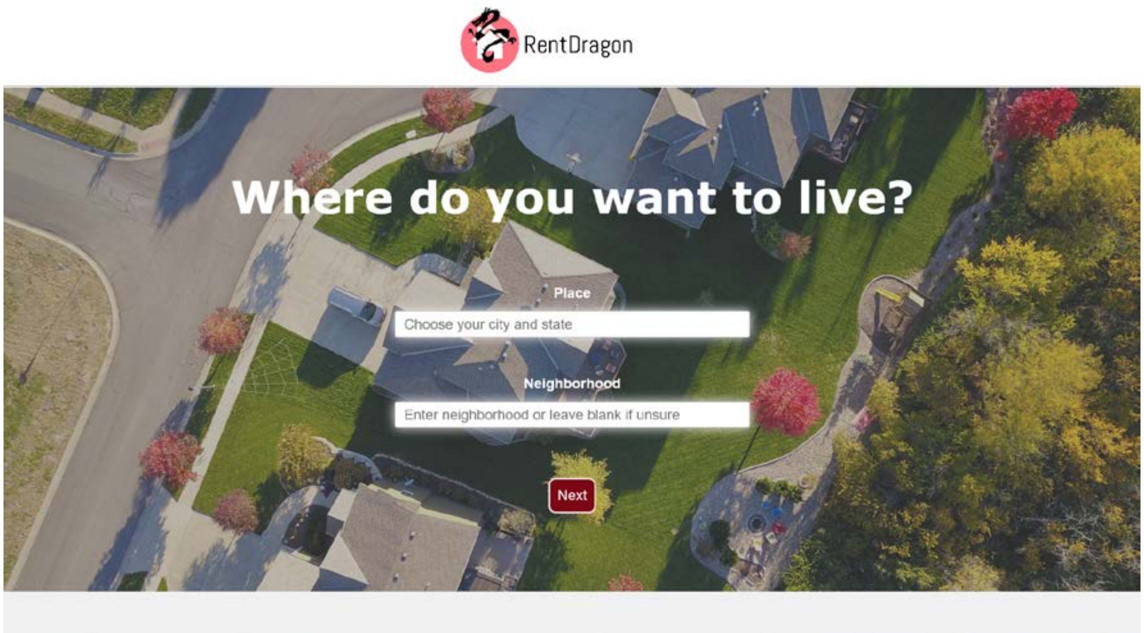

Figure 1. The design of our first filter page. Participants were required to enter their location ("place") and had the option of specificying their neighborhood. As participants typed their preferred city, Google Maps would auto-fill possible options, allowing researchers to reliably examine location-specific metrics.

[3] While rental listing websites can vary in design, we identified common design characteristics among 13 popular rental listing websites to create a simplified website design that reflected real websites. Appendix A includes more information about our design process.

[4] Appendix A provides more information about how and why we chose these specific characteristics for our filter pages.

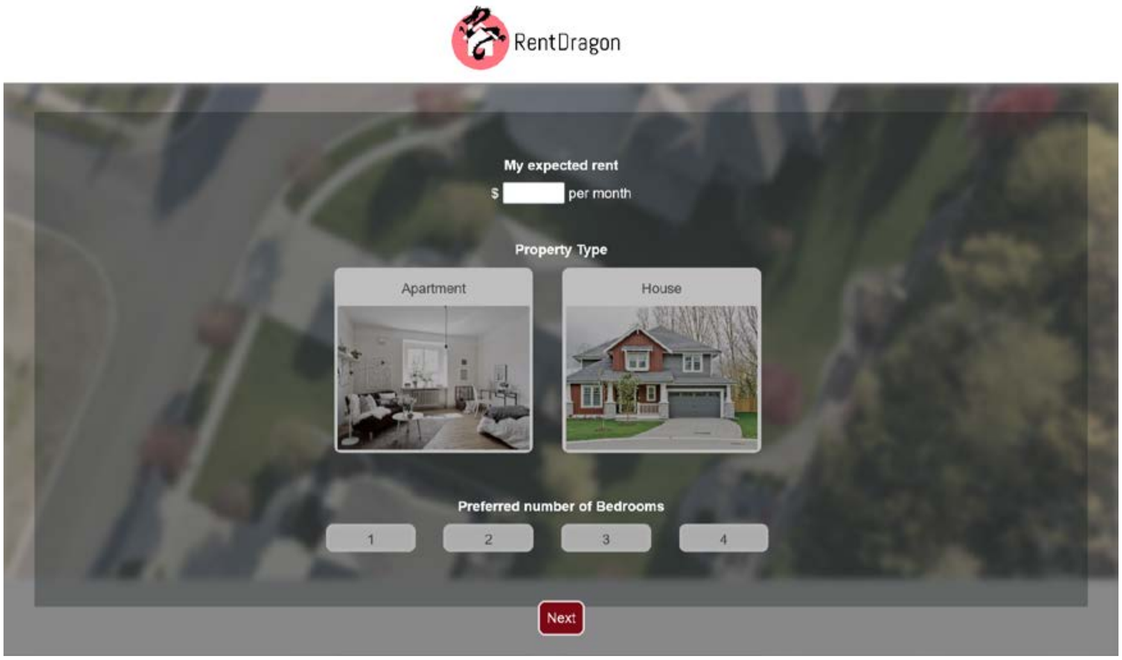

Figure 2. The second filter page design. After submitting their preferred location, participants were shown this second page where they entered additional preferences for expected rent, property type, and preferred number of bedrooms.

After submitting their preferences on the filter pages, the webpage showed six sets of "search results" with three options (or "listings") each. The so-called "search results" were carefully designed DCE choice sets that were customized based on participants' initial characteristic specifications. For example, if participants said they were looking for an apartment with two bedrooms for $1,500, they were presented with choice options that had one, two, or three bedrooms and cost $1,353, $1,451, $1,459, or $1,646. Appendix A shows the factors we used to calculate pivot prices and other attributes. Participants were each shown six sets, each of which had three choice options, and were asked to select the rental unit they preferred the most in each set. Figure 3 shows an example choice set.

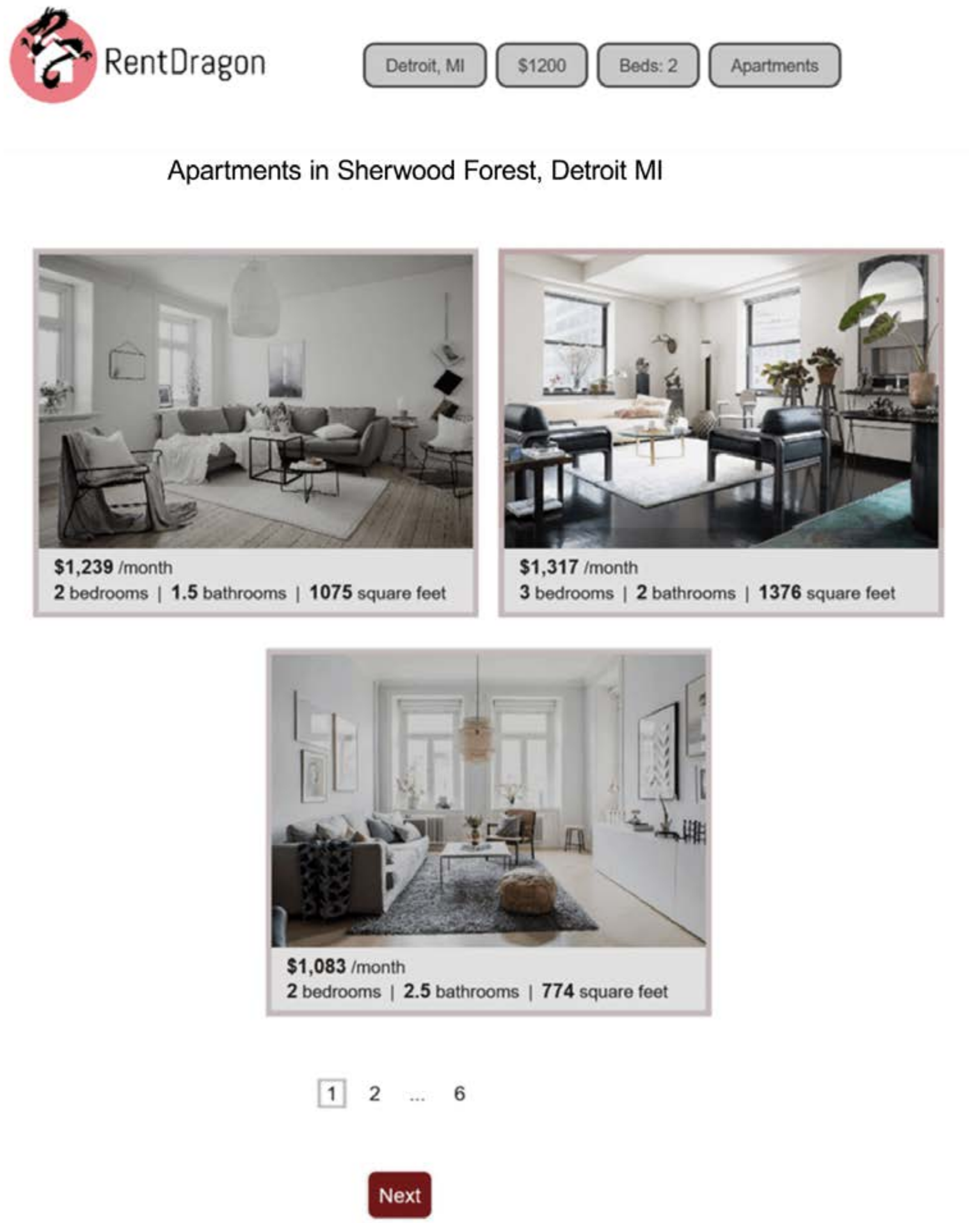

Figure 3. An example choice set. Renters were shown six choice sets that featured three rental-unit choice options each. They were asked to select the unit they preferred the most in each set.

Each rental listing in each choice set had six attributes, five of which we selected based on the most common criteria used on actual rental websites: a photo, monthly rent, number of bedrooms, number of bathrooms, and square footage. In addition to these five, we added energy information to test its potential influence on decision making.[5] Although photos are not usually used in DCEs, they were important in this case because they were critical to the realism of the experiment. We controlled for the potential effects of photos on decision making by systematically rotating the same three photos of apartments (or houses, depending on participant preferences) throughout the experiment. To choose the photos, we conducted a preliminary survey and a Google image search to find images that had similar desirability ratings. Appendix A offers further details about how we chose the photos.

Our experiment included an additional layer of complexity that made it unusual among DCE studies. This additional layer transformed the DCE into a true experiment capable of demonstrating that the way energy information is presented can *cause* a change in renter decision making. To achieve this, we randomly assigned renters to one of seven groups (conditions) who each saw the *exact same DCE choice sets*, except that the energy efficiency information attribute was presented in a different format. For six of the groups (experimental conditions), the listings showed energy information with various labels; for the seventh group (control condition), the energy information was hidden (as is typical of nearly all current real-world listings). Table 1 shows how energy information was presented to renters in each of the seven groups, and figure 4 shows the different labels used in the experiment.

[5] Appendix A offers more information about our design methodology.

Table 1. Energy label designs for each group

Group	Description	Image
1	Estimated monthly energy costs, customized by rental location	Monthly Energy Bills: **$XX**
2	Estimated monthly costs along a continuum, customized by rental location	Monthly Energy Bills $ $$ $$$
3	Energy score[1]	Home Energy Score: **X/10** Building Energy Score: **X/10**
4	Energy score along a continuum[2]	Home Energy Score 1 X 10 Building Energy Rating 1 X 10
5	Rent with energy costs included, customized by rental location	**$X,XXX** / month (including energy costs)
6	Voluntary label for only highly efficient houses and apartments[3]	Home Energy Score: **X/10** Energy Star Home Building Energy Score: **X/10** Energy Star Building
7	Control condition in which energy information was hidden from renters	Control: Energy Costs Hidden

1. U.S. Department of Energy (DOE) Home Energy Score for single-family homes or DOE Building Energy Asset Score (Asset Score) for apartments.

2. Home Energy Score (for single-family homes) or Asset Score (for apartment buildings) on a continuum from 1 (least efficient) to 10 (most efficient).

3. This condition presented energy efficiency information only for the most efficient homes. The label showed the energy score as well as an energy certification logo (for Home Performance with Energy Star).

Condition 1
Estimated Energy Costs

$1,239 / month
2 bedrooms | **1.5** bathrooms | **1075** square feet
Monthly energy bills: **$155**

Condition 2
Estimated Energy Costs on a Continuum

$1,239 / month
2 bedrooms | **1.5** bathrooms | **1075** square feet
Monthly Energy Bills
$ 88 100 112 126 146 $155 178 193 213 234

Condition 3
Energy Score

$1,239 / month
2 bedrooms | **1.5** bathrooms | **1075** square feet
Building Energy Score: **8/10**

Condition 4
Energy Score on a Continuum

$1,239 / month
2 bedrooms | **1.5** bathrooms | **1075** square feet
Building Energy Rating
1 2 3 4 5 6 7 8 9 10

Condition 5
Cost included in rent

$1,239 / month (including energy costs)
2 bedrooms | **1.5** bathrooms | **1075** square feet

Condition 6
Voluntary Label for Most Efficient Units

$1,239 / month
2 bedrooms | **1.5** bathrooms | **1075** square feet
Building Energy Score: **8/10** Energy Star Building

Condition 7
Control (energy information hidden)

$1,239 / month
2 bedrooms | **1.5** bathrooms | **1075** square feet

Figure 4. Unit listing designs for each group

In addition to completing the DCE, we required participants to complete a brief survey that asked about their demographic information, home preferences, and current rental situations.

By measuring participant behavior during the experiment, we were able to calculate whether they clicked on more (or less) efficient rental units as a result of seeing specific labels, and how much they were willing to increase their monthly rents for an increase in energy efficiency. Appendices A and C provide more information about our analysis methodology.

PARTICIPANTS

We worked with Branded Research, a panel research firm, to recruit a nationally representative group of 2,493 current renters.[6] After excluding inattentive responders[7] and those who stated that they did not understand the task they were asked to complete, we were left with 2,455 renters for our final analyses.[8] The sample was nationally representative in terms of age and income; it also closely resembled the general population of U.S. renters in terms of race and geographic region.

Compared to the general U.S. renter population, our sample had a slight under-representation of renters with less than high school education (–10.4%) and of those with "some college or associates degree" education (–7.1%). It also had a slight over-representation of renters with high school or equivalent education (+8.4%) and "bachelor's degree or higher" (+8.2%). Renters in our sample also stated that they intended to rent detached homes more frequently than typical U.S. renters actually do (+9.7%). The slight underrepresentation of 1–2 member households in our sample (–16%) could be a limitation of the study, as these households may deal with utility bills more directly than larger households (e.g., in larger households, all adults might not all see household energy bills

[6] Of our participants, 66% were not only renting their current homes, but also planning to rent their next homes, while 10% were not planning to move again, and 24% were planning to move into a non-rental. Of the participants who were planning to move and rent their next residence, most stated that they would do so within the next two years (33% within one year and 24% within one to two years),

[7] Participants who failed at least two of three attention questions, who provided nearly identical answers to all questions, or who provided nonsense text in the open-ended text boxes were excluded from the analyses.

[8] We later also excluded one experimental condition from the analyses (the costs-plus-score condition) due to problems with the label design. That condition had 305 participants; excluding them brought the total sample down to 2,150. However, for descriptive purposes, we present the demographic profile of all 2,455 participants in table 2. This costs-plus-score condition showed participants a label with both estimated monthly energy costs and energy score along a continuum. It had to be removed from the analysis because of a flaw in the label's text, which said "Building Energy Use" rather than "Building Energy Score." As such, many participants interpreted the label in the opposite direction than intended (higher scores meaning *more* energy consumption, rather than less). This ambiguity meant that the information was not communicated correctly to all participants and thus results from that condition were uninterpretable.

every month). Table 2 shows the participant demographic data for our sample and for the overall U.S. population.

Table 2. Participant demographic data compared to U.S. population

Category	Study sample % (*N* = 2,455)	United States %[9]
Age		
< 35 years old	36.4%	34.4%
35–44 years old	19.0%	19.9%
45–54 years old	16.2%	15.6%
55–64 years old	14.0%	13.7%
65–74 years old	11.1%	8.9%
75–84 years old	2.9%	4.8%
> 85 years old	0.3%	2.8%
Income		
< $5,000	7.3%	5.2%
$5,000–9,999	4.3%	5.4%
$10,000–14,999	7.1%	6.9%
$15,000–19,999	6.7%	6.1%
$20,000–24,999	7.9%	6.4%
$25,000–34,999	14.1%	11.6%
$35,000–49,999	14.3%	14.8%
$50,000–74,999	18.8%	17.8%
$75,000–99,999	8.7%	10.3%
$100,000–149,999	7.0%	9.3%
> $150,000	2.8%	6.2%
Don't know or prefer not to answer	1.2%	
Education		
Less than high school	3.2%	13.6%
High school graduate or equivalent	34.9%	26.5%

[9] U.S. Census Bureau. 2019. *US Census Data*. https://www.census.gov/data.html.

Category	Study sample % (*N* = 2,455)	United States %[9]
Some college or associate degree	24.5%	31.6%
Bachelor's degree or higher	36.5%	28.3%
Race		
Asian	5.4%	5.4%
Native American, American Indian, or Alaska Native	2.6%	1.0%
White	70.8%	64.1%
Black or African American	17.8%	20.3%
Native Hawaiian or Other Pacific Islander	0.3%	0.2%
Other	5.3%	6.0%
Prefer not to answer	1.5%	
Geographic Region		
Northeast	18.8%	18.9%
Midwest	19.6%	19.7%
South	38.5%	36.4%
West	23.1%	25.0%
Preferred rental type[10]	(Sample intended rental type)	(Actual U.S. rental type)
Single-family	47.5%	37.8%
Apartment	52.5%	62.2%
Household size[11]		
1 person	26.6%	49.5%
2 people	35.2%	28.0%
3 people	18.6%	11.5%
4 or more	19.7%	11.0%

[10] Source: Energy Information Administration. 2015. *Residential Energy Consumption Survey*. www.eia.gov/consumption/residential/index.php.

[11] National Multifamily Housing Council. 2020. *Household Characteristics.* www.nmhc.org/research-insight/quick-facts-figures/quick-facts-resident-demographics/household-characteristics/.

ENERGY BURDEN

Energy burden is the proportion of household income spent on energy costs. The median energy burden for renters is 13% higher than the median burden for homeowners (3.4% versus 3.0%) (Drehobl et al. 2020). We evaluated how accurately our sample reflected the energy burdens experienced by renters in the United States. Among renters in our sample who provided their estimated monthly energy costs (n = 1,810), the median energy burden was approximately 4.11%,[12] which is slightly higher than what was found in another study of renters in the 25 largest U.S. metropolitan areas (3.1%) (Drehobl et al. 2020). In our sample, more than one-third of participants (36%) who pay their energy bills (n = 1,798)[13] reported high energy burdens (>6%), and 23% had severe energy burdens (>10%). This is higher than is typically seen in U.S. metro areas (Drehobl et al. 2020) but, given sampling differences, we think our sample matches what would be expected from a national sample of U.S. renters.

Our sample also closely matched American renters' experiences of energy security. At least once during the year prior to the survey (August 2020 to August 2021), one-third of participants (34%) "went without necessities to pay an energy bill," 22% "kept [their] home at unsafe or unhealthy temperature levels to save money," and 22% "received a disconnection notice." This is consistent with the percentages reported in the most recent Residential Energy Consumption Survey (RECS) (EIA 2018). As expected, these numbers were higher among low-income and high-energy-burden renters in our sample than other renters. Energy burden can translate to negative effects for landlords (e.g., higher rent delinquency rates and lower occupancy rates) and thus may be another motivation for landlords to upgrade the efficiency of their units. This could be the subject for additional future research.

LIMITATIONS

Although we created a realistic rental listing website, our experiment has some limitations. For one, our search results were separated into six blocks of three choices each, whereas real rental listing websites have hundreds of choices listed in sequential order without breaks. Similarly, our results could not vary in the same way as real search results because we were limited to six key attributes (only those typically found on the front page of rental listing sites), each with three or four levels (e.g., high, moderate, and low). Real rental listing websites have many more attributes (e.g., amenities, distance to public transport, pet allowances) and many more levels of those attributes. These limitations were a necessary tradeoff to maximize the DCE's efficiency and interpretability and to allow us to conduct a national survey encompassing all regions, renter demographics, and climates. Given our

[12] We estimated energy burden using self-reported energy costs, and we divided those costs by the midpoint of participants' self-assigned income ranges.

[13] In our sample, 42% of renters paid all their energy costs. For the rest, the rent might include hot water, heating, air-conditioning, electricity, and/or gas costs.

success with this approach in two previous studies (Sussman et al. 2020; Long et al. 2021), we were confident that our experiment would produce accurate and actionable information.

Our ability to accurately compare our sample demographics to U.S. renters may be limited due to changes in living habits brought on by the COVID-19 pandemic. We used 2019 census data to identify the demographics for our sample. Some demographics may have changed during 2020, including household size, household income, and the types of homes people sought to rent. Despite these potential minor shifts, we are confident that our sample generally reflects current U.S. renter demographics.

Findings

In conducting our statistical analyses (see Appendix C), we had three outcomes of interest: (1) the frequency with which participants selected the most efficient homes across six choice sets, (2) the frequency with which participants selected the least efficient homes across six choice sets, and (3) the estimated willingness of participants to increase monthly rent for a one-unit increase in energy score. Below we summarize the answers to these three research questions.

DO RENTERS CLICK ON MORE EFFICIENT HOMES WHEN RENTAL LISTINGS CONTAIN ENERGY EFFICIENCY INFORMATION?

Presenting energy efficiency information to renters significantly increased their selection of efficient homes. When we included energy efficiency information in rental listings, renters clicked on the most efficient homes 21% more frequently than when that information was absent. They also clicked on the least efficient homes 21% less frequently than when energy efficiency information was absent.[14] On average, renters were willing to increase their monthly rent by 1.8% for a one-unit increase in energy score (Home Energy Score or Building Energy Asset Score, ranging from 1 to 10).[15] On an average-priced rental unit, this would translate into more than $400 of additional rental revenue per unit per year for landlords for each increase in energy score; as demonstrated later, this value could go up to

[14] In this comparison, we pooled all experimental conditions.

[15] "Energy score" refers to the Building Energy Asset Score (or Asset Score; see https://www.energy.gov/eere/buildings/building-energy-asset-score) for apartment buildings, or Home Energy Score (https://betterbuildingssolutioncenter.energy.gov/home-energy-score) for detached homes (both are on a 10-point scale). This calculation excludes participants in the voluntary label condition, the costs-plus-score condition, and the control condition because the energy information in these conditions was either absent, not presented for all options, or presented with an inappropriate label (with "use" instead of "score").

as much as $520 with some labels.[16] Furthermore, many cities have older buildings that could likely increase their scores by two or three points with existing retrofit technologies, thus earning $800–1,200 additional revenue per year. Given our study design, we can infer that the labels *caused* the change in preference among renters.[17] Therefore, we can conclude that presenting energy information to renters in rental listings can affect their choices to click on certain listings for further information. Moreover, willingness to increase rent for energy efficiency can be increased further with the right energy label. The specific results of our statistical tests for this inference are available in Appendix D.

WHAT IS THE BEST WAY TO DISPLAY ENERGY EFFICIENCY INFORMATION IN RENTAL LISTINGS?

Most Labels Work, but Context Matters

As figures 5 and 6 show, nearly all the labels in our experiment significantly encouraged renters to click the most efficient rental options more frequently and the least efficient rental options less frequently. The exceptions were labels that presented estimated monthly energy costs (not along a continuum) and labels that were attached only to the highest-scoring (efficient) homes. Participants who saw one of those labels did not change their behavior significantly from those who saw no energy label at all.

Labels with good context information (i.e., those with information presented along a continuum or alongside the maximum possible score) were the most effective. This could be a result of a context effect (e.g., Sussman et al. 2021) or an "anchoring and adjustment" effect (Tversky and Kahneman 1974), in which decision makers are disproportionally influenced to make judgments biased toward initial information (the information about the maximum possible score, in this case). The effectiveness of presenting the energy score as a simple number out of 10 is important for two reasons: 1) it requires minimal space on the label, and 2) it is among the most feasible approaches from a policy perspective.

As figure 7 shows, most labels resulted in a willingness to increase rent by 1.11–2.32% for a one-unit increase in energy score. Thus, for an average-priced rental unit (currently $1,877, because pandemic drove up prices (Bhattarai 2022), the best labels could allow landlords to charge up to $520 more per year for each one-unit increase in energy score (and more than $1,500 more per year for a three-unit energy score improvement). Of course, these findings should be confirmed with real-world experiments and followed up with examinations of

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[16] Average monthly rental prices rose 14% in 2021 to $1,877/month nationwide (Bhattarai 2022).

[17] Our study design allowed us to infer causality by controlling for the effect of other factors, such as the pre-existing motivations of participants.

sales data, but they provide good preliminary evidence that some energy labels could increase renters' willingness to pay more in rent for improved energy efficiency.

Figure 5. Choosing the most efficient homes. Renters saw six choice sets and thus could choose the most efficient homes up to six times. The x-axis shows the average number of times participants clicked on the most efficient homes in each condition (i.e., the maximum is six and minimum is zero). Labels with enhanced context information, such as information presented along a continuum or alongside a maximum possible score, were the most effective for encouraging renters to click on the highest efficiency homes. Labels with less context, such as the voluntary label (which appeared on only the most efficient homes in each choice set) and energy costs not shown along a continuum were not better than the no-information control for changing renter decisions.

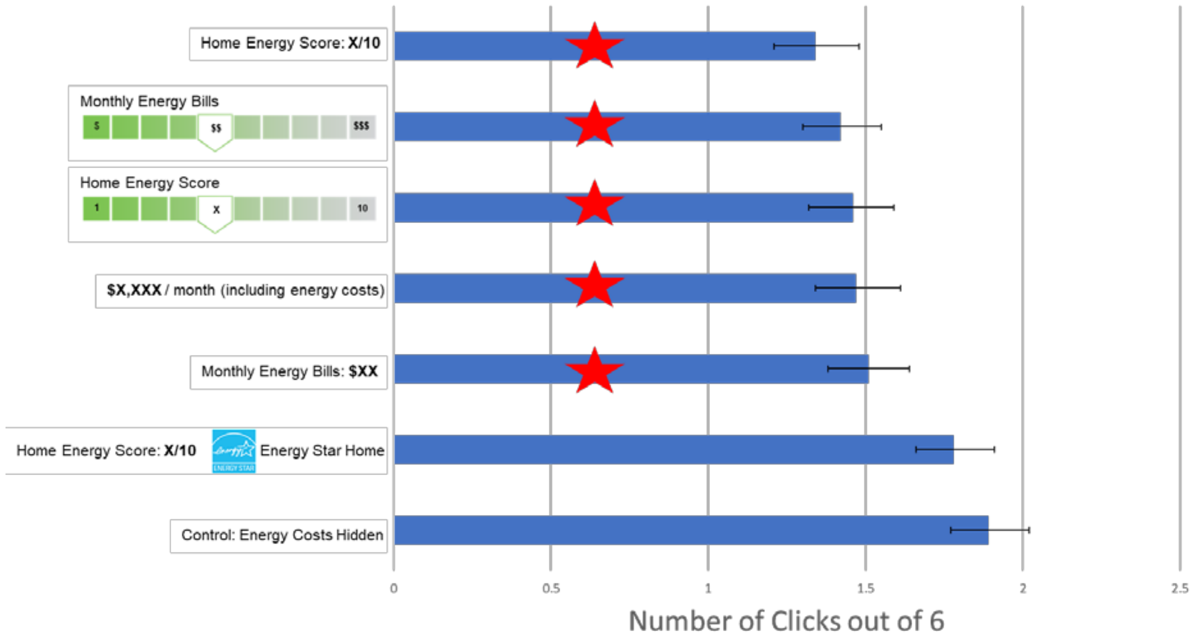


Figure 6. Choosing the least efficient homes. Renters saw six choice sets and thus could choose the least efficient homes up to six times. The x-axis shows the average number of times participants clicked on the least efficient homes in each condition (i.e., maximum is six and minimum is zero). Labels with context information, such as information presented along a continuum or along a maximum possible score, were most effective for discouraging renters from clicking on the lowest efficiency homes. The voluntary label (which appeared on only the most efficient homes in each choice set) had less context information and was not better than the no-information control. The energy costs condition without a continuum was only slightly better than the no-information control.

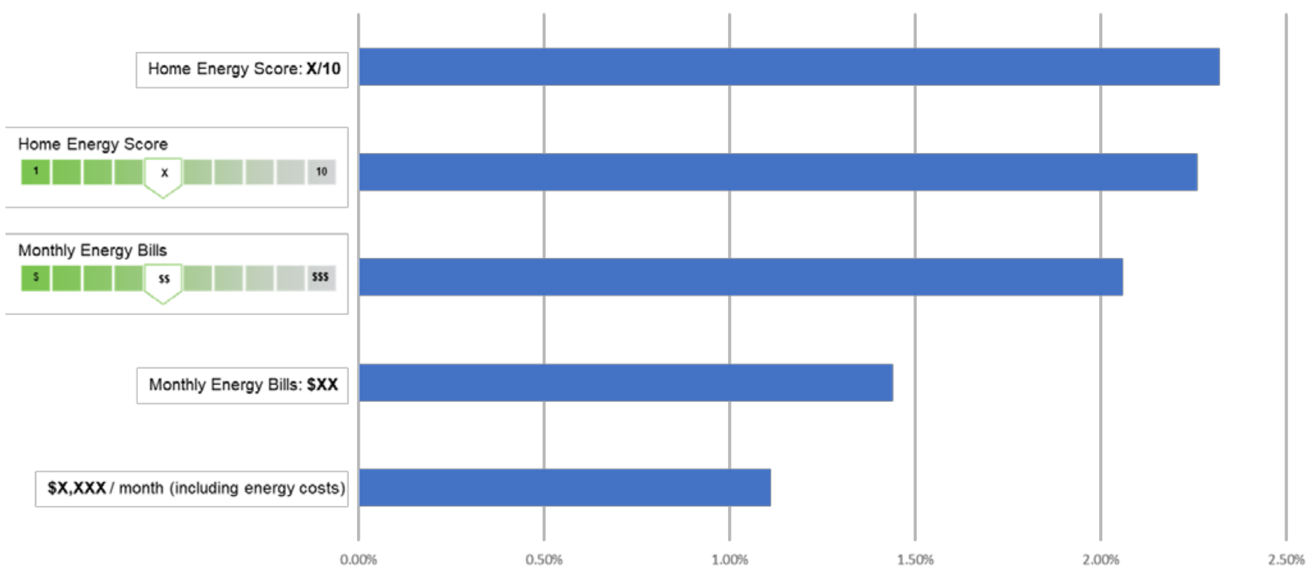


Figure 7. Percentage of willingness to increase rent for a one-unit increase in energy score. Voluntary label and control conditions could not be included in this type of analysis.

Estimated Monthly Energy Costs

The estimated monthly energy costs label (with energy costs as a stand-alone number) was significantly effective only for discouraging selection of the least efficient homes; it did not significantly encourage selection of the most efficient homes. This is similar to what we found in our previous study of real estate listings (Sussman et al. 2020).

Interestingly, however, when energy costs were placed along a continuum of possible energy costs in that rental's geographic region, the label did significantly influence behavior. It seems that energy costs, on their own, without the context information provided by the continuum, were less persuasive. For a one-unit reduction in energy costs (equivalent to a one-unit increase in energy score), renters were willing to increase their rent by 2.06% when shown energy costs along a continuum, but willing to so only by 1.44% when the information was shown without a continuum. For an average rental unit of $1,877/month that would be a willingness to increase rent by $39/month when shown energy costs along a continuum, and only $27/month when shown energy costs without a continuum (a 30% difference in willingness to increase rent).

Perhaps even more interestingly, labels with energy costs included in rent were also more effective than labels with stand-alone energy costs. When energy costs were added to the cost of rent and tagged as "(including energy costs)," renters responded by clicking on the most efficient listings more frequently and the least efficient listing less frequently. That is, when the label showed energy costs separately, renters were unlikely (or unwilling) to do the mental arithmetic needed to combine monthly energy costs and rent. Energy costs represent only a portion of total rental costs, which may explain why the label with stand-alone costs was less impactful than the label showing costs included in rent.

Although calling out the energy costs separately may not cause renters to click on the most efficient homes more often, it does make renters somewhat more aware of the value of efficiency. When energy costs are called out separately (as a simple dollar amount) renters are willing to increase their rent by 1.44%, whereas when they are included in rent, renters were willing to increase by only 1.11%. This suggests that including energy costs in rent may effectively encourage selection of more efficient homes but may not increase the amount renters are willing to pay for those homes by much. This strategy is therefore less recommended than using explicit home energy labels.[18]

[18] In the condition in which energy costs were included with rent, all homes in the choice set were labeled as "including energy costs." Participants did not see a mix of homes in which some had costs included in rent and others had costs as stand-alone numbers. Thus, we can draw only limited conclusions about whether one presentation or the other affects renters who might see *both*. Instead, these data provide information on what renters might do if all options were presented in one way or the other.

Voluntary Labels

Our voluntary label condition showed energy information only for the most efficient homes and apartments. This condition was designed to replicate a real-world scenario in which landlords and owners market their rentals as "efficient" or "green" if they have certifications such as ENERGY STAR or LEED, which most existing rentals listed do not have. Without a mandate to score and list energy information for *all* rentals, this is the type of scenario that renters may encounter in some cities.

Our experiment found that voluntary energy labels did not significantly influence home renters in deciding which homes to click on. We found this same effect with home buyers in our previous study of real estate listings (Sussman et al. 2020). This is likely because context information is important for decision making; when energy efficiency is not known for all options, renters lack the context necessary to comprehend the efficiency information and understand how much better or worse the labeled home is compared to others (Sussman et al. 2021). Notably, in this version of our experiment, we strengthened the impact of the voluntary label (by adding an "ENERGY STAR" logo) to make it more noticeable than in our previous real estate experiment, but we found the same (null) result. This is unfortunate because voluntary labeling programs are typically the easiest labeling option to implement.

WHICH RENTERS VALUE EFFICIENCY THE MOST?

We used data analytics to identify which renter demographics (if any) valued energy efficiency more (or less) than others. We found that renters' willingness to increase their rent for a one-unit increase in energy score was affected by their age, the region in which they lived, the type of home they planned to rent, and the number of people they lived with. It was not predicted by household income or level of energy burden.

The Place

House versus Apartment

In our sample, 52.5% of renters searched for apartments and 47.5% searched for detached houses.[19] As table 3 shows, renters who searched for apartments were willing to increase their rent significantly more for a one-unit increase in energy rating than those searching for houses (1.90% versus 1.62%).

We found that apartment renters were also more responsive to energy labels than house renters, especially when participants were presented with energy information in the form of energy scores. Although energy ratings for both houses and apartments ranged from 1

[19] We defined "apartment" as including large and small multifamily buildings, as well as suites within detached homes, such as basement apartment units.

(inefficient) to 10 (efficient), apartment ratings were titled "Building Energy Rating" (i.e., pertaining to the whole building) and home energy ratings were titled "Home Energy Score" (i.e., pertaining entirely to the renter's living space). This reflects most accurately the tools available in the market for apartment and single-family home residents. Given that energy scores affect house renters more directly, one might have guessed that house renters would be more influenced by the energy rating. Instead, we found the opposite—apartment renters appeared to value efficiency more than house renters.[20]

Renters did not seem dissuaded by the efficiency rating being related to the entire building rather than their specific unit. This may be because house renters think they can control their energy use and reduce their consumption even in the face of a low Home Energy Score. Alternatively, apartment renters may be concerned about whole-building efficiency because wasted energy use in the common areas and throughout the building could lead to rent increases or be passed along to them if the apartments are not individually metered. These possibilities require further investigation; regardless, the finding that apartment renters value efficiency more than house renters can help target and focus energy labeling efforts.

Table 3. Renters searching for apartments were willing to increase their rent by a significantly higher percentage for energy efficiency than were renters searching for houses

	House	Apartment
Monthly rent	$1,354	$1,221
WTP for 3 units [SD]	$65.99 [5.12]	$69.75 [4.0]
WTP for 1 unit	$22.00	$23.25
WTP as a percentage of rent	1.62%	1.90%
Annual revenue increase for 3-unit improvement	$791.88	$837.00

WTP = willingness to pay; unit = a unit of Home Energy Score (for detached homes) or Building Energy Asset Score (for apartments); SD = standard deviation

[20] Although renters who selected apartments had slightly lower incomes than those who selected detached houses, income level was not related to valuation of energy efficiency, overall (as described later in this report).

Geographic Region

The physical location of rental units has the potential to affect the value renters place on efficiency and whether or not they respond to efficiency labels. We examined three regional variables and found that census region and climate zone helped predict renter decisions, but urban–rural differences were not statistically significant. Renters in regions with milder weather appeared less interested in energy efficiency.

In terms of major U.S. census regions, renters in the West region valued energy efficiency the least. In this region, a one-unit increase in energy efficiency score was worth a 1.06% increase in rent, whereas in the Midwest, Northeast, and South, a one-unit increase was worth 1.88–1.92% increases (see figure 8). Two reasons for this difference could be (1) milder weather in coastal regions leading to less need for efficiency,[21] and (2) a history of efficiency programs, renewable energy proliferation, and building codes that may lead renters in coastal regions to think that all rental units already meet basic efficiency standards (and thus they need not think about it when making rental decisions).

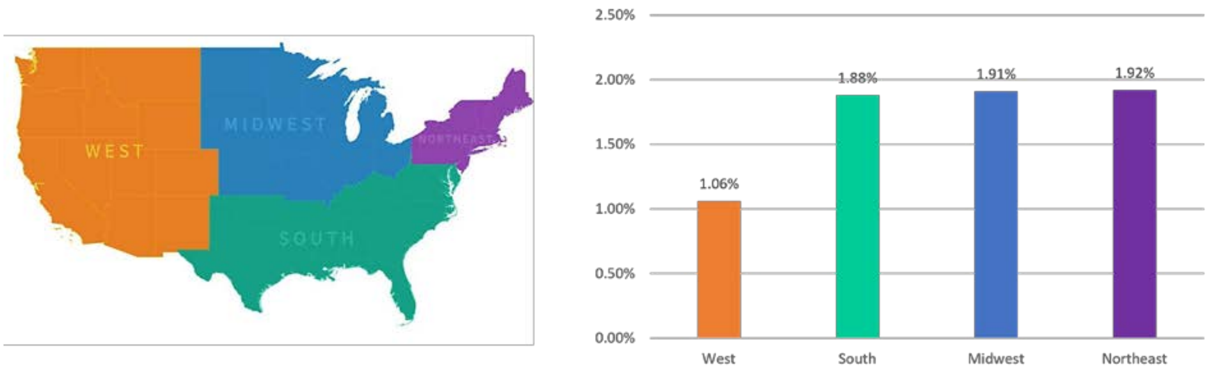


Figure 8. Renters in the West census region were willing to increase their rent significantly less than other regions for a one-unit increase in energy score.

Climate zone also helped predict renter decisions, as figure 9 shows. The United States has seven major climate zones, which (generally) decrease in average temperature from 1 (hottest) to 7 (coldest). Zones 1 and 7 are found in only a few U.S. regions. Renters in our study who were located in the hottest and coolest regions (regions 1 and combined 6-7) were willing to increase their rent most for a one-unit increase in energy efficiency. This could be because energy efficiency has the largest potential impact on comfort and cost in

[21] Sixty-five percent of participants in the West region were from coastal states. This is a much higher percentage of participants from potentially mild climates than those in other U.S. regions in our sample.

those areas. However, those regions hold only a moderate number of participants (39 and 82, respectively, both lower than any other regions), so these findings are tentative.[22]

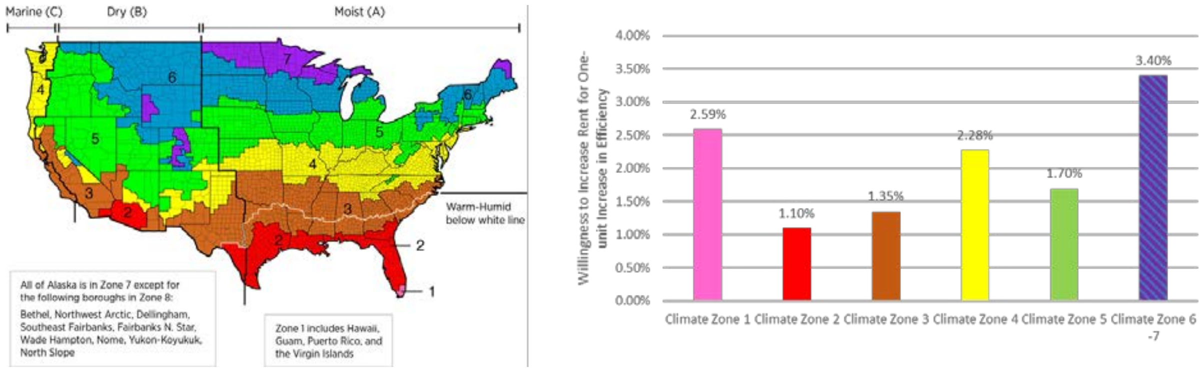


Figure 9. Willingess to increase rent for a one-unit increase in energy efficiency by climate zone

Urban–rural differences were not significant. We coded participants' current zip codes as "metro" or "non-metro" using the most recent urban–rural classification codes from 2010. Using these classifications, we found that renters in urban regions were willing to increase their rent by a higher percentage for a one-unit increase in energy score (1.84% versus 1.03%), but this difference was not statistically significant because of the much larger number of urban participants and higher variance in their willingness to pay.

The Participants

Age

As table 4 shows, younger renters (under 45 years old) were willing to pay more than older renters for energy efficiency (in terms of percentage increase in rent). This increase was slight, but significant (1.72% versus 1.63% for a one-unit increase in energy score).

Table 4. Younger participants were willing to pay a higher percentage rent increase than older participants for a one-unit increase in energy score

	Under 45 years old	45+ years old
Monthly rent	$1,388	$1,284
WTP for 3 units [SD]	$71.85 [5.25]	$62.69 [3.45]
WTP for 1 unit	$23.95	$20.90

[22] We combined climate zones 6 and 7 because zone 7 had only 11 participants. Zone 1 occurs only in southern Florida and Hawaii.

	Under 45 years old	45+ years old
WTP as a percentage of rent	1.72%	1.63%
Annual revenue increase for 3-unit improvement	$862.20	$752.28

WTP = willingness to pay; unit = a unit of Home Energy Score (for detached homes) or Building Energy Asset Score (for apartments); SD = standard deviation

LIVING WITH TWO OR MORE OTHER PEOPLE

Renters who currently live in households of three or more people were willing to pay significantly higher rent for one-unit increases in energy efficiency than those living by themselves or with just one other person ($24/month versus $21/month in average priced rental units). However, this willingness to increase rent was offset by the higher base rental cost for rentals with 3+ household members; the percentage willingness to increase rent was therefore the same for both groups (1.74%), as table 5 shows. The relationship between household size and willingness to pay for efficiency deserves further examination.

Table 5. Average willingness to pay for an increase in energy score among renters in small households (1–2 people) and large households (3+ people)

	1–2 residents	3+ residents
Monthly rent	$1,207	$1,405
WTP for 3 units [SD]	$63.08 [2.9]	$73.45 [7.97]
WTP for 1 unit	$21.03	$24.48
WTP as percentage of rent	1.74%	1.74%
Annual revenue increase for 3-unit improvement	$756.96	$881.40

WTP = willingness to pay; unit = a unit of Home Energy Score (for detached homes) or Building Energy Asset Score (for apartments); SD = standard deviation

Table 6. The demographic breakdown of participants who live in small (1–2 person) and large (3+ person) households

	1–2 person households (*n* = 1,517)	3+ person households (*n* = 938)
Live with children	10% (152)	60% (564)
Live with parents	4% (57)	17% (156)

	1–2 person households (*n* = 1,517)	3+ person households (*n* = 938)
Live with other family	4% (60)	22% (207)
Live with roommates	7% (101)	14% (131)
Live with significant other	34% (517)	56% (527)
Live with other	<1% (2)	2% (17)

The percentages in the 1–2 person household column total less than 100% because many renters live alone. The percentages in the 3+ person household column total more than 100% because respondents usually live with others from multiple categories

Income, Education, and Intended Rental Price

Generally, income and education are closely linked, and therefore, it is not surprising that we found a similar result for both demographic variables. Neither income nor education appeared to significantly affect preferences for energy efficient rental units. We examined eight household income bands, ranging from under $10,000/year to over $100,000/year, as well as comparing households below 200% of the Federal Poverty Level (low-income qualified households) to those above it.[23] We also looked for differences based on five education levels, from "less than high school" to "graduate or professional degree." In each of these analyses, we found no significant differences or patterns in preference for energy efficient rentals or willingness to increase rent for efficiency. Appendix C provides details on these analyses.

Only when examining intended rental price (the monthly rental price that participants stated they intended to look for) did we see differences in willingness to pay for efficiency. As figure 10 shows, renters looking for expensive rental units (above the median of $1,000/month) were willing to pay a significantly smaller percentage in rent increase (1.11–1.12%) for energy efficiency than renters looking for cheaper rentals (up to $1,000/month; 1.37–1.47%).[24]

[23] Federal Poverty Level (FPL) differs based on household size. We used the most recently available FPL table (HHS 2021) to look up our participants, using the midpoint of their salary ranges and their household sizes. Using the 200% of FPL cutoff as an indicator of low income is a common practice for establishing income eligibility for government programs, and the measure has been used extensively in reports and journal articles (e.g., Drehobl 2021).

[24] Higher income renters tend to rent more expensive homes. That is, with every increase in income bracket, from $10,000/year to $100,000+/year, intended rental price increased. However, for reasons that are unclear, the lowest income bracket was an exception to this trend. The lowest income bracket ($0-10,000/year) intended to rent homes that cost more than those earning as much as $34,999.

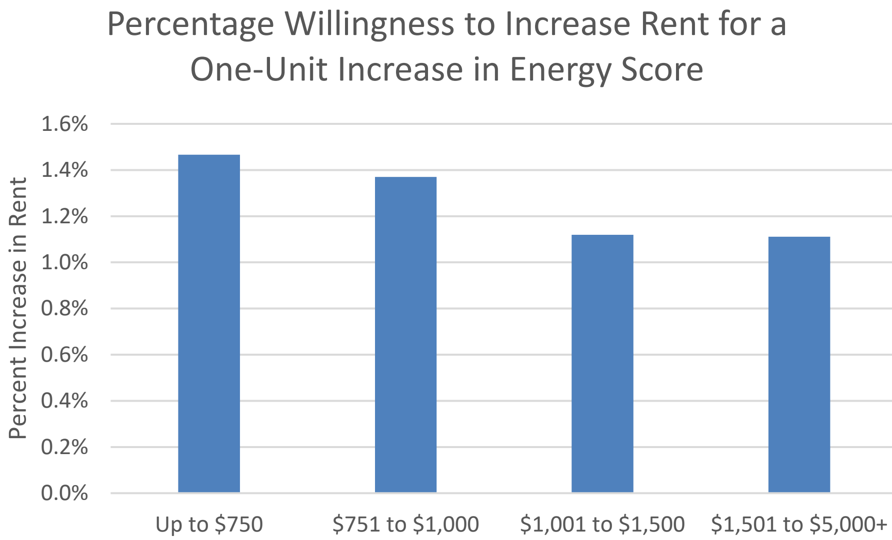


Figure 10. Renters with high monthly rental prices (above the median of $1,000/month) were willing to pay the least for a one-unit increase in energy score (Home Energy Score or Building Energy Asset Score)

Our sample was representative of U.S. renters in terms of age and income. It also closely resembled the census data for renters in terms of education levels and race. Thus, we can conclude that if real-life low-income renters were presented with energy efficient options in rental listings, they would be somewhat more likely to select them. They would be just as interested in clicking on those options as higher-income earners.

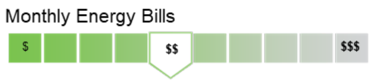
Energy Burden

We found that neither having high nor severe energy burdens significantly affected the rates of clicking on the most or least efficient homes. These burdens also did not significantly influence willingness to increase rent for an increase in efficiency. Thus, renters experiencing high or severe energy burdens were similar to other renters in terms of their responses to energy labels. Appendix C offers more details on our energy burden analyses.

Summary of Findings

Table 7. Summary of findings: Energy labels

Energy label	Percentage willingness to increase rent	Clicking the most efficient rental option in each choice set (relative to control condition)	Clicking the least efficient rental option in each choice set (relative to control condition)
Home Energy Score: **X/10**	2.32%	32% increase	29% decrease
Home Energy Score 	2.26%	23% increase	23% decrease

Energy label	Percentage willingness to increase rent	Clicking the most efficient rental option in each choice set (relative to control condition)	Clicking the least efficient rental option in each choice set (relative to control condition)
	2.06%	26% increase	25% decrease
Monthly Energy Bills: **$XX**	1.44%	Not significant	20% decrease
$X,XXX / month (including energy costs)	1.11%	21% increase	22% decrease
Home Energy Score: **X/10** Energy Star Home		Not significant	Not significant

Willingness to increase rent could not be calculated for the voluntary label condition.

Table 8. Summary of findings: Renter characteristics

Demographic characteristic	Finding
House versus apartment	Apartment renters were willing to increase rent by a higher percentage than house renters for a one-unit increase in energy rating.
Region	Renters in the West region were willing to increase rent by a lower percentage for energy efficiency than renters in the Midwest, Northeast, and South. Renters in the hottest and coolest climate zones were willing to increase their rent by the highest percentage for a one-unit increase in energy ratings. We found no significant difference between renters in urban and rural areas.
Age	Younger renters (under 45 years old) were willing to increase their rent by a higher percentage than older renters for a one-unit increase in energy ratings.
Rental price	Renters searching for more expensive rentals (greater than the median price of $1,000/month) were willing to increase rent by a smaller percentage for energy efficiency than renters looking for cheaper rentals.
Number of household members	Inconclusive; willingness to increase rent was the same, in terms of percent of rent, for renters who lived in small (1–2 person) versus large (3+ person) households. However, renters with large households were willing to spend significantly more for efficiency in absolute dollar amounts.

Income	We found no significant difference between renters with different income levels.
Education	We found no significant difference between renters with different education levels.

HOW DO RENTERS COMPARE TO BUYERS?

Our study built on previous ACEEE research that used a similar methodology to examine real estate listings in the United States (Sussman et al. 2020) and Canada (unpublished). We now discuss how these earlier studies compare to our findings.

Context Information Determines the Best Labels

Renters and buyers tend to respond similarly to energy label designs. Context information appears critical to the persuasiveness of energy labels and their ability to help interested customers find the most efficient homes (Sussman et al. 2021). Thus, home labels that describe energy use with rich context information—such as a continuum of possible energy scores or costs—tend to encourage both home buyers and renters to select more efficient homes and accept higher prices for them. Likewise, situations with less context information—such as when homes are labeled voluntarily, and thus only the most efficient homes get labels—are least persuasive and tend not to affect customer decision making.

Indeed, our study on rental labels offers methodological improvements over our previous study of real estate labels, and thus further supports and strengthens those findings about the importance of context information. For example, in our previous study of real estate labels, we found that labels that simply displayed stand-alone energy costs were not as effective as other labels with more context information. We hypothesized that this was because the label lacked context information; as a result, our current study included a condition with costs displayed along a continuum of possible costs in the same area. Unlike the label that simply presented costs as a dollar figure, this new label was effective for encouraging the selection of efficient homes and significantly increased willingness to pay for efficiency. Our hypothesis was thus borne out, and we further established the importance of context.

In the voluntary label condition, only the most efficient homes were labeled with an energy score (and an ENERGY STAR logo). Thus, context information was extremely scarce in this condition; renters lacked information about how each home compared to population-wide averages, maximums, and minimums, as well as how each home compared to others in the choice set. This condition performed similarly poorly in this experiment as in the real estate study, despite our testing a stronger label this time around.

The current study added an ENERGY STAR™ logo—which market research shows is a trusted and well-recognized energy efficiency brand (ENERGY STAR 2022)—to the highest performing buildings. Nevertheless, the voluntary label was still insufficient in our current experiment to sway renters toward more efficient homes. It is not clear why voluntary labeling with an ENERGY STAR logo did not work in this case when it has demonstrated effectiveness for other products. It could be related to the logo, how it was used, or whether it was familiar to renters as a home efficiency label. Thus, although voluntary labeling continued to be less effective than other labels in this experiment, there may still be labels out there that could have a stronger impact if they were more familiar (e.g., LEED) or perhaps presented differently. Our current recommendations, based on this finding, continue to be that voluntary labels be used as stepping-stones toward the ultimate goal of mandatory labeling requirements for all homes. Voluntary programs are a more feasible policy option to implement than mandatory labeling, but they may not garner the same level of effect.

Lower Willingness to Pay

Overall, renters were generally less willing to pay for increases in efficiency than buyers were in our previous studies. American homebuyers were willing to increase the purchase prices of their homes by 5–11% for one point increase (out of 10) in a Home Energy Score, and Canadian homebuyers (in an identically designed experiment) were willing to increase prices by 2–5% for those increases. In the current study, renters were willing to increase rent by 1.44–2.26% for one-unit increases in energy ratings (or 1.11% when energy costs were embedded in rental price).

There are several potential reasons for these differences. First, renters may value energy efficiency less than buyers. This could be because renters see their homes as temporary and are less interested in energy investments than buyers. Indeed, in our study, about one-third of renters (35%) expected not to remain in their current homes after their lease expired and, separately, one-third planned to leave within two years (36%). Moreover, about two-thirds expected their next homes to also be rentals (66%). Conversely, in the previous study, the majority of home buyers already owned their current homes (72%) and 43% stated that they had last purchased a home more than 10 years prior to the study. It may be that the transience we observed among renters might make them less concerned with energy costs, as such costs appear less permanent.

Another reason renters might value energy efficiency less than buyers could be that their energy costs are lower, especially for high-efficiency apartments. In our U.S. real estate study (conducted two years before the current study), average monthly home energy costs across states for high-efficiency houses were calculated at approximately $120/month. Most renters in the current study were looking for apartments (rather than detached homes), which typically use less energy. The costs for high-efficiency apartments were therefore much lower—an average of only $103/month, across all states[25]—than for high-efficiency homes. Higher costs mean a stronger financial incentive to invest in efficiency. This sort of difference could partly account for the higher percentage of willingness to pay for efficiency in our previous real estate study than in this study.

Renters might pay lower energy costs than owners for a few reasons. Whereas homeowners pay the entire energy bill themselves, renters' energy bills may be divided among tenants, partially covered by landlords, or included in rent. Buildings with multiple units benefit from shared heating and cooling infrastructure (one building envelope around all units), and landlords sometimes cover utilities such as heat, hot water, and air-conditioning. Indeed, in our study, 50% of renters lived in units with hot water included, 35% lived in units with heat included, 29% lived in units with air-conditioning included, 26% lived in units with electricity included, and 24% lived in units with gas included. Only 42% paid their entire energy bill themselves.

A difference in labels between our rental study and the previous ACEEE real estate studies could also account for part of the difference in willingness to pay for efficiency. In our real estate study, labels that included a continuum of energy scores (from inefficient to efficient) also had explicit tags "inefficient," "efficient," and "average," describing in words where the home placed relative to others. Indeed, those "continuum" labels were most effective for encouraging home buyers to value efficiency. The tags were removed in the current study because research advisors felt they would be infeasible to implement as opposition to negative tags from landlords and others would be too strong. The absence of these explicit tags may thus partially explain why the rental labels triggered a lower willingness to pay.

Real-World Preliminary Testing with RentLab

Based on our online experiment's results, we worked with a partner website to test three high-performing energy efficiency labels on actual rental listings. Although limited, this preliminary real-world replication of our experiment showed that website visitors clicked efficient listings more often when they had energy labels that included the energy score presented as a number out of 10 and along a continuum, compared to listings without energy information (control condition). This aligns with the results of our mock rental listing website experiment. A label with energy costs placed along a continuum of possible costs did not perform as expected, but that may be because the costs and efficiency were not perfectly related in this dataset (cost is not a great predictor of efficiency in the real world).

[25] Average efficiency homes also had slightly higher monthly energy costs in the real estate study than in the rental listings study. The energy costs of low-efficiency homes showed the opposite trend, with the real estate study finding lower monthly energy costs than in our rental listings study, but the difference was much smaller than that of high-efficiency homes.

These real-world results should be replicated with a larger sample, as our results were not statistically significant. Appendix F offers further details of the RentLab study.

Recommendations for Policymakers

ACEEE research suggests that addressing energy efficiency and affordability in rental housing will require a multipolicy and program approach (Samarripas and Jarrah 2021). These policies could include—but are not limited to—energy disclosure policies, energy efficiency programs, and building performance requirements. This experiment showed that energy disclosure policies can influence how renters value energy efficiency and build demand for more efficient rentals. Energy labels on listing websites have the added benefit of generally raising awareness of utility costs and energy efficiency in buildings, which could have larger impacts over time. The labels were particularly impactful in the country's hottest and coldest regions (climate zones 1 and 6/7 and census regions other than the West). Based on our experiment, we would specifically recommend the following actions to city-level policymakers.

Require disclosure of energy-use information at time of listing. Our study found that providing energy-use information in rental listings impacted renter behavior. Renters choose more efficient properties and avoid less efficient properties when they see an energy label. This demonstrates that they value efficiency and prefer efficient homes when they are available. ACEEE research provides information on best practices for writing and implementing energy disclosure policies at the local (city) level (ACEEE 2018; Samarripas and Jarrah 2021). Additionally, cities with existing benchmarking ordinances for multifamily buildings can consider adding a time-of-listing requirement to their policies.

Use a multipolicy approach to overcome the split-incentive problem. Our study found that renters are willing to increase their rent by a statistically significant percentage (1.44–2.32%) in exchange for increases in energy efficiency. However, depending on the measure, this increase may not be large enough to offset the costs of upgrades and therefore might fail to motivate landlords to invest in efficiency. Policymakers should pursue simultaneous incentive and financing programs to address the split-incentive issue more fully. Furthermore, policymakers should consider implementing policies that set minimum efficiency requirements for rental properties.[26] Such policies exist in Boulder, Colorado; Burlington, Vermont; Gainesville, Florida; and New York City. These policies are an important step toward ensuring that renters live in more efficient, comfortable, and healthy housing.

[26] ACEEE recommends that all building performance requirements include mechanisms to protect market-rate affordable and subsidized housing (Samarripas and Jarrah 2021).

Move toward context-rich labels and away from voluntary labels, if possible. Labels providing rich context information, such as placing the home along a continuum from least to most efficient potential homes, is the most effective labeling option. Programs that remove context information—such as voluntary programs, which result in only the highest-scoring rentals being labeled—are the least effective. As such, voluntary programs should be considered stepping-stones to the goal of mandating labeling for all units. Similarly, in jurisdictions where state laws prohibit mandatory disclosure policies, voluntary programs can improve transparency in the rental market. Fortunately, labels that provided the energy score as a number out of 10 were quite effective in our study. These relatively simple labels take up little space on the listing and are potentially easier to implement.

Use an intuitive rating system. Our experiment used two energy scoring systems: Home Energy Score and Building Energy Asset Score. Both systems provided clear, simple ratings out of 10 for houses and apartments, respectively. Both also influenced participant behavior regardless of familiarity with the rating systems (average familiarity with these programs was rated 39 and 27 out of 100, respectively). HES and BEAS are well-established programs that are designed to be easily incorporated into building labeling programs and policies.

Engage apartment renters. In our study, apartment renters valued efficiency significantly more than house renters. Thus, policymakers operating in regions with primarily apartment rentals will likely have rental labeling policies that are most effective.

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Appendix A. Experiment Design Details

SELECTING ATTRIBUTES

We selected the main attributes for each simulated rental listing based on (1) an analysis of 13 representative rental listing websites, and (2) a review of previous literature to determine which attributes were examined in similar studies and which attributes of a rental listing are most important to renters. We chose our set of 13 representative rental listing websites by conducting a Google search of the "best rental websites"; by examining the popularity of these websites (determined by their number of unique visitors); by noting which websites were used in previous similar studies; and by looking at recommendations for rental listing websites on other websites.

After selecting our set of representative rental listing websites, we developed a list of attributes that these websites commonly shared. We then coded the attributes by level of importance, assigning each attribute scores between 1 and 4 representing the difficulty of seeing that attribute on the rental listing website: (1) the attribute was on the home page, (2) the attribute was on the first page of search results, (3) the attribute was on the individual listing page, and (4) the attribute did not appear on the website at all. Intermediate pages were valued with an extra 0.5. We thereby found the average page value for each attribute and determined the frequency with which it appeared on each page to determine the most important attributes of a typical rental listing website.

Following our analysis, we decided to include the following attributes in our experiment: a thumbnail photo, monthly rent, number of bedrooms, number of bathrooms, square footage, and (for all conditions except the control) energy efficiency information. Based on our analysis, these attributes were all most likely to appear together on the first search results page of a rental listing website.

SELECTING PHOTOS

The photos used for each simulated rental listing were taken from our previous real estate listing study, in which they were pre-tested for similarity in desirability (Sussman et al. 2021). We used the same three photos for each DCE choice set and were able to control for the effects of the photos by considering them as one of the attributes of each simulated listing and randomizing them within the DCE.

DESIGNING PRESENTATION FORMATS

SIMULATED WEBSITE DESIGN

Rental listing websites are one of the top tools that renters use in their search for a rental property, so we aimed to design the simulated rental listing website used in this experiment in a way that would most realistically portray a typical rental listing website (Apartments.com and Google 2016). Our simulated rental listing website consisted of three page types: 1) a home page, 2) a filters page, and 3) a search results page. For the home page, we included a logo, a location search bar, a tagline, and a background image, as these features and functions were included on the home page of the majority of the 13 websites analyzed. A logo was most common (appearing on all 13 website home pages), followed by a location search bar (12 home pages), a tagline (11 home pages), and a home page image (9 home pages).

After viewing the home page, participants were asked to select filters for their preferred monthly rent, their desired property type (house or apartment), and their preferred number of bedrooms. None of the rental listing websites we analyzed had this type of intermediate filters page before the search results, but each website did have filter options on the search results page. We opted for a separate filters page in order to maintain a simpler user interface. Additionally, although real rental listings websites also typically included preferred number of bathrooms as a filter, we did not include it in this study due to problems it caused in data analysis for our real estate listings study (Sussman et al. 2021).

Once we decided which main attributes to include in our experiment, we conducted a more detailed analysis of their representation on the 13 representative rental listing websites. We focused on the location of the attributes within each website's filters and the format of the filter for each attribute (i.e., the user interface for the filters). Based on this analysis, we chose to use a text box for the price filter and buttons for filtering the number of bedrooms.

After participants input their rental preferences, they were presented with their search results. On the search results page, they could see their previously selected filters along the top of the page, along with three simulated rental listings at a time. Each rental listing consisted of a thumbnail image, followed by the key attributes: monthly rent, number of bedrooms, number of bathrooms, square footage, and (except for in the control group) energy efficiency information.

For the energy efficiency information attribute, participants might see one of seven conditions or the control condition. For all non-control groups, the displayed energy efficiency information included the energy costs or energy rating in various forms. The control group saw no energy information.

ENERGY COSTS AND INFORMATION LABELS

Several rating systems and labels exist for energy information in homes. We chose to use the Department of Energy (DOE) Home Energy Score (for single-family homes) and Building Energy Asset Score (Asset Score, for apartment buildings) because they are commonly used throughout the United States to rate homes and multifamily buildings, respectively. Both rating systems evaluate the performance of buildings based on the assets within them, such as envelope measures (i.e., foundation, roof/attic, walls, windows, insulation, etc.) and major equipment (i.e., heating, cooling, hot water, and, if present, solar photovoltaic systems). Both rating systems score buildings on a 1–10 scale and standardize the results across the United States.

Given our experimental design, it was critical that we choose rating systems that had the information we needed to calculate the monthly energy costs associated with a rental unit at each rating level. This let us ensure that each condition displayed equivalent information that only varied in the form of presentation. For example, to compare the results of participants seeing energy ratings along a continuum and participants seeing monthly energy costs along a continuum, the energy ratings and costs had to be consistent. DOE provided us the data necessary to make these calculations for both the Home Energy Score and Asset Score.

As our pervious report noted, unfamiliar scoring scales can have limited impact on audiences. However, if the scale is easily understood, unfamiliar rating systems can still be effective with audiences. We found that both the Home Energy Score and the Asset Score were intuitive enough to influence participants.

Designing Our Energy Labels

Currently, no rental listing website has a built-in location for energy ratings. The only city that currently requires disclosure of home energy ratings is Portland, Oregon, and that policy covers only homes listed for sale rather than rentals. A search for homes to rent on Zillow, reveals that not all homes in Portland present a Home Energy Score rating. The homes that do present it typically include it in the description, as in figure A1.

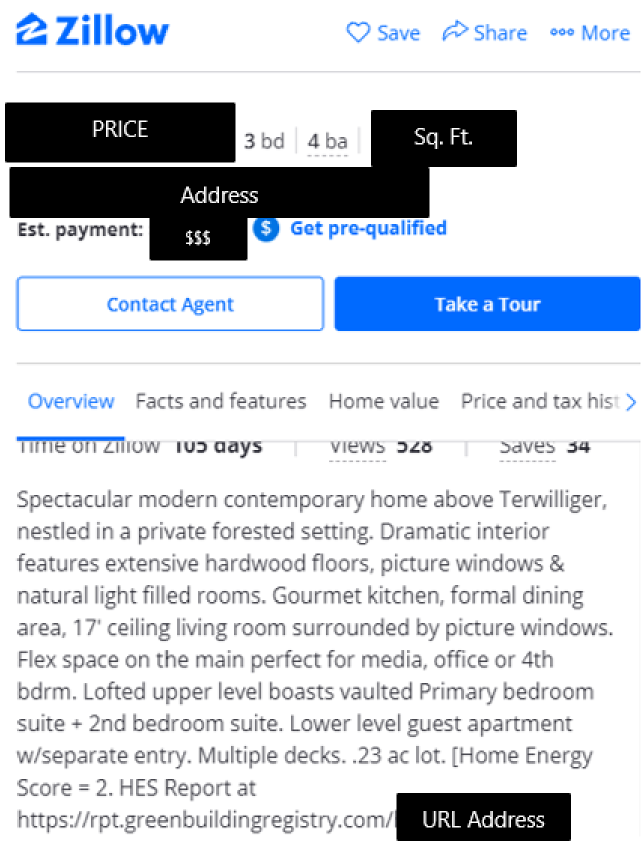


Figure A1. Screenshot of a Zillow rental listing in Portland, Oregon, that includes Home Energy Score information

Because there is no standard way of presenting energy information on rental listing websites, we chose to design several labels with different information so that we could evaluate and compare their impact. These labels differed in the information that they provided and how the information was displayed. One label showed the monthly energy cost, one showed the monthly energy cost along a continuum, one showed the energy rating, one showed the energy rating along a continuum, and one showed both the energy cost and rating along a continuum. We based our design for the continuum scale on DOE's Home Energy Score and Building Energy Asset Score label designs.

SELECTING DCE ATTRIBUTE LEVELS

We chose attribute levels based on our previous research (Sussman et al. 2020) and conversations with the DOE about Home Energy Score and Building Asset Score. We identified several constraints based on our previous research: (1) for both apartments and houses, the smallest square footage could not coexist with the largest number of bedrooms; (2) for apartments, the lowest number of bedrooms (studio) could not coexist with the highest three levels of bathrooms (1.5, 2, or 2.5 bathrooms); (2) for apartments, the second lowest number of bedrooms (one bedroom) could not coexist with the highest two levels of bathrooms (2 or 2.5 bathrooms); and (3) for houses, the lowest number of bedrooms (one bedroom) could not coexist with the highest two levels of bathrooms (2 or 2.5 bathrooms). The final D-efficiency of the experimental design (a measure of the balance of the matrix of options, which determines how cleanly we can interpret the results) was 88.48% (*D error* = .02). Table A2 below shows the attribute levels.

Table A1. Attribute levels

Attribute	Single-family	Apartment
1. Photo	Photo A Photo B Photo C	Photo D Photo E Photo F
2. Listing price	a. $[90.25% stated price] b. $[96.75% stated price] c. $[103.25% stated price] d. $[109.75% stated price]	
3. Preferred number of bedrooms	Stated minimum # of bedrooms –1 [_bds] Stated minimum # of bedrooms [_bds} Stated minimum # of bedrooms +1 [_bds]	
4. Number of bathrooms	a. 1 bath b. 1.5 bath c. 2 bath d. 2.5 bath	
5. Square footage (28% above and below the median)	a. 1,627 square feet b. 2,261 square feet c. 2,894 square feet	a. 774 square feet b. 1,075 square feet c. 1,376 square feet
7. Energy efficiency information		
Condition 1: Control (efficiency information is hidden)	N/A	
Condition 2: Energy cost	a. $[Average estimated monthly energy costs per state for houses with Home Energy Score = 2] b. $[Average estimated monthly energy costs per	a. $[Average estimated monthly energy costs per state for apartments with Asset Score = 2] b. $[Average estimated monthly energy costs per

Attribute	Single-family	Apartment
	state for houses with Home Energy Score = 5] c. $[Average estimated monthly energy costs per state for houses with Home Energy Score = 8]	state for apartments with Asset Score = 5] c. $[Average estimated monthly energy costs per state for apartments with Asset Score = 8]
Condition 3: Energy cost along a continuum	a. $[Average estimated monthly energy costs per state for houses with Home Energy Score = 2] on continuum b. $[Average estimated monthly energy costs per state for houses with Home Energy Score = 5] on continuum c. $[Average estimated monthly energy costs per state for houses with Home Energy Score = 8] on continuum	a. $[Average estimated monthly energy costs per state for apartments with Asset Score = 2] on continuum b. $[Average estimated monthly energy costs per state for apartments with Asset Score = 5] on continuum c. $[Average estimated monthly energy costs per state for apartments with Asset Score = 8] on continuum
Condition 4: Energy cost included in rent	a. $[Rent price] + $[Average estimated monthly energy costs per state for houses with Home Energy Score = 2] b. $[Rent price] + $[Average estimated monthly energy costs per state for houses with Home Energy Score = 5] c. $[Rent price] + $[Average estimated monthly energy costs per state for houses with Home Energy Score = 8]	d. $[Rent price] + $[Average estimated monthly energy costs per state for apartments with Asset Score = 2] e. $[Rent price] + $[Average estimated monthly energy costs per state for apartments with Asset Score = 5] $[Rent price] + $[Average estimated monthly energy costs per state for apartments with Asset Score = 8]
Condition 5: Energy rating out of 10 (number only)	a. Home Energy Score 2/10 b. 5/10 c. 8/10	a. Asset Score 2/10 b. 5/10 c. 8/10

Attribute	Single-family	Apartment
Condition 6: Energy rating along a continuum	d. 2/10 e. 5/10 f. 8/10	d. 2/10 e. 5/10 f. 8/10
Condition 7: Voluntary label (show rating only for most efficient and add ENERGY STAR label)	- - 8/10 ENERGY STAR label	- - 8/10 ENERGY STAR label

RANDOMIZATION PROCEDURES: CONDITION, BLOCK, AND PRESENTATION

We followed the same procedure for randomization as our previous experiment (Sussman et al. 2020). We randomly assigned participants to one of the eight conditions outlined in table A1. Aside from the efficiency information attribute, all other attributes and levels were identical in each condition.

Appendix B. Participant Details

This appendix provides more detailed information about the participants who completed the experiment.

Table B1. Detailed information about participants' current rentals

Current rental	% (*n*)
Duration in current rental	
Less than 1 year	24.1% (591)
1 year	17.5% (430)
2–4 years	27.7% (679)
5–9 years	18.4% (451)
10 or more years	12.4% (304)
Current rental property type	
Single-family home	33.9% (832)
Apartment/condominium/co-op with more than 6 units	31.2% (766)
Home/apartment with up to 6 units	20.7% (507)

Current rental	% (*n*)
Rowhouse/townhouse with more than two units	8.2% (201)
Manufactured/mobile home	2.8% (69)
Other	3.3% (80)
Energy costs included in rent	
Heat	35.4% (869)
Hot water	50.2% (1,233)
AC	29.1% (715)
Gas	24.4% (600)
Electricity	26.4% (647)
None of the above	42.0% (1,030)
Not sure	15.7% (386)
Currently live in subsidized or rent-stabilized home (versus market rate)	
Live in rent-stabilized housing	23.6% (580)
Rent is partly or completely subsidized by a program	9.9% (244)
None of the above	66.4% (1,631)

Table B2. Experience searching for rental residences

Rental Search		
Perceived number of options available	Mean rating	Standard deviation
1 (very few choices) to 100 (very many choices)	45.32	26.928
Number of apartments viewed before renting	% (n)	
1–2 options	15.3% (376)	
3–5 options	52.8% (1,296)	
6–8 options	15.3% (376)	
9 or more options	13.0% (320)	

Rental Search		
Most popular rental listing websites	% (n)	
Apartments.com	26.2% (644)	
Zillow.com	24.8% (610)	
Craigslist.com	12.4% (304)	
Trulia.com	10.9% (267)	
Apartmentfinder.com	10.3% (254)	
Willingness to pay for $0 energy bill	Average rent increase	Standard deviation
How much (if any) would you be willing to increase your monthly rent so that your energy bills would be $0?	$311.47	$617.47
When will you start to search for your next rental residence?	% (n)	
Less than 1 year from now	21.1% (519)	
1 year from now	15.2% (374)	
2–4 years from now	10.3% (254)	
5 or more years from now	3.4% (83)	
Unsure	15.2% (379)	
Not Applicable (not planning to rent next residence, or not planning to move from current residence)	34.5% (846)	

Table B3. Information about financial impacts from COVID-19 pandemic

Impact from COVID pandemic	% (n)
Unemployment benefits during pandemic	
Received unemployment benefits	23.4% (575)
Did not receive unemployment benefits	76.6% (1,880)
Ability to pay rent during pandemic	
COVID-19 had no effect on ability to pay rent	45.2% (1,109)

Impact from COVID pandemic	% (n)
Able to pay rent every month but it was harder than in pre-COVID years	28.5% (700)
Unable to pay rent for one or more months but was not evicted	10.8% (264)
Was evicted because was not able to pay rent	1.9% (47)
Ability to pay rent improved during the pandemic	3.1% (75)
Not applicable	10.8% (264)

Table B4. Low-income qualification

Participants falling below 200% of federal poverty level (FPL)	% (n)
Income below 200% of FPL	48.5% (1,191)
Income at or above 200% of FPL	50.3% (1,235)
“Don’t know” income	1.2% (29)

Table B5. Energy burdens by income group

Went without necessities to pay energy bill				
	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Low-income*	165 (13.9%)	184 (15.4%)	160 (13.4%)	682 (57.3%)
Not low-income	99 (8.0%)	116 (9.4%)	101 (8.2%)	919 (74.4%)
Kept home at unsafe or unhealthy temperature levels**				
	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Low-income	119 (10.0%)	106 (8.9%)	93 (7.8%)	733 (61.5%)
Not low-income	98 (7.9%)	73 (5.9%)	57 (4.6%)	893 (72.3%)
Received a disconnection notice				

	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Low-income	135 (11.3%)	126 (10.6%)	75 (6.3%)	855 (71.8%)
Not low-income	78 (6.3%)	73 (5.9%)	50 (4.0%)	1,034 (83.7%)
Energy bills have caused anxiety				
	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Low-income	254 (21.3%)	262 (22.0%)	214 (18.0%)	461 (38.7%)
Not low-income	272 (22.0%)	181 (14.7%)	143 (11.6%)	639 (51.7%)
Received home energy assistance				
	Yes	No	Decline to say	
Low-income	260 (21.8%)	877 (73.6%)	54 (4.5%)	
Not low-income	138 (11.2%)	1,013 (82.0%)	84 (6.8%)	
Would move out early due to surprise high energy bill				
	Yes	No	Maybe	
Low-income	303 (25.4%)	446 (37.4%)	442 (37.1%)	
Not low-income	278 (22.5%)	517 (41.9%)	440 (35.6%)	

***Low-income group defined as having income below the 200% federal poverty level.**
****This question was shown only to those who pay for at least one utility.**

Table B6. Familiarity with Home Energy Score, Building Energy Asset Score (BAS), and Home Performance with ENERGY STAR ratings

Rating system	Mean score	Standard deviation
Familiarity with Home Energy Score prior to study	39.96 out of 100	29.77
Familiarity with Building Energy Asset Score prior to study	26.89 out of 100	28.749

Rating systems were scored from 1 (completely unfamiliar) to 100 (completely familiar).

Appendix C. Detailed Results of Statistical Analyses

In conducting our statistical analyses, our outcomes of interest were (1) the frequency with which renters selected the most efficient homes across six choice sets, (2) the frequency with which respondents selected the least efficient homes across six choice sets, and (3) the estimated willingness of respondents to increase monthly rent for a one-unit increase in energy score.

Although our primary outcome for most research questions was the willingness to increase rent, we included the "click rate" analyses (frequency of clicking most and least efficient options) for comparing labels and the presence and absence of labels, because we could not analyze one label condition (voluntary label) for willingness to increase rent and could not include the control condition in that type of analysis. Thus, to enable us to compare all six conditions and to compare presence versus absence of labels, we analyzed click rates.

Click rates were analyzed as "frequency of clicking on most efficient options" or "frequency of clicking on least efficient options" in each choice set. Although these two analyses often converged (i.e., they found the same labels to be most effective for changing behavior) they sometimes did not. Moreover, if labels encourage renters to avoid low-efficiency homes rather than encouraging uptake of high-efficiency homes, that could have policy implementation implications.

LABEL DESIGN

Willingness to Increase Rent for Energy Efficiency

$p < .001$ (statistically significant)[27]

	Energy costs	Energy costs along a continuum	Energy costs included in rent	Energy score as a number out of 10	Energy score along a continuum
Monthly rent	1,280	1,312	1,334	1,188	1,310
WTP for 3 units [SD]	55.23 [6.9]	81.21 [9.03]	44.28 [3.14]	82.68 [8.29]	88.97 [12.69]
WTP for 1 unit	18.41	27.07	14.76	27.56	29.66
WTP percentage	1.44%	2.06%	1.11%	2.32%	2.26%

[27] The voluntary label and control conditions could not be included in the multinomial logit model used to calculate these willingness to pay values because of how they asymmetrically present information to participants.

	Energy costs	Energy costs along a continuum	Energy costs included in rent	Energy score as a number out of 10	Energy score along a continuum
n	308	301	306	310	307

Clicking Most Efficient Rental Option Across Six Choice Sets

Each participant was randomly assigned to view home rental options on the mock *RentDragon* website with one of six labeling strategies (six conditions). We compared the frequency of participants selecting the most efficient home options across the six conditions using an ANOVA. Participants in each condition saw the same six choice sets and made six selections of their preferred homes; therefore, the outcome variable (selecting the most efficient home) could range from zero to six (i.e., they could select the most efficient home up to six possible times).

After adjusting the degrees of freedom to account for unequal variances, we found a significant effect of condition on frequency of selecting the most efficient rental option, $F(7, 1{,}047.98) = 7.61$, $p < .001$. Post-hoc tests revealed that four conditions significantly encouraged participants to select the most efficient homes more than the no-information control condition. Those four conditions were: energy cost along a continuum, energy cost included in rent, home energy score out of 10, and home energy score along a continuum. The most efficient option was not clicked on significantly more often in the estimated monthly energy costs and voluntary label conditions compared to the no home energy information condition.

Clicking Least Efficient Rental Option Across Six Choice Sets

After adjusting the degrees of freedom to account for unequal variances, we found a significant effect of condition on frequency of selecting the least efficient rental option, $F(7, 2{,}447) = 8.39$, $p < .001$. As with the most efficient options, post-hoc tests revealed that four conditions significantly discouraged participants from selecting the least efficient homes compared to the no-information control condition: *energy cost along a continuum*, *energy cost included in rent*, *energy score out of 10*, and *energy score along a continuum*. The least efficient option was not clicked on significantly less often in the *estimated monthly energy costs* and the *voluntary label* conditions compared to the *no home energy information* condition.

STATISTICALLY SIGNIFICANT DEMOGRAPHIC VARIABLES

Age

Willingness to Increase Rent for Energy Efficiency

$p = .02$ (statistically significant)

	Under 45 years old	45+ years old
Purchase price	1,388	1,284
WTP for 3 units [SD]	71.85 [5.25]	62.69 [3.45]
WTP for 1 unit	23.95	20.90
WTP percentage	1.72%	1.63%

Intended Monthly Rental Price

Willingness to Increase Rent for Energy Efficiency

$p < .001$ (statistically significant)

	Up to $750	$751–1,000	$1,001–1,500	$1,501–5,000+
Purchase price	570	912	1,319	2,434
WTP for 3 units [SD]	25.06 [0.6]	37.49 [1.57]	44.3 [2.38]	81.17 [15.81]
WTP for 1 unit	8.35	12.50	14.77	27.06
WTP percentage	1.47%	1.37%	1.12%	1.11%

Intended Rental Type

Willingness to Increase Rent for Energy Efficiency

$p < .01$ (statistically significant)

	House	Apartment
Purchase price	1,354	1,221
WTP for 3 units [SD]	65.99 [5.12]	69.75 [4.0]

WTP for 1 unit	22.00	23.25
WTP percentage	1.62%	1.90%

U.S. Census Region

Willingness to Increase Rent for Energy Efficiency

p < .001 (statistically significant)

	Midwest	Northeast	South	West
Purchase price	1,161	1,353	1,256	1,373
WTP for 3 units [SD]	66.63 [5.21]	78.06 [9.97]	70.96 [5.32]	43.6 [4.2]
WTP for 1 unit	22.21	26.02	23.65	14.53
WTP percentage	1.91%	1.92%	1.88%	1.06%

Climate Zone

Willingness to Increase Rent for Energy Efficiency

p < .01 (statistically significant)

	Climate zone 1	Climate zone 2	Climate zone 3	Climate zone 4	Climate zone 5	Climate zone 6–7
Purchase price	1,356	1,313	1,334	1,250	1,262	1,016
WTP for 3 units [SD}	105.59 [87.92]	43.4 [4.19]	53.9 [4.9]	85.66 [9.07]	64.36 [4.97]	92.66 [18.04]
WTP for 1 unit	35.20	14.47	17.97	28.55	21.45	30.89
WTP percentage	2.59%	1.10%	1.35%	2.28%	1.70%	3.04%

Number of Residents

Willingness to Increase Rent for Energy Efficiency

$p < .001$ (statistically significant)

NOTE: the difference in willingness to increase rent between groups is significant, but when accounting for the higher base cost of rent in the 3+ household group, this difference is wiped out. That is, the absolute difference in dollar amount is different, but the percentage is not.

	1–2 residents	3+ residents
Monthly rent	1,207	1,405
WTP for 3 units [SD]	63.08 [2.9]	73.45 [7.97]
WTP for 1 unit	21.03	24.48
WTP percentage	1.74%	1.74%

STATISTICALLY NON-SIGNIFICANT DEMOGRAPHIC VARIABLES

Income

Willingness to Increase Rent for Energy Efficiency

$p = .24$ (not statistically significant)

	Under $10,000	$10,000–19,999	$20,000–24,999	$25,000–34,999	$35,000–49,999	$50,000–74,999	$75,000–99,999	$100,000 or more
Purchase price	1,104	972	977	1,067	1,289	1,392	1,649	1,965
WTP for 3 units [SD]	51.88 [6.85]	65.71 [6.42]	36.37 [2.51]	44.48 [3.25]	61.13 [6.09]	70.13 [6.86]	70.7 [15.12]	133.17 [48.77]
WTP for 1 unit	17.29	21.90	12.12	14.83	20.38	23.38	23.57	44.39
WTP percentage	1.57%	2.25%	1.24%	1.39%	1.58%	1.68%	1.43%	2.26%

Low-Income

Willingness to Increase Rent for Energy Efficiency

p = .21 (not statistically significant)

	Low income	Non-low income
Purchase price	1,087	1,480
WTP for 3 units [SD]	55.8 [2.72]	79.32 [6.4]
WTP for 1 unit	18.60	26.44
WTP percentage	1.71%	1.79%

High Energy Burden

Willingness to Increase Rent for Energy Efficiency

p = .4 (not statistically significant)

	High energy burden	Non-high energy burden
Purchase price	1,147	1,359
WTP for 3 units [SD]	43.84 [2.48]	89.43 [7.29]
WTP for 1 unit	14.61	29.81
WTP percentage	1.27%	2.19%

Severe Energy Burden

Willingness to Increase Rent for Energy Efficiency

p = .22 (not statistically significant)

	Severe energy burden	Non-severe energy burden
Purchase price	1,206	1,304
WTP for 3 units [SD]	101.42 [20.3]	62.79 [3.07]
WTP for 1 unit	33.81	20.93
WTP percentage	2.80%	1.61%

Education

Willingness to Increase Rent for Energy Efficiency

P = .29 (not statistically significant)

	Less than high school	High school graduate or equivalent (e.g., GED)	Associate degree (community college, technical college, vocational school, etc.)	College graduate (bachelor's degree)	Graduate or professional degree
Purchase price	1,256	1,217	1,257	1,345	1,406
WTP for 3 units [SD]	54.58 [8.56]	62.34 [4.94]	65.8 [6.43]	70.89 [6.4]	93.2 [14.09]
WTP for 1 unit	18.19	20.78	21.93	23.63	31.07
WTP percentage	1.45%	1.71%	1.75%	1.76%	2.21%

Urban Versus Rural

Willingness to Increase Rent for Energy Efficiency

p = .17 (not statically significant)

	Metro	Non-metro
Purchase price	1,289	1,244
WTP for 3 units [s.e.]	70.97 [3.68]	38.41 [2.48]
WTP for 1 unit	23.66	12.80
WTP percentage	1.84%	1.03%

Appendix D. Pooled Overall Models

LABEL VERSUS NO LABEL

To learn whether seeing any energy label significantly changed renters' choices, we conducted an independent samples *t*-test, comparing frequency of clicking on the most efficient home option in control and (pooled) experimental conditions, as well as a second *t*-test comparing these same groups on their frequencies of clicking on the least efficient home options. For each comparison, frequencies could range from 0 (never clicking on most efficient or least efficient) to 6 (clicking on the most efficient or least efficient in each of the six choice sets).

After adjusting degrees of freedom to account for unequal variances, we found a significant effect of being shown an efficiency label versus seeing no label in terms of how often the most efficient option was selected, $t(468.27) = -5.72$, $p < .001$. On average, participants shown an efficiency label clicked on the most efficient option more often ($M = 2.37$) than participants shown no efficiency label ($M = 1.96$). This amounted to a 21% increase in clicking on the most efficient home option in the presence of an energy efficiency label.

After adjusting degrees of freedom to account for unequal variances, we found a significant effect of being shown an efficiency label versus seeing no label on how often the least efficient option was selected, $t(441.18) = 5.88$, $p < .001$. On average, participants shown an efficiency label clicked on the least efficient option less often ($M = 1.50$) than participants shown no efficiency label ($M = 1.89$). This amounted to a 21% decrease in clicking on the least efficient home option in the presence of an energy efficiency label.

Knowing that labels both increase clicks on the most efficient homes and decrease clicks on the least efficient homes helps justify labeling policies. For example, it informs policymakers that landlords with both average *and* below average buildings could benefit from efficiency improvements. It also helps justify the targeted implementation of incentives for low-income building owners with below-average efficiency scores. This group would benefit substantially from improvements—and has the greatest difficulty paying for them.

OVERALL POOLED MULTINOMIAL LOGIT MODEL

We used the pooled multinomial logit model to calculate willingness to pay for each attribute of the rental units, including energy efficiency. These values can be compared against values for each specific label or by particular demographic segments.

Attributes	Coefficient	*p-value*	WTP [SD] (in USD)
Monthly rent	–0.0034	*p < .001*	$1,284.53
Photo		*p = .26*	
1	–0.0171		–5. [0.24]
2	0.0261		7.65 [0.36]

3	–0.0091		–2.65 [0.13]
Bedrooms (customized by participant)*		*p < .001*	
Level 1	–0.5312		–155.47 [14.69]
Level 2	0.2896		84.75 [5.2]
Level 3	0.2416		70.72 [4.35]
Number of bathrooms		*p < .001*	
1 bath	–0.2709		–79.28 [5.89]
1.5 bath	–0.1176		–34.43 [2.3]
2 bath	0.199		58.23 [3.79]
2.5 bath	0.1896		55.48 [3.66]
Square footage**	0.198	*p < .001*	57.99 [2.95]
Energy efficiency information (three energy score units)	0.236	*p < .001*	69.19 [3.24]
Alternative		*p < .001*	
1	–0.0516		–15.11 [0.73]
2	–0.0496		–14.51 [0.76]
3	0.1012		29.62 [1.55]

Note: This overall multinomial logit model excludes participants in the control and voluntary label conditions because the asymmetric information in those conditions made it inappropriate to run this type of model with those participants. It also excludes the costs-plus-score condition that was removed from all analyses due to an error in wording of the label.

*Bedrooms was customized based on each participant's stated preference. Level 2 was the preferred number of bedrooms they stated they were looking for, which could vary from one to four (Levels 1 and 3 are one less and one more bedroom, respectively)

** WTP for a one level increase in square footage (each level was 28% above or below the median for that home type)

Appendix E. Additional Demographic Questions

In this appendix, we present additional descriptive statistics related to our sample that were not presented in the body of our report. Although these statistics were not directly relevant to our primary research questions, we include them here as they may be of interest to some readers. The additional demographic statistics centered around the following four questions.

WHAT PERCENTAGE OF RENTERS' INCOMES DO PROSPECTIVE RENTERS EXPECT TO PAY ON ENERGY BILLS?

Among renters in our sample who provided their estimated monthly energy costs (*n* = 1,810), the median energy burden was about 4.11%, which is only slightly higher than what was found in another study of renters in the 25 largest U.S. cities (3.1%) (Drehobl et al. 2020). In our sample, more than one-third of participants (36%) who pay their energy bills (*n* = 1,798) had "high" energy burdens (>6%), and 23% had "severe" energy burdens (>10%). This is higher than typically seen in U.S. cities (Drehobl et al. 2020), but our calculations did not include participants who reported not paying any energy costs. Therefore, our sample is likely consistent with what would be expected from a national sample of U.S. renters.

HOW MANY PARTICIPANTS REPORT THAT THEIR ENERGY BILLS CAUSE ANXIETY?

Energy bills have caused anxiety				
	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Yes (energy burden >6%)	154 (23.7%)	173 (26.7%)	155 (23.9%)	167 (25.7%)
No (energy burden <6%)	268 (23.3%)	176 (15.3%	128 (11.1%)	577 (50.2%)

Would move out early due to surprise high energy bill			
	Yes	No	Maybe
Yes (energy burden >6%)	183 (28.2%)	224 (34.5%)	242 (37.3%)
No (energy burden <6%)	238 (20.7%)	492 (42.8)	419 (36.5%)

HOW MANY PARTICIPANTS WENT WITHOUT NECESSITIES IN THE PAST YEAR TO PAY ENERGY BILLS?

Went without necessities to pay energy bill				
	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Yes (energy burden >6%)	104 (16.0%)	122 (18.8%)	104 (16.0)	319 (49.2%)
No (energy burden <6%)	106 (9.2%)	99 (8.6%)	93 (8.1%)	851 (74.1%

Received a disconnection notice				
	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Yes (energy burden >6%)	96 (14.8%)	88 (13.6%)	52 (8.0%)	413 (63.6%
No (energy burden <6%)	81 (7.0%)	65 (5.7%)	36 (3.1%)	967 (84.2%)

Received home energy assistance			
	Yes	No	Declined to say
Yes (energy burden >6%)	174 (26.8%)	454 (70.0%)	21 (3.2%)
No (energy burden <6%)	125 (10.9%)	958 (83.4%)	66 (5.7%)

HOW MANY PARTICIPANTS KEPT THEIR HOME AT AN UNSAFE OR UNHEALTHY TEMPERATURE TO REDUCE ENERGY COSTS?

Kept home at unsafe or unhealthy temperature levels				
	At least once during 1–2 months	At least once during 3–9 months	At least once during 10–12 months	Never
Yes (energy burden >6%)	88 (13.6%)	73 (11.2%)	71 (10.9%)	417 (64.3%)
No (energy burden <6%)	97 (8.4%)	65 (5.7%)	65 (5.7%)	922 (80.2%)

Appendix F. Testing Labels with RentLab

RentLab is a company with the mission of driving efficiency, sustainability, and affordability in rental housing using data transparency and customized community analytics. They partner with city governments and universities to create customized rental listing websites that share and emphasize important information that is often not included in traditional listing websites. This can include energy costs, energy efficiency scores, recycling service availability, walk scores, and onsite renewable energy. Figure F1 shows an example of a rental listing on RentLab's website.

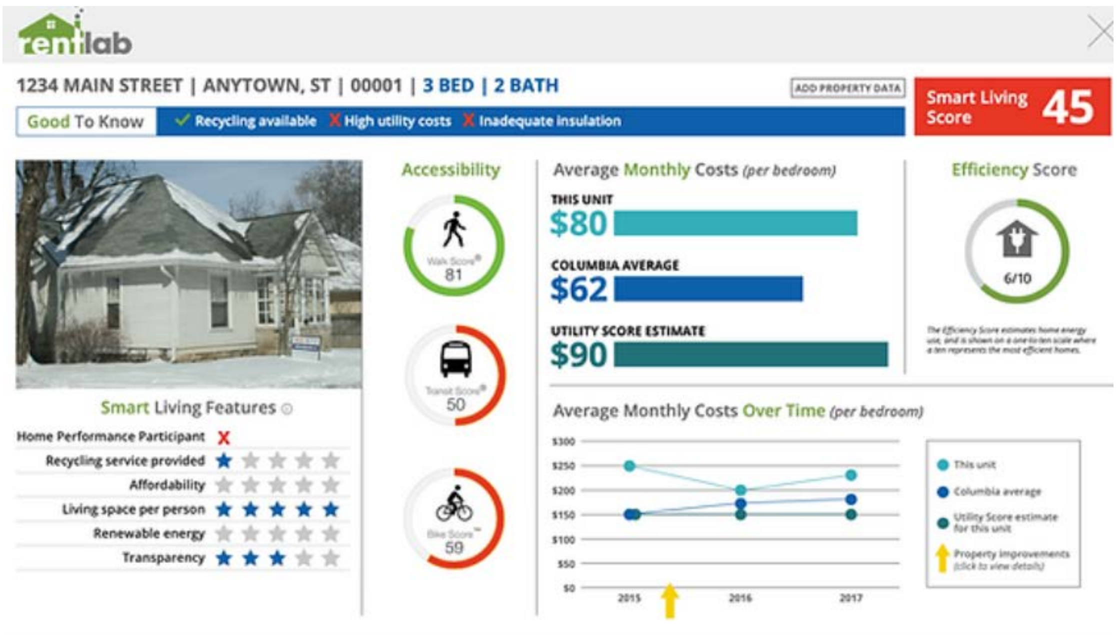
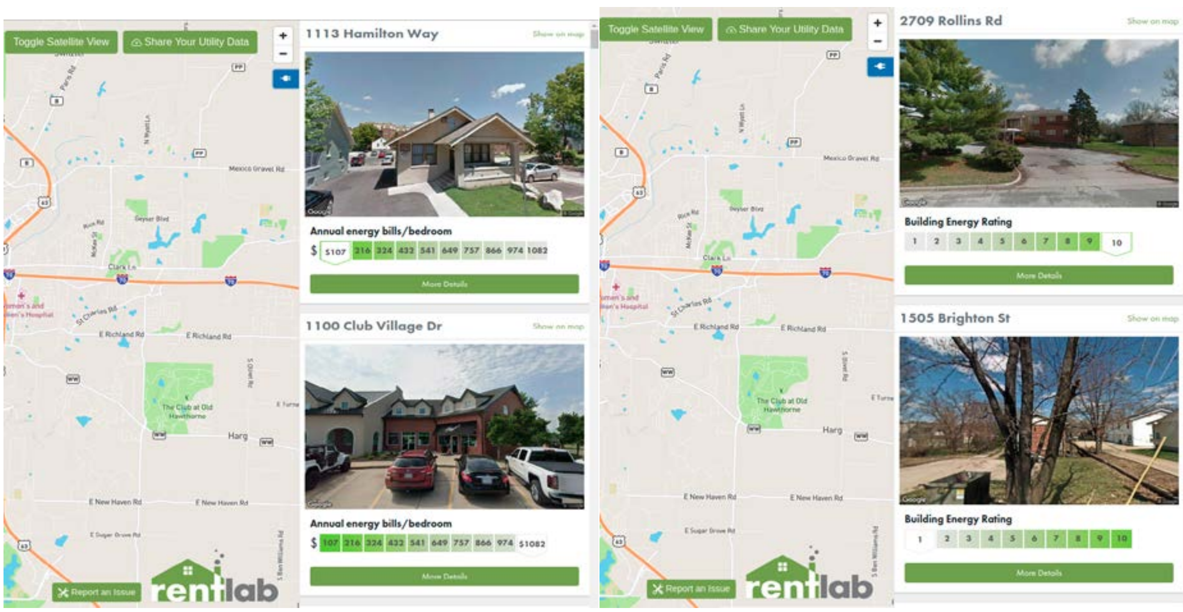


Figure F1. Example rental listing on RentLab

We partnered with RentLab to run an experiment on their website to test how real renters responded to various energy labels when looking for housing. They allowed us to change the label designs used on their site for Columbia, Missouri, which has a renter population dominated by college students looking for apartments during the school year. The site is not a traditional rental listing website, in that it is primarily used as a companion to other sites, allowing students to look up apartments they may be interested in renting to learn about nontraditional characteristics, such as transit accessibility, energy score, and energy bills. Despite the small, specific sample (students in one city already interested in nontraditional apartment characteristics), it was an excellent venue for preliminary testing of our energy efficiency labels because (1) it has a large database of apartment complexes with energy efficiency information, and (2) it is less concerned with "selling" rental units than informing customers, and it could therefore systematically change the energy label more freely than a traditional rental listing website.

We ran the experiment from October 27–November 24, 2021, in four phases of seven days each. During each of the week-long phases, website visitors saw only one of the four different labels: cost on a continuum, energy score on a continuum, energy score as a number out of 10, or no label (control condition). Although participants were not randomly assigned to a condition, the distribution of participants to label conditions by week provided a strong quasi-random design. All four phases took place during busy times of rental searching by students and none of the weeks were drastically different from others in terms of external events (e.g., holidays or weather changes).

The procedure's strength was that the same rental properties could be shown to all participants, with nothing changing between conditions except for how energy efficiency information was presented on each property. Also, rather than showing specific rental units, RentLab properties are displayed as building complexes that often have multiple vacancies and, as such, are searched for by students throughout the semester. The figures below show the user interface for the cost continuum and energy score continuum conditions.



FINDINGS

The average energy consumption per square foot of the properties that participants clicked on when energy information was hidden (control condition), was 0.28 kWh/SQFT. When participants saw an energy efficiency score along a continuum, this went down slightly to 0.22 kWh/SQFT, and when they saw an energy efficiency score as a number out of 10, this went down further to 0.16 kWh/SQFT. When energy information was presented as monthly energy bills along a continuum, the energy use of viewed properties actually increased slightly to 0.36 kWh/SQFT. This was likely because energy costs in the real world are not good predictors of energy efficiency; thus, while site visitors may have chosen homes with lower actual energy bills, those may not have been the most efficient homes. In our simulation experiment, energy costs were estimated from energy efficiency scores (by region).[28]

It is important to note that the small sample size (149–219 visitors per phase, spread across 93 properties) reduced the experiment's power to find a statistically significant result. Tests of statistical significance that we could apply in this case—such as repeated measures ANOVAs or paired-sample *t*-tests—had only small numbers of properties that were viewed in each phase to input and, as such, we could not effectively apply these tests. The small number of views of properties in each phase were "drowned out" by the much larger number of properties that were not viewed. Thus, the effect was too small, and we could examine only the overall averages of energy efficiency per view in each phase. This examination did not allow us to calculate statistical significance.

[28] For each of these averages, we controlled for the total number of visitors to the website in each phase of the experiment. The number of views per building were divided by the total number of views in that phase of the experiment. In this way, labels presented during phases of the experiment in which more users came to the website, in general, did not receive more weight.