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Greenhouse gas mitigation benefits and cost-effectiveness of weatherization treatments for low-income, American, urban housing stocks[1]

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Abstract

This paper investigates how greenhouse gas (GHG) mitigation benefits and cost-effectiveness of weatherization treatments vary geographically due to differences in climate, energy production mix, and housing stock. Using a treatment cost database and methods that estimate the residential energy savings from weatherization, we estimated energy cost savings, GHG savings, and measurements of cost-effectiveness. Combinations of three weatherization treatments were modeled: replacing a standard thermostat with a programmable thermostat, installing attic

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[1] **Abbreviations:** A – Attic insulation; ACH50 – Air Changes per Hour at 50 pascals; AHS – American Housing Survey; CO2 – Carbon dioxide; CO2e – Carbon dioxide equivalent; EIA – Energy Information Administration; eGRID – Emissions & Generation Resource Integrated Database; GHG – Greenhouse Gas; GJ – Gigajoule; HES – Home Energy Saver; MSA – Metropolitan Statistical Area; NREMD – National Residential Efficiency Measure Database; S – Air sealing; T – Programmable thermostat; U.S. – United States; WAP – Weatherization Assistance Program

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insulation, and envelop air sealing. These treatments were modeled for the low-income housing stock of six contrasting American urban areas: Orlando, Florida; Los Angeles-Long Beach, California; Seattle, Washington; Philadelphia, Pennsylvania; Detroit, Michigan; and Milwaukee, Wisconsin. Results show that (1) regional variations have high impact on the cost-effectiveness of weatherization treatments, (2) housing stocks with substantial electric space conditioning tend to offer greater energy cost and GHG savings, (3) the effect of a GHG price is small compared to energy cost savings when evaluating the cost-effectiveness of weatherization treatments, and (4) installing programmable thermostats is the most cost-effective treatment. This study highlights the importance of thoughtful consideration of weatherization program goals when selecting cities or regions to prioritize because different goals suggest different weatherization strategies.

Keywords: Weatherization; Residential building retrofit; Building energy modeling; Energy efficiency; Greenhouse gas emissions; Cost-benefit analysis; Low-income housing;

1 Introduction

Largely inspired by concerns with energy production and climate change, residential energy use is a topic of significant interest, particularly within the fields of engineering and public policy. In the United States (U.S.), the residential building sector is responsible for 21% of primary energy consumption, of which 36% is used for space conditioning (i.e., heating and cooling) [1]. By reducing energy use for space conditioning, weatherization treatments can make buildings more energy-efficient, and, consequently, offer substantial reductions in greenhouse gas emissions (GHGs). In the U.S., residential buildings are responsible for approximately 21% of annual emissions of greenhouse gases (GHGs) [2], and research suggests that retrofitting strategies are more effective at stabilizing GHG emissions compared to other building strategies, such as the construction of net zero houses or other high performance green buildings [3]. Moreover, among the opportunities for energy-efficiency improvements in different sectors, buildings are recognized as the sector in which the potential for efficiency is the largest, least expensive, and requires the shortest lead time to implement [4]. In particular, in the residential sector, space cooling is the end-use with the greatest potential for electricity savings through energy-efficiency measures [5].

In addition to these environmental impacts, residential energy consumption includes a substantial social impact. For low-income households, energy use often represents a significant financial cost; these households pay approximately 14% of their income on energy bills, compared to 3% for other households [6]. Contributing to this burden, compared to middle- and high-income houses, low-income houses are, on average, 20% less energy-efficient [7] and have more than twice as much leakage as [8]. Furthermore, improvements in space conditioning in low-income housing represents 19% of the available energy efficiency gains in the residential sector [9]. With the primary goal of reducing the burden of energy costs on low-income households, the U.S. Department of Energy administers the Weatherization Assistance Program (WAP), which provides grants to improve energy-efficiency in low-income residences. Since its creation in 1976, WAP has helped fund projects to weatherize over 7 million homes across the country, more than one million of which have been completed since 2009, when the American Recovery and Reinvestment Act of 2009 allocated $5 billion for WAP [10]. In addition to reducing annual household energy bills by typically $250 to $400 [6,10], these retrofits include several external benefits, namely decreased energy consumption, lower GHG emissions, improved air quality, higher home values, job creation, and enhanced national security [11–14].

While the environmental and social issues associated with residential energy use affect communities across the country, there has been little research into the geographic distribution of potential costs and benefits of weatherization treatments. Readers seeking a detailed literature review of housing retrofit analysis studies at various scales are referred to Hoşgör and Fischbeck [15]; while these studies present various novel methods for measuring or predicting energy use and the effectiveness of retrofits, a limited number of those studies (highlighted below) compare energy savings across regions at the housing stock scale, and fewer detail regional variations in weatherization costs and benefits other than energy conservation. Previous research by the authors has evaluated the energy savings expected from weatherization treatments in six different American cities and confirmed that these savings vary substantially due to differences in climate and housing stock [16]. In particular, that study found that greater energy savings generally existed among housing stock in colder climates; however, it did not assess the costs of these weatherization treatments or any benefits beyond energy savings, which, as discussed above, is just one of several benefits of weatherization. In a study of smart meter data from residences in multiple U.S. states, Kavousian et al. [17] confirmed that weather, house location, and physical building characteristics (namely, floor area) were the most important determinants of electricity use, a portion of which is due to space conditioning. A later Oak Ridge National Laboratory WAP evaluation study supported the conclusion that energy savings were generally greater in colder climates [14,18]; this study also found that weatherization treatments were typically more cost-effective in colder climates, though there is limited discussion about how regional trends in housing stock and energy production mix contribute to this finding. In their studies of Greek housing stock, Droutsa et al.[19] and Balaras et al. [20] evaluated how weatherization treatment costs, energy savings, and GHG savings vary due to differences in building type and climate;

these studies did not include an assessment of variations in energy production mix or energy prices within the subject housing stocks.

The purpose of our current study is to help close this knowledge gap by evaluating how costs and additional benefits of weatherization vary among low-income housing stock in American cities. Specifically, this paper compares the costs of completing a weatherization treatment with the benefits associated with reduced energy bills and GHG emissions. Through a comparative analysis of low-income housing stocks in six American cities, this study investigates how the costs and various benefits of weatherization treatments relate to one another and vary due to differences in factors such as climate, physical characteristics of the housing stock, energy prices, and the carbon-intensity of energy sources. A goal of our study is to demonstrate a method that decision-makers can use to evaluate tradeoffs associated with different weatherization program strategies across the country; in particular, they can make more informed decisions about where weatherization treatment programs are the most likely to meet social or environmental objectives, such as reducing energy costs or GHG emissions.

2 Methods

2.1 Review of household data and building energy modeling

This study followed the methods established by Bradshaw, Bou-Zeid, and Harris [16] to model potential energy savings in low-income, urban housing stock in six American Metropolitan Statistical Areas (MSAs) across a range of climate zones: Orlando, Florida (hot); Los Angeles-Long Beach, California (mild); Seattle, Washington (cool); Philadelphia, Pennsylvania (cool); Detroit, Michigan (cold); and Milwaukee, Wisconsin (coldest). To briefly summarize this approach, American Housing Survey data was used to describe the low-income urban housing stock in these six cities, which represent a range of geographic and climatic areas. These data served as inputs into the Home Energy Saver model, which was used to simulate current energy consumption and the predicted energy savings from a combination of three weatherization treatments: replacing a standard thermostat with a programmable thermostat (T), installing attic insulation (A), and envelope air sealing (S). In addition to these three treatments being the ones modeled by Bradshaw, Bou-Zeid, and Harris [16], the WAP and other research specifically identify these as three of the most simple and effective weatherization treatments [10,14]. Energy savings are reported by fuel type based on the type of space conditioning equipment in the building; for example, if a residence uses a gas furnace for heating, then the model reports both the gas and electricity savings associated with the heating system. The method was evaluated in the previous study [16] by comparing the simulated savings to observations in Philadelphia; a good agreement was generally found although the model tends to overestimate the savings from combined treatment scenarios. Therefore, no further evaluation of the model’s skill in capturing energy savings is conducted in this study. For reference, Figure 1 shows the average end-use energy savings expected with these weatherization treatments for the six cities. Although this figure is reproduced from Bradshaw, Bou-Zeid, and Harris [16], it is included in this paper to provide useful context for the current study's results and discussion.

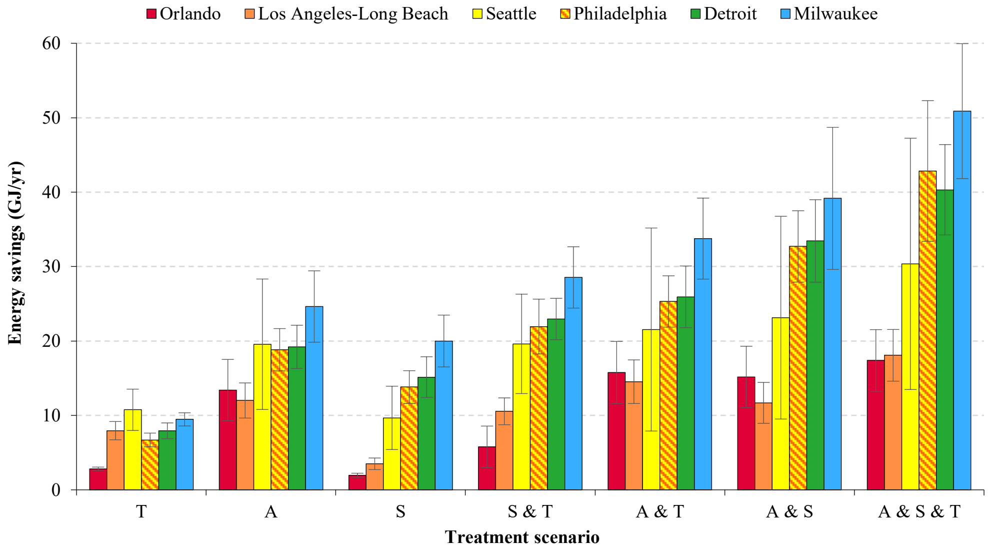

Figure 1. Average low-income household end-use energy savings from retrofits by city and treatment scenario. Error bars represent the 90% confidence interval. Reproduced from Bradshaw, Bou-Zeid, and Harris [16].[3] (Note to editor: 1.5 column-fitting image)

2.2 Costs and benefits of energy savings

Beyond the modeling method established in Bradshaw, Bou-Zeid, and Harris [16], which only examined the energy savings associated with weatherization, our current study considers the costs of these weatherization treatment and how the energy savings result in reduced energy bills and GHG abatement. Prior studies (e.g., [19,20]) of the costs and benefits of residential weatherization retrofits at a large scale applied a national conversion factor to compute the GHGs associated with energy production. Given the geographic variability in the fuel mix used for heating and electricity production, we hypothesize that the cost savings and GHG abatement per unit saved energy will vary significantly. The following subsections describe the methods used to estimate these parameters. To calculate the city-wide average of a parameter, we first

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[3] Reprinted from Energy and Buildings, Vol 69, Bradshaw, J. L., E. Bou-Zeid and R. H. Harris, *Comparing the effectiveness of weatherization treatments for low-income, American, urban housing stocks in different climates*, 535-543, 2014, with permission from Elsevier.

calculated the parameters individually for each of the residence types described in our AHS subset of interest (i.e., low-income housing in six cities); these residences were distinguished by whether they were attached or detached, and by their type of foundation, number of floors, vintage, heating equipment, the cooling equipment. Subsequently, in computing the parameter averages and variances, we weighted the results of each modeled house according to the sampling weights provided in the American Housing Survey. Variance is caused by heterogeneity within a city’s housing stock, with higher variance indicating that differences in physical building characteristics or space conditioning equipment result in a wider range of expected retrofit costs or benefits within a city.

2.2.1 Weatherization treatment costs

We estimated the costs of the three weatherization treatments using data from the National Residential Efficiency Measure Database (NREMD) [21]. The National Renewable Energy Laboratory developed this database to provide users with cost information required to evaluate the cost-effectiveness of different residential retrofits; in particular, these data are intended for use in models that evaluate residential efficiency measures, a description fitting our current study [22]. NREMD's cost estimates were based on various data sources, including publically available databases (e.g., the Residential Energy Consumption Survey, which is managed by the U.S. Energy Information Administration [EIA]), private industry databases (e.g., RS Means), and web-based resources from major home improvement retail stores [22,23]. The NREMD presents the mean, 10th percentile, and 90th percentile cost values, which have been adjusted to a nationally-indexed value to account for regional differences in labor costs. To estimate weatherization costs in our study, we use the mean cost values. This decision is based on the absence of information that describes where the housing stocks we model are located within the distribution of costs, such as a specific breakdown of total treatment costs into materials and labor and the weights needed to adjust these costs to the six metropolitan areas we are evaluating.

While costs for programmable thermostats are a flat rate ($170 per house), NREMD's cost data for attic insulation and air sealing are presented as unit costs that are normalized by physical building parameters, respectively, the cost per unit of building footprint and cost per unit of conditioned floor area. Additionally, these costs depend on the level of attic insulation and tightness before and after the retrofit. We selected the levels corresponding to the physical conditions incorporated in the energy modeling performed by Bradshaw, Bou-Zeid, and Harris [16]. Specifically, for the attic insulation treatment, we selected costs for installing R-38 insulation in a previously uninsulated attic; this treatment has a mean cost of $16.15 per square meter of house footprint. For envelope air sealing, we selected costs for reducing leakage in the house from 10 ACH50 (Air Changes per Hour at 50 pascals) to 8 ACH50; this treatment has a mean cost of $5.60 per square meter of conditioned space. This fractional change in leakage rates corresponds to energy model’s simulated performance, and these specific rates were selected based on typical residential leakage rates and data available in the NREMD database. In the U.S., residences typically have a leakage rate between 4.0 and 8.0 ACH50 [24], and as referenced above, low-income houses tend to be leakier than other houses.

Because the attic insulation and air sealing costs are normalized by area, we calculated the treatment cost for each modeled house by multiplying the unit cost by the appropriate areas, which are included in the AHS database. To be explicit, to compute the total cost of attic insulation, we multiplied the attic insulation cost per square meter by the building footprint area; similarly, to compute the total cost of air sealing, we multiplied the air sealing cost per square meter by the conditioned building area. The costs for the combination treatment scenarios are equal to the sum of the individual components (e.g., the cost for treatment scenario A&T is equal to the sum of individual treatment scenarios A and T)

2.2.2 Energy prices and cost savings

We estimated energy cost savings using the modeled energy savings from Bradshaw, Bou-Zeid, and Harris [16] and energy price data published by the EIA. Energy cost savings are the reductions in energy bills resulting from reduced energy use; consequently; they are calculated as the product of energy savings and energy prices. Prices vary by location and fuel type—in this study, electricity, natural gas, or fuel oil. Because consistently reported energy price data were not readily available at the city scale, we instead used statewide average data for residential energy prices. We used price data for 2012, the most recent year available for which EIA published data for all three of the fuel sources in our study [25–27]. Figure 2 illustrates these prices for the six states considered in our study. Residential energy prices vary by state for a number of reasons, such as state policies and the availability of various energy sources in the state. These considerations are discussed further in subsequent sections.

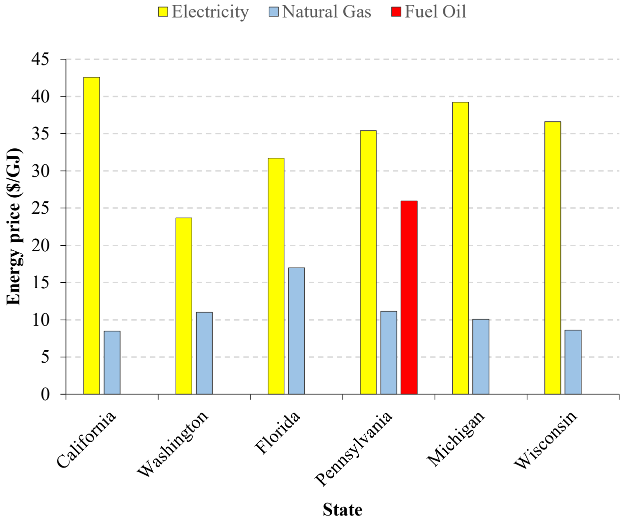

Figure 2. Average residential energy price by state and fuel type. Fuel oil price data is included only for Pennsylvania because none of the modeled households in the other states featured fuel oil space conditioning equipment. Data Source: [25–27]. (Note to editor: single column-fitting image)

2.2.3 Greenhouse gas savings

The greenhouse gas savings associated with a weatherization treatment are based on the GHG-intensity of the energy conserved from the treatment. This GHG-intensity depends on the fuel source used to generate that energy. In the context of our study of residential space conditioning, there are three different fuels to consider: electricity, natural gas, and fuel oil (also known as heating oil). That is, residential space conditioning equipment uses one of these fuels to generate heating or cooling.

The GHG-intensity of natural gas and heating oil is a physicochemical property of the fuel. Specifically, GHG-intensity depends on the chemical composition of the fuel and the Global Warming Potential (GWP) of the emissions associated with its combustion, which reflect the average duration the compound remains in the atmosphere and how much energy is absorbed by it [28]. The composition of natural gas and heating oil are standardized such that approximately constant emission factors can be used to describe their GHG-intensity; for this study, we used emission factors reported by the U.S. Environmental Protection Agency [29]. For applications in which fuels are consumed directly on-site, such as through a gas furnace, we used these emission factors to estimate the avoided GHG-emissions associated with conserved energy.

While we can model as constant the GHG-intensity of natural gas and heating oil because it is a physiochemical property of the fuel, the GHG-intensity of the electricity varies among our six cities because of the mix of energy sources used to generate the electricity. Figure 3 illustrates how the electricity energy mix varies substantially among the states of the cities modeled in our study. Similar to how energy costs vary by state, the mix of energy sources for electricity also vary due to a number of factors, including state policies and the relative abundance of some energy sources over others. For example, states that have adopted renewable portfolio standard policies have more in-state generation of renewable energy [30], which in turn reduces the GHG-intensity of the state's electricity mix [31]. This energy mix determines the GHG-intensity of electricity in that state, which is plotted in Figure 4 using data from the Emissions & Generation Resource Integrated Database (eGRID) [32]. Managed by the U.S. Environmental Protection Agency, this database includes air emission rates associated with almost all electric power generation in the U.S., and eGRID is specifically intended to support estimating carbon footprints and avoided emissions, which is how we use this data in our study [33]. Specifically, we used the statewide average GHG-intensity values plotted in Figure 4 to estimate the avoided GHG-emissions from electricity conserved through weatherization treatments.

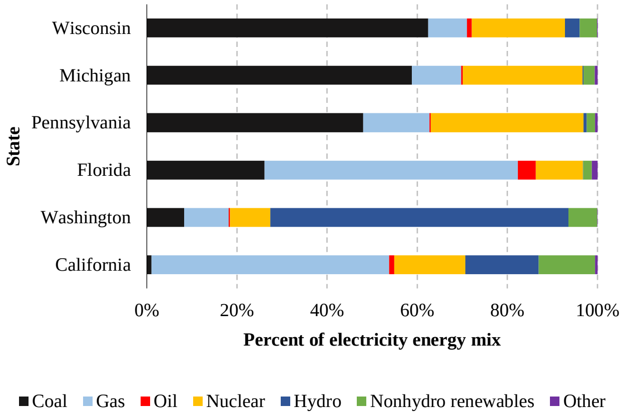

Figure 3. Electricity energy mix by fuel type and state. Percentages are relative to the state's net energy generation. Data source: [32]. (Note to editor: single column-fitting image)

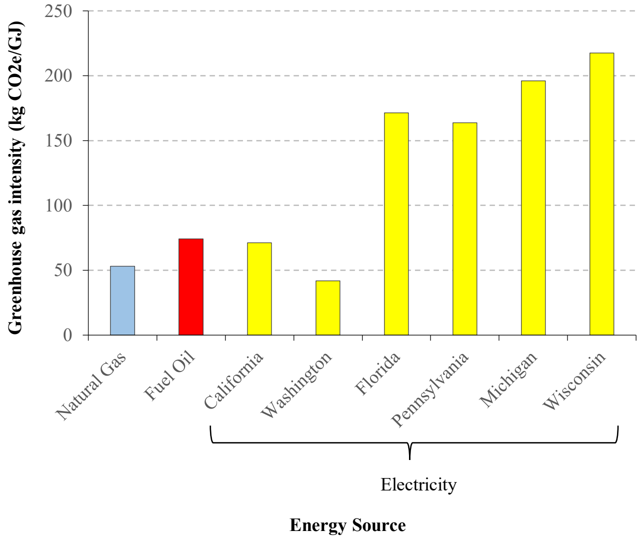

Figure 4. Greenhouse gas intensity of residential energy sources. Electricity values are statewide averages. Fuel oil data refers to Number 2 distillate fuel oil. Data sources: [29,32]. (Note to editor: single column-fitting image)

2.3 Metrics of cost-effectiveness

Based on the parameters discussed above, we calculate several different metrics of cost-effectiveness. Specifically, we calculate an energy abatement cost, GHG abatement cost, and a simple payback period. The energy abatement cost is calculated as the cost of the weatherization treatment divided by the annual energy savings. Similarly, the GHG abatement cost is calculated as the cost of the weatherization treatment divided by the annual GHG savings. The simple payback period is an estimate of the time required to recoup the cost of the initial cost of the weatherization treatment without accounting for the time value of money (e.g., no discounting is applied to future cash flows). Here, this is calculated as the weatherization treatment cost divided by the annual cost savings, where cost savings include not only the savings associated with a reduced energy bill (i.e., energy cost savings) but also savings associated with reduced GHG-emissions, which were estimated using a price of $37/ ton CO2e. This price represents the Social Cost of Carbon established by the federal government in 2013 and is the price used for regulatory impact analysis [34,35]. Including this price in our analysis demonstrates how the effect of internalizing GHG emissions costs influences the cost-benefit analysis of weatherization treatments. For reference, this $37/ ton CO2e price is on the low end of recently suggested optimal price range of $32–103/ ton CO2 based on economic modeling [36].

These metrics were selected because of their potential usefulness in planning housing retrofit programs at a large scale. Each metric relates to different values that decision-makers may consider, and examining each one is useful for understanding the potential effects of prioritizing certain cities or treatments. For example, if the goal of a weatherization program is to retrofit as many houses as possible under a constrained budget, the treatment cost metric is useful for understanding the effect of selecting different cities or treatments. The metric of energy cost savings describes the effect that retrofits will have on occupants’ utility bill, thereby connecting to the WAP’s goal of reducing the economic burden of energy costs on low-income households. The metric of GHG savings is useful for informing potential policy goals of using residential weatherization as a strategy for reducing GHG emissions. Last, the measures of cost-effectiveness can be used to further examine economic considerations of weatherization priorities.

3 Results and Discussion

3.1 Weatherization treatment costs

As discussed in Section 0, this study uses nationally-indexed unit costs for air sealing and attic insulation, but total costs for these treatments vary by city due to physical differences in the cities' housing stocks. These cost variations are plotted in Figure 5 for the low-income housing stock in our six cities of interest. As can be seen in the figure, although the expected air sealing costs vary somewhat by city, each city's air sealing costs fall within all the other cities' confidence intervals, thereby suggesting that the differences are small. As our cost model for air sealing is a linear function of conditioned floor area, we can attribute the narrow range in costs to relatively similar building sizes across the cities: low-income housing stock in five of the six cities have average conditioned floor areas between 140 and 154 square meters; only Milwaukee falls outside this range, with an average of 180 square meters [16].

In contrast to the programmable thermostat (T) and air sealing (S) treatment scenarios, attic insulation (A) costs vary substantially by city, with the average low-income houses in Orlando and Los Angeles-Long Beach costing more to insulate attics than the other cities considered. These costs reflect differences in regional construction trends; namely, while residences in most of the cities examined have similar quantities of conditioned space, the majority of low-income houses in Orlando and Los Angeles-Long Beach are single story, in contrast to the other cities where the housing stock has two or more floors [16]. Consequently, for the same area of conditioned space, houses in Orlando and Los Angeles-Long Beach have larger attics, which are more expensive to insulate. In addition to showing more inter-city variation in costs, attic insulation is also more expensive than programmable thermostats or air sealing.

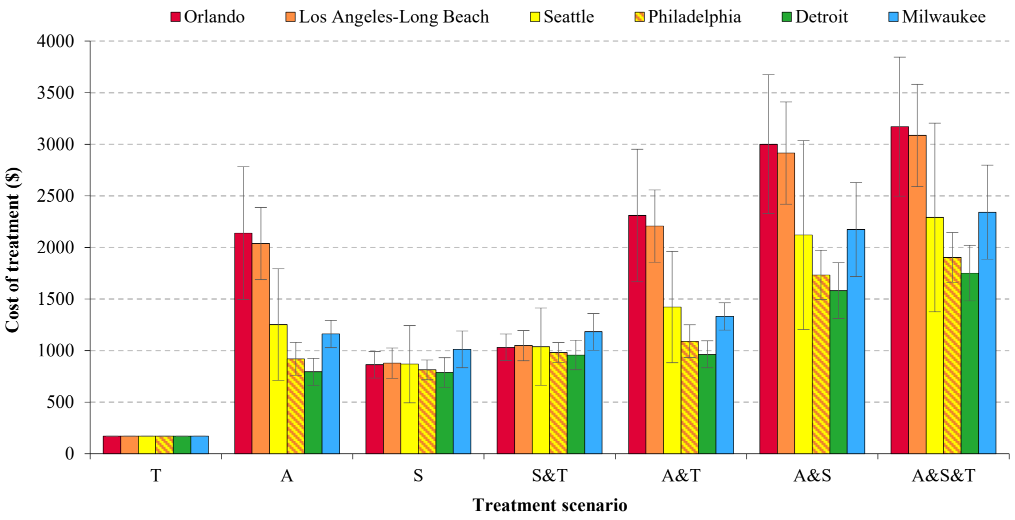

Figure 5. Average low-income household cost of retrofit by city and treatment scenario. Error bars represent the 90% confidence interval. (Note to editor: 1.5 column-fitting image)

3.2 Energy cost savings

In our comparative analysis, energy cost savings appear to be very weakly coupled to energy savings. Figure 6 displays the average household energy cost savings in each of the six cities and for each of the seven treatment scenarios considered. In contrast to Figure 1, in which there was a trend for colder climates to achieve greater energy savings, no such trend is apparent for energy cost savings. The apparent decoupling of these two variables is most apparent in the examples of Orlando (the city in the hottest climate zone) and Milwaukee (the city in the coldest climate zone). Compared to other cities, the housing stock in Orlando offers among the lowest energy savings, but among the highest energy cost savings. Even though the energy savings are relatively low, energy cost savings are high because electrical air conditioning units dominate the space conditioning energy demand in Orlando [16]. As illustrated in Figure 2, costs for electricity are substantially higher than those for natural gas or fuel oil, so Orlando's small energy savings translate into high energy cost savings. Conversely, Milwaukee, generally has the highest energy savings, but some of the lowest energy cost savings because the conserved energy is in the form of natural gas [16]; as shown in Figure 2, natural gas is much less expensive than electricity and, furthermore, Wisconsin has the lowest natural gas prices of the states considered. Consequently, Milwaukee has relatively low energy cost savings despite high energy savings.

Another notable observation from Figure 6 is that, under most treatment scenarios, the housing stock in Philadelphia has the greatest energy cost savings. These high savings are attributable to the combination of high energy savings and high energy costs. As shown in Figure 2, Pennsylvania has higher natural gas prices than four of the other five states evaluated, and fuel oil—which is only used in the Philadelphia housing stock—is substantially more expensive than natural gas.

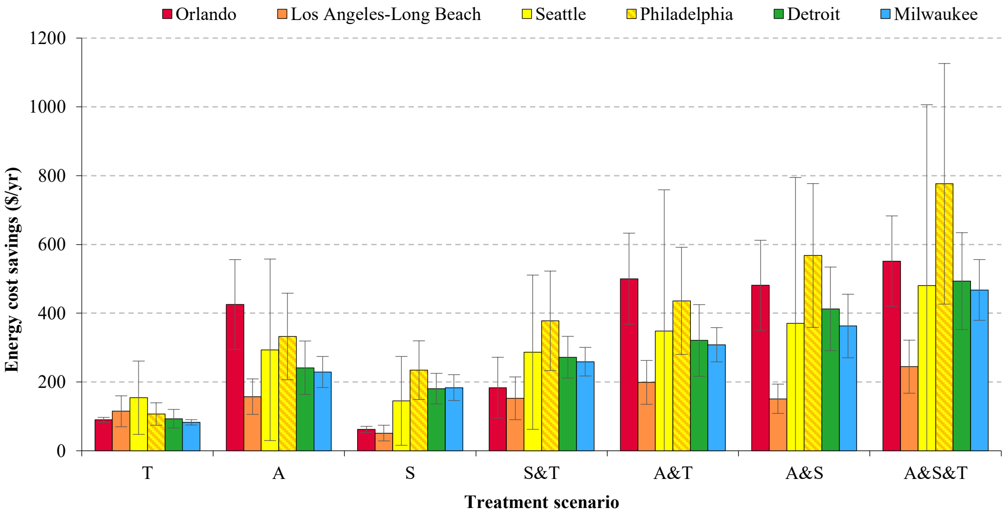

Figure 6. Average low-income household energy cost savings from retrofits by treatment and city. Error bars represent the 90% confidence interval. (Note to editor: 1.5 column-fitting image)

3.3 Greenhouse gas savings

Because greenhouse gas savings are the product of energy savings and the GHG-intensity of the conserved energy, GHG savings are highest in the cities with high energy savings, high GHG-intensity of space conditioning energy, or both. Figure 7 plots how GHG savings vary by city and treatment scenario. For all cities except Orlando, there is a similar trend for GHG savings and energy savings—that is, there are generally greater savings in colder climates. The housing stock in these cities primarily rely on natural gas for heating, so the GHG-intensity of the conserved energy in these cities is similar enough that the quantity of energy savings drives GHG savings. Orlando housing stock diverges from this trend because electricity is the main space conditioning fuel (for both heating and cooling); in contrast, housing stock in each of the other cities use primarily natural gas for heating, and their cooling loads are smaller than Orlando's because they are located in cooler climate zones. Furthermore, as displayed in Figure 4, Florida's electricity is substantially more GHG-intensive than natural gas; consequently, energy savings in Orlando housing stock result in relatively greater GHG savings.

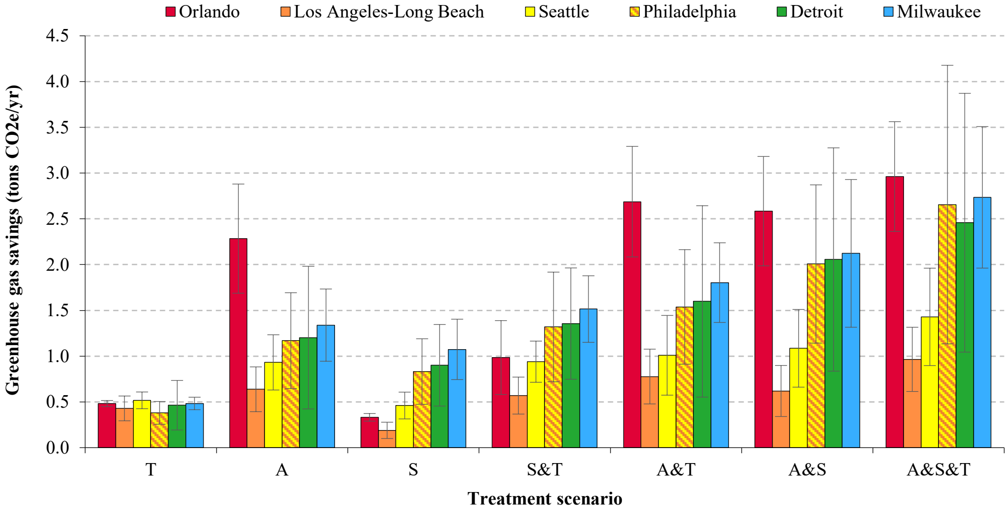

Figure 7. Average low-income household greenhouse gas savings from retrofits by city and treatment scenario. Error bars represent the 90% confidence interval. (Note to editor: 1.5 column-fitting image)

3.4 Cost-effectiveness

3.4.1 Energy abatement cost

Figure 8 plots the average energy abatement costs, which can be interpreted as the capital cost of conserving a unit of energy per year. This metric could be useful, for example, if energy providers are operating near capacity and are comparing options to increase energy supply (e.g., by constructing new electricity or natural gas infrastructure) or reduce demand. For treatment scenarios with attic insulation and air sealing, the results illustrate how lower abatement costs are generally associated with colder climates. Programmable thermostats have similar abatement costs across the cities we examined, except for Orlando. For each treatment, Orlando, and in some cases, Los Angeles-Long Beach, have substantially higher abatement costs compared to the other cities. This behavior is a result of relatively low energy savings (Figure 1) and relatively high treatment costs (Figure 5). Because the remaining four cities all have similar treatment costs, their abatement costs are primarily driven by energy savings, which are generally greater in colder climates; consequently, Milwaukee has the lowest abatement costs under most treatment scenarios.

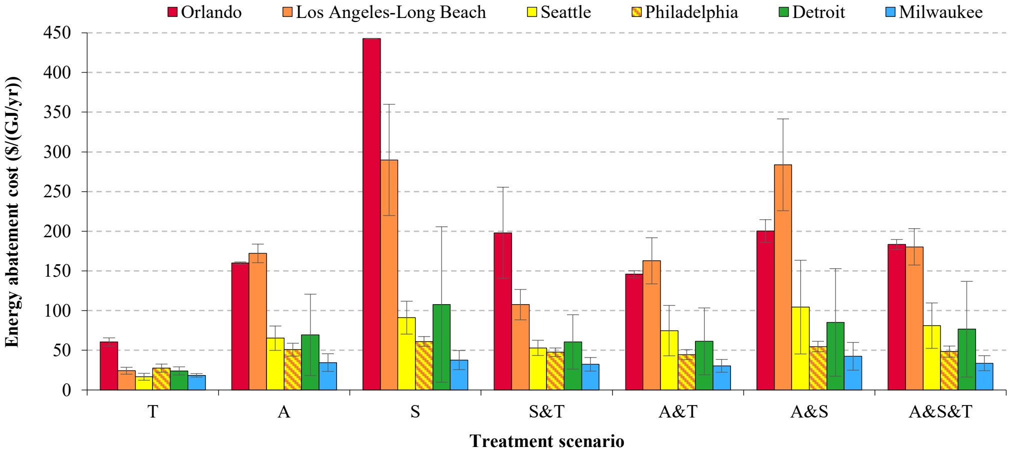

Figure 8. Average energy abatement costs for low-income household retrofits by city and treatment scenario. Error bars represent the 90% confidence interval. (Note to editor: 1.5 column-fitting image)

3.4.2 Greenhouse gas abatement cost

Relative to the energy abatement cost, the GHG abatement cost is more intricate because of regional variations in the GHG-intensity of space conditioning energy. GHG abatement cost could be a useful metric, for example, if government agencies or programs like WAP want to identify which cities and treatments were the most cost-effective for achieving reductions in GHG emissions. Figure 9 displays the GHG abatement costs for each city and treatment scenario. Qualitatively, the energy and GHG abatement cost plots show similar trends of lower costs in colder climates. Orlando stands out as an exception since its greenhouse abatement costs are comparable to those in colder climate while its energy abatement costs are much higher. As was the case for energy cost savings and GHG savings, Orlando diverges from the typical trend because electricity is the primary space conditioning energy fuel and because of the high GHG-intensity fuel mix for electricity in Florida. These factors combine to drive Orlando's abatement costs closer to the costs of Seattle, Philadelphia, Detroit, and Milwaukee. Across nearly all treatment scenarios, Milwaukee housing stock has the lowest GHG abatement cost because of the high energy savings associated with the treatments.

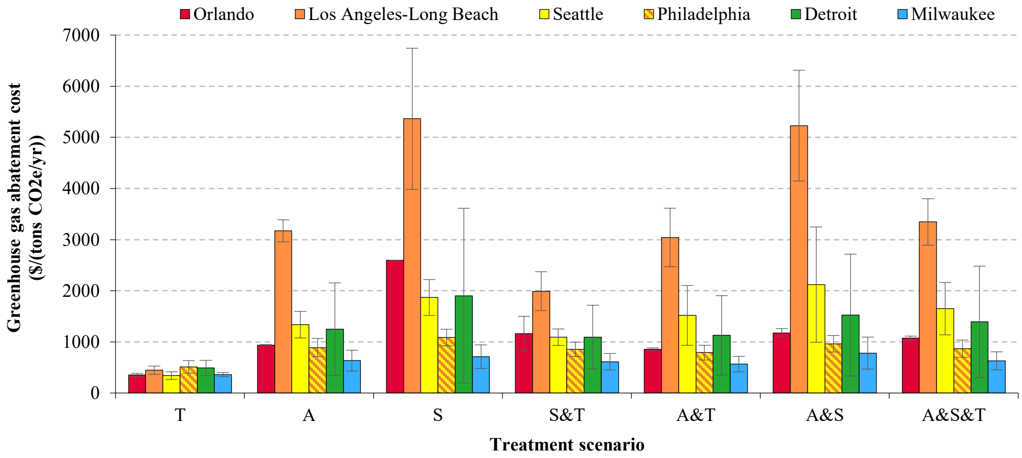

Figure 9. Average greenhouse gas abatement costs for low-income household retrofits by city and treatment scenario. Error bars represent the 90% confidence interval. (Note to editor: 1.5 column-fitting image)

3.4.3 Simple payback period

The simple payback period considers the monetary costs and benefits of the treatments; in our application, it is a measurement of how the treatment cost compares to the benefit of energy and GHG cost savings. This is a useful metric for weatherization agencies focused on understanding which treatment strategies are the most economically favorable. Figure 10 plots the simple payback period accounting for each city’s average energy cost savings (Figure 6) and GHG savings (Figure 7), which have been monetized by applying a GHG price of $37/ ton CO2e. The plot's error bars show the range of payback periods with a GHG price ranging from $0 to $74/ ton CO2e. In other words, the upper end of the error bar signifies the payback period with no

GHG price, and the lower end of the error bar signifies the payback period with double the GHG price. Consequently, the error bars illustrate the effect of a GHG price on the payback period.

Figure 10, in conjunction with the other plots above, demonstrates the complex relationships among all the variables underlying the payback period calculation (i.e., treatment costs, energy savings, energy prices, GHG intensity of energy, and GHG pricing). In some ways, this plot resembles the inverse of Figure 6, which plotted energy cost savings. This result is expected given that energy cost savings are much greater than savings from a GHG cost; at a price of $37/ ton CO2e and among the treatment scenarios considered, the GHG cost savings is between approximately 10 and 20% of the energy cost savings. In other words, the cost savings from reduced energy consumption are five to ten times greater than the cost savings from reduced GHG emissions. Consequently, the energy price savings dominate the payback period calculations. Nevertheless, the GHG price can have a noticeable impact. For example, Seattle and Milwaukee have similar payback periods across the treatment scenarios, but their differences in energy prices and GHG-intensity of energy make Milwaukee more sensitive to the GHG price. Under the A&S&T scenario, the GHG-related fraction of cost savings for Seattle and Milwaukee are 12 and 22%, respectively; in the plot, Milwaukee's greater sensitivity is apparent as longer error bars compared to Seattle's error bars.

The results plotted in Figure 10 suggest that all of the treatments are cost-effective means of weatherizing low-income urban housing stock for most of the cities we modeled. In particular, regardless of GHG price, programmable thermostats have a payback period of less than two years, and attic insulation has a payback period of less than six years in all cities except Los Angeles-Long Beach. Air sealing also has a payback period of less than six years for the four coolest cities we modeled. These values compare to expected treatment lifetimes of 10-15 years for programmable thermostats, 20-25 years for attic insulation, and 15-20 years for air sealing [37,38], meaning all treatments have simple payback periods less than their expected lifetimes for all cities except Los Angeles-Long Beach. Specifically, with no price on carbon, air sealing in Los Angeles-Long Beach has an average simple payback period of 17 years, exceeding 15 years—the low-end estimate of this treatment lifetime.

The data in Figure 10 can also be used to examine in which cities the treatments are most cost-effective; specifically, treatments are generally most cost-effective in Detroit and Philadelphia and least cost-effective in Los Angeles-Long Beach. These results generally agree with an earlier study that found treatments in cold and cool climates are the most cost-effective, while mild climates are the least cost-effective [18].

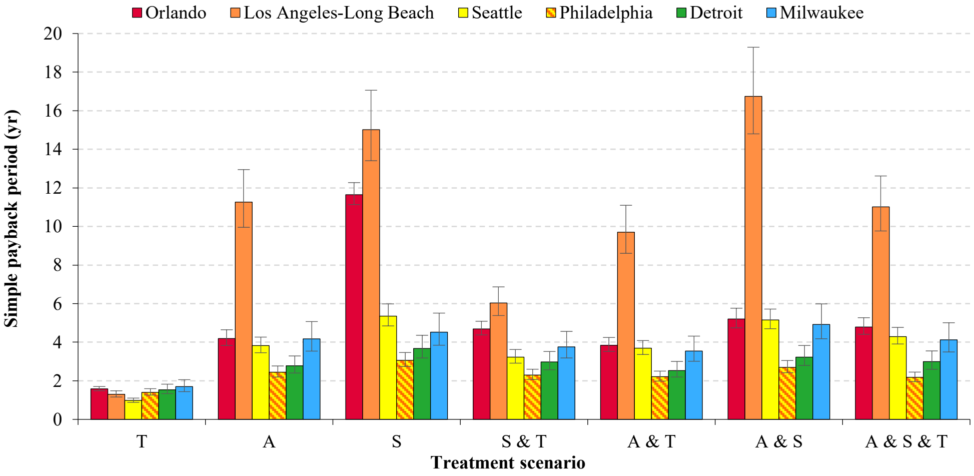

Figure 10. Average simple payback period for low-income household retrofits by city and treatment scenario accounting for energy cost savings and a $37/ ton baseline CO2e price. Error bars represent the range of the payback period with a CO2e price ± 100% from the baseline. (Note to editor: 1.5 column-fitting image)

4 Conclusions and future work

This paper advances the understanding of how the GHG mitigation benefits and cost-effectiveness of specific weatherization treatments vary across the U.S. Using a national database describing treatment costs and previously established methods to estimate the expected energy savings in low-income urban housing stock, this study estimated several other variables important for understanding the cost-effectiveness and performance of these treatments; specifically, we evaluated how treatment costs, energy cost savings, greenhouse gas savings, and combinations of these parameters (i.e., abatement costs, payback periods) vary by location. The results of this study support the following conclusions:

1. Regional variations in climate (i.e., demand for heating and cooling), space conditioning technologies (e.g., gas, fuel oil, or electric heating), and house constructions (e.g., size of house and number of floors) have a high impact on the cost-effectiveness of weatherization treatments.
2. Because electricity tends to be more expensive and more GHG-intensive relative to other space conditioning energy fuels (i.e., natural gas and fuel oil), weatherization of housing stocks with greater electric space conditioning (e.g. Orlando) tend to offer greater energy cost and GHG savings.
3. Within the range of GHG prices suggested by the U.S. government ($37/ ton CO2e), energy cost savings dominate the calculation of payback periods.
4. Regardless of any pricing on GHGs, programmable thermostats are the most cost-effective treatment for the low-income housing stocks in all of the cities considered; this treatment has payback periods of two years or less, compared to an expected lifetime of 20-25 years. Attic insulation and air sealing are respectively the second and third most

cost-effective treatments; these treatments also have relatively short payback periods of six years or less for all cities except Orlando and Los Angeles-Long Beach.

This study’s findings support arguments that weatherization is an attractive strategy from both individual and societal perspectives. With the exception of air sealing in Los Angeles-Long Beach, any of the three treatments considered will pay off over the lifetime of the treatment, and in many cases the payback period is substantially shorter. Consequently, these treatments generate value for the individual by virtue of being cost-effective methods for residents to reduce their energy bills. Governments can spur the creation of this value through subsidies, with current weatherization assistance programs contributing the added societal benefit of helping to alleviate poverty by reducing energy bills for low-income households. Furthermore, weatherization creates value for broader society by reducing energy-related GHGs that contribute to global climate change.

This study's methodology and conclusions could be valuable when planning strategies for large-scale weatherization programs, such as WAP. Building off the underlying work of Bradshaw, Bou-Zeid, and Harris [16], this study contributes to the first weatherization study spanning several geographic regions with varying climates and housing stocks, as well as multiple weatherization treatment options; consequently, the findings provide a unique comparative analysis for weatherization program decision makers. Moreover, future research could use this study's modeling methodology as the basis for further development of models or databases that describe the effectiveness of additional weatherization treatments and include additional locations and households aside from those identified as low-income and urban. Future research could also expand this study to evaluate some of the other benefits of weatherization, such as effects on residence values, air quality, job creation, and national security.

For policy-makers and other stakeholders in the field of residential energy retrofits, this research highlights the importance of thoughtful consideration when selecting cities in which to prioritize weatherization retrofits at state or national scales. Because of the complex relationships between energy savings and prices, GHG-intensity, and treatment costs, the optimal strategy for selecting weatherization treatments and target cities will depend on the optimization metric: i.e., whether the goal is to maximize energy savings, energy cost savings, GHG mitigation, or cost-effectiveness. That is, decision-makers must consciously consider how they value these different performance metrics because, examined individually, each metric may suggest a different strategy. As demonstrated in this paper, our modeling methodology can be used to compare the outcomes of different weatherization strategies and assess the effect of GHG prices. These outcomes could also be compared to other options for mitigating energy use and GHG emissions, such as reforestation, increasing renewable energy production, improving automobile efficiency, and other options presented in abatement cost curves (e.g., [9,39])

There are limitations to how our methodology should be applied and how our results should be interpreted. Our study includes several sources of error carried over from Bradshaw, Bou-Zeid, and Harris's model to estimate energy savings [16]. These errors are discussed in detail in that previous paper, but are briefly summarized here. First, modeled savings should be interpreted as the savings that are possible assuming that treatments are properly installed and residents' do not change their energy consumption behavior; actual savings decrease if treatments are improperly installed or residents increase consumption in response to increased efficiency—circumstances classified as "rebound effects" [9,40,41]. Previous research suggests these rebound effects reduce efficiency gains by 10 to 30% for residential space heating and between 0 and 50% for space cooling [42], though a more recent study argues the rebound effect on space heating is negligible

[14]. Second, the quantitative precision of the methodology depends on the data used to drive it, which is AHS in this study. However, while the model's precision could be improved with a larger sample size or building details beyond which the AHS provides, the qualitative results (e.g., which housing stock is more cost-effective to weatherize) should not be substantially affected. Last, this methodology estimates the predicted average costs and benefits of weatherization treatments over a large housing stock; consequently, this method is not intended to predict the costs and savings of an individual house.

In addition to these inherited errors, this study introduces additional sources of error associated with the resolution of the treatment cost and benefit data. Specifically, because our cost data is based on nationally-indexed values and our energy price and fuel mix data are based on state averages, the data in our study do not account for local variations at the city level due to political and market conditions that affect prices and energy sources. In future research, this error could be reduced by computing costs and benefits with higher resolution data that better describe the local conditions. Similar to above, this source of error affects our methodology's quantitative precision, but we expect the qualitative comparison among the six cities we evaluated remains valid.

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