Energy Efficiency in Real Estate Listings: A Controlled Experiment

BY REUVEN SUSSMAN,
CHRISTINE KORMOS, CELINE PARK,
AND EMMA COOPER

ACEEE Research Report
AUGUST 2020

ACEEE
American Council for an Energy-Efficient Economy

Contents

About the Authors

Reuven Sussman conducts research on energy efficiency behavior change programs and co-chairs the annual conference on Behavior, Energy, and Climate Change (BECC). He has authored academic papers and book chapters on the psychology of climate change, behavioral interventions to encourage energy efficiency, and the psychological determinants of pro-environmental behavior. Dr. Sussman is an advisor for organizations, including the G20, that implement energy efficiency behavior change programs, and a reviewer for the AR6 IPCC report on climate change. He is the winner of the 2019 Early Career Award from the Environmental, Population, and Conservation Psychology division of the American Psychological Association and currently sits on the editorial board of the *Journal of Environmental Psychology*. Reuven Sussman earned his Ph.D. in social and environmental psychology from the University of Victoria, Canada.

Christine Kormos is a behavioral scientist who conducts research related to energy and sustainability. She also designs and implements behavior change interventions, applying behavioral insights to policies and programs. In addition to authoring academic papers and book chapters, she has also authored public sector reports for government policymakers and worked as a behavioral economics consultant on sustainability-related projects. Dr. Kormos earned a Ph.D. in applied social and environmental psychology from the University of Victoria, Canada.

Celine Park is an undergraduate student majoring in mechanical engineering at Princeton University interested in sustainability, energy, and business development in addition to engineering. On campus, as a co-president of the Sustainable Engineering and Development Scholars student group, she helped Princeton undergraduates explore and find passions in a variety of sustainability-related fields. Celine interned at ACEEE in 2019.

Emma Cooper assists with research in ACEEE's behavior program and in the State and Local Policy Programs. She has worked with outside organizations to implement a pilot home energy report program in Taiwan and has authored chapters in both the *State* and *City Scorecards*. Prior to joining ACEEE, Emma worked at the Alliance to Save Energy on the policy and research teams and as a consultant at SB Works, assisting small businesses in sustainable business practices. Emma holds a master of science in climate change and policy from Bard Center for Environmental Policy and a bachelor of arts in earth science and psychology from DePauw University.

Acknowledgments

This report was made possible through the generous support of NYSERDA. The U.S. Department of Energy's Buildings Technologies Office helped support the dissemination of this report but not the design, implementation, or analysis of the experiment. The authors gratefully acknowledge the external reviewers, internal reviewers, colleagues, and sponsors who supported this report. External expert reviewers included James Geppner from NYSERDA; Bertine Stelzer from BC Hydro; Steve Conrad from Simon Fraser University; Samantha Caputo, Bryan Evans, and Carolyn Sarno from Northeast Energy Efficiency Partnerships; Julie Saporito from the Office of Climate Action in Denver; and Pamela Brookstein from Elevate Energy. External review and support do not imply affiliation or endorsement. Internal reviewers included Steve Nadel, Jen Amann, Naomi Baum, and

Hannah Bastian. The authors also gratefully acknowledge the assistance of Dan Howard. Last, we would like to thank Fred Grossberg and Rachel Siegel for developmental editing, Mary Robert Carter and Mariel Wolfson for managing the editing process, Rachel Siegel for copy editing, Kate Doughty and Eric Schwass for graphics design, and Maxine Chikumbo, Ben Somberg, and Wendy Koch for their help in launching this report.

Suggested Citation for This Report

Sussman, R., C. Kormos, C. Park, and E. Cooper. 2020. *Energy Efficiency in Real Estate Listings: A Controlled Experiment*. Washington, DC: American Council for an Energy-Efficient Economy. aceee.org/research-report/b2002.

Executive Summary

KEY TAKEAWAYS

- Energy efficiency information encouraged home buyers to avoid the least efficient homes and choose more efficient homes in a simplified simulation of a real estate website.
- Presenting efficiency information for only the most efficient homes did not encourage home buyers to choose more efficient homes in our simulation. This suggests that a voluntary labeling policy might be less effective than a mandatory labeling policy in which all home listings must include energy efficiency information.
- Energy efficiency information was most valued (in terms of willingness to pay) by relatively wealthy and educated home buyers who planned to spend the most to buy their next homes. [1]
- Home buyers valued efficiency most when it was presented as an image depicting the home's efficiency score along a continuum (a line) from inefficient to efficient. [2]

Energy efficiency information may be useful to potential home buyers and may encourage them to buy efficient homes. Real estate listing websites are perhaps the most obvious means of communicating efficiency information, as nearly all home buyers start their searches on these sites (93% overall, and 99% for millennials). [3] Currently, however, few buildings are assessed for energy efficiency, and none of the major American real estate websites include efficiency information in their listings. [4] If home efficiency information was provided, and even required, then the market could provide a direct link between sellers and buyers willing to pay for efficient homes. Field observations show that efficient homes tend to command higher sale prices than inefficient homes, [5] but multiple non-energy factors could contribute to this difference.

---

[1] Home buyers in our simulation were given the freedom to specify the approximate amount they intended to spend on their next home purchase. This number was used as the basis for prices in their simulated search results.

[2] We used the U.S. Department of Energy's Home Energy Score as a measure of residential energy efficiency in this study because it is a commonly used efficiency scoring tool in the United States. Other, similarly intuitive scoring tools may also be effective, but we did not test them. Instead, we tested different forms of presentation of the Home Energy Score and associated estimated annual home energy costs, assuming the lessons could be translated to other scoring tools.

[3] NAR (National Association of REALTORS). 2018. "Real Estate in a Digital Age 2018 Report." www.nar.realtor/sites/default/files/documents/2018-real-estate-in-a-digital-world-12-12-2018.pdf.

[4] Although this field may be available in many multiple listing service databases, most realtors do not provide the information, and major real estate websites rarely present it.

[5] For example: "Energy Performance Certificates in Buildings and Their Impact on Transaction Prices and Rents in Selected EU Countries." https://ec.europa.eu/energy/en/studies/energy-performance-certificates-buildings-and-their-impact-transaction-prices-and-rents.

A controlled experiment could strengthen the evidence that energy efficiency in particular causes this increase in sale price. Policymakers have not historically had access to this type of experimental evidence in publicly available sources, which may be one reason why we lack policies encouraging real estate websites to display efficiency information. This evidence gap may also prevent real estate professionals from wanting to disclose energy efficiency information.

The current study drew on a large national sample of participants (closely resembling the demographics of new home buyers, *N* = 1,538) who planned to purchase a new home within the next five years. We asked participants to imagine they were using a website to search for an actual home. The website showed participants six sets of search results, each with three homes, and asked them to click on the home they preferred the most within each set.[6] Search results were actually discrete choice experiment (DCE) choice sets, customized based on location, preferred price, number of bedrooms, and number of bathrooms.[7] Only some participants saw the home's energy efficiency in the choice sets presented on their screens. When such information was present, we randomly altered the form of presentation, so the efficiency information was shown in one of five possible ways (shown in figure 3 of the body of the report). These were: as a simple Home Energy Score (HES)[8] (e.g., "Home Energy Score: 5/10"); as the HES along a continuum (a line) from inefficient to efficient; as estimated annual home energy costs; as estimated annual home energy costs plus HES along a continuum (together); or as a Home Energy Score for only above-average homes (simulating a voluntary labeling program). Using these data, we were able to calculate how much participants were willing to pay for each attribute of the home and whether they clicked more (or less) often on efficient homes.

DO HOME BUYERS CLICK ON MORE EFFICIENT HOMES WHEN REAL ESTATE LISTINGS CONTAIN ENERGY EFFICIENCY INFORMATION?

Home buyers in our experiment who saw energy efficiency information clicked on the least efficient option less often (23% less), and the most energy-efficient option more often (14% more) than those who did not see efficiency information.

WHAT IS THE BEST WAY TO DISPLAY EFFICIENCY INFORMATION IN REAL ESTATE LISTINGS?

Home buyers attributed the highest value (willingness to pay) to energy efficiency, relative to purchase price, when it was presented as an efficiency score along a continuum from inefficient to efficient. Presenting the score as a number (from 1–10), without a continuum, also influenced home buyers to click on (i.e., indicate preference for) more efficient home

---

[6] Participants were asked to "click on the option you prefer the most."

[7] DCEs are controlled simulations that show participants several sets of choices, each with the same attributes, and ask which they prefer. Researchers use DCEs to assess consumer preferences without asking open-ended questions that may be influenced by various biases and that cannot account for preference tradeoffs. For example, they may be used to estimate willingness to pay for attributes of various purchases. DCE results have influenced policy decisions (e.g., Greene 2010).

[8] HES is an energy efficiency score based on the home's envelope (foundation, roof, walls, insulation, windows) and heating, cooling, and hot-water systems. It provides a total energy use estimate, as well as estimates by fuel type assuming standard operating conditions, and occupant behavior (DOE 2019b).

options. This did not increase the value of efficiency information to the same extent as presenting it along a continuum, but it nevertheless increased it significantly more than presenting no information.

Presenting estimated annual home energy costs was one of the less effective strategies for encouraging home buyers to click on more efficient listings. One possible explanation is that these costs may have appeared relatively insignificant compared to the price of the home. Future studies should further explore our finding that in the Northeast, where energy costs are higher, home buyers were willing to pay the most for energy efficiency. One approach would be to evaluate buyers' behavior when they are given more context for the potentially high annual cost of energy, perhaps by comparing energy to annual taxes or insurance fees.

The least persuasive presentation method was only showing efficiency information for the most efficient homes, as might be the case in a voluntary energy labeling program. In this scenario, home buyers only saw efficiency information for one of three homes in each choice set: the most efficient home. Voluntary energy information labeling programs are not recommended by the Collaborative Labeling and Appliance Standards Program because they are assumed to be less effective (Wiel and McMahon 2005). Some field data also suggest that participation in voluntary labeling programs can be low. [9] To the best of our knowledge, however, this study offers the first experimental support for the assumption that mandatory labeling programs are more effective than voluntary programs for nudging home buyer behavior.

WHICH HOME BUYERS VALUE EFFICIENCY MOST?

In our simulation, energy efficiency information was valued (in terms of willingness to pay) most by relatively wealthy and educated home buyers with the highest home-buying budget. The urbanness and climate zone of the home buyers did not affect the value they placed on efficiency (relative to purchase price), except for home buyers in the Northeast, who valued efficiency more than home buyers in the other three census regions. That may have been because average residential energy costs were highest in the Northeast, or because that region has a history of residential energy efficiency programs, which could have created more awareness of the benefits.

[9] McNutt, L. 2018. Pers. Comm. to S. Nadel on Jan. 5, 2018. Dunsky Consulting, Montreal.

RECOMMENDATIONS FOR POLICYMAKERS

Results from this study support the following recommendations:

- *Include efficiency information in real estate website listings because home buyers value it.* Efficiency information significantly affected home buyer decisions in our simulation, especially the decision to not click on the least efficient homes, but also to select the most efficient homes.
- *Ensure that listings include efficiency information for all homes, not just the most efficient homes*. In our simulation, home buyer decisions were minimally affected by energy efficiency information when it was only presented for high-efficiency homes, as might be the case in voluntary energy labeling programs.
- *Use an intuitive energy scoring system to present energy information*. We used the U.S. Department of Energy's Home Energy Score (HES) system, which is a more accurate measure of efficiency than a home's energy costs. [10] The score persuaded home buyers to click on efficient homes, and worked especially well when it was presented along a continuum from inefficient to efficient. Home buyers' decisions were influenced by the score regardless of their familiarity with it, suggesting that it was intuitively understandable.
- *Research and develop complementary policies*. If policies are enacted to require efficiency information in real estate listings, then home buyers may be driven away from the least efficient real estate listings. In that case, policymakers may consider programs that help homeowners, especially those with low incomes, increase the efficiency of their homes before listing or after purchasing them.

[10] Unlike energy costs, Home Energy Score is not affected by energy prices, the number of people in the home, or other extraneous factors.

Introduction

Residential homes account for 55% of buildings' energy use in the United States (EIA 2018a). The average household consumes 77.1 million Btus per year, which amounts to over 9.1 quadrillion Btus (site energy) and $219.3 billion in energy expenditures (EIA 2018b). The National Renewable Energy Laboratory estimates the U.S. residential building stock could save $49 billion in annual energy costs (about a 22% energy use reduction) through efficiency improvements (NREL 2017). The residential sector also emitted about 950 million metric tons of carbon dioxide in 2019 (EIA 2020). Thus, retrofitting existing building stock is a crucial piece of any climate change mitigation or energy efficiency plan, and policies should encourage homeowners' and home sellers' investment in energy efficiency upgrades.

Home buyers, especially during periods of high economic growth (including the data collection period for this project), [11] approach homebuying as an investment opportunity (Shiller 2007) and might, therefore, be interested in upgrades that maximize the value of their investments. They have several options to increase their homes' values, including aesthetic or functionality upgrades such as quartz countertops, a finished basement, or a nice outdoor area (DiClerico 2016). Another option is efficiency upgrades. In studies comparing sale prices of homes with or without green labels, buyers pay more to acquire efficient homes (Kahn and Kok 2014; Fuerst et al. 2015; Walls et al. 2017). In California, "an otherwise identical dwelling with a 'green' certification will transact for about 2–4% more" (Kahn and Kok 2014). [12]

Research on how homeowners and renters value energy efficiency is limited. Some survey studies that simply ask participants to explicitly state their home-buying preferences show that homeowners can be convinced to do energy upgrades during some home renovations (Achtnitcht and Madlener 2014), and that apartment renters and owners in Sweden sometimes take sustainability into account when choosing where to live (Zalejeska-Jonsson 2014). [13] A discrete choice analysis showed that home energy upgrades were preferred over behavioral measures in one UK study (Poortinga et al. 2003).

One of the hypotheses of this study is that efficiency information may be useful to potential home buyers and is significant in their real estate search decisions. For consumers who care about energy efficiency, presenting the information in a meaningful metric generally

[11] The current study was conducted before COVID-19 became a national emergency in the United States, when real estate prices in the United States were generally high (January to February of 2020).

[12] Statistically modeling consumer behavior using real-world revealed preferences demonstrates that home buyers do pay a premium for efficiency. However, revealed preferences research has its drawbacks. For example, revealed-preference studies do not account for consumers' inabilities to choose options that do not exist. Given much of the current housing stock is either inefficient or efficient but expensive, revealed preference studies can fall short in showing what home buyers would do if they had affordable efficient options available to them. These studies are also not strictly experimental and do not control for the effects of various other home attributes. As such, these studies are not "experimental" and only offer partial support for the idea that "greenness" causes price to increase.

[13] Explicit surveys may suffer from limitations such as recall bias, social desirability bias, and the availability heuristic (biases in thinking that affect how people remember facts and respond to surveys).

increases the likelihood of purchasing efficient products. Information labels act as signposts that both activate the consumers' preexisting values, attitudes, and goals, and tell them how likely the product is to meet those goals (Ungemach et al. 2017). For example, vehicle fuel economy labels with greenhouse gas emission information allow consumers who care about the environment to choose vehicles that emit less pollution (Ungemach et al. 2017). Information labels can sway consumers to purchase energy-efficient appliances (e.g., Newell and Siikamaki 2014) and personal vehicles (e.g., Kormos and Sussman 2018).

Enervee, a company that provides consumer-facing websites that rate appliance efficiency, found that, in a randomized control study, their efficiency information labels can increase clicks on efficient products (Niederberger and Champniss 2018). Endorsement labels (such as Energy Star) usually only apply to the highest-efficiency products. They do not help customers differentiate among above- (or below-) average products, but together with information labels (such as EnergyGuide), they complement each other and mutually reinforce energy-efficient purchasing (Thorne and Egan 2002). Government-led information labeling initiatives, such as Energy Star, are particularly effective for encouraging energy-efficient purchases because they are credible, financially stable, and long lasting (Banerjee and Solomon 2003).

Efficiency Recommendations in Real Estate Listings

Extending the research on energy labels to real estate listings is crucial to informing information labeling initiatives. Real estate listing websites are perhaps the most obvious means for communicating efficiency information. Nearly all home buyers start their search on these sites (93% overall, and 99% for millennials; NAR 2018), and click on listings to learn additional information about a home. Presenting critical information at the point of decision making can change behavior (e.g., Russell, Dzewaltowski, and Ryan 1999). Therefore, getting efficiency information in front of home buyers at this moment may affect those critical decision-making clicks.

If homes were assessed for efficiency and websites were required to include this information, then the value of energy efficiency upgrades to home sellers could increase. Currently, however, few buildings are assessed for energy efficiency, and none of the major American real estate aggregation websites include efficiency information, except in cities like Portland, Oregon.[14] Indeed, although energy scoring with the Home Energy Score (HES) or a similar metric is mandated or suggested to some extent in 14 jurisdictions,[15] Portland is the only city requiring that sellers include efficiency scores in descriptions of homes that they list (thus ensuring that real estate aggregators such as Redfin or Zillow present this information in the listing).

The question remains as to how much home buyers would value this information and whether it would change their decisions. Evidence of a causal link between efficiency information and real estate website clicks is currently unavailable. Before enacting policies

[14] In Portland, Oregon, efficiency information has been required in real estate listings since January 1, 2018.

[15] A description of the HES program is available in Appendix B. This map shows current energy scoring real estate policies in each jurisdiction: www.naseo.org/issues/buildings/home-energy-labeling.

encouraging real estate websites to display efficiency information, policymakers should have evidence that this would change home buyer behavior. Moreover, this type of research could help real estate stakeholders and policymakers see that these policies can make a tangible difference.

Research Questions

This project was designed to systematically test how much home buyers value energy efficiency information in real estate listings. It was created to provide information to policymakers in jurisdictions considering home energy efficiency information labeling requirements.

We ask three questions:

- Do home buyers click on more efficient homes when real estate listings contain energy efficiency information?
- What is the best way to display efficiency information in real estate listings?
- Which home buyers value efficiency most?

Method

DISCRETE CHOICE EXPERIMENTS

Carefully controlled experimental studies allow researchers to delve into granular questions about when and how real estate decisions are influenced on an individual level. Discrete choice experiments (DCEs) are choice simulation tools that have been used to influence policy decisions in the past (e.g., Greene 2010). These tools allow researchers to assess consumer preferences when tradeoffs must be made, using choice sets instead of open-ended questions that may be influenced by various biases.

DCEs can be used to estimate willingness to pay for attributes of various purchases within a controlled simulation. They work by showing participants several sets of choices, each with different levels of the same attributes, and asking which they prefer most. For example, researchers may show participants choice sets with three cars that have different prices, safety ratings, and reliability ratings. One may have a low price, but also low safety rating and poor reliability, whereas another may have a high price, high safety rating, and high reliability. Participants would each see a few of these choice sets. Based on the choices of hundreds of participants seeing several choice sets each, researchers can determine how much participants are willing to pay for each attribute and the types of tradeoffs they are willing to make.

Some real estate research has been conducted using DCEs. In a review, Marmolejo-Duarte and Bravi (2017) note that real estate research in Spain, Canada, Switzerland, Korea, and Singapore has used this procedure. DCEs in these studies helped examine the value of various energy-related home attributes such as energy certifications, heating systems, renovations with or without energy retrofits, and "green" home features. In 2018, a European research group called Consumer Energy Efficiency Decision Making (CONSEED) reported on a DCE to determine willingness to pay for energy-efficient real estate properties when energy efficiency information was presented either in physical units (kWh per year) or monetary terms (euros per year) (CONSEED 2018). The researchers found that consumers valued efficiency more highly when it was presented in monetary terms. See Appendix A for more details.

These DCEs are useful for simulating a context-free decision-making process and are generally useful for gauging home buyer preferences. However, context is important in these decisions. Hainmueller, Hangartner, and Yamamoto (2015) explain that as an experiment more accurately represents the real-world backdrop for behavior, the validity of the experiment increases. The current project therefore increased the realism of the decision-making context by loosely simulating a real estate website. As label design can influence perceptions of information, we also did a controlled test of different ways to display efficiency information.

Given the difficulties of conducting experiments using actual real estate websites, DCEs can provide useful proxy experimental information. The results are also more precise and flexible. The ability to strictly control and manipulate non-efficiency factors in the simulation (such as price, square footage, and photos) allows us to better understand the precise value of efficiency relative to other attributes, and the tradeoffs that buyers make. [16]

OUR STUDY

For the current study, we drew on a large national sample of participants, closely resembling the demographics of new home buyers, who planned to purchase a new home within the next five years. [17] We designed the DCE to look like a simplified real estate website named *Willow* and asked participants to imagine they were using the website to search for an actual home. We instructed them to specify realistic characteristics for their home search, such as price and home type. Figure 1 shows the customization filters pages for our simulated website.

[16] One drawback of DCEs is that they may be susceptible to a "hypothetical bias" (Loomis 2011) in the form of overstatement of valuation. Nevertheless, they have relatively good external validity (Lancsar and Swait 2014) and can predict real-world behavior such as travel choices (Wardman 1988). Furthermore, surveying consumers about their intentions may be a valid approach to understanding their behavior because intentions, as suggested by the theory of planned behavior (Ajzen 1991), are a good predictor of actual behavior (e.g., Armitage and Conner 2001).

[17] The study was modeled after a similar online study of fuel economy for vehicle purchases (Kormos and Sussman 2018). We conducted the DCE in January–February 2020, before the coronavirus SARS-CoV-2 became a global pandemic and stay-at-home orders were issued across the United States.

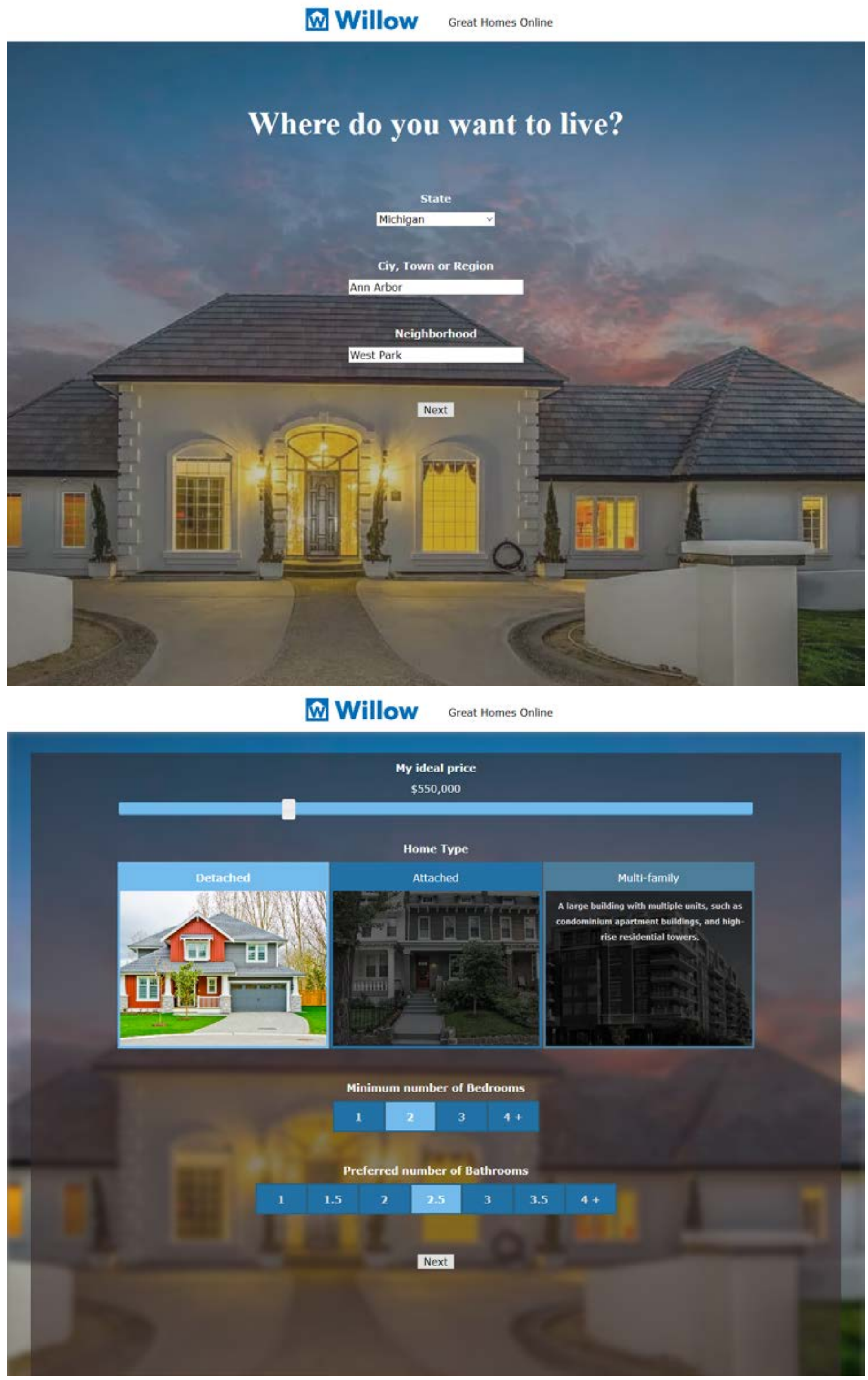


Figure 1. Customization filters pages on which participants specify the type of home they are looking to buy and where they plan to buy it

The simulated real estate website showed participants six sets of search results, each with three homes, and asked them to select the home they preferred the most within each set. The search results were actually DCE choice sets that we customized based on participants' initial specification of location, preferred price, number of bedrooms, and number of bathrooms. [18] Each home in each choice set had six attributes: a photo, price, number of bedrooms, number of bathrooms, square footage, number of days on the market, and (in some cases) energy efficiency. We quantified and controlled for the effects of the photo by rotating the same three photos throughout the entire experiment. [19] These home attributes were most likely to be displayed on the first pages of actual real estate website search results, based on our extensive preliminary research (available in Appendix A). [20] Figure 2 shows a choice set that included no efficiency information.

[18] Only the location name was changed to match the participants' preferred location. Other attributes related to the location (e.g., photos) remained static.

[19] The value of the photo of each home was quantified, like the other home attributes in the DCE. The purpose was not to determine which photos were best, but to control for the effect of the photo. Photos can have a disproportionate effect on real estate decisions, and we wanted to ensure our findings were relevant, regardless of the photo attached to the listing. To gauge the value of the home photos we rotated the same three photos throughout the entire experiment (i.e., each of the six choice sets showed the same three photos). Although each home option attached to those photos had different characteristics, the photos themselves remained constant throughout the experiment. Participants were instructed to treat each set as though they were three new homes (despite looking the same). See Appendix B for a detailed explanation of how photos were chosen (table B1 has the photos themselves).

[20] We arrived at these attributes after a thorough literature review and content analysis of 14 national real estate websites, four regional websites, and one global website, as explained in Appendix B.

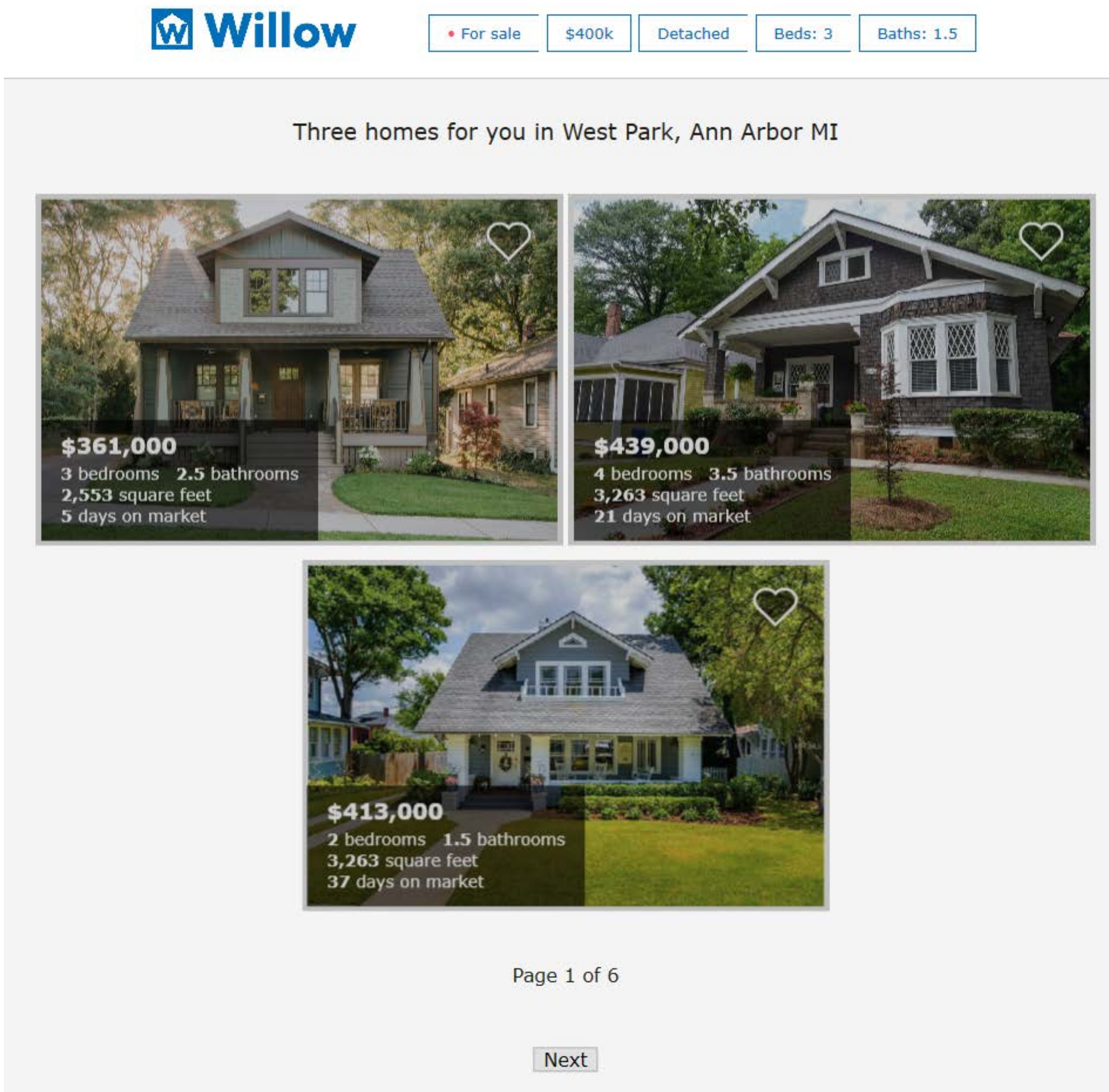


Figure 2. A sample choice set for participants in the control condition (no efficiency information)

We randomly assigned participants either to see information indicating energy efficiency levels or not to see it. We randomly altered the presentation form of energy efficiency information, when it was present, to display in one of five possible ways. This was a "between-subjects design" in that each participant only saw the choice sets presented in one way, and we compared participants to each other (more details are available in Appendix B).

Each form of presentation included some form of the U.S. Department of Energy's HES or equivalent estimated regional annual home energy costs. HES is an energy efficiency score based on the home's envelope (foundation, roof, walls, insulation, windows) and heating, cooling, and hot-water systems. It provides a total energy use estimate, as well as estimates by fuel type assuming standard operating conditions and occupant behavior (DOE 2019b).

The HES is already used to rate the physical energy efficiency of about 115,000 homes across the United States, with 550+ assessors across 31 states (Salzman 2019). We used the HES because it is common throughout the United States, but other residential energy efficiency ratings programs also exist and deliver similar results.

When we randomly assigned participants to see energy efficiency information in the simulated real estate search results, we further randomized them to see the information in one of the following possible ways:

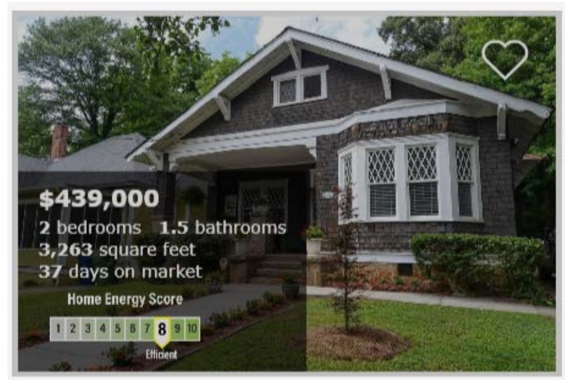
- HES on a scale of 1–10
- HES along an image of a continuum from inefficient to efficient
- Estimated annual energy costs [21]
- Estimated annual energy costs plus the HES on a continuum
- HES only for homes with above-average efficiency and not for the other two homes in the choice set. This was called the "voluntary label" condition. [22]

Figure 3 shows each of these information labels and the control condition.

[21] Annual energy costs were estimated by the Department of Energy Home Energy Score program for this project. The estimates are based on the state average utility rates and the assumed fuel mix given the heating and cooling degree days for each weather station (DOE 2019a). The ratios are applied to the site energy estimates for each weather station bin and then multiplied by the utility rate and averaged by state. The fuel mix is based on natural gas and electricity only. Full details on how DOE estimates energy costs for home energy scores is available at Better Buildings Solution Center.

[22] In the voluntary label condition, only one of the three homes in each choice set was given that information label. That home always had an HES of 8 out of 10.

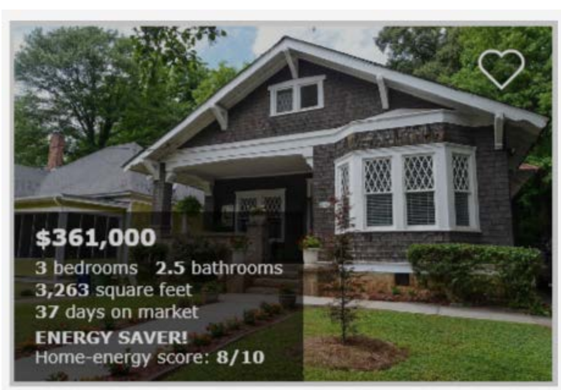
HES on a scale of 1-10



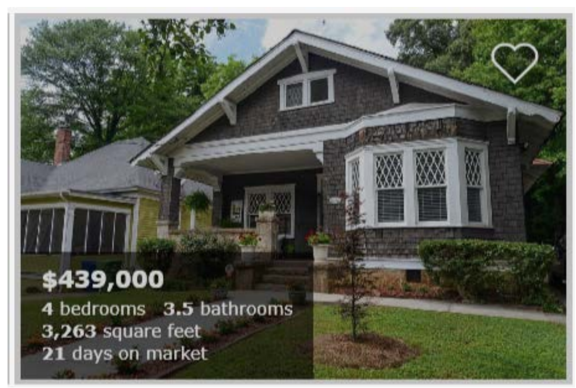
HES on a continuum

Estimated annual home energy costs

Estimated annual home energy costs + HES on a continuum



Only labeled one of three homes in choice set (the home with an HES of 8/10)



Control condition

Figure 3. Efficiency presentation formats for each condition

Figure 4 shows a choice set with HES along a continuum.

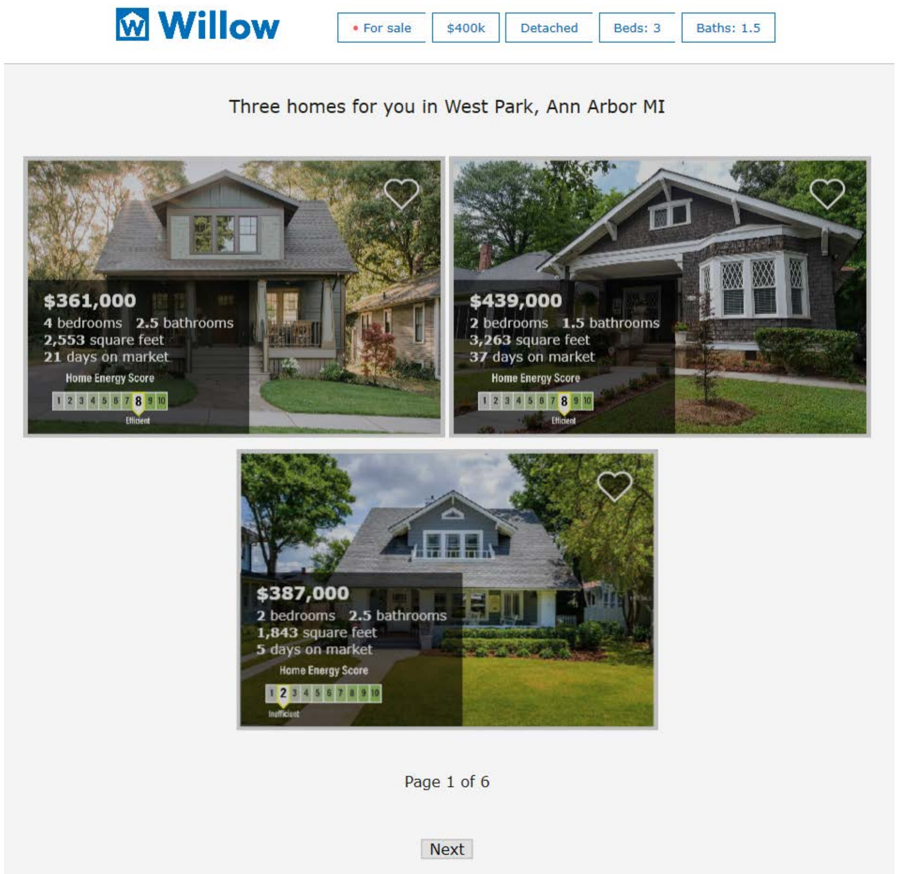


Figure 4. Sample choice set in which energy efficiency is presented as an HES along a continuum. Participants were asked to select the home they preferred the most.

This methodology allowed us to calculate how much participants were willing to pay for each attribute of the homes, and whether they clicked more (or less) often on efficient homes. See Appendix B for full details of the study methods.

Additional Survey Questions

In addition to completing the DCE, participants answered questions about their demographics, current homes, home-buying preferences, familiarity with the HES, and attitudes toward energy use; they also answered a free-response question about home preferences.

PARTICIPANTS

Using a panel research firm (Branded Research), we recruited *N* = 1,538 participants who indicated they were planning to purchase a home within the next five years. The demographics of the sample closely resembled those of recent home buyers, in terms of age and income (Ford 2019), except for being slightly older (more participants over 65 and fewer under 30). A majority (77.7%) of the participants had an associate degree or higher (associate, college, graduate, or professional degree).

Our sample was distributed throughout the four major census regions of the United States (South, West, Northeast, and Midwest), with more participants looking to buy homes in the South than other regions. In 2019, the South census region had more home sales than the other three regions, so we felt this distribution made our results more generalizable (Census Bureau 2020). In this sample, 89% resided in metropolitan regions (using 2013 Urban–Rural Continuum Codes) and 76% resided in climate zones 3, 4, or 5 (a region stretching east to west across most of the central United States and along the entire West Coast). [23]

Mirroring 2019 home sale information (Ford 2019), nearly all participants (86.7%) stated that they were looking for a single-family detached home for their next home purchase, with the remainder looking for an attached home (8.3%) or a multifamily home (5.0%). Most participants (72%) already owned a home. Age, income, preferred geographic region, and intended home type are presented in table 1, alongside nationally representative statistics. Full details of participants' demographics, home-buying preferences, and attitudes toward energy conservation can be seen in Appendix C.

[23] Climate zones 3–5 encompass all but the hottest and coldest region of the United States. Figure 7 shows the U.S. climate zone map.

Table 1. Age, income, preferred region, and preferred home type

Category	Study sample % (*n*)	United States % [24] [25]
Age		
<30 years old	9.9% (152)	22%
30–34 years old	10.2% (157)	10%
35–44 years old	12.7% (195)	10%
45–54 years old	24.6% (378)	23%
55–64 years old	24.0% (369)	22%
>65 years old	18.5% (284)	13%
Prefer not to answer	0.2% (3)	
Income		
<$20,000	7.2% (111)	7%
$20,000–39,999	12.6% (194)	10%
$40,000–59,999	14.7% (226)	14%
$60,000–79,999	17.0% (262)	16%
$80,000–99,999	13.1% (201)	12%
$100,000–199,999	28.3% (436)	31%
>$199,999	5.1% (78)	11%
Don't know or prefer not to answer	2.0% (30)	
Preferred geographic region		
South	44.5% (685)	58.4%
West	23.5% (362)	26.7%
Midwest	15.9% (244)	10.6%
Northeast	16.1% (247)	4.4%
Preferred home type		
Single-family detached	86.7% (1,333)	85%
Attached	8.3% (128)	9%
Multifamily	5.0% (77)	6%

LIMITATIONS

We designed this experiment to estimate participants' valuation of energy efficiency, relative to other home attributes, and to do so in an actual decision-making context (a simulated real estate website). We also used research methodology that allowed us to apply a uniform strategy for home buyers across the country. However, this methodology necessitated tradeoffs. The experiment was not a perfect simulation of a real estate website because it could only present a limited number of "search results," and these could not vary

[24] Data collected in 2019 by the National Association of Home Builders (NAHB) on recent home buyers (Ford 2019).

[25] Census Bureau 2020.

in all the ways that listings in different geographic regions can change. We used photos that were generic and pre-tested for similarity in desirability, but they nevertheless had an influence on decision making. This influence was controlled for in our experiment, but further testing could help explain what makes some photos more (or less) influential. Furthermore, actual real estate websites display more variety and provide richer information than our simplified search results.

In order to address these limitations, we chose a procedure that simulated just the first page of real estate search results as closely as possible. Although the effect of energy efficiency information may decrease amid the presence of other additional information, our controlled experiment, in which some other information was kept constant, demonstrated that energy efficiency information can influence home buyer decisions.

Findings

The answers to our three primary research questions are summarized below, with more detailed statistical analyses presented in Appendix D.

DO HOME BUYERS CLICK ON MORE EFFICIENT HOMES WHEN REAL ESTATE LISTINGS CONTAIN ENERGY EFFICIENCY INFORMATION?

To answer this question, we compared click rates of all participants who saw efficiency information to click rates of participants who saw the choice sets without efficiency information. [26] We also calculated the participants' overall willingness to pay for efficiency, relative to other attributes. We complemented these analyses with a summary of participants' responses to an open-ended question on home preferences.

Click Rates

The presence of energy efficiency information significantly influenced home buyers' click rates. Each choice set that participants saw contained one inefficient home (equivalent to HES of 2 out of 10), one average-efficiency home (equivalent to HES of 5 out of 10), and one high-efficiency home (equivalent to HES of 8 out of 10). [27] Participants who saw energy efficiency information were statistically significantly more likely to choose the most energy-efficient option (14% more often), and less likely to choose the least efficient option (23% less often), relative to control participants.

If this finding holds for actual real estate search behavior, and buyers are nudged away from inefficient homes, low-income home sellers could be adversely affected. Given that homes owned by low-income households tend to be less efficient than those owned by non-low-income households (Hernández and Bird 2010), disclosing energy efficiency information could depress the prices of homes sold by low-income home sellers.

---

[26] "Click rates" refers to the number of times home buyers click on a home option within a choice set. We examined how often they clicked on the most and least efficient options in each choice set.

[27] This includes home buyers in all five intervention conditions. The DCE presented Home Energy Scores in different forms depending on the condition home buyers were randomly assigned to. This analysis pooled all the different forms to get an overall average that could be compared to the control condition.

Policymakers should research complementary policies to address this issue and improve social equity.

Willingness to Pay for Efficiency Relative to Other Home Attributes

DCEs are designed to allow researchers to calculate how much participants are willing to pay for each home attribute in the experiment, including energy efficiency. [28] Across all housing types, participants were willing to increase the purchase price of their homes by about 6% for a one-point HES increase (out of a 10-point scale), although we could not determine if the increase is strictly linear. [29] The total amount they were willing to pay varied depending on the participants' intended purchase price: a lower absolute purchase price coincided with a lower willingness to pay for efficiency and a higher price with a higher willingness to pay. As described later, this value also fluctuated depending on preferred housing type and how efficiency information was presented.

Although we were unable to calculate the precise amount that home buyers would save by buying a home that was one unit higher in HES, a 6% increase in purchase price is usually more than the value of the associated savings. Home buyers in this simulation may have placed a high value on efficiency partly because it comes with a host of non-energy benefits (such as environmental, comfort, or health benefits) that consumers want (Knight et al. 2006). They may also have slightly overstated their willingness to pay because this is common in DCEs (Loomis 2011).

Efficiency was valuable, but not the most valuable attribute. Home efficiency lies along a continuum with square footage and bedrooms. A one-unit increase in energy efficiency score was valued less than one additional bedroom: the bedroom, in our simulation, was a little more valuable than a three-point increase in the listing's HES, as respondents were willing to increase purchase price by an average of 20% for an additional bedroom and by 6% for one unit of HES. An increase in HES of just over one unit (1.25 units) was valued, in our simulation, the same as a 25% increase in square footage.

Home Preferences in a Free-Response Question

The post-experiment survey included one free-response question: "What do you look for when buying a new home?" This question was useful for identifying the information that home buyers currently believe influences their home-buying decisions. It can be biased by the way memories are stored and recalled (e.g., availability bias) as well as a possible desire

---

[28] Willingness to pay is calculated using a statistical procedure known as a multinomial logit model (MNL). Details of the methods and results pertaining to this procedure are presented in Appendices B and C.

[29] This was extrapolated from participants' willingness to pay for a three-point increase in HES (i.e., from 2 to 5 or from 5 to 8). A three-point increase was worth a 17% increase in purchase price. A one-point increase between certain specific ratings (e.g., rating of 2 to rating of 3) may be more or less valuable than a one-point increase between other specific ratings (e.g., 7 to 8), but the average was 6% per point. We could not determine the exact increase for each specific increase in ratings. Another way to conceptualize it is that for an average home (with an average price of $417,542 for participants in our sample), participants were willing to pay $71,054 for a three-point HES increase or $23,684 for a one-point increase. More details are available in Appendix D.

to provide the "right" answer (social desirability bias), but it is helpful in gauging what participants say they want.

We used qualitative data analysis software (NVivo) to automatically code themes in the answers of our home buyer sample (*N* = 1,538). As shown in Appendix D, the most common answers were "location," "price," and "size." Interestingly, participants did not typically mention energy efficiency although their decision making in the DCE clearly demonstrated that the information affected their choices. This shows the importance of using multiple methods, including DCEs, to assess home buying and energy efficiency attitudes and behaviors.

WHAT IS THE BEST WAY TO DISPLAY EFFICIENCY INFORMATION?

To answer this question, we compared click rates of participants in each of the five experimental conditions and the control condition. We also calculated the participants' willingness to pay for efficiency in each condition as a further measure of which condition was most persuasive. Specific details of the analyses are available in Appendix D.

Click Rates

When participants saw efficiency information presented in almost any form, it influenced them to not choose the least efficient option and to choose the most efficient home option.

The two exceptions were (1) the "voluntary label" condition showing an energy score only for high-efficiency homes, and (2) the "annual cost" condition showing only estimated annual energy costs. The voluntary label condition did not sway home buyers away from the least efficient option and only barely pushed respondents to the most efficient option. [30] Some home buyers may have doubted whether the voluntarily labeled homes were actually more efficient than the others, as previous research suggests that the lack of comparative information among all choices was a more important reason for the ineffectiveness of this condition. Indeed, this supports guidelines suggesting that voluntary information labeling policies are less effective than mandatory policies (Wiel and McMahon 2005).

The annual cost condition did discourage home buyers from choosing the least efficient homes but did not push them to pick the most efficient homes unless it was accompanied by an HES. We discuss hypotheses for why this condition was not more effective in "Conclusions about How Best to Display Energy Efficiency Information," below.

With the exception of the voluntary labeling and annual cost conditions, none of the labeling conditions caused home buyers to click on efficient listings significantly more or less than any other. However, the energy information labels did change the value (willingness to pay) that participants assigned to energy information.

[30] The voluntary label condition was statistically significantly less effective than other conditions for pushing respondents away from the least efficient option. It was also less effective than the other conditions for pulling people toward the most efficient option, but this difference in "pushing away" was not statistically significant from other forms of energy efficiency presentation. See Appendix D for specific differences between conditions.

Willingness to Pay for Efficiency

As shown in figure 5, home buyers attributed the highest value (they were willing to increase purchase price by 11% for a one-unit increase in HES) to energy efficiency, relative to purchase price, when it was presented as the HES along a continuum from inefficient to efficient. When participants saw efficiency information presented only as estimated annual energy costs, they were willing to pay for it, but they were less willing than when they saw the information in other forms (willing to increase purchase price by 5%, rather than 6% or more). We could not calculate values for the voluntary labeling condition because information was only shown for the most efficient homes.

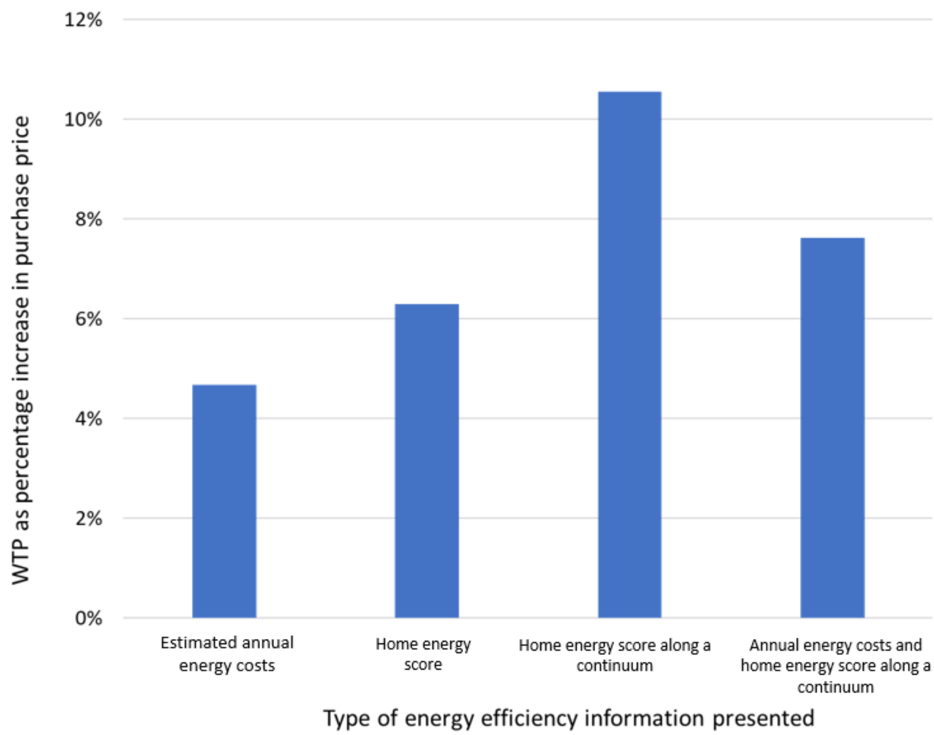


Figure 5. Relative value of energy efficiency (willingness to pay for a one-unit increase in Home Energy Score), given different efficiency information labels. Values are standardized for variations in anticipated purchase price across the experimental conditions. Willingness to pay could not be calculated for the Energy Saver condition because the efficiency information was not presented for all three options in the choice set. WTP = Willingness to pay.

Conclusions about How Best to Display Energy Efficiency Information

The HES is an intuitive concept: we found that this score swayed participants who were unfamiliar with it just as much as those who already knew what it was. [31] The HES presented along a continuum from inefficient to efficient was most effective for encouraging selection of efficient homes and assigning a high value to efficiency. This could be because

[31] See Appendix D for details of the regression testing whether familiarity with Home Energy Score was a significant predictor of real estate selections.

the information was clear and allowed buyers to see how each score ranks relative to the overall average.

Another notable finding is that even a simple HES number (out of 10), without a continuum, is persuasive. It does not increase the value of efficiency information to the same extent as presenting it along a continuum, but it nevertheless gets more clicks than no information and does not get significantly fewer clicks than other intervention conditions.

This finding is important because this simple number takes up relatively little space on the listing and does not require a graphic. It suggests that even the most basic reporting requirement policy, requiring just a number out of 10 on the front page, can make a difference to initial housing decisions. A policy that further requires a link to more information about the HES assessment (such as implemented in Portland, Oregon) can capitalize on this initial interest and provide more assistance to home buyers wanting to increase their score. [32]

Presenting efficiency as estimated annual home energy costs was one of the less effective strategies. We included this condition on the assumption that financial costs would be easy to understand, and therefore an effective tool for shifting decisions. In fact, the CONSEED study (Kallbekken et al. 2018) had found that showing annual energy costs led to a higher willingness to pay than seeing information on physical energy consumption (in kWh). This strategy may have been less effective in our experiment because energy costs are generally lower in the United States than in Europe (Sönnichsen 2019).

Additionally, the face value of estimated costs (the total for one year) was low relative to the price of the home. Due to an anchoring heuristic, people will unconsciously compare two numbers when they are presented side-by-side, even if they understand they are not exactly comparable (Bucchianeri and Minson 2013; Tversky and Kahneman 1974).

The perception of energy costs could be changed by changing the home buyers' frames of reference, for example, by presenting estimated annual energy costs in the context of other similar annual costs such as annual mortgage costs, insurance, taxes, or other utility costs. Indeed, homeowners are often surprised to learn that utility costs (energy and water) are similar, and in some cases higher, than their insurance and taxes (Grant 2017; Olsen 2017). Furthermore, although home buyers can usually obtain insurance and tax estimates before home purchases, they most often cannot obtain utility cost information and rarely think to do so. These strategies could potentially sway behavior. [33]

The finding that the voluntary label condition was not effective shows that energy efficiency information is most persuasive when it is available for all homes, as opposed to just the

[32] We note, however, that the Portland mandate does not require that efficiency information be included in the first page of real estate search results. Indeed, this information is usually relegated to the bottom of the home description, visible only to readers who click through and read to the bottom of the listing.

[33] Sussman and Chikumbo (2017) found that using the anchoring heuristic as a method of choice-context manipulation is effective in the presentation of home energy upgrade recommendations.

most efficient. This falls in line with research showing that voluntary labeling is not as effective as mandatory labeling for changing non-energy behavior (e.g., Roe, Teisl, and Deans 2014). The Collaborative Labeling and Appliance Standards Program suggests that mandatory energy information labeling schemes are more effective than voluntary schemes (Wiel and McMahon 2005), but the current study is the first, to our knowledge, to offer controlled experimental support for this suggestion.

WHICH HOME BUYERS VALUE EFFICIENCY MOST?

The Place

THE NORTHEAST IS WILLING TO PAY THE MOST

In an analysis of results from participants looking to buy homes in each of the four major census regions (Northeast, South, West, and Midwest), we found that home buyers in the Northeast were willing to pay roughly twice as much (total dollars) for efficiency than participants in any other region. When we take into account the high purchase prices in the Northeast, the difference between regions is smaller, but those home buyers were nevertheless willing to pay the highest proportion of purchase price for efficiency (8%). This difference can be seen in figure 6, below.

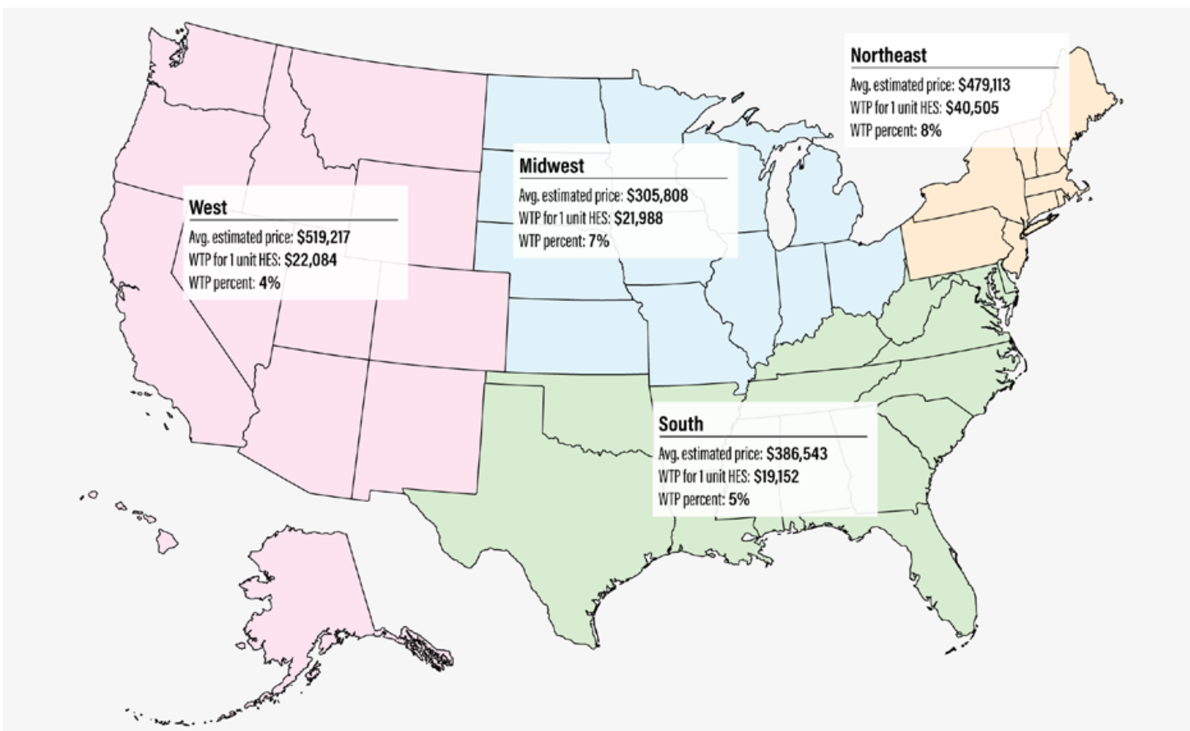


Figure 6. Willingness to pay for energy efficiency in the Northeast versus other regions. WTP = Willingness to pay; HES = Home Energy Score; Avg. estimated price = Average anticipated home purchase price for home buyers in the region.

The difference in willingness to pay between regions might derive from higher energy costs in the Northeast or because the region has a stronger track record of residential efficiency programs than the rest of the country (thereby increasing the understanding of, and desire for, efficient housing). Indeed, the estimated annual energy costs we received from DOE for use in our experiment were higher in Northeastern states than others. Average estimated costs are presented in table 2.

Table 2. Estimated annual home energy costs (in USD) for homes with Home Energy Score of 5 (out of 10)

	Midwest	Northeast	South	West
Estimated annual home energy costs for an average home	$1,675	$2,344	$1,539	$1,786

HOME BUYER PREFERENCES FOR EFFICIENCY ARE NOT AFFECTED BY RURALNESS OR CLIMATE ZONE

Using 2013 urban–rural continuum codes, we compared home buyers in metropolitan counties to those in non-metropolitan counties. [34] Given purchase prices are generally much higher in urban regions, the total absolute amount home buyers in those regions were willing spend on efficiency was also higher. Controlling for the differences in expected purchase prices between these two regions, however, home buyers were willing to spend roughly the same proportion of purchase price on efficiency. Table 3 shows the amount home buyers were willing to pay for efficiency in urban and rural regions.

Table 3. Willingness to pay (in USD) for efficiency by urban and rural region. WTP = Willingness to pay. "1 unit" = One-unit increase in Home Energy Score

	Metropolitan regions	Non-metropolitan regions
Anticipated purchase price	432,067	295,854
WTP for 1 unit	23,729	15,155
WTP percent	5%	5%

Based on the U.S. Department of Energy's guide to climate zones (Baechler et al. 2015), we also compared home buyers interested in buying homes in six of the American climate zones. [35] As shown in table 4, home buyers in climate zones 1–6 were willing to pay approximately the same amount in purchase price for energy efficiency. [36] There were no significant differences among home buyers in these climate zones.

[34]As shown in Appendix 2, metropolitan counties include counties with urban–rural codes 1, 2, and 3. These are metropolitan regions from under 250,000 people to over 1,000,000 people. Non-metropolitan counties are coded 4, 5, 6, 7, 8, and 9. These include regions that are completely rural (fewer than 2,500 people), as well as urban populations over 20,000 people. Some non-metropolitan regions (4, 6, and 8) are adjacent to metropolitan counties.

[35] These climate zones contained 99.1% of the U.S. population.

[36] We had insufficient numbers of participants in climates zone 7 (very cold) and 8 (subarctic) to calculate willingness-to-pay values. Approximately 0.9% of the American population resides in these regions.

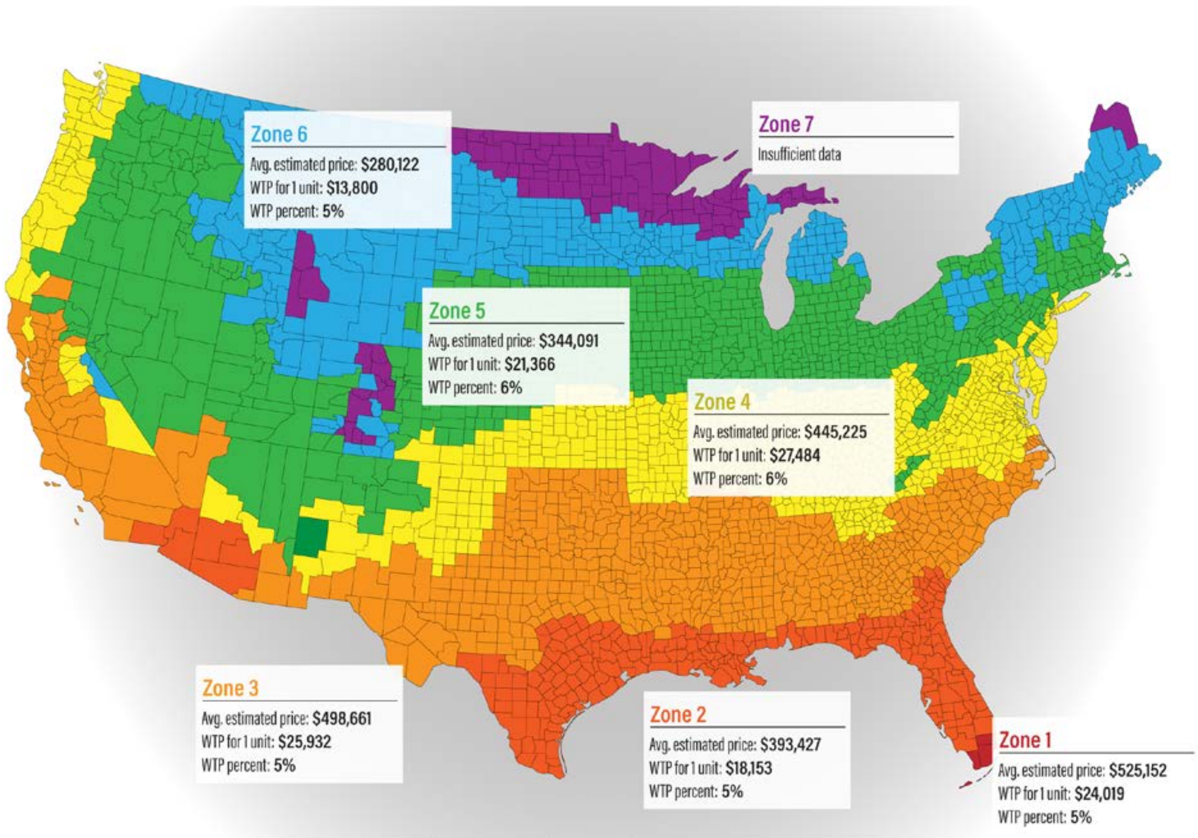


Figure 7. Willingness to pay for energy efficiency in climate zones 1–6 of the United States, as determined by the International Energy Conservation Code (IECC). WTP = Willingness to pay; HES = Home Energy Score; Avg. estimated price = Average anticipated home purchase price for home buyers in the region. Note: We had insufficient numbers of participants in climate zones 7 and 8 to calculate WTP values. *Source:* Baechler et al. 2015.

The Person

BUYERS WITH THE HIGHEST INCOMES AND INTENDED PURCHASES PRICES SPEND MORE ON EFFICIENCY

In the general population, education generally predicts income: those with more education tend to have more wealth. Such is the case within our sample as well. The wealthiest also tend to spend the most on their homes and be most interested in efficiency. As shown in figures 8 and 9, home buyers with the highest household incomes and education levels were willing to pay most for energy efficiency, even after controlling for intended purchase price.

At the lowest incomes, home buyers were also willing to pay a high proportion of purchase price for energy efficiency. This could be because low-income residents have higher energy burdens than others (Drehobl and Ross 2016) or because the result was driven by a sub-population in our sample of high-education, low-income buyers (e.g., recent university graduates). More details about income, intended purchase price, and willingness to pay for efficiency can be found in Appendix D.

Figure 8. Percentage increase in purchase price that participants are willing to pay for one unit of HES across household income levels. WTP = Willingness to pay. "1 unit" = One-unit increase in Home Energy Score.

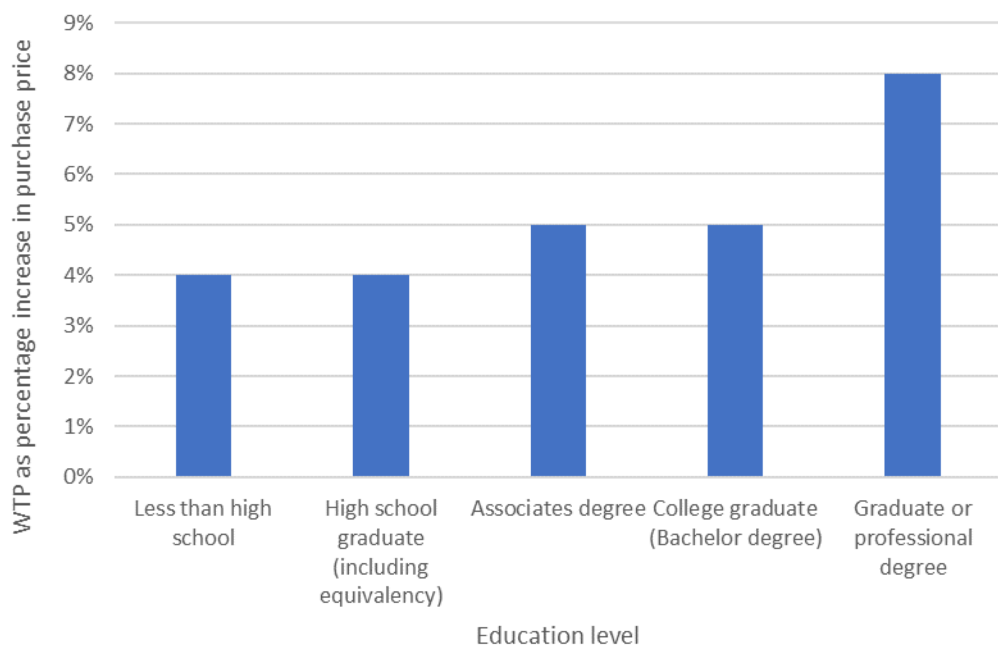


Figure 9. Percentage increase in purchase price that participants are willing to pay for one unit of HES across education levels. WTP = Willingness to pay. "1 unit" = One-unit increase in Home Energy Score.

Complementing our household income findings, we also learned that home buyers looking to purchase the most expensive homes ($750,000 and up), were willing to pay more for energy efficiency than other groups. They were willing to spend the greatest amount on efficiency and the highest proportion of purchase price on efficiency, relative to the other groups. This difference can be seen in figure 10, below, and in table D10 in Appendix D. [37]

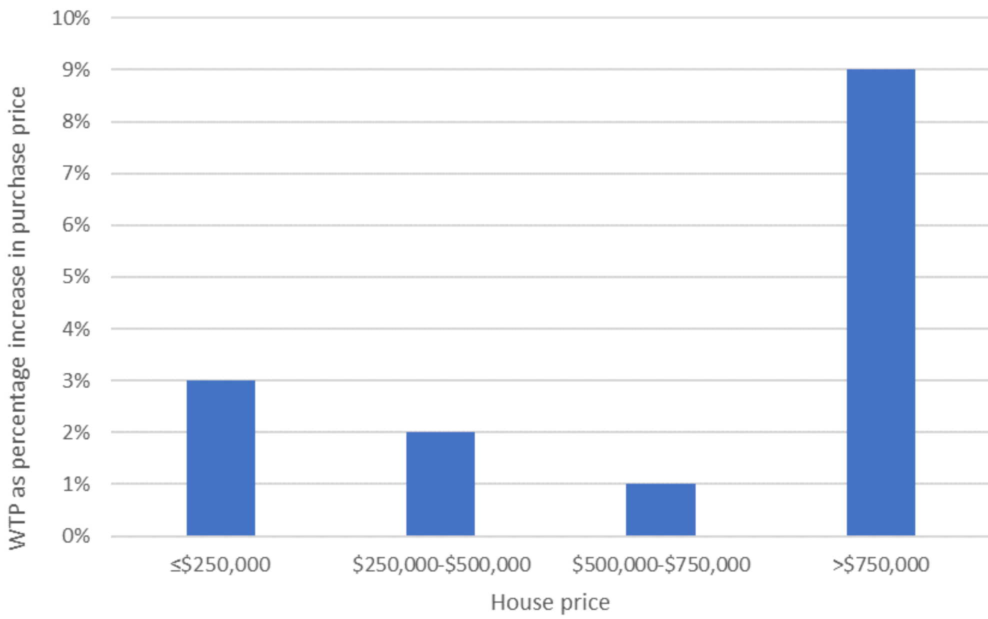


Figure 10. Percentage increase in purchase price that participants are willing to pay for one unit of HES across house prices. WTP = Willingness to pay. "1 unit" = One-unit increase in Home Energy Score.

No Clear Age-Related Effects

As shown in figure 11, in our sample, home buyers in the 65–74 age range were willing to pay most for a one-unit increase in HES. That said, there was no clear trend or correlation between age and valuation of energy in general (valuation did not increase or decrease with age in a predictable way).

[37]The distribution of willingness-to-pay values was broadest in the highest and lowest income levels. Those at the highest income level (over $200,000) had willingness-to-pay values within one standard error of the mean of 3% to 10% per dollar for a one-unit increase in HES, those at the $20,000–29,999 level had values between 3% and 8%, and those at the under the $20,000 level had values between 5% to 8%.

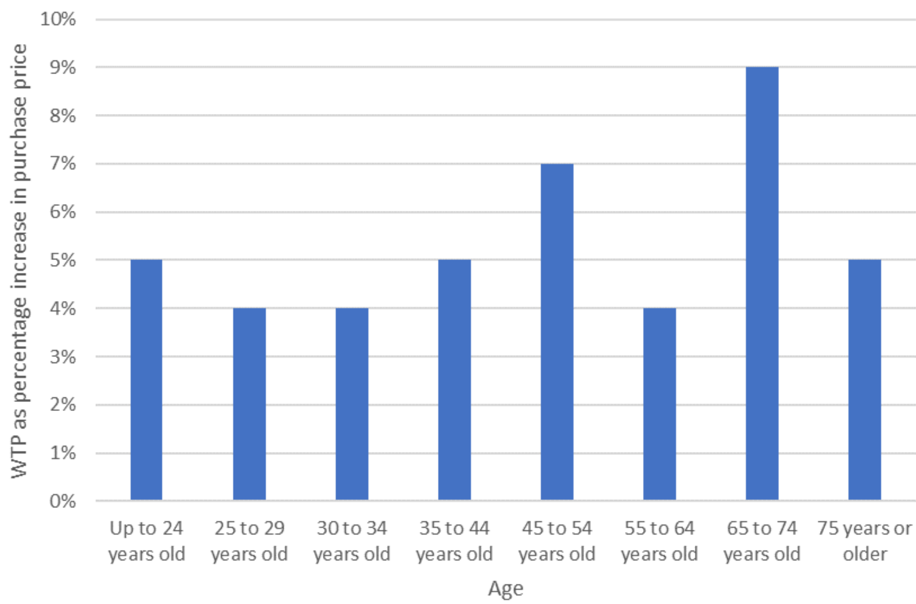


Figure 11. Percentage increase in purchase price that participants are willing to pay for one unit of HES across ages. WTP = Willingness to pay. "1 unit" = One-unit increase in Home Energy Score.

Recommendations for Policymakers

We have several recommendations for policymakers mandating the practice of including efficiency information in real estate listing websites.

Include efficiency information in real estate website listings because home buyers value it. Efficiency information significantly affected home buyers' decisions in our simulation, especially the decision to not click on the least efficient homes, but also to select the most efficient homes.

Ensure that all listings include efficiency information, not just the most efficient. In our simulation, home buyers' decisions were minimally affected by energy efficiency information when it was only presented for high-efficiency homes, as might be the case in voluntary energy labeling programs. Therefore, mandatory policies should be the ultimate goal, with voluntary policies used only as a stepping stone to reach that goal.

Use an intuitive energy scoring system to present energy information. In our simulation we used the U.S. Department of Energy's Home Energy Score system, which is a more accurate measure of efficiency than a home's energy costs. [38] The score persuaded home buyers to click on efficient homes, and worked especially well when it was presented along a continuum (a line) from inefficient to efficient. Decisions were influenced by the score regardless of home buyers' familiarity with it, suggesting that it was intuitively understandable. Other scoring systems, such as those used in Minneapolis or Austin, which

[38] Unlike energy costs, Home Energy Score is not affected by energy prices, the number of people in the home, or other extraneous factors.

are optimized to emphasize the most important efficiency elements for those more extreme climates, may also be persuasive if they are intuitive and easy to understand.

Research and develop complementary policies. If policies are enacted to require efficiency information be included in real estate listings, then our simulation shows that this may drive home buyers away from the least efficient real estate listings. In that case, policymakers should consider researching programs that help home sellers, especially low-income sellers, increase the efficiency of their homes.

As home buyers with lower incomes tend to purchase less expensive homes, labeling policies may have the unintended effect of making it more difficult for low-income buyers to purchase energy-efficient homes. Indeed, we found that at the lowest household income levels (under $30,000), home buyers in our study wanted to spend the same or more for energy efficiency as low-moderate income ($30,000–79,999) buyers, but this meant they would have to pay a higher proportion of their purchase price and, therefore, have to trade off other attributes.

Future Research

The next step in this research is to experimentally test the effects of energy efficiency information on actual real estate listings websites. We would like to see a listings website A/B test this idea by creating mirror websites with efficiency information present in different forms (or absent) from the listings. Researchers could then compare the click rates on actual listings with and without efficiency information. However, based on the findings we present above, efficiency information would likely only be effective if it were available for every listing and would be most effective if presented as a score along a continuum (from inefficient to efficient). Therefore, every home on the website would have to be assessed and assigned an HES in order to compare the effects of clicks with and without the score. This type of test could only be administered in jurisdictions such as Portland, Oregon, where HES assessments are required for every home that is put on sale. Mandatory labeling policies are, therefore, recommended.

Notably, the U.S. Department of Energy's HES is the only residential efficiency certification program we included in this experiment. Other programs may also be persuasive for changing home buyer decisions, and this should be tested in future research.

Building on the findings from this study, future research could also investigate whether information about the costs to increase the HES after purchase can affect home buyers. Aside from the likelihood of purchasing an efficient home, how likely are home buyers to upgrade homes they decided to purchase? A review from 2016 (Hill et al. 2016) begins to address this question, but as mandates for the HES and other efficiency scores become more widespread, this could be a fruitful area for further exploration.

Another area for future research could be related to marketing and messaging. Home buyers may be moved to purchase based on emotion and what their day-to-day experience will feel like in the home. Studies and experiments can be designed to leverage this inclination to encourage efficient purchases. For example, messages could be tested about a home being warm and inviting, safe for families, or quiet and calm.

Last, research should be conducted on policies that complement a mandate for efficiency scores in real estate listings. Aiding homeowners that might be negatively affected by efficiency labeling could increase equity and mitigate pushback from stakeholders. Research in this area might be particularly important for homeowners with low or moderate incomes.

References

Achtnitcht, M., and R. Madlener. 2014. "Factors Influencing German House Owners' Preferences on Energy Retrofits." *Energy Policy* 68: 254–63. www.sciencedirect.com/science/article/abs/pii/S0301421514000111.

Ajzen, I. 1991. "The Theory of Planned Behavior." *Organizational Behavior and Human Decision Processes* 50 (2): 179–211. www.sciencedirect.com/science/article/pii/074959789190020T.

Allcott, H. 2011. "Consumers' Perceptions and Misperceptions of Energy Costs." *American Economics Review: Papers & Proceedings* 101 (3): 98–104. pubs.aeaweb.org/doi/pdfplus/10.1257/aer.101.3.98.

Anderson, C., and J. Claxton. 1982. "Barriers to Consumer Choice of Energy Efficient Products." *Journal of Consumer Research* 9 (2): 163–70. academic.oup.com/jcr/article/9/2/163/1813223.

Armitage, C., and M. Conner. 2001. "Efficacy of the Theory of Planned Behaviour: A Meta-Analytic Review." *British Journal of Social Psychology* 40 (4): 471–99. onlinelibrary.wiley.com/doi/abs/10.1348/014466601164939.

Baechler, M., T. Gilbride, P. Cole, M. Hefty, and K. Ruiz. 2015. *High-Performance Home Technologies: Guide to Determining Climate Regions by County*. Prepared by Pacific Northwest National Laboratory. Washington, DC: DOE. www.energy.gov/sites/prod/files/2015/10/f27/ba_climate_region_guide_7.3.pdf.

Banerjee, A., and B. Solomon. 2003. "Eco-Labeling for Energy Efficiency and Sustainability: A Meta-Evaluation of US Programs." *Energy Policy* 31 (2): 109–23. www.researchgate.net/publication/222421154_Eco-Labeling_for_Energy_Efficiency_and_Sustainability_A_Meta-Evaluation_of_US_Programs.

Better Buildings Solution Center. 2020. "About the Home Energy Score." Accessed July. betterbuildingssolutioncenter.energy.gov/home-energy-score/home-energy-score-about-score.

Bucchianeri, G., and J. Minson. 2013. "A Homeowner's Dilemma: Anchoring in Residential Real Estate Transactions." *Journal of Economic Behavior & Organization* 89: 76–92. scholar.harvard.edu/files/juliaminson/files/home_buyers_are_not_a_herd.pdf.

Bull, J. 2012. "Loads of Green Washing—Can Behavioural Economics Increase Willingness-to-Pay for Efficient Washing Machines in the UK?" *Energy Policy* 50: 242–52. www.sciencedirect.com/science/article/pii/S0301421512005769.

Cadario, R., B. Parguel, and F. Benoît–Moreau. 2016. "Is Bigger Always Better? The Unit Effect in Carbon Emissions Information." *International Journal of Research in Marketing* 33 (1): 204–7. www.sciencedirect.com/science/article/pii/S0167811615001184.

Census Bureau. 2020. "New Residential Sales." www.census.gov/construction/nrs/historical_data/index.html.

DiClerico, D. 2016. "8 Ways to Boost Your Home Value." *Consumer Reports*, February 9. www.consumerreports.org/home-improvement/8-ways-to-boost-your-home-value/.

DOE (Department of Energy). 2019a. "Home Energy Saver & Score: Engineering Documentation." Accessed December. sites.google.com/a/lbl.gov/hes-public/calculation-methodology/bill-calculation/bill-calculation-scoring-tool.

——. 2019b. "Home Energy Score." www.energy.gov/eere/buildings/downloads/home-energy-score.

Drehobl A. and L. Ross. 2016. "Lifting the High Energy Burden in America's Largest Cities: How Energy Efficiency Can Improve Low-Income and Underserved Communities." *American Council for an Energy-Efficient Economy*: Washington, DC. www.aceee.org/research-report/u1602.

EIA (Energy Information Administration). 2018a. *2015 Residential Energy Consumption Survey*. Washington, DC: EIA. www.eia.gov/consumption/residential/reports/2015/overview/.

——. 2018b. "Table CE1.1 Summary Annual Household Site Consumption and Expenditures in the U.S.—Totals and Intensities, 2015." *2015 Residential Energy Consumption Survey*. Washington, DC: EIA. www.eia.gov/consumption/residential/data/2015/c&e/pdf/ce1.1.pdf.

——. 2020. "Table 18. Energy-Related Carbon Dioxide Emissions by Sector and Source." *Annual Energy Outlook 2020*. Washington, DC: EIA. www.eia.gov/outlooks/aeo/data/browser/#/?id=17-AEO2020&cases=ref2020&sourcekey=0.

Ford, C. 2019. "Characteristics of Recent Home Buyers." *HousingEconomics.com,* February 1. www.nahbclassic.org/generic.aspx?sectionID=734&genericContentID=266248&channelID=311.

Fuerst, F., P. McAllister, A. Nanda, and P. Wyatt. 2015. "Does Energy Efficiency Matter to Home–Buyers? An Investigation of EPC Ratings and Transaction Prices in England." *Energy Economics* 48: 145–56. www.repository.cam.ac.uk/bitstream/handle/1810/246914/ENEECO-D-13-00679_main_doc_FF%20%282%29.pdf?sequence=1.

Grant, K. 2017. "The $9,000 Tab That Surprises Homeowners." *CNBC Personal Finance*, July 31. www.cnbc.com/2017/07/31/homeowners-are-surprised-by-the-cost-of-taxes-utilities-maintenance.html.

Greene, D. 2010. *How Consumers Value Fuel Economy: A Literature Review*. Prepared by Oak Ridge National Laboratory. Washington, DC: EPA (Environmental Protection Agency). tinyurl.com/unfbm6j.

Hainmueller, J., D. Hangartner, and T. Yamamoto. 2015. "Validating Vignette and Conjoint Survey Experiments against Real-World Behavior." *Proceedings of the National Academy of Sciences* 112 (8): 2395–400. doi.org/10.1073/pnas.1416587112.

Heinzle, S. 2012. "Disclosure of Energy Operating Cost Information: A Silver Bullet for Overcoming the Energy-Efficiency Gap?" *Journal of Consumer Policy* 35 (1): 43–64. link.springer.com/article/10.1007/s10603-012-9189-6.

Hernández, D., and S. Bird. 2010. "Energy Burden and the Need for Integrated Low–Income Housing and Energy Policy." *Poverty Public Policy* 2 (4): 5–25. www.ncbi.nlm.nih.gov/pmc/articles/PMC4819257/#R14.

Hill, A., J. Boutin, F. Boulanger, R. Faesy, and J. Dalton. 2016. "Predicting Home Energy Rating and Disclosure Program Impacts for North American Jurisdictions." In *Proceedings of the 2016 ACEEE Summer Study on Energy Efficiency in Buildings*. 7: 1–13. Washington, DC: ACEEE. www.aceee.org/files/proceedings/2016/data/papers/7_218.pdf.

HUD (Department of Housing and Urban Development). 2020. "HUD USPS Zip Code Crosswalk Files." www.huduser.gov/portal/datasets/usps_crosswalk.html.

Kaenzig, J., and R. Wüstenhagen. 2010. "The Effect of Life Cycle Cost Information on Consumer Investment Decisions Regarding Eco-Innovation." *Journal of Industrial Ecology* 14 (1): 121–36. onlinelibrary.wiley.com/doi/full/10.1111/j.1530-9290.2009.00195.x.

Kahn, M., and N. Kok. 2014. "The Capitalization of Green Labels in the California Housing Market." *Regional Science and Urban Economics* 47 (July): 25–34. www.sciencedirect.com/science/article/abs/pii/S0166046213000574.

Kallbekken, S., Brazil, W., Carroll, J. Skourtos, M., Kontogianni, A., Damigos, D., Lakić, and A. Gubina. 2018. *Report on Choice Experiments on the Effectiveness of Providing Information on Energy Costs on Energy Related Decisions in Households*. Dublin: CONSEED (CONSumer Energy Efficiency Decision making) Project. storage.googleapis.com/wzukusers/user-26722815/documents/5bdc498d817b6austD3Q/CONSEED-D4.2_choice-experiments.pdf.

Knight, R., L. Lutzenhiser, and S. Lutzenhiser. 2006. "Why Comprehensive Residential Energy Efficiency Retrofits Are Undervalued." In *Proceedings of the 2006 ACEEE Summer Study on Energy Efficiency in Buildings* 7: 141–50. Washington, DC: ACEEE. www.aceee.org/files/proceedings/2006/data/papers/SS06_Panel7_Paper12.pdf.

Kormos, C., and R. Sussman. 2018. *Auto Buyers' Valuation of Fuel Economy: A Randomized Stated Choice Experiment*. Yonkers, NY: Consumers Union.

advocacy.consumerreports.org/research/auto-buyers-valuation-of-fuel-economy-a-randomized-stated-choice-experiment/.

Lancsar, E., and J. Swait. 2014. "Reconceptualising the External Validity of Discrete Choice Experiments." *PharmacoEconomics* 32 (10): 951–65. link.springer.com/article/10.1007/s40273-014-0181-7.

Lembregts, C., and M. Pandelaere. 2012. "Are All Units Created Equal? The Effect of Default Units on Product Evaluations." *Journal of Consumer Research* 39 (6): 1275–89. academic.oup.com/jcr/article/39/6/1275/1825385.

Loomis, J. 2011. "What's to Know about Hypothetical Bias in Stated Preference Valuation Studies?" *Journal of Economic Surveys* 25 (2): 363–70. onlinelibrary.wiley.com/doi/full/10.1111/j.1467-6419.2010.00675.x.

Marmolejo-Duarte, C., and M. Bravi. 2017. "Does the Energy Label (EL) Matter in the Residential Market? A Stated Preference Analysis in Barcelona." *Buildings* 7 (2): 53–69. www.mdpi.com/2075-5309/7/2/53.

NAR (National Association of REALTORS). 2018. *Real Estate in a Digital Age: 2018 Report*. Washington, DC: NAR. www.nar.realtor/sites/default/files/documents/2018-real-estate-in-a-digital-world-12-12-2018.pdf.

Newell, R., and J. Siikamäki. 2014. "Nudging Energy Efficiency Behavior: The Role of Information Labels." *Journal of the Association of Environmental and Resource Economists* 1 (4): 555–98. www.journals.uchicago.edu/doi/abs/10.1086/679281.

Niederberger, A., and G. Champniss. 2018. "Flip Sides of the Same Coin? A Simple Efficiency Score versus Energy Bill Savings Information to Drive Consumers to Choose More Energy-Efficient Products." *Energy Efficiency* 11: 1657–71. link.springer.com/article/10.1007/s12053-017-9542-3.

NREL (National Renewable Energy Laboratory). 2017. *ResStock – Targeting Energy and Cost Savings for U.S. Homes.* Washington, DC: DOE. www.nrel.gov/docs/fy17osti/68653.pdf.

Olsen, S. 2017. "Hidden Costs of Homeownership Top $9,000 a Year." *Zillow Research*, July 31. www.zillow.com/research/hidden-costs-of-homeownership-16072/#_ftn3.

Poortinga, W., L. Steg, C. Vlek, and G. Wiersma. 2003. "Household Preferences for Energy-Saving Measures: A Conjoint Analysis." *Journal of Economic Psychology* 24 (1): 49–64. www.sciencedirect.com/science/article/abs/pii/S016748700200154X.

Roe, B., M. Teisl, and C. Deans. 2014. "The Economics of Voluntary versus Mandatory Labels." *Annual Review of Resource Economics* 6: 407–27. www.annualreviews.org/doi/full/10.1146/annurev-resource-100913-012439.

Russell, W., D. Dzewaltowski, and G. Ryan. 1999. "The Effectiveness of a Point-of-Decision Prompt in Deterring Sedentary Behavior." *American Journal of Health Promotion* 13 (5): 257–9. www.ncbi.nlm.nih.gov/pubmed/10538638.

Salzman, M. 2019. *Home Energy Score™*. Washington, DC: DOE. www.energy.gov/sites/prod/files/2019/05/f62/bto-peer%E2%80%932019-ast-lbnl-pnnl-homeenergyscore.pdf.

SCE (Southern California Edison). 2016. *Dimensions of Energy Behavior: Psychometric Testing of Scales for Assessing Behavioral Interventions in Demand Side Management Programs*. San Francisco: CPUC (California Public Utilities Commission). www.etcc-ca.com/reports/et15sce8010-dimensions-energy-behavior-psychometric-testing-scales-assessing-behavioral.

Shiller, R. 2007. "Understanding Recent Trends in House Prices and Homeownership." In *Proceedings – Economic Policy Symposium – Jackson Hole* 89–123. Prepared by National Bureau of Economic Research. Kansas City: Federal Reserve Bank of Kansas City. www.nber.org/papers/w13553.

Sönnichsen, N. 2019. "Electricity Prices Worldwide by Country 2018." *Statista,* November 18. www.statista.com/statistics/263492/electricity-prices-in-selected-countries/.

Sussman, R., and M. Chikumbo. 2017. *How to Talk about Home Energy Upgrades.* Washington, DC: ACEEE. aceee.org/research-report/b1701.

Thorne, J., and C. Egan. 2002. "The EnergyGuide Label: Evaluation and Recommendations for an Improved Design." In *Proceedings of the 2002 ACEEE Summer Study on Energy Efficiency in Buildings* 8: 357–70. Washington, DC: ACEEE. www.aceee.org/files/proceedings/2002/data/papers/SS02_Panel8_Paper29.pdf.

Tucker, C., J. Zhang, and T. Zhu. 2013. "Days on Market and Home Sales." *The RAND Journal of Economics* 44 (2): 337–60. dspace.mit.edu/bitstream/handle/1721.1/88161/Tucker_Days%20on%20market.pdf?sequence=1&isAllowed=y.

Tversky, A., and D. Kahneman. 1974. "Judgment under Uncertainty: Heuristics and Biases." *Science* 185 (4157): 1124–31. science.sciencemag.org/content/185/4157/1124.

Ungemach, C., A. Camilleri, E. Johnson, R. Larrick, and E. Weber. 2017. "Translated Attributes as Choice Architecture: Aligning Objectives and Choices through Decision Signposts." *Management Science*. 64 (5): 1975–2471. pubsonline.informs.org/doi/abs/10.1287/mnsc.2016.2703.

Walls, M., T. Gerarden, K. Palmer, and X. Bak. 2017. "Is Energy Efficiency Capitalized into Home Prices? Evidence from Three U.S. Cities." *Journal of Environmental Economics and Management* 82: 104–24. www.sciencedirect.com/science/article/abs/pii/S0095069616304508.

Wardman, M. 1988. "A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour." *Journal of Transport Economics and Policy* 22: 71–97. www.jstor.org/stable/20052836?seq=1.

Weber, H., and M. Chediak. 2015. "US Power Grid's $2 Trillion Upgrade Needs European Efficiency." *Renewable Energy World*, April 24. www.renewableenergyworld.com/2015/04/24/us-power-grids-2-trillion-upgrade-needs-european-efficiency/#gref.

Wiel S., and J. McMahon. 2005. *Energy-Efficiency Labels and Standards: A Guidebook for Appliances, Equipment, and Lighting*. Second edition. Washington, DC: CLASP (Collaborative Labeling and Appliance Standards Program). lasp.ngo/publications/energy-efficiency-labels-and-standards-a-guidebook-for-appliances-equipment-and-lighting.

Zalejeska-Jonsson, A. 2014. "Impact of Energy and Environmental Factors in the Decision to Purchase or Rent an Apartment: The Case of Sweden." *Journal of Sustainable Real Estate* 5 (1): 66–85. www.josre.org/wp-content/uploads/2017/11/impact-of-energy-and-environmental-factors-in-the-decision-to-purchase-or-rent-an-apartment-the-case-of-sweden.pdf.

Appendix A. CONSEED Study of Energy Information Labels

CONSEED conducted a DCE to determine willingness to pay for energy-efficient properties when energy efficiency information was presented either as actual usage (kWh per year) or annual cost. The study found that consumers valued efficiency more highly when it was presented in monetary terms. This is a useful reminder that not all information labels are equally effective and that the form of presentation matters.

The CONSEED study is a step forward, but it only tested two presentation forms and still leaves several research questions unanswered. Is the use of a visual presentation of the efficiency information important (a line indicating a continuum from inefficient to efficient) or could the same effect be achieved with a simple number? Could the effect be produced with a more accurate measure of efficiency, such as the Department of Energy's HES, or is estimated annual cost the only useful measure? Do home buyers of different demographics or in different regions (with potentially different energy costs) value efficiency in listings equally or is the information more valuable to some home buyers than others? Our study builds on the CONSEED study by testing five different forms of presentation and attempting to answer these questions.

The study was also limited in that it used the classic DCE method, presenting options in a table format, with static and plain information. The study we conducted is more externally valid in that it is customized to the participants' preferences (preferred price, preferred number of bedrooms, and minimum number of bathrooms) and is designed to look like a real-world decision-making context (a website).

Finally, the CONSEED study sampled Slovenians in Europe, where prices and cultural norms are different than those in the United States. For example, since 2000, several countries in Europe have spent a combined $150.3 billion on energy efficiency programs where the United States has spent only $96.7 billion (Weber and Chediak 2015).

The CONSEED study provides a useful framework for a study on energy efficiency home information labels. The current study extends these findings, answering questions about home buyer demographics, homebuying in an American context, decision making on real estate websites, and decision making in the context of a variety of label designs.

Appendix B. Method Details

SELECTING ATTRIBUTES TO INCLUDE IN EACH SIMULATED LISTING

We derived the list of primary attributes to include in each simulated real estate listing by (1) consulting previous literature to learn which attributes other researchers used in similar studies, and (2) by conducting a systematic content analysis of real estate listing websites. Through this process we developed a complete list of home attributes that had been included on any one website, and then narrowed that list to just those that attributes that websites included in their first-page search results.

We found real estate websites to code by searching Google with the key words "best real estate listing websites." In our content analysis, we included each search result on the first search page, excluding the sponsored ads. We included only websites that listed all different types of home sales in one platform. Websites that only showed specific types of sales (luxury homes, foreclosures, etc.) were excluded.

Our search procedure left us with 11 national real estate listing websites to code and analyze. We developed a list of attributes to code by cross-referencing the three most popular real estate listing websites on our list, as determined by Google search results (Zillow, Redfin, and Compass). After creating the list of attributes, we coded all 11 national websites (including the three used to create the initial attributes list), and three regional websites, including one in Portland, Oregon, because that region requires that HES be added to all real estate listings.

In addition to coding which attributes are included in each website, we also coded the attributes in terms of level of importance. The most important attributes (coded "1") were those that were always presented on the website's first page. Other attributes were categorized as 1.5, 2, or 3 as they decreased in importance.

For this experiment we only included attributes that we coded as "level 1" or "level 1.5" on most websites. Listing price, photo, number of bedrooms, number of bathrooms, and address were always present on real estate websites' first pages, with "square feet" on the first page for all but three websites (and never as a "level 3" attribute). Other important attributes were real estate listing agency, property type, open house times, building age, "new listing," neighborhood, days on website, multiple listing service number, and lot size.

Given our simulated real estate website provided "search results" only in the participants' preferred locations, we did not include address or neighborhood as attributes in our DCE. In addition to price, photo, number of bedrooms, number of bathrooms, and square feet, we chose to include "number of days on website" as an attribute because it was an important attribute on many sites and because some evidence suggests it can affect real estate decision making (Tucker, Zhang, and Zhu 2013).

SELECTING PHOTOS

Typically, DCEs do not include photos (or they use the same photo for all options) because photos can distract participants from other attributes in the experiment. However, photos are critical on real estate listing websites and, in order to maximize the realism of the experiment, we chose to include them. We used the same three photos for each DCE choice set and were able to control for the effects of the photos by randomizing them within the DCE. As such, the photo was one of six attributes of each home. We also minimized the effect of the photo by choosing photos that were similar in desirability and did not differ in distinct ways from one another.

For detached and attached homes, we included photos from directly in front that concealed the true size of the home and did not have distinguishing features, such as a garage. All homes looked similar and could conceivably be found in most climate regions in the United States. The photos allowed for each home to potentially range in size from the largest to smallest options.

As is customary for multifamily units, the cover image was a photo of the interior of the home. We avoided images with distinguishing features such as large bookcases, fireplaces, terrace doors, or windows with attractive (or unattractive) views. The images were all of rooms of similar size and angle.

We found images through a Google image search and selected 20 to 22 high resolution images of single-family detached, attached, and multifamily homes. A convenience sample of friends, colleagues, and family from across the United States (n = 142) rated each image. The convenience sample lived in all four census regions, were mostly female (69%), ranged in ages but skewed young (28% under 25), and were relatively highly educated (77% with at least an associate degree). They currently lived in homes ranging from under 1,000 square feet to over 3,000 square feet. For each home photo we asked, "All else being equal, how likely would you be to click on a real estate listing with this photo?" Participants answered using a slider from extremely unlikely (scored as 1) to extremely likely (scored as 100). We presented the photos to each participant in a randomized order.

Upon gathering all home ratings, we examined the distribution and measures of central tendency for each photo and selected three of each category for the DCE. We did not select the most or least preferred homes, but those that were most similar in desirability. To further minimize the effect of the photo in the DCE, we asked participants to carefully consider all aspects of each home (as opposed to just the photo), and we randomized the order of homes within each choice set of the DCE.

SELECTING CONDITIONS AND DESIGNING INFORMATION LABELS TO TEST

Designing Presentation Formats

Simple changes in information label design can affect how consumers perceive products. From a rational economic perspective, this should not occur. The form of the data does not affect its content and, therefore, should not affect consumers' perception of those products. Nevertheless, research on information labels shows that this can happen (e.g., Ungemach et al. 2017).

Consumers will look for the information that is most relevant to their objectives and use that to make their decisions. Information label readers look for the metric that matters most to them, and make their decision based primarily on that metric. For example, a broad-spectrum information label, such as the current EPA vehicle fuel economy label, allows those who are interested in environmental sustainability to use the CO_2 emissions or smog information, and those who are interested in financial considerations to use the annual or five-year fuel cost information (Kormos and Sussman 2018). Conversely, information labels that lack sufficient metrics may be less effective for encouraging energy-efficient purchases (Newell and Siikamaki 2014).

Energy Costs in Information Labels

Studies suggest that cost savings are a key reason that consumers invest in home efficiency upgrades (e.g., Sussman and Chikumbo 2017). Choice experiments on appliance purchase decisions, for example, show that cost savings are more important than physical energy use or carbon dioxide emissions (Newell and Siikamaki 2014). Appliance consumers are also swayed to purchase energy-efficient products if the information labels include life-cycle costs (Kaenzig and Wustenhagen 2010) or operating costs (Anderson and Claxton 1982; Bull 2012; Newell and Siikamaki 2014). Therefore, information labels that include energy cost information may be particularly effective for guiding real estate decisions. This is one reason we chose to include an energy cost condition in our experiment.

However, simply providing the information does not guarantee that the item will be chosen; it also has to appear efficient relative to others. Cognitive biases and heuristics can influence how information is perceived. This is one reason why presenting costs and savings using larger numbers, such as lifetime costs or savings, can sometimes be more effective than presenting smaller units, such as annual costs or savings (e.g., Bull 2012; Heinzle 2012). When making decisions, the large face-value difference between numbers is used more often than the smaller proportional difference, as is the case when using larger units to represent the same information (Cadario, Parguel, and Benoit-Moreau 2016).

We tested energy efficiency real estate information labels that included estimated annual home energy costs.[39] We hypothesized that home buyers would find energy costs useful to their decision making and that annual costs would be more persuasive than monthly costs because the absolute number was larger. Nevertheless, when compared to the overall purchase price, annual costs were relatively small. This could be one reason that energy costs were one of the less effective strategies for increasing the value of efficiency in our experiment.

The Home Energy Score on Information Labels

Although estimated annual home energy costs may be important and familiar to home buyers, experts agree that energy costs are not ideal measures of energy efficiency (Allcott 2011). Costs are strongly influenced by non-efficiency factors such as energy prices, household behavior, and occupancy (number of people in the home). For that reason, the U.S. Department of Energy's Home Energy Score (HES) may be a more useful measure of

[39] Annual energy costs were estimated by the Department of Energy Home Energy Score program for this project. The estimates are based on the state average utility rates and the assumed fuel mix given the heating and cooling degree days for each weather station (DOE 2019a). The ratios are applied to the site energy estimates for each weather station bin and then multiplied by the utility rate and averaged by state. The fuel mix is based on natural gas and electricity only. Full details on how DOE estimates energy costs for Home Energy Scores is available at [Better Buildings Solution Center](https://betterbuildingssolutioncenter.energy.gov).

residential energy efficiency. The HES is already used to rate the physical energy efficiency of about 115,000 homes across the United States, with 550+ assessors across 31 states (Salzman 2019). Many utilities require the HES as part of their standard assessment for every home, but that requirement does not necessarily apply to real estate transactions. Indeed, although energy scoring with the HES or a similar metric is mandated or suggested to some extent in 14 jurisdictions, [40] Portland is the only city requiring that sellers include efficiency information in descriptions of homes they list (making it the only city in which real estate aggregators such as Redfin or Zillow present this information in listings). Home Energy Scores are generally concentrated in Oregon, California, Colorado, Missouri, Michigan, Wisconsin, New Jersey, and Connecticut. This is due to programs in these states that either require Home Energy Score as part of standard utility assessments, require HES as part of real estate transactions, or provide incentives/rebates for voluntary HES.

HES is an energy efficiency score based on the home's envelope (foundation, roof, walls, insulation, windows) and heating, cooling, and hot water systems. It provides a total energy use estimate, as well as estimates by fuel type assuming standard operating conditions and occupant behavior (DOE 2019b).

One possible drawback of using various energy scoring systems as measures of efficiency is that the score is unfamiliar to most home buyers. Audiences can more fluently process scales that are familiar to them, and therefore attributes that are presented on familiar scales may receive more weight than those that are unfamiliar (Lembregts and Pandelaere 2012). If an energy score is unfamiliar and not understandable then it will be ineffective. However, if the concept of an energy score (HES or other program) is fairly intuitive then it may work as effectively as any other metric, even if home buyers had never actually heard of it before. In our experiment we found that HES was intuitive enough to be influential to participants, regardless of how familiar they were with it prior to the experiment.

RANDOMIZATION PROCEDURES: CONDITION, BLOCK, AND PRESENTATION

Home buyers who completed the experiment were randomly assigned to a condition. Each condition was the same, except that the energy efficiency attribute of homes in the choice sets were presented in different formats. All the other attributes and levels of those attributes were identical in each condition. The specific levels of each attribute are presented below.

A second level of randomization took place within the DCE itself. To minimize the number of choice sets that each participant would need to rate, we randomized participants within each condition to one of four blocks. Within each block, each participant only had to rate six choice sets and, by combining the choices of all participants in each condition, we were able to analyze results using our planned multinomial logit model (a standard procedure for calculating willingness to pay from DCEs).

[40] A description of the HES program is available in Appendix B. This map shows current energy scoring real estate policies in each jurisdiction: www.naseo.org/issues/buildings/home-energy-labeling.

Finally, photos within each choice set were presented to participants in a random order so that each photo option varied in position on the screen from first to last.

Discrete Choice Experiment Attribute Levels

We chose attribute levels for the DCE based on preliminary research and consultation with experts at the Department of Energy HES experts. We adjusted attribute levels based on realism and preliminary testing. Preliminary testing included two soft launches of the experiment with 160–190 participants each. The three realism-based constraints we included were: (1) the smallest number of bedrooms could not co-exist with the largest number of bathrooms, (2) the smallest square footage could not co-exist with the largest number of bedrooms, and (3) the smallest square footage could not co-exist with largest number of bathrooms. The final D-efficiency of the experimental design was 85.6%. The matrix of attribute levels is shown in table B1.

Table B1. Matrix of DCE attribute levels

Attributes	Single-family detached	Single-family attached	Multi-family
1. Photo *(Constrained in the design such that the images for the three alternatives in each choice set will each show a different photo)*	Photo A  Photo B  Photo C 	Photo D  Photo E  Photo F 	Photo G  Photo H  Photo I 
2. Listing price *(Pivoted around the midpoint of each respondent's stated intended purchase price range, for a 19.5% spread)*	$[90.25% stated price] $[96.75% stated price] $[103.25% stated price] $[109.75% stated price]		
3. Number of bedrooms *(Customized based on self-reported minimum # of bedrooms)*	Stated minimum # of bedrooms – 1 [_bds] Stated minimum # of bedrooms [_bds] Stated minimum # of bedrooms + 1 [_bds]		
4. Number of bathrooms *(Customized based on self-reported ideal # of bathrooms)*	Stated ideal # of bathrooms [_ba] Stated ideal # of bathrooms + 1 [_ba] Stated ideal # of bathrooms + 2 [_ba]		
5. Square footage *(28% difference from median)*	1,843 sq. ft. 2,553 sq. ft. 3,263 sq. ft.	1,009 sq. ft. 1,397 sq. ft. 1,785 sq. ft.	637 sq. ft. 882 sq. ft. 1,127 sq. ft.
6. Number of days on the market	5 days 21 days 37 days		

Attributes	Single-family detached	Single-family attached	Multi-family
7. Home energy information			
Condition 1: Estimated annual energy costs *(Customized based on self-reported intended state)*	$[Average estimated annual energy costs per state for homes with HES = 2] [41] $[Average estimated annual energy costs per state for homes with HES = 5] $[Average estimated annual energy costs per state for homes with HES = 8] [42]		
Condition 2: Home energy score (number only)	2 / 10 5 / 10 8 / 10		
Condition 3: Home energy score along a continuum (with '5' indicated as the average)	2 / 10 5 / 10 8 / 10		
Condition 4: Estimated annual energy costs + Home energy score along a continuum (with '5' indicated as the average) *(Customized based on self-reported intended state)*	$[Average estimated annual energy costs per state for homes with HES = 2] + 2 / 10 $[Average estimated annual energy costs per state for homes with HES = 5] + 5 / 10 $[Average estimated annual energy costs per state for homes with HES = 8] + 8 / 10		
Condition 5: Only above-average HES (number only)	- - 8 / 10		
Condition 6: No home energy information (control condition)	N/A		

Note: HES = Home Energy Score

PLANNED ANALYSES: ANOVA AND MNL

We calculated how much home buyers were willing to pay for energy efficiency and other home attributes using multinomial logit models (MNLs), which is a common approach for DCEs. Additionally, we used *t*-tests and analyses of variance (ANOVAs) to determine if home buyers clicked on efficient listings more often.

[41] On average, this is 125% of the estimated costs for homes with scores of 5 out of 10. It can vary slightly, based on state, from 119% to 128%.

[42] On average, this is 82% of the estimated costs for homes with scores of 5 out of 10. It can vary slightly, based on state, from 80% to 86%.

Appendix C. Participant Details

This appendix describes home buyers who completed the experiment. The scope of our report is limited to our specific research questions, but future research could potentially delve further into these descriptions for additional insights. For example, we note that 19% of home buyers in our sample did not already own a home. Future research could investigate whether owning a home affects perceptions of energy efficiency information.

Overall Recruitment

In total, we recruited N = 1,538 American home buyers who planned to purchase a home within five years of completing the study. Respondents (n = 2,358) who attempted the survey and were excluded from the analyses either answered two of three attention questions incorrectly (n = 162), did not consent to participate (n = 61), were not planning to purchase a home within five years (n = 195), provided nonsensical answers (n = 47), answered too many questions with the exact same answer (n = 7), did not understand the task we asked of them (n = 1), or exceeded our quota requirements in specific demographic categories (n = 1,885). Overall, 834 (54.2%) home buyers included in the analyses identified as female, 703 (45.7%) identified as male, and 1 (0.1%) identified as "other or prefer not to answer."

Age, Income, Preferred Region, and Preferred Home Type

Age, income, preferred home type, and desired geographic regions closely resembled a nationally representative sample. These are summarized in the body of the report in table 1.

Education

Table C1. Education

Education	% (n)
Less than high school	0.7% (11)
High school graduate or equivalent	20.4% (313)
Associate degree	20.4% (314)
College degree	36.6% (563)
Graduate or professional degree	20.7% (319)

CURRENT HOME

Table C2. Current home

Current home	% (*n*)
Years since last home purchase	
0–1 year ago	4.9% (76)
2–5 years ago	15.0% (230)
5–10 years ago	17.9% (275)
Over 10 years ago	42.9% (660)
Never purchased a home	19.3% (297)
Real estate website used for last home purchase [43]	
Zillow	66.3% (1,019)
Realtor	43.0% (662)
Trulia	33.6% (517)
Century 21	17.9% (275)
Remax	17.8% (273)
Redfin	15.8% (243)
Current home type	
Single-family detached	72.1% (1,109)
Attached	8.6% (132)
Multifamily	15.7% (241)
Other or unknown	3.7% (56)
Currently rent or own	
Own	71.5% (1,100)
Rent	28.1% (432)
Unknown	0.4% (6)

NEXT HOME TO BE PURCHASED

Table C3. Next home to be purchased

Next home	% (*n*)
Climate zone [44]	
1	2.1% (33)
2	16.1% (248)
3	23.8% (366)
4	26.0% (400)

[43] Participants could indicate having used multiple websites

[44] Baechler et al. 2015

Next home	% (*n*)
5	25.7% (396)
6	5.3% (82)
7	0.7% (11)
8	0.1% (2)
Urban–rural continuum code (2013)	
Metropolitan areas with population 1 million or more	60.3% (928)
Metropolitan areas with population 250,000 to 1 million	20.4% (313)
Metropolitan areas of fewer than 250,000 population	8.6% (133)
Non-metro areas with populations of 20,000 or more	4.5% (69)
Non-metro areas with populations of 2,500 to 19,999	4.2% (64)
Non-metro areas with populations under 2,500	2.0% (31)
Reason for next home purchase [45]	
For self, friends, or family to live in	95.3% (1,465)
To rent for short-term stays (up to one month)	2.8% (43)
To rent for long-term stays (over one month)	3.8% (59)
To resell	4.0% (62)

FAMILIARITY WITH RESIDENTIAL ENERGY EFFICIENCY BEFORE THIS STUDY

Table C4. Familiarity with residential energy efficiency before this study

	Mean score (out of 100) [46]	Standard deviation
Familiarity with Home Energy Score prior to study	59.74	29.71
Considered energy efficiency in most recent home purchase	60.13	30.86

PSYCHOSOCIAL VARIABLES

At the end of the study, we asked participants a series of previously validated questions about attitudes, beliefs, and opinions surrounding their energy use behavior. These questions were designed to evaluate attitude changes that may occur alongside behavior change intervention programs for household energy (SCE 2016). We used them to better understand the general energy-use attitudes and energy conscientiousness of our sample.

[45] Participants could select multiple reasons for purchasing their next home.

[46] Scores ranged from 0 (low consideration or familiarity) to 100 (high consideration or familiarity).

Table C5. Psychosocial variables

	Mean score (out of 100) [47]	Standard deviation
General factors affecting household energy use and conservation		
Energy bill	79.92	20.76
Comfort	75.34	21.06
Habit	67.06	24.53
Convenience	66.60	24.71
Environmental impact	65.58	28.04
Moral obligation	60.33	29.32
Societal benefit	54.23	30.38
Psychological factors affecting energy use and conservation		
Energy literacy (combined items)	75.74	21.46
Performance efficacy (combined items)	75.52	18.99
Personal norms (combined items)	73.46	20.76
Social norms (combined items)	56.22	28.32
Objective household energy knowledge		
Energy quiz (number correct out of six True or False questions)	4.83 out of 6	1.1

[47] Scores ranged from 0 (low or strongly disagree) to 100 (high or strongly agree).

Appendix D. Detailed Results of Statistical Analyses

In this appendix, we present details of our statistical analyses for readers with an understanding of social science statistical methods.

DO HOME BUYERS CLICK ON MORE EFFICIENT HOMES WHEN REAL ESTATE LISTINGS CONTAIN ENERGY EFFICIENCY INFORMATION?

Click Rates

We compared the choices of participants in the control condition to those in the six experimental conditions. Respondents who were presented with home energy information (i.e., in the experimental conditions) chose homes that were statistically different from those who did not see home energy information (i.e., in the control group). Specifically, independent samples' *t*-tests revealed that respondents tended to choose houses that were ranked higher in-home energy efficiency for all of the newly created dependent variables.

In each choice set, we asked home buyers to choose from three homes, each with different levels of efficiency: Level 1 (least efficient, equivalent to a HES of 2/10), Level 2 (average efficiency, equivalent to a HES of 5/10), and Level 3 (most efficient, equivalent to a HES of 8/10).

Home buyers who saw the energy efficiency information of the homes selected a higher total number of Level 3 homes (M = 2.69, SD = 1.45) than those who did not see the energy information (M = 2.36, SD = 1.28), $t(1536)$ = 3.31, p = .001. Similarly, home buyers who saw the energy efficiency information also chose fewer Level 1 homes (M = 1.38, SD = 1.23) than those who did not see this information (M = 1.80, SD = 1.25), $t(1536)$ = –4.89, p < .001.

Willingness to Pay for Efficiency

We estimated an overall multinomial logit (MNL) choice model using choice data from all the conditions that included energy efficiency information (i.e., not the control condition). In the pooled model, all attribute coefficients, except days on the market, were significant (table D1). Specifically, respondents preferred lower levels of purchase price, but they preferred higher levels of energy efficiency and greater square footage and number of bedrooms (table D1). They also significantly preferred fewer bathrooms because we only provided options with at least the number of specified bathrooms (i.e., we customized to the experiment based on the minimum number of required bathrooms as opposed to the preferred number of bathrooms).

Willingness to pay for each attribute is calculated as the value of an additional unit of a particular home attribute in relation to an increase or decrease in purchase price. We calculated willingness to pay using coefficient estimates that were statistically significant at the 95% confidence level or higher (table D1). In this sense, willingness to pay is the average dollar amount in purchase price that the sample is given for an additional unit of a particular home attribute (e.g., one bedroom). As shown in table 5, the pooled model across the five experimental conditions revealed that participants were willing to pay $71,053 (*s.e.* = 6,774) for a three-unit increase in HES. This is equivalent to $23,684 for a one-unit increase. However, given that we asked home buyers to specify their own specific intended purchase prices, this value was inextricably connected to the price they specified (i.e., if they specified a higher price, they were necessarily willing to pay more for energy efficiency). Therefore, we standardized willingness-to-pay values by dividing them by intended purchase price. With the average intended purchase price of the entire sample being $417,542, home buyers in the sample were willing to pay $0.06 of every purchase price dollar for energy efficiency. Another way to conceptualize this is to say that participants were willing to increase purchase price by 6% for a one-unit increase in HES.

Table D1. Pooled choice model results (excluding respondents from the control condition). WTP = Willingness to pay; HES = Home Energy Score

Attributes	Coefficient	*p*-value	WTP [s.*e.*] (in USD)
Purchase price	−0.004	$p < .001$	-
Photo		$p < .001$	
1	0.06		15,496 [4,352]
2	0.07		15,760 [4,503]
3	−0.13		−31,256 [5,144]
Number of bedrooms	0.35	$p < .001$	84,305 [7,406]
Number of bathrooms	−0.09	$p < .001$	−20,704 [4,405]
Square footage	0.16	$p < .001$	38,601 [5,522]
Number of days on market	0.02	*ns*	–
Energy efficiency information (three HES units)	0.3	$p < .001$	71,054 [6,774]
Alternative		$p = .002$	
1	0.005	*ns*	
2	−0.06	$p < .001$	−14,105 [4,495]
3	0.05	$p < .001$	12,898 [4,643]

Open-Ended Question

The post-experiment survey included one open-ended question asking participants "What do you look for when buying a new home?" This question was useful for identifying the information that home buyers currently believe influences their home-buying decisions. It can be biased by the way memories are stored and recalled (e.g., availability bias) as well as a possible desire to provide the "right" answer (social desirability bias), but it is helpful in gauging what participants say they want.

We used qualitative data analysis software (NVivo) to automatically code themes in the answers of our home buyer sample (N = 1,538). The software generated 17 themes, of which 13 were categories that accurately identified unique features. These 13 categories were then further consolidated into 11 groups. The groups of features that participants said they looked for were:

- Location
- Price

- Size
- Bedrooms
- Garage
- Kitchen
- Other rooms
- Schools nearby
- Condition of home
- Yard
- Pool (mentioned very infrequently)

Familiarity with Home Energy Score

A multiple regression analysis conducted on those in the experimental conditions (i.e., excluding the control condition), revealed that "How much did you consider energy efficiency when purchasing your recent home?" and "How familiar were you with Home Energy Scores before this study?" did not significantly predict the level of home energy efficiency chosen, $F(2, 1041) = 1.92$, *ns*, with an adjusted R^2 of .004. An additional multiple regression analysis was performed without the control condition as well as the only voluntary label condition and the estimated annual energy cost condition. Results revealed that these two predictor variables were not significantly associated with the average level of energy efficiency information attribute chosen, $F(2, 622) = 2.01$, *ns*, with an adjusted R^2 of .003. As such, familiarity with the HES did not significantly predict choosing more efficient homes.

Single-Family Detached Homes

The vast majority of home buyers in our sample (86.7%) intended to purchase a single-family detached home. This group expected to spend less ($402,678) on their homes than those intending to purchase attached ($569,453) or multifamily ($422,338) units. This is likely because home buyers in our sample who intended to purchase attached and multifamily units lived in more densely populated regions with typically more expensive real estate markets.[48] As shown in table D2, participants intending to purchase detached homes were willing to increase their purchase price by an average of approximately 5% ($21,000) for a one-point increase in HES. Although this analysis is tangential to our primary research questions, it presents some interesting potential avenues for future research.

[48] Based on 2010 county population data, home buyers who intended to purchase single-family detached homes lived in counties with average populations of 1,081,826 people. Those who intended to purchase attached homes lived in counties with average populations of 1,481,303 people. Those who intended to purchase multifamily units, lived in counties with average populations of 1,751,274 people.

Table D2. Multinomial logit model for only single-family detached homes. WTP = Willingness to pay; HES = Home Energy Score

Attributes	Coefficient	*p*-value	WTP [s.e.] (in USD)
Purchase price	-0.005	$p < .001$	-
Photo 			
1	0.06	$p < .001$	12,708 [3,955]
2	0.08	$p < .001$	15,707 [12,598]
3	–0.14	$p < .001$	–28,415 [4,672]
Number of bedrooms	0.35	$p < .001$	71,171 [6,270]
Number of bathrooms	–0.09	$p < .001$	–17,911 [4,005]
Square footage	0.14	$p < .001$	29,016 [4,756]
Number of days on market	0.02	*ns*	–
Energy efficiency [3 HES units]	0.31	$p < .001$	62,804 [5,946]
Energy efficiency [1 HES unit]			20,934
Alternative			
1	0.01	*ns*	–
2	–0.06	$p < .001$	–12,849 [13,910]
3	0.06	$p < .001$	11,724 [4,247]

There were three types of home buyers interested in buying single-family detached homes. The first group (43% of the sample) were "needs-driven." They were significantly sensitive to all attributes except purchase price and number of days on the market and were especially sensitive to the number of bedrooms. The second group (29% of the sample) were "price conscious." They were especially sensitive to price and insensitive to the number of days on the market. The third group (28% of the sample) were motivated to obtain the "most for less." They were highly sensitive to the number of bedrooms and square footage, as well as—to a lesser extent—the number of days on the market.

WHAT IS THE BEST WAY TO DISPLAY EFFICIENCY INFORMATION?

Click Rates

Using analyses of variance (ANOVAs), we tested whether the least efficient homes (Level 1) received fewer clicks and whether the most efficient homes (Level 3) received more clicks, given different presentations of the same efficiency information. All these analyses revealed a significant causal effect of condition on the energy level of choices made.

As shown in figure D1, there was an overall significant difference among the means of the conditions on the total number of Level 3 homes chosen for the energy information attribute across the six choice sets, $F(5, 1532) = 4.05$, $p = .001$. Post-hoc tests, using Tukey HSD, revealed that three of the experimental conditions resulted in significantly more frequent selection of Level 3 homes compared to the control condition ($M = 2.36$, $SD = 1.28$):

- Annual energy costs + HES on a continuum ($M = 2.84$, $SD = 1.49$, $p < .01$)

- HES alone (*M* = 2.79, *SD* = 1.47, *p* = .01)
- HES along a continuum (*M* = 2.74, *SD* = 1.44, *p* < .05)

The control condition did not differ significantly from the voluntary label condition, in which only above-average homes were highlighted (*M* = 2.55, *SD* = 1.39). Nor did it differ significantly from the "estimated annual energy cost" condition (*M* = 2.56, *SD* = 1.45).

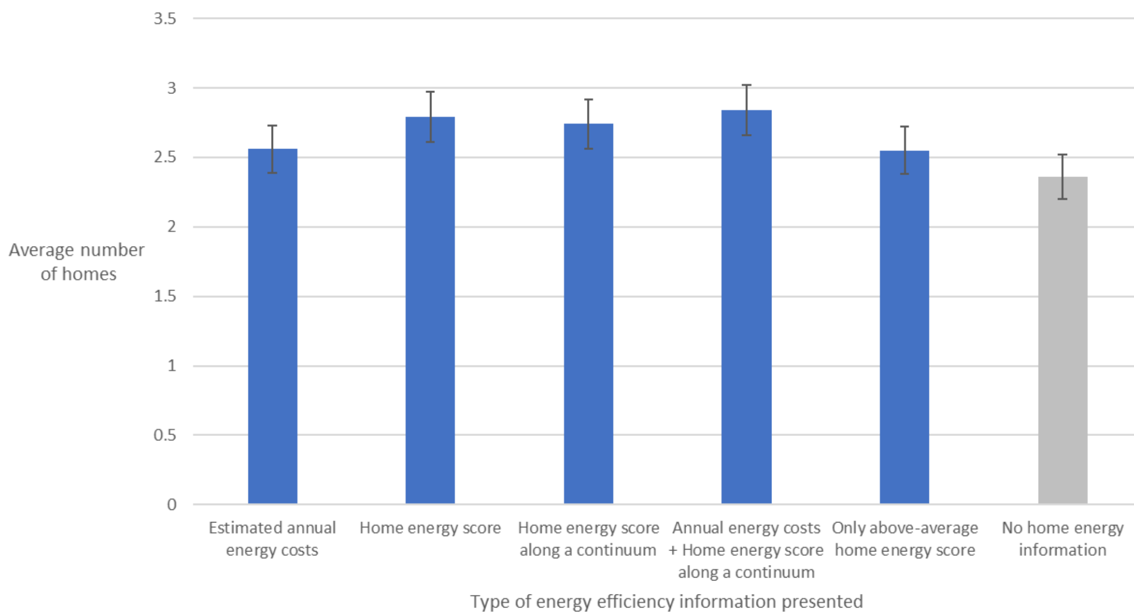


Figure D1. Condition means of the conditions on the total number of Level 3 chosen for energy information attribute across the six choice sets

As shown in figure D2, we also found an overall significant difference among the means of the conditions on the total number of Level 1 homes chosen for the energy information attribute across the six choice sets, $F(5, 1532) = 11.20$, $p < .001$. Tukey HSD post-hoc tests revealed that four of the experimental conditions resulted in significantly fewer selections of inefficient homes compared to the control condition (*M* = 1.80, *SD* = 1.25):

- HES on a continuum (*M* = 1.21, *SD* = 1.14, *p* < .001)
- Annual energy costs + HES on a continuum (*M* = 1.23, *SD* = 1.27, *p* < .001)
- HES alone (*M* = 1.27, *SD* = 1.28, *p* < .001)
- Estimated annual energy costs condition (*M* = 1.49, *SD* = 1.16, *p* < .05)

Only the voluntary label condition did not significantly change home buyer decisions (to click on most or least efficient homes), relative to the control condition.

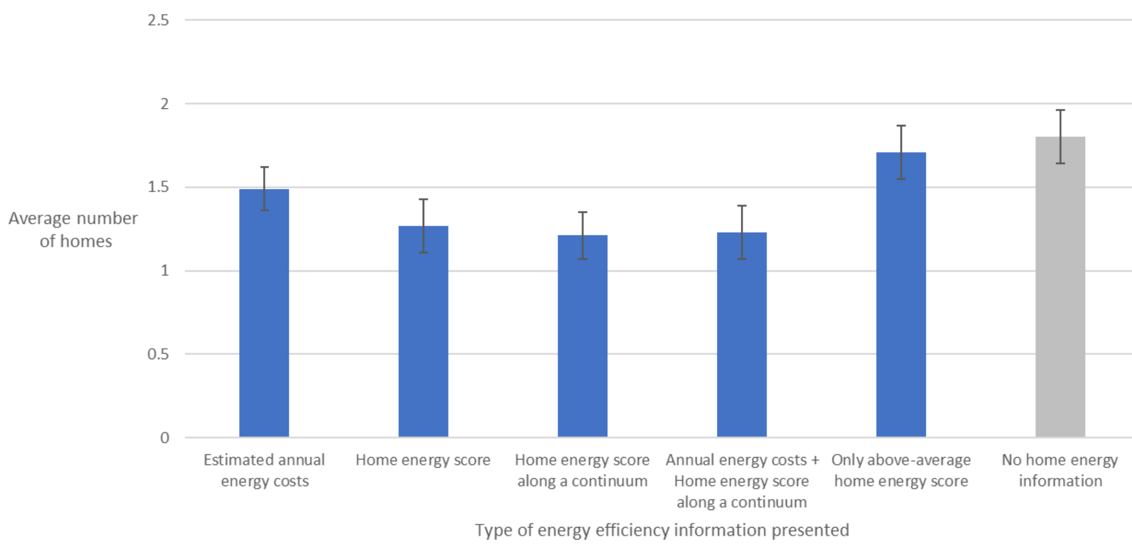


Figure D2. Condition means of the conditions on the total number of Level 1 chosen for energy information attribute across the six choice sets

Willingness to Pay for Efficiency

Each experimental condition used the same DCE but with the energy efficiency attribute displayed differently. We estimated an MNL for each of the five experimental conditions (excluding the control) to determine how much home buyers were willing to pay for efficiency, and whether that value changed depending on how the efficiency information was displayed.

As shown in table D3 and figure D3, home buyers in our sample were willing to pay most for energy efficiency when the information was presented as HES along a continuum (from inefficient to efficient). When we presented the information in this form, home buyers were willing to increase purchase price by 11% for a one-unit increase in HES, which was extrapolated from 32% for a three-unit change.

Table D3. Willingness to pay (in USD) for one unit of increase on the HES, standardizing for intended purchase price, across the experimental conditions. WTP = Willingness to pay; HES = Home Energy Score

	Estimated annual energy costs condition	Home energy score condition	Home energy score along a continuum condition	Annual energy costs and home energy score along a continuum condition
Anticipated purchase price	421,805	419,297	446,502	373,004
WTP for energy efficiency (3 units on energy efficiency scale) [s.e.]	59,095 [14,252]	79,263 [15,418]	141,307 [36,513]	85,228 [17,669]
Confidence intervals	Min. 31,160 Max. 87,028	Min. 49,044 Max. 109,481	Min. 69,740 Max. 212,870	Min. 50,596 Max. 119,857
WTP for energy efficiency (1 unit of energy efficiency scale)	19,698	26,421	47,102	28,409
WTP percent	5%	6%	11%	8%

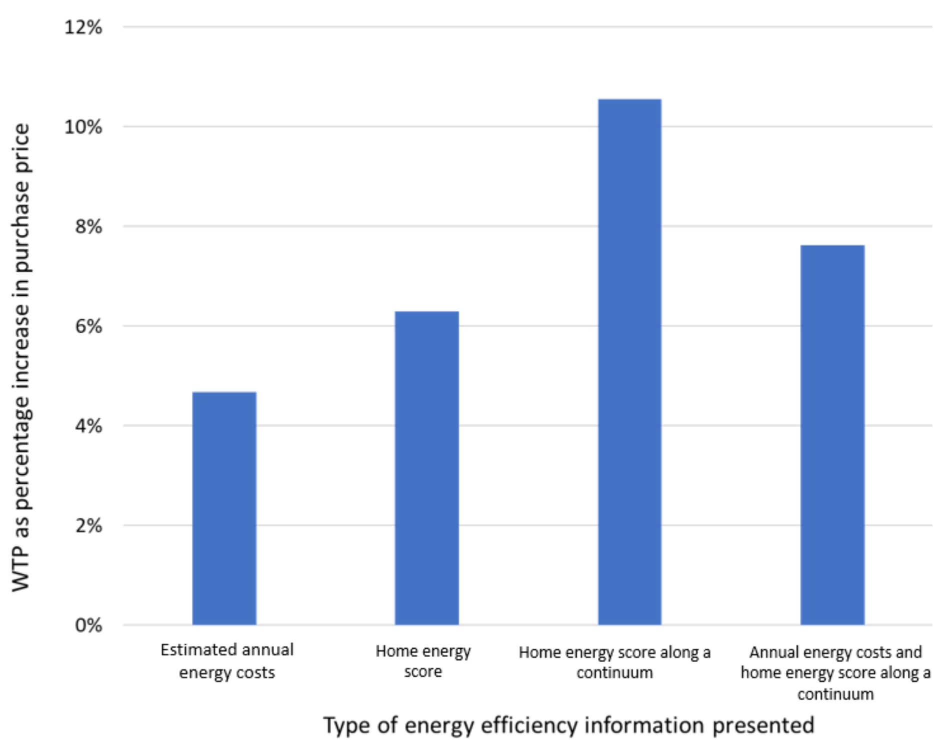


Figure D3. The percentage that participants were willing to increase purchase price for one unit of increase in HES, across the six experimental conditions. WTP = Willingness to pay. HES = Home Energy Score.

WHICH HOME BUYERS VALUE EFFICIENCY MOST?

We performed a series of known-class MNL models to evaluate potential demographic differences in valuation of home energy efficiency across all conditions.

The Place

CENSUS REGION

Known class models revealed significant coefficients for purchase price and energy efficiency across all four census regions. As shown in table D4, controlling for variations in purchase price, respondents looking to purchase homes in the Northeast had the highest valuation of energy efficiency: twice as much as those looking to purchase in the West.

Table D4. Willingness to pay (in USD) for one unit of increase in Home Energy Score, standardized for intended purchase price, across census regions. WTP = Willingness to pay. HES = Home Energy Score

	Midwest	Northeast	South	West
Anticipated purchase price	305,808	479,113	386,543	519,217
WTP for 3 units of HES [s.e.]	65,963 [14,026]	121,515 [40,584]	57,455 [7,990]	66,253 [12,422]
WTP for 1 unit of HES	21,988	40,505	19,152	22.084
WTP percent	7%	8%	5%	4%

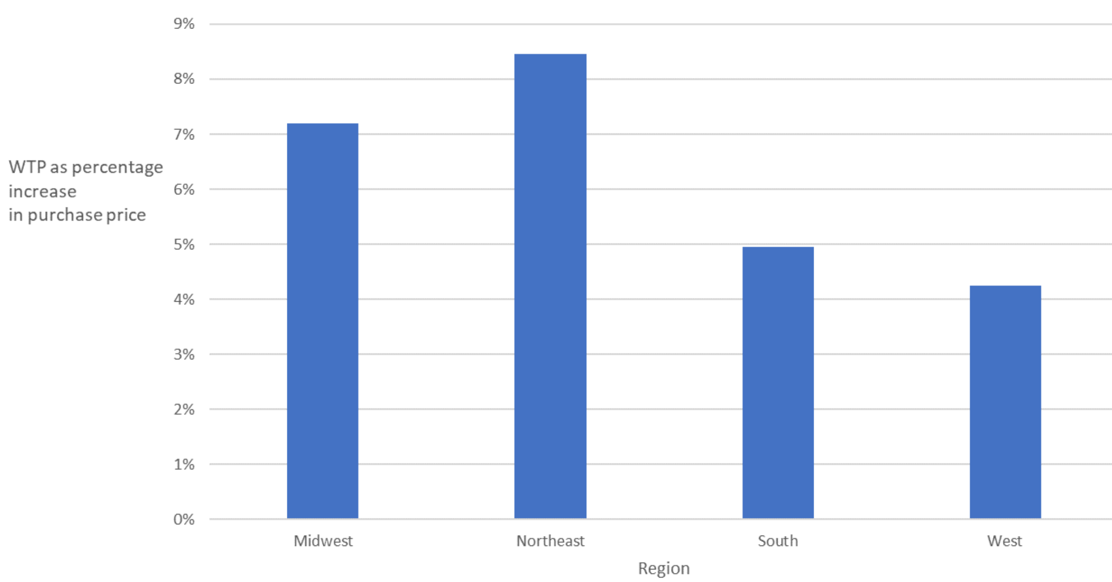


Figure D4. The percentage that participants were willing to increase purchase price for one unit of increase in HES, across the four census regions

URBAN-RURAL DIFFERENCES

Using the most recent U.S. Housing and Urban Development agency crosswalk files (HUD 2020) to convert ZIP codes to Federal Information Processing Standard codes and then adding the 2013 urban–rural continuum codes, we were able to determine if each home buyer was located in either a metropolitan or non-metropolitan region. We performed analyses for home buyers from metropolitan and non-metropolitan regions,[49] as defined by 2013 urban–rural continuum codes from U.S. Department of Housing and Urban Development. Metropolitan county codes (coded 1–3) were compared to non-metropolitan county codes (coded 4–9). Coefficients for purchase price and energy efficiency were significant for metropolitan and non-metropolitan county code analyses. Results reveal a lack of difference between the two known classes. Although urban home buyers were willing to pay more for energy efficiency in an absolute sense, this difference disappeared when we controlled for purchase price. Results can be seen in table D5.

Table D5. Willingness to pay (in USD) for a one-unit increase in Home Energy Score, standardized for intended purchase price, across urban–rural codes. WTP = Willingness to pay; HES = Home Energy Score

	Metropolitan regions	Non-metropolitan regions
Anticipated purchase price	432,067	295,854
WTP for 3 units of HES [s.e.]	71,186 [7,614]	45,465 [7,870]
WTP for 1 unit of HES	23,729	15,155
WTP percent	5%	5%

CLIMATE ZONE

Using the U.S. Housing and Urban Development agency crosswalk files (HUD 2020) to convert ZIP codes to Federal Information Processing Standard codes and then adding the Energy Star climate zone map (downloaded November 2019), we were able to determine the climate zone where each home buyer resided. We assessed a known class model to evaluate potential differences in home energy efficiency across climate zones.[50] Coefficients for purchase price and home energy efficiency attributes were significant for all climate zones, except for climate zone 7 or 8 (in which the sample size was very low). Controlling for purchase price, findings revealed little variation in valuation of energy efficiency across climate zones 1–6. These can be seen in table D6.

[49] Unlike the census region analysis, which could be based on the U.S. state that participants intend to move to, this analysis was based on home buyers' current ZIP code. ZIP code is required for determining urban–rural codes, and home buyers generally do not know the ZIP code of the region they plan to move to unless they already live there.

[50]This analysis was based on home buyers' current ZIP code. ZIP code is required for determining climate zone and home buyers generally do not know the ZIP code of the region they plan to move to unless they already live there.

Table D6. Willingness to pay (in USD) for a one-unit increase in Home Energy Score, standardized for intended purchase price, across climate zones. WTP = Willingness to pay; "1 unit" = One-unit increase in Home Energy Score

	Climate zone 1	Climate zone 2	Climate zone 3	Climate zone 4	Climate zone 5	Climate zone 6
Purchase price	525,152	393,427	498,661	445,225	344,091	280,122
WTP for 3 units [s.e.]	72,058 [36,171]	54,458 [12,518]	77,797 [15,184]	82,451 [18,658]	64,097 [11,781]	41,400 [10,072]
WTP for 1 unit	24,019	18,153	25,932	27,484	21,366	13,800
WTP percent	5%	5%	5%	6%	6%	5%

The Person

INCOME

Known class models performed for gross annual household income[51] categories revealed significant purchase price and energy efficiency coefficients for all income categories, except for those making between $40,000 and $49,999. Controlling for variations in purchase price, those respondents with incomes of $200,000 or more had the highest valuation of energy efficiency (willing to increase purchase price by 7% for a one-unit increase in HES). This can be seen in table D7.

Table D7. Willingness to pay (in USD) for a one-unit increase in Home Energy Score, standardized for intended purchase price, across income categories. WTP = Willingness to pay; "1 unit" = One-unit increase in Home Energy Score

	Under $20,000	$20,000 to $29,999	$30,000 to $39,999	$50,000 to $59,999	$60,000 to $79,999	$80,000 to $99,999	$100,000 to $119,000	$120,000 to $199,999	$200,00 or more
Purchase price	210,541	252,614	215,943	303,983	389,924	420,547	472,715	571,193	903,590
WTP for 3 units of energy scale [s.e.]	38,835 [9,612]	41,105 [19,640]	21,891 [6,092]	37,525 [9,146]	43,674 [7,496]	78,017 [18,322]	66,101 [25,203]	82,068 [23,786]	176,780 [96,111]
WTP for 1 unit	12,945	13,702	7,297	12,508	14,558	26,006	22,034	27,356	58,927
WTP percentage	6%	5%	3%	4%	4%	6%	5%	5%	7%

EDUCATION

Home buyers in our sample were sensitive to purchase price and energy efficiency across all categories of education. As shown in table D8, controlling for variations in purchase price, those with graduate or professional degrees were willing to pay the most for energy efficiency (willing to increase purchase price by 8% for a one-unit increase in HES), and those with less than high school and high school graduates were willing to pay the least for energy efficiency (willing to increase purchase price by 4% for a one-unit increase in HES).

[51] Income was defined as being from all sources, before taxes.

Table D8. Willingness to pay (in USD) for a one-unit increase in Home Energy Score, standardized for intended purchase price, across education categories. WTP = Willingness to pay; "1 unit" = One-unit increase in Home Energy Score

	Less than high school	High school graduate (including equivalency)	Associate degree	College graduate (bachelor degree)	Graduate or professional degree
Purchase price	317,778	271,086	317,611	445,648	616,144
WTP for 3 units of energy scale [s.e.]	34,958 [17,551]	33,795 [7,083]	48,804 [8,393]	65,126 [9,395]	141,624 [42,019]
WTP for 1 unit of energy scale	11,653	11,265	16,268	21,709	47,208
WTP percentage	4%	4%	5%	5%	8%

AGE

All age categories are significantly sensitive to variations in price and energy efficiency information. Controlling for variations in purchase price, those 65 to 74 years old were willing to pay the most for energy efficiency (willing to increase purchase price by 9% for a one-unit increase in HES), and those 25–29, 30–34, and 55–64 years old were willing to pay the least for energy efficiency (willing to increase purchase price by 4% for a one-unit increase in HES). This can be seen in table D9.

Table D9. Willingness to pay (in USD) for a one-unit increase in Home Energy Score, standardized for intended purchase price, across age categories. WTP = Willingness to pay; "1 unit" = One-unit increase in Home Energy Score

	Up to 24 years old	25 to 29 years old	30 to 34 years old	35 to 44 years old	45 to 54 years old	55 to 64 years old	65 to 74 years old	75 years or older
Purchase price	407,971	445,301	522,038	555,590	436,323	399,377	326,680	392,250
WTP for 3 units of energy scale [s.e.]	61,108 [31,870]	57,762 [21,477]	62,579 [23,376]	77,970 [24,122]	86,839 [20,129]	38,704 [6,408]	85,882 [16,901]	57,232 [40,869]
WTP for 1 unit of energy scale	20,369	19,254	20,860	25,990	28,946	12,901	28,627	19,077
WTP percentage	5%	4%	4%	5%	7%	4%	9%	5%

INTENDED PURCHASE PRICE

Coefficients for the purchase price and energy efficiency attributes were significant for all categories of price. Specifically, analyses revealed that, controlling for variations in purchase price, home buyers in our sample were willing to pay most (9% increase in purchase price for a one-unit increase in HES) if they were planning to purchase homes for more than $750,000. This can be seen in table D10.

Table D10. Willingness to pay (in USD) for a one-unit increase in Home Energy Score, standardized for intended purchase price, across purchase price categories. WTP = Willingness to pay; "1 unit" = One-unit increase in Home Energy Score; HES = Home Energy Score

	<=$250,000	$250,000 –500,000	$500,000 –750,000	>$750,000
Purchase price	171,040	361,405	619,882	1,160,297
WTP for 3 units of HES [s.e.]	12,955 [1,170]	26,539 [2,965]	22,493 [9.534]	313,365 [196,979]
WTP for 1 unit	4,318	8,846	7,498	104,455
WTP percentage	3%	2%	1%	9%