COST-EFFECTIVENESS OF WEATHERIZATION IN LOW-INCOME URBAN HOUSING STOCK

Jonathan L. Bradshaw

April 12, 2010

Advisors: Elie Bou-Zeid and Robert H. Harris

Submitted in partial fulfillment
of the requirements for the degree of
Bachelor of Science in Engineering
Department of Civil and Environmental Engineering
Environmental Engineering Program,
Princeton University

I hereby declare that I am the sole author of this thesis.

I authorize Princeton University to lend this thesis to other institutions or individuals for the purpose of scholarly research.

Jonathan L. Bradshaw

I further authorize Princeton University to reproduce this thesis by photocopying or by other means, in total or in part, at the request of other institutions or individuals for the purpose of scholarly research.

Jonathan L. Bradshaw

ACKNOWLEDGEMENTS

I would not have been able to create this thesis without the support of many people. First and foremost, I would like to thank Professors Elie Bou-Zeid and Robert H. Harris of the Civil and Environmental Engineering Department at Princeton University for their guidance and help developing this project throughout the year. I would further like to thank Dr. Harris for his constant support as I researched the topic of building energy-efficiency, a topic he introduced me to a year and a half ago. I would like to thank Michael Blasnik of M. Blasnik and Associates for the generous time he spent explaining to me his understanding of the state of building science for low-income houses, for his help locating impact evaluations, and for his help understanding his impact evaluations. I would like to thank Gregory Homan, Principal Research Associate at Lawrence Berkeley National Laboratory for his help using and understanding the Home Energy Saver software. I would like to thank Michael Donnelly, Alex Acs, and Phillip Connor at Princeton University's Data and Statistical Services lab for their help in understanding how to query American Housing Survey data. I would like to thank Julia Taylor, Director of Planning at Isles, Inc. for her assistance researching energy efficiency in low-income housing during the summer of 2009, and I would like to acknowledge the financial support of the Siebel Energy Grand Challenges during that time. I would like to acknowledge Professor Xenia Morin and Ashley Thrall of the Environmental Studies Program and Civil and Environmental Engineering Department, respectively, for their senior thesis workshops, which were both useful and motivational.

On a more personal level, I would like to thank my family, and especially my parents, for their never-ending support throughout my life and college career. And finally, I would like to acknowledge the members of the 2 Dickinson St. Food Cooperative (2D), who made 2D such a special place and provided me with many of my favorite memories the past two years.

LIST OF ABBREVIATIONS

AHS—American Housing Survey

CDD—Cooling Degree Day

CO_2—Carbon dioxide

CWP—Conservation Works Program

DEER—Database of Energy Efficiency Resources

DOE—Department of Energy

ECA—Energy Coordinating Agency

EIA—Energy Information Administration

FAR—Floor Area Ratio

GHG—Greenhouse Gas

HDD—Heating Degree Day

HES—Home Energy Saver

HUD—Department of Housing and Urban Development

NPV—Net present value

PRISM—Princeton Scorekeeping Method

RECS—Residential Energy Consumption Survey

SMSA—Standard Metropolitan Statistical Area

WAP—Weatherization Assistance Program

Wx—Weatherization assistance

EXECUTIVE SUMMARY

With energy and climate policy at the forefront of domestic and international politics, scientists, policy-makers, companies, and citizens are seeking cost-effective strategies for reducing fossil fuel consumption and lowering emissions of climate change-causing greenhouse gases. Some promising methods, such as alternative energy sources require significant investment of both time and money, and will likely not result in significant energy or carbon savings for many years. Searching for ways to reduce carbon emissions more immediately, policy research groups and the Obama Administration have identified energy-efficiency measures, and specifically residential retrofits, as a realistic source of significant energy savings. The Obama Administration has increased funding for residential retrofitting programs, including the Weatherization Assistance Program (WAP), which funds programs nationwide that weatherize low-income houses to reduce space conditioning energy consumption. WAP evaluations show these programs are net-present-value positive not only because of the direct value of energy cost savings, but also because of the indirect value of, among other things, job creation, improved environmental quality, lower energy prices, and reduced dependence on foreign energy sources.

Multiple studies have evaluated the cost-effectiveness of all residential retrofits at a nationwide scale, but do not thoroughly address how energy consumption and the value of retrofits vary geographically because of variations in climate and housing stock, particularly low-income housing stock. Analysis of national energy consumption data reveals that while average energy consumption among all houses for purposes other than space conditioning (e.g. lighting, appliances, water heating) is roughly constant, energy

consumed for space conditioning varies widely among climate zones and Census regions due to differences in space conditioning demands and physical differences in residential housing construction type and space conditioning equipment.

Motivated by the importance of understanding how investments in weatherizing low-income houses affect the cost of saving energy and reducing carbon emissions, the objective of this thesis was to develop an approach that can evaluate weatherization cost-effectiveness at a scale finer than the national level. This approach consisted of using the Home Energy Saver (HES) energy modeling software to model energy use in low-income urban housing stocks in six urban areas in varying climate zones in the U.S. HES relies on user input, housing stock statistics, and engineering thermodynamic models to approximate whole-house energy consumption, potential energy savings with various retrofit treatments and the costs of such treatments. To specifically model the low-income urban housing stocks, HES was driven with data from the American Housing Survey (AHS), a biennial survey of roughly 55,000 homes nationwide that includes information on house characteristics—such as house vintage, conditioned floor area, number of floors, and space conditioning equipment—and information on household characteristics—such as household size and income. After modeling energy savings, average state-wide energy prices and electricity energy mix were used to determine how these energy savings translated into energy cost and carbon abatement.

Because past evaluations of energy modeling software like HES indicate that projected energy savings typically exceed actually energy savings by up to 50% as a result of some combination of shortfall (technical estimation error or improper weatherization treatment installation) and take-back (behavioral energy consumption changes), modeled energy consumption was compared to energy savings measured in the Philadelphia Gas Work's Conservation Works Program. The comparison between observed and modeled energy savings in low-income Philadelphia housing stock revealed that the model performed reasonable well in estimating pre-retrofit energy consumption. Regarding energy savings, the model slightly underestimated observed energy savings from programmable thermostats and attic insulation, but overestimated observed saving in every other treatment scenario (air sealing and the various combinations of air sealing, attic insulation, and programmable thermostats). The model performed particularly poorly when modeling treatment combinations that included blower-door guided air sealing, suggesting that either the model overestimated pre-retrofit leakage or that observed savings were uncharacteristically low due to take-back or improper air-sealing, as has been commonly observed in other weatherization assistance (Wx) programs.

To evaluate how weatherization energy savings and cost-effectiveness in low-income houses vary geographically, six metropolitan areas from different climate zones and Census regions were selected for modeling based on data availability and on how representative that metropolitan area's entire urban housing stock was of the entire urban housing stock in that Census region. The central cities of these metropolitan areas were Milwaukee, Detroit, Philadelphia, Orlando, Seattle, and Los Angeles-Long Beach. Modeled energy consumption mirrored nationwide residential energy consumption trends indicating that houses in colder climates consume more energy than those in warmer climates, and as expected, weatherization treatments were more effective—that is, energy savings were greater—for cities in colder climate zones than in warmer climate zones. Regional differences in low-income housing stock result in different costs of retrofits. In particular, larger attic sizes per conditioned floor area in Orlando, Los Angeles-Long beach, and Seattle resulted in higher projected installation costs for attic insulation compared to the other three cities. Net Present Value (NPV) calculations showed that all combinations of weatherization treatments were profitable in almost every instance, especially in Orlando, where the high price of space conditioning made retrofitting treatments among the most profitable calculated for any city.

Using information about each state's energy mix for electricity, the carbon abatement potential of weatherization treatments were calculated for each of the cities. Carbon savings showed similar effectiveness trends as energy savings, with colder climates saving more than warmer climates, with the exception of Orlando. Carbon abatement from weatherization in Orlando, where carbon-intensive electricity provides all space conditioning energy, did not follow this trend, but was instead among the largest of the six cities modeled. Even after applying model error correction factors and a 50% installation cost inflation, the NPV of most treatment scenarios in all six cities were around or below recently proposed U.S. carbon prices, indicating that even if these measures aren't strictly NPV-positive at present (though most of them are), the weatherization measures modeled would be expected to be profitable should the government institute proposed carbon pricing.

In conclusion, the results of this thesis demonstrated the utility of city-level weatherization cost-effectiveness analysis. The results also suggested the value of such analysis, since geographic variations in climate, housing stock, and energy prices all result in widely varying levels of cost-effectiveness. The results indicated that programmable thermostats are consistently profitable investments over widely different geographical areas, although the relative cost-effectiveness of other treatments varies among cities and whether the objective is to minimize end-use energy (i.e. maximize residential energy-efficiency) or minimize residential carbon emissions. Fully utilizing this research approach to identify where weatherization treatments can have the best results will require careful considerations of the priorities of weatherization programs.

The major limitation of this analysis was data availability, both housing stock data to drive HES and Wx impact evaluation data to compare modeled to observed results. HES is a comprehensive model that accepts very detailed descriptions of the individual houses modeled, but the availability and depth of data describing different urban housing stocks limited analytical thoroughness. Additionally, more detailed information on actual energy savings from Wx program investments would facilitate a more thorough assessment of HES's validity, though it is expected that the discrepancy between modeled and observed energy savings is attributable to take-back or improper installation more than errors in the model itself. If this is the case, modeled savings should therefore be interpreted as the energy savings possible with proper installation and assuming no changes in residents' energy consumption behavior. Proper installation training and resident education are necessary to ensure that a higher percentage of potential energy savings is realized.

The approach described in this thesis is applicable for modeling typical energy consumption and retrofit savings in housing stocks other than the low-income urban stock examined. Future investigations could, for instance, modeling non-low income houses or the housing stock at a scale larger than the metropolitan area. In each case, this approach can be useful in comparing the expected cost-effectiveness of weatherization among different housing stocks for the purpose of prioritizing which housing stocks to target for lowering residential energy consumption, household energy bills, and residential carbon emissions.

In conclusion, the major finding of this thesis suggest the following:

- Most weatherization treatments examined are profitable
- Greater energy efficiency will be realized by retrofitting houses in colder climates
- Regional variations in energy prices significantly affect the cost-effectiveness of weatherization retrofits
- Greater carbon efficiency can be realized by retrofitting houses with electric space conditioning
- Weatherization strategies aimed at energy savings, carbon savings, and cost-effectiveness may not lead to the same conclusion
- Programmable thermostats provide cost-effective savings in any setting

TABLE OF CONTENTS

1 INTRODUCTION

This chapter discusses the motivation for analyzing the cost-effectiveness of urban weatherization assistance programs. The first section briefly describes the concept of weatherization and the history of weatherization assistance programs in the United States. The second section reviews the present understanding of weatherization's cost-effectiveness and how to measure it. This chapter concludes with a section describing the specific purpose of our research project and briefly summarizes our approach.

1.1 *INSULATION, WEATHERIZATION, AND ENERGY-EFFICIENCY*

This section provides a brief background about the history of weatherization and its benefits in the U.S. The first subsection introduces the concept of weatherization and describes how weatherization became a centerpiece of U.S. environmental and economic policy. The second subsection describes the benefits—both realized and potential—of residential weatherization and specifically weatherization assistance (Wx) programs

1.1.1 Background

Insulation has been an essential part of building design for thousands of years. From the adobe houses of the Pueblo Native Americans to the thatched huts of the South Sea Islanders, civilizations across the world have used materials like cork, straw, sea grass, and clay to keep buildings more comfortable by preventing the exchange of heat between indoors and outdoors (Close 1947; Lotz 2006). The mass production of manufactured insulation used today—such as rock wool, organic foam, and glass fiber—began after World War I, and from that time, buildings have been made increasingly well-insulated to minimize space conditioning energy consumption (Lotz 2006).

Building insulation gained national attention during the energy crises of the 1970s as the U.S. government looked for ways to reduce energy consumption, decrease U.S. dependence on foreign energy sources, and relieve the impact of high energy prices on low-income households (US DOE 2008). Shortly after the first oil embargo in 1973, the Community Services Administration [i] funded the first residential retrofit project in Maine, where roughly 90% of homes used heating oil (US DOE 2008). The objective of this program was to reduce energy consumption and lower energy bills by sealing

[i] The Community Services Administration is now a part of the Office of Community Services under the Department of Health and Human Services

building envelope leaks. These retrofitting processes, initially classified as "winterization," eventually became known as "weatherization" [ii] to reflect terminology used in similar residential retrofitting programs developed across the country (Rios 1981). In 1976, the Energy Conservation and Production Act created the Weatherization Assistance Program (WAP) under the Department of Energy (DOE) to provide funding and technical guidance to facilitate the creation and operation of weatherization assistance programs across the country (US DOE 2008, 2009). WAP still exists today, and to date it has sponsored weatherization programs that have retrofitted more than 6.2 million low-income houses across the country at a present rate of approximately 100 thousand houses per year.

After the 1970s energy crisis, energy prices returned to—and have basically remained at—relatively stable levels until recently. Although energy prices are presently abnormally low as a result of the global financial crisis, prior to the economic downturn energy prices rose sharply to 30 year highs (Figure 1.1). From 2003-2008, residential electricity and natural gas prices rose 30% and heating oil prices rose 135% (Nevin 2010). The price of oil has already largely recovered, returning to 2007 prices of roughly $80 per barrel (EIA 2010), and the Energy Information Administration (EIA) projects that overall energy prices will resume escalating toward record highs in the coming years

[ii] Although the terms are sometimes used interchangeably, there is a distinction between insulation and weatherization. Generally, insulation measures seek to reduce conductive heat gain or heat loss by installing thermally resistant materials. Weatherization measures seek to reduce convective heat gains or losses by sealing a building to reduce infiltration. In practice, insulation and weatherization are frequently coupled, as building insulation requires some level of weatherization to properly function, and insulation to some extent blocks air leakage. As many, but not all, weatherization assistance programs include insulation measures, we will use the term weatherization as an umbrella term to refer to both insulation and weatherization measures unless specified otherwise. Weatherization programs sometimes also include tuning, upgrading, or replacing heating equipment, such as malfunctioning boilers. Although these measures do not strictly reduce conductive or convective heat transfers but do reduce energy loss by increasing efficiency, these measures are also sometimes categorized as weatherization.

as the rapidly growing economies like China and India compete for a larger share of world energy consumption (EIA 2009d, e).

In addition to the threat of continually escalating energy prices, growing concerns over global climate change—and Americans' disproportionate contribution to it—have also contributed to the recently renewed interest in weatherization. Until 2006, the U.S. was the single-largest emitting country of the greenhouse gas (GHG) carbon dioxide (CO_2), the most highly emitted GHG worldwide (IPCC 2007). Although China now emits slightly more CO_2 than the U.S., each of these two countries emits roughly 20% of global CO_2 emissions. In the U.S., 93% of GHG emissions result from the production and consumption of energy (John Horowitz 2009), and 90% of that energy comes from fossil fuels [iii], the use of which is the single largest and fastest growing source of CO_2 emission (IPCC 2007). Studies in academia (e.g. Pacala and Socolow 2004) and the energy industry (e.g. EPRI 2009) recognize that energy efficiency is among the most viable options for decreasing fossil fuel consumption and consequently reducing GHG emissions. Reflecting on cost-effective measures to reduce energy consumption, Secretary of Energy Steven Chu has said, "Energy efficiency isn't just low hanging fruit; it's fruit laying on the ground." (Charles 2009). Energy-efficiency is widely considered to be cost-effective and can be implemented quickly, unlike other likely carbon-mitigating options like alternative energy which, as illustrated in Figure 1.2, energy analysts project to take many years before gaining significant market share even at high growth rates (EIA 2009b).

[iii] EIA reports that U.S. energy consumption reached 101.5 billion MMBTU in 2007. The energy sources were liquids (e.g. oil, gasoline), 40 billion MMBTU; natural gas , 24 billion MMBTU; coal, 23 million MMBTU; nuclear, 8 billion MMBTU; hydropower, 2 billion MMBTU; and non-hydopower renewables, 4 billion MMBTU. Source: data from Figure 4 (EIA 2009e).

Energy-efficiency has also recently earned attention as a means of stimulating the economy. The American Recovery and Reinvestment Act (ARRA) of 2009, invests a total of $65 billion in the energy sector (Recovery Accountability and Transparency Board 2009), including $500 million for the creation of jobs in energy efficiency and renewable energy (111th United States Congress 2009a) and $5 billion to expand the Weatherization Assistance Program (WAP) (111th United States Congress 2009a sec. H.R.1-24). On December 8, 2009, President Obama announced plans for the Homestar Energy Efficiency Retrofit Program that would reimburse homeowners for purchasing energy-efficient appliances and installing insulation, allegedly creating tens of thousands of jobs and reducing the equivalent energy of three coal-fired power plants per year (Office of the Press Secretary 2010).

The Obama Administration has demonstrated that its commitment to energy-efficiency extends beyond this period of economic recovery. In February 2010, President Obama released his budget proposal for Fiscal Year (FY) 2011, which includes half a billion dollars for developing and advancing energy-efficient technologies in vehicles, buildings, and industrial processes. This proposal also includes a $300 million budget for WAP, marking a 43% increase from FY 2010 (US DOE 2010).

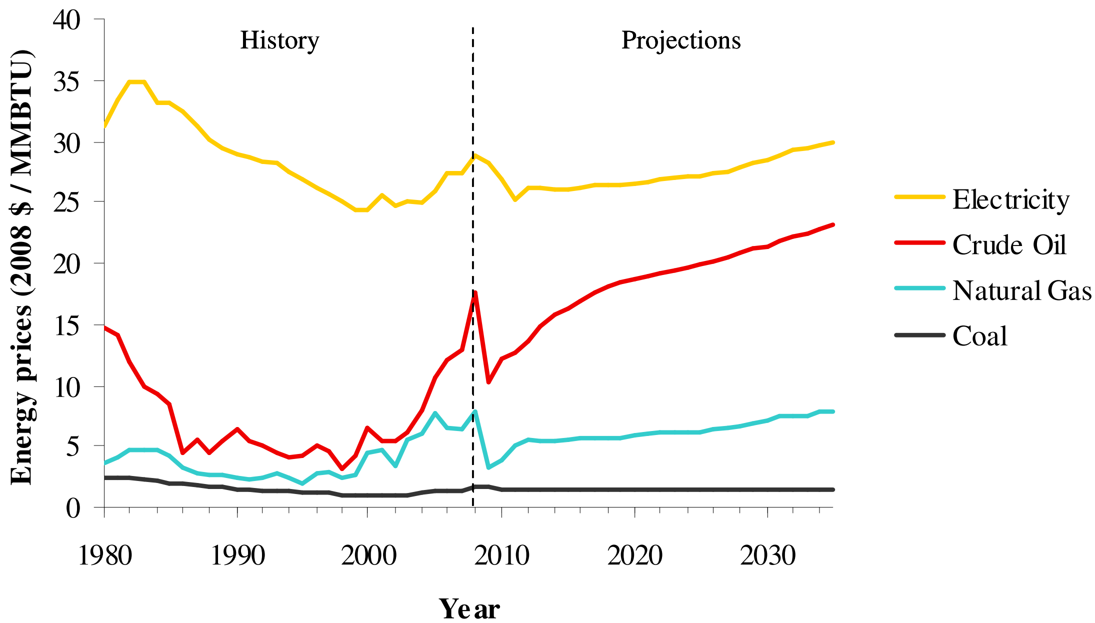

Figure 1.1. U.S. Energy Prices by Fuel. ***Energy prices peaked in 2008 before falling as a result of the global economic downturn in 2008. Once the economic recovers, energy prices are expected climb to record highs. Data to the left of the dashed line (at year 2008) represents historical energy consumption, and data to the right of the dashed line are EIA projections. Based on Figure 1*** **(EIA 2009e)**

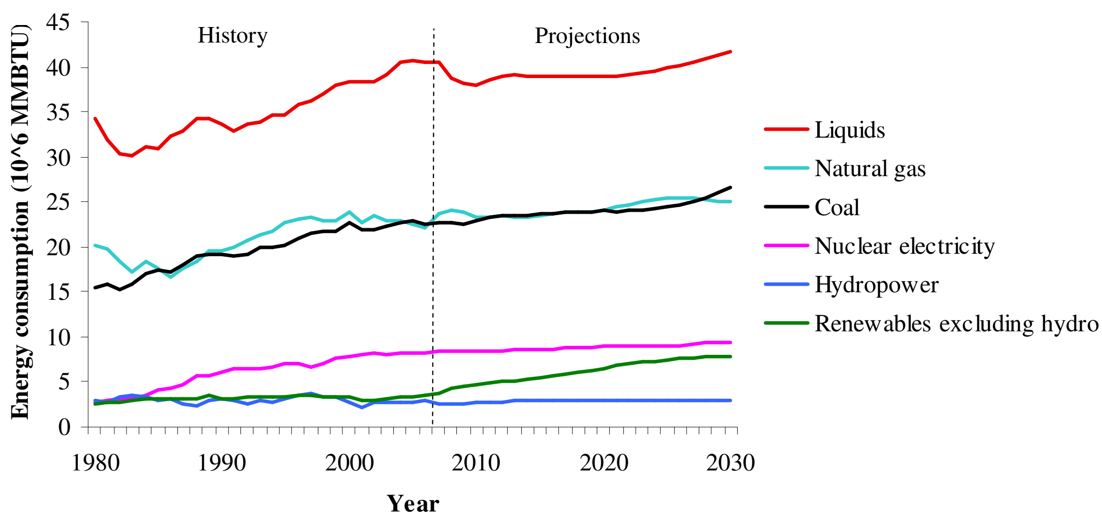

Figure 1.2. U.S. Energy Consumption by Fuel. ***From 1980 to present, total energy demand has grown, but the share of renewable energy has been small and growth was stagnant. Data to the left of the dashed line (at year 2006) represents historical energy consumption, and data to the right of the dashed line are EIA projections. Based on Figure 4*** **(EIA 2009e).**

1.1.2 Benefits of weatherization

There are many different benefits to weatherization, both energy and non-energy related. One study examining the potential for non-transportation-related energy-efficiency suggests that, by 2020, cost-effective energy-efficiency measures, including weatherization, can result in a 23% reduction in energy consumption below the business-as-usual projection, saving 4.2 quadrillion BTU (Granade et al. 2009). Of the projected energy savings through efficiency gains, residential buildings represent a substantial source: in the U.S., residential buildings account for 21%, or 21.5 quadrillion BTU, of national primary energy consumption (Figure 1.3) and 33%, or 1.4 quadrillion BTU, of the profitable projected energy-efficiency gains outside the transportation sector (Granade et al. 2009).

Aside from lower energy bills, reduced energy consumption includes several environmental co-benefits including reduced GHG emissions and regulated air pollution. Residential buildings are responsible for 23% of the country's energy-related carbon dioxide (equivalent) emissions (EIA 2009b). One study estimates that energy savings from insulation retrofits would result in 3,100 fewer tons of particulate matter $PM_{2.5}$, 100,000 fewer tons of NOx, and 190,000 fewer tons of SO_2 per year, creating public health and economic savings of $1.3 billion and $5.9 billion per year, respectively (Levy et al. 2003).

These environmental benefits help contribute to making WAP a highly net present value (NPV) positive public assistance programs. The DOE reports that that NPV of lifetime energy savings outweigh Wx retrofit costs by, on average, a ratio of 1.54 (Office of Energy Efficiency and Renewable Energy 2008). These evaluations also identified indirect, non-environmental, public and private benefits including job creation, lower energy costs for those homes not participating in Wx programs, and increased national security (Schweitzer and Tonn 2002).

Weatherization programs create jobs performing energy audits and retrofits, as well as jobs for those administering the retrofitting programs. And frequently many of these jobs go to people living in the low-income communities served by the Wx program.

In many cases, utilities provide low-income households with lower energy prices subsidized by customers that pay full rate. Reducing energy consumption in low-income households can lead to lower energy costs for not only those households receiving retrofitting treatments, but also for the standard ratepayer since the utility sells less subsidized energy.

Reduced consumption of fossil fuels encourages energy independence and is beneficial for national security. The U.S. imports roughly 1/3 of its energy (Brownsberger 2008), much of which comes from politically volatile regions with regimes that are either themselves hostile toward the U.S. or host groups that are hostile towards the U.S.

Analysts value these non-energy savings at $1.15 for every dollar invested in Wx program. Including the $1.54 per dollar invested from energy savings brings the total value of the Wx programs to $2.69 for every dollar spent (Office of Energy Efficiency and Renewable Energy 2008). Other evaluations conservatively estimate a WAP benefit-to-cost ratio of 1.61 for energy savings alone, and 1.72 for total societal value (Brown and Berry 1993).

In addition to low-income households being those most in need of lower energy bills, low-income housing is among the least energy efficient and therefore among the most cost-effective to retrofit. Low-income houses are on average 20% more energy intensive than non-low-income houses (D&R International, Ltd 2009 sec. 2.9.10). In their mathematical analysis of a national leakage database, McWilliams and Jung (2006) found that leakage [iv] is 145% higher in low-income houses than non-low-income houses (McWilliams and Jung 2006 p. 50).

Conventional wisdom suggests that low-income houses tend to be energy-inefficient because low-income residents or their landlords tend not to invest in retrofitting treatment. This tendency could exist because they lack the necessary capital, they do not have access to information about the long-term cost-effectiveness of retrofitting, or as high relocation rates [v] may suggest, they lack the incentive to invest in a building they may not own or live in long enough to recover their economic investment. Wx programs provide the mechanism to overcome these market failures and improve residential energy efficiency.

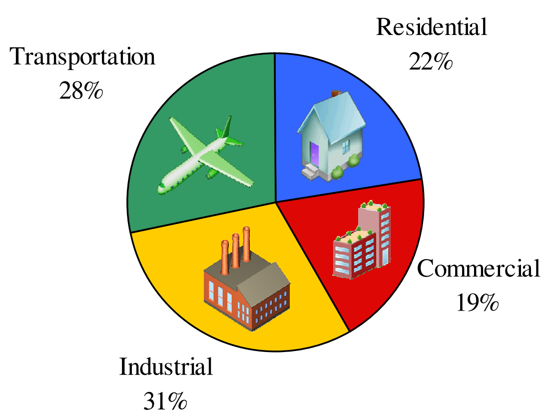

Figure 1.3. U.S. Primary Energy Consumption by Sector. ***The residential energy sector accounts for almost one-fourth of total energy consumption. Data source:*** **(EIA 2009e)*.***

[iv] Leakage refers to convective heat gains or losses due to air infiltration. Some academic studies report that infiltration accounts for approximately 50% (Sherman and Matson 1997) of total space condition energy use nationwide, but non-academic professionals generally estimate that leakage accounts for only one-third of space conditioning energy use (Blasnik 2009b).

[v] 48% of households at or under 150% federal poverty line—18.4 million households—rent their homes, representing 56% of the renting population of 33 million households (Energy Information Administration 2008).

1.2 IDENTIFYING COST-EFFECTIVE WEATHERIZATION OPTIONS

This section provides an overview of typical measures used to project and measure energy savings resulting from weatherization retrofits with reference to specific applications. The first subsection briefly describes how energy auditors and Wx program evaluators model the cost-effectiveness of weatherization measures. The second subsection describes the main components of energy modeling and highlights some of its applications in weatherization literature. The final subsection describes how WAP evaluations and national consumption data both suggest that the effectiveness of weatherization vary geographically due to variations in climate and housing stock; this subsection also discusses how the cost-effectiveness of weatherization varies geographically due to differences in energy prices.

1.2.1 Background

Starting in 1990, the introduction of energy auditing software allowed weatherization service providers to comprehensively analyze houses individually to determine the most cost-effective weatherization treatments. DOE credits these comprehensive energy audits for an 80% increase in energy savings per dwelling over the span of 1989 to 1996 (US DOE 2008).

Based on energy audit and building simulation software, conventional wisdom within the building science community suggests that reductions in household energy consumption of at least 30%—equivalent to national energy consumption reduction of approximately 6.7% [vi]—are possible through a combination of retrofits that increase the energy-efficiency of space conditioning (i.e. heating and cooling), water heating, lighting,

[vi] As displayed in Figure 1.3, residential energy accounts for 22% of total US energy consumption.

and appliance end-uses. Studies conducted by a variety of public interest and research institutes refer to similar projected savings. The Center for American Progress, recently published a report asserting that cost-effective retrofits using existing technology could produce energy savings of 20 to 40% (Hendricks et al. 2009). Similarly, a recent National Center for Healthy Housing article outlines an energy-efficiency stimulus package that would reduce low-income energy bills by 30-50% (Nevin 2010). Secretary of Energy Chu has testified to Congress that implementing existing energy-efficiency technologies in new buildings can reduce their energy consumption by 40%, and cost-effective retrofits in older buildings can halve building energy consumption (Charles 2009). More specifically but anecdotally, EAM Associates, a New Jersey-based consulting group specializing in energy audits, audited five low-income houses in Trenton and projected that cost-effective retrofits could decrease space heating energy consumption by an average of 38% (Weissinger et al. 2009).

1.2.2 Energy modeling

EAM's estimates and other reports with a similar focus base their analysis on energy modeling software calculations. There are several different types of auditing software, each of which uses different models to estimate energy use, suggest retrofit measures, and project energy savings based on inputs about the physical characteristics of the building and how its occupants use energy. The efficiency of a building's heating and cooling systems depend on how the heating and cooling is produced, distributed and ultimately lost. The production and distribution of heat depends largely on the technical specifications of the heating and ventilation system. Buildings lose heat mainly through conductive and convective transfers through the thermal envelope. These transfers can be minimized by repairing any dilapidated surfaces in the thermal envelope, installing insulation, and air-sealing the building shell. Finally, how its occupants use energy is a behavioral variable. Obviously if an occupant leaves a window open in winter while the house is heating, the building is not efficiently heated. Technologies like programmable thermostats can also affect space conditioning consumption as they provides a simple, automatic way to turn down the space conditioning equipment when less conditioning is needed, such as during sleeping hours or during the day when occupants are not at home.

One of the most recent and thorough analyses of the current state of energy efficiency is McKinsey & Company's *Unlocking Energy Efficiency in the U.S. Economy* (Granade et al. 2009). In this report, the authors calculated the expected costs and benefits of residential retrofitting using the Home Energy Saver (HES) model driven with data from the Residential Energy Consumption Survey (RECS). HES is a web-based energy model developed by the Lawrence Berkeley National Laboratory (LBNL) that estimates building energy use based on user-provided building descriptions. It also provides retrofitting recommendations and corresponding energy savings projections (EIA 2009a). RECS is a national area-probability sample study conducted by the Energy Information Administration (EIA) that collects energy-related data for occupied primary housing units and includes housing unit physical characteristics and household descriptions. By analyzing RECS data through HES, Granade et al. estimate that retrofitting existing buildings can produce almost 40% energy savings by the year 2020 at a net present value of $41 billion.

Past evaluations of energy models question the capability of energy models, such as the one Granade et al. used, to predict actual energy savings. Comparisons of energy savings projected using energy modeling software with measured energy savings suggest that modeling software typically overestimates savings by 30-50% (Berger and Carroll 2007). Past evaluations of retrofit effectiveness reveal that retrofits do not always lead to reduced energy consumption: an analysis of RECS data from 1981-1983 found that only 51% of retrofitted homes saved energy, while 29% consumed the same amount of energy, and 20% consumed more energy (Longstreth and Topliff 1990). Discrepancies between modeled and observed savings are classified as "rebound effects," primarily caused by some combination of "shortfall" and "take-back." "Shortfall" is a technical estimation error that occurs when engineering projections overestimate actual energy savings. Improper installation of energy-saving measures (such as attic insulation or window caulking) can reduce savings by 20-30%, and energy modeling simplifications can overestimate savings by 50% (Sorrell 2007). "Take-back" occurs when end-users change their energy-consumption behavior after energy-savings measures are implemented, resulting in decreased savings of up to 50% (Martin and Watson 2006). One frequently observed example of take-back is when end-users set indoor temperatures to a more comfortable 1 to 3°F higher after receiving insulation upgrades, decreasing energy savings by 15 to 30%.

Because of these significant modeling shortcomings, there is reason to question energy savings projection derived from their use. The only actual way to measure energy savings is to compare a household's energy consumption before and after retrofitting. These comparisons must be normalized for weather conditions, since energy used for space conditioning depends on outside weather conditions. Because of weather variations and other factors, it is standard practice to use an entire year of energy consumption before and after retrofitting in order to determine energy savings. The industry standard for analyzing these data is the Princeton Scorekeeping Method (PRISM). PRISM is a statistical model developed at Princeton University that processes weather data and a year of monthly energy bills to produce a weather-normalized measure of energy consumption (Fels 1986).

1.2.3 Geographic variations

In addition to the risks of modeling error discussed above, one limitation of the McKinsey & Co's reports is that they project savings on the national scale. Such nationwide analysis can be useful, for example, in comparing the cost-effectiveness and scale of energy savings achievable from residential retrofits to other national energy-saving strategies such as wind energy or greater automobile fuel efficiency. But for the purposes of evaluating Wx programs on a regional basis, it is important to consider that energy savings and the cost-effectiveness of weatherization treatments may vary substantially depending on the location of the retrofitted house. For example, a 1993 nationwide evaluation of the WAP-sponsored retrofitting programs found that retrofits were more cost-effective in cold and moderate climates than in hot climates (Brown and Berry 1993). The evaluators identified different retrofitting approaches as the primary sources of this discrepancy: Wx programs in cold and moderate climates were more cost-effective because of their focus on inexpensive but effective measures like energy audits, leakage control and insulation, while programs in hot climates focused on door and window replacement, which are less cost-effective measures.

While different retrofitting approaches may be responsible for past inconsistencies in retrofitting effectiveness, there are other reasons to suspect that weatherization may be more effective in colder climates. Analysis of RECS data shows that average household energy consumption is higher in colder climates than in warmer climates. Figure 1.5 shows how end-use energy consumption varies by climate zone (Figure 1.4 shows the boundaries for climate zones). As seen in this figure, while energy use for water heating, lighting, and appliances are relatively independent of climate zone, space conditioning energy consumption can vary dramatically between climate zones. Even if retrofitting treatments have the same relative effectiveness (i.e. efficiency improvement) across climate zones, houses in climate zones that initially consume greater quantities of energy for space conditioning will reap greater energy savings from weatherization treatments.

Climate variations certainly affect the effectiveness of different retrofitting measures, but variations in the regional housing stock do as well. Due to continually improving building technologies and building practices, newer houses tend to be better insulated and more tightly sealed than older houses. Statistical analysis of national leakage data showed that among houses that had never received weatherization treatments, leakage rates increased approximately 1% for each year since the house was built (McWilliams and Jung 2006).

Sherman and Matson (1997) observed that the Northeast and Midwest regions contain the leakiest houses, which also happen to be the regions with the oldest housing stock (Figure 1.6 shows region definitions) according to U.S. Census data. The median house age in the Northeast and Midwest is 53 and 41 years, respectively, while the South and West are more newly developed regions with median house ages of 32 and 34 years, respectively [vii]. Figure 1.7 illustrates in more detail how housing stock age varies across regions. Figure 1.8 shows how household energy consumption varies with region, though as there is some correlation between region and climate zone, it is unclear how much of these variations are due to housing stock differences rather than climate differences.

Differences in construction characteristics and HVAC equipment are also responsible for some regional variations in energy consumption and potential energy savings. For example, statistical analysis of national leakage data shows that houses with crawlspaces or unconditioned basements are an average of 8% leakier than comparable houses with conditioned basements or concrete slab foundations (McWilliams and Jung 2006). The type of heating equipment is another important factor for space conditioning energy consumption. Per unit of end-use space heating energy consumption, natural gas heating systems currently in most homes are less efficient (78%) than their electric counterpart (~98%) (Mills 2008). Trends in construction characteristics and HVAC equipment are correlated with climate and region as well. RECS analysis shows that houses in most cold Census divisions tend to have gas heaters and basements, but houses in the warmer Census divisions are built on concrete slabs, and most houses in the South Atlantic Division use electricity for heating (Mills 2008).

Regional differences in energy prices will also affect the cost-effectiveness of retrofits. Energy prices vary across the country depending on the local energy market, which in turn vary depending on factors like energy infrastructure and energy policies at the state, or even municipal level.

[vii] From Table 2-1, (US Census Bureau and HUD/U.S. 2008 p. 47)

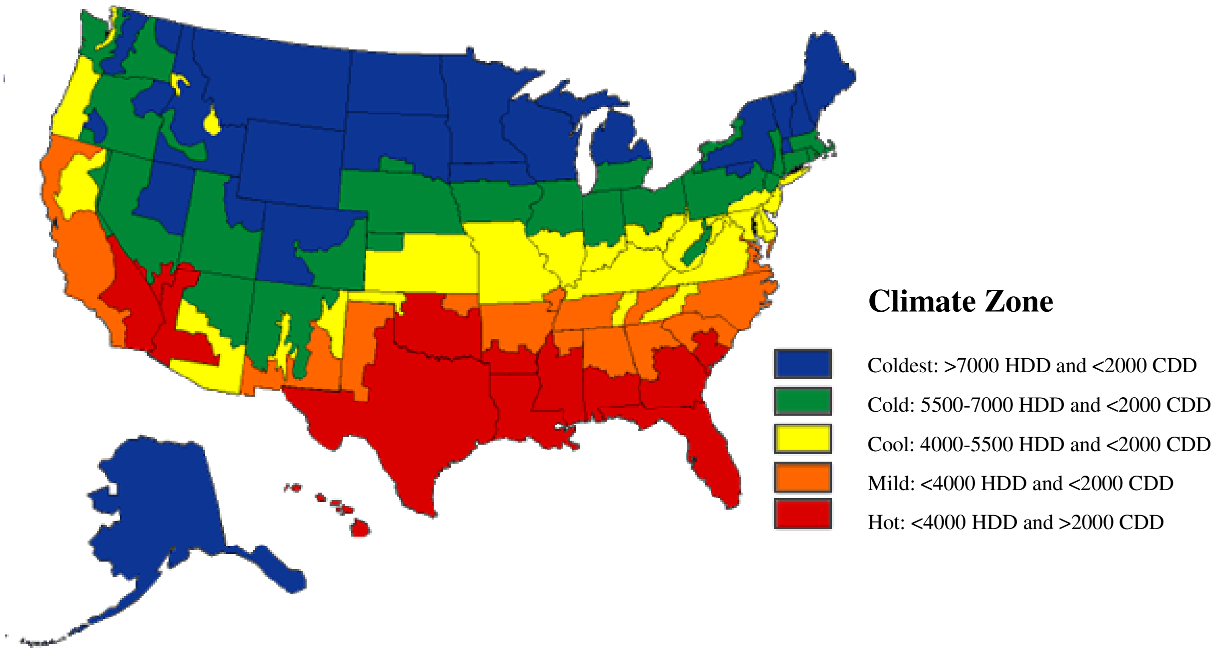

Figure 1.4. U.S. Climate Zones Map. ***EIA uses five different climate zones as defined by the heating degree and cooling degree days. Source:*** **(EIA 2002).**

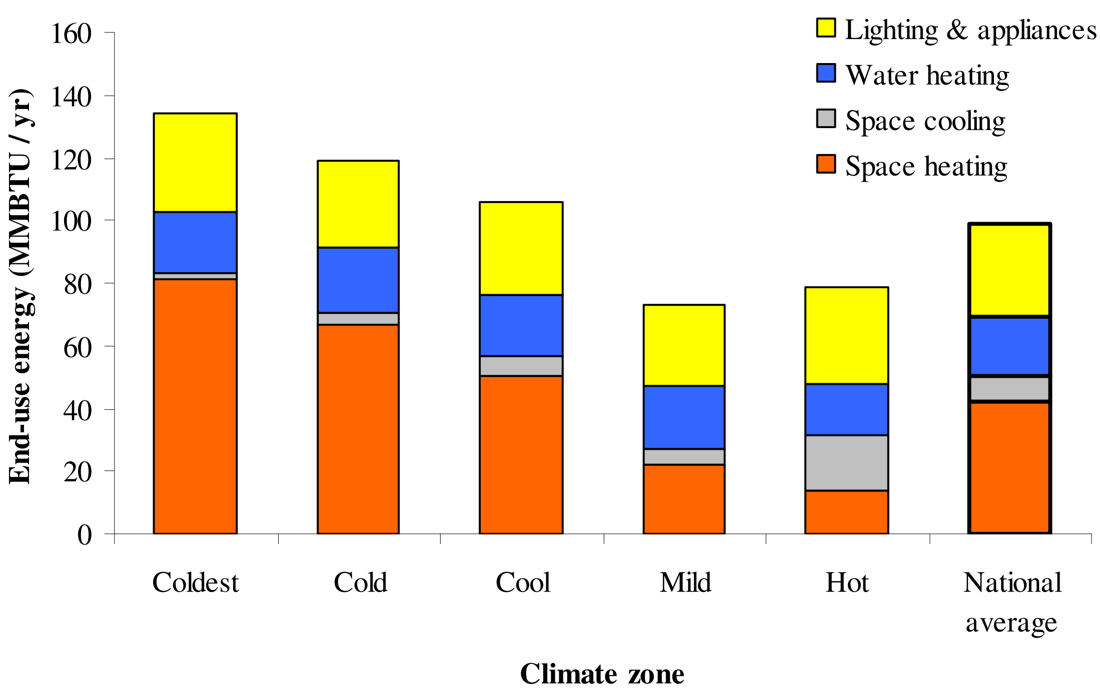

Figure 1.5. Average U.S. Household Energy Use by End-use and Climate Zone. ***The energy used for lighting & appliances and water heating remains fairly constant across climate zones, but space conditioning (i.e. space cooling and space heating) varies significantly among zones with cooler zones (i.e. coldest, cold and cool) consuming more energy for space conditioning than warmer zones (mild and hot) do. Calculated from RECS 2005 microdata.***

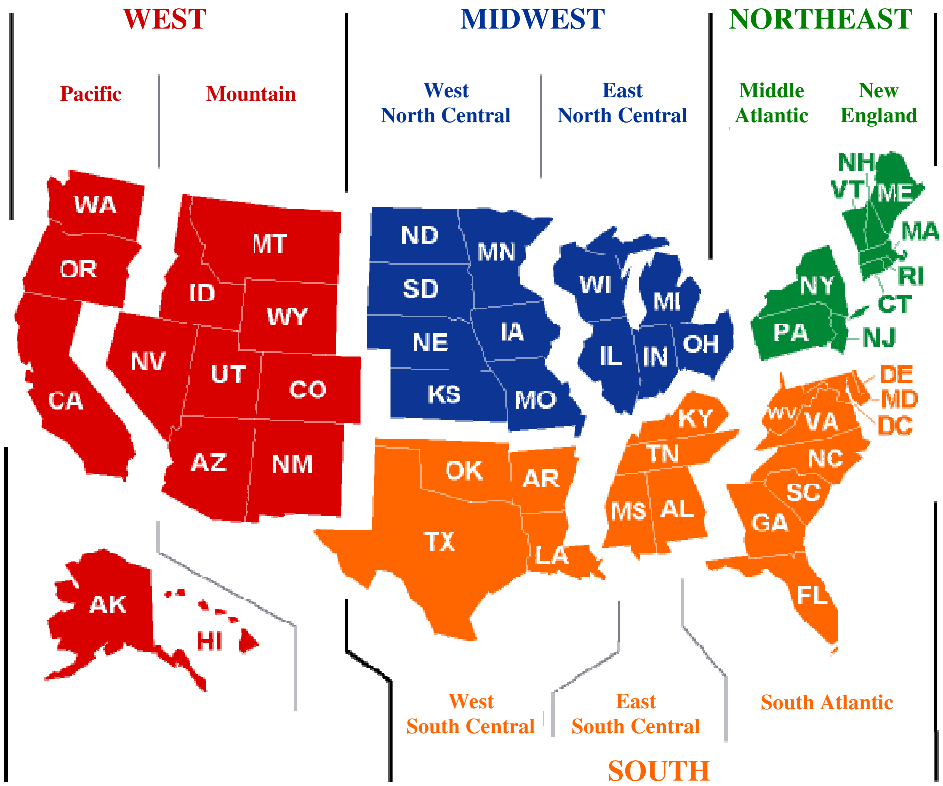

Figure 1.6. U.S. Census Regions and Divisions. ***There are four census regions (distinguished by color), and the regions are divided into a total of nine census divisions (distinguished by spatial grouping). Source:*** **(EIA 2000).**

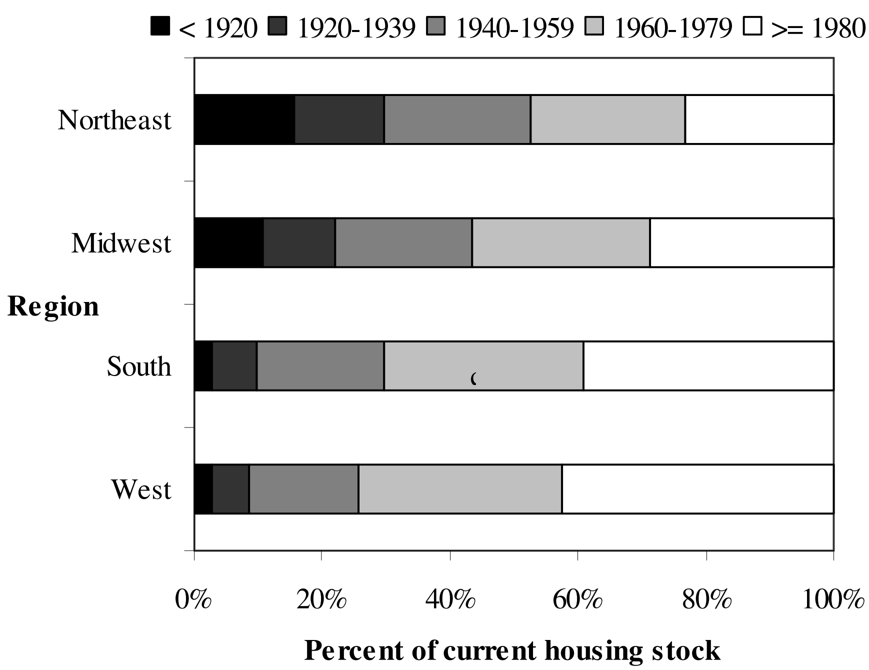

Figure 1.7. Regional housing stock age composition. ***The Northeast and Midwest regions consist of a greater proportion of older homes than the West or South regions.*** **Data source: Table 2-1 (US Census Bureau and HUD/U.S. 2008).**

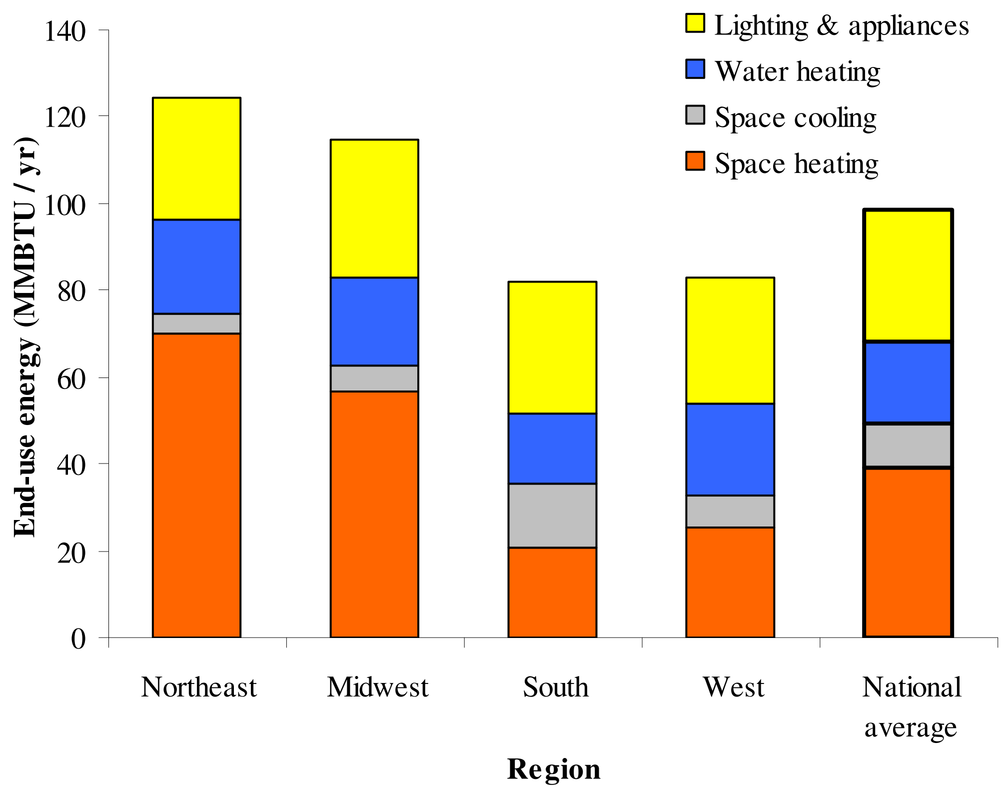

Figure 1.8. Delivered Energy for an Average Household by End-use and Census Region. ***Households in all regions use comparable quantities of energy for lighting & appliances and water heating, but the energy consumed for average household in the Northeast and Midwest uses more energy than the average household in the South and West, predominantly because of greater space heating use. Data source: Table 2.1.11,*** **(D&R International, Ltd 2009 pp. 2-8).**

1.3 RESEARCH PURPOSE

With the recent surge of interest in weatherization and energy-efficiency, government at all levels is allocating substantially more funding for programs in these fields. It is advantageous to determine how this funding might be best applied. The purpose of this research project was to develop information that can contribute to this decision-making process by developing an approach that can be used to project the benefits and cost-effectiveness of Wx programs in different urban areas.

Urban areas are likely to be where Wx programs will have the greatest impacts, as they frequently contain zones of concentrated unemployment, underemployment, and poverty. As such, these areas not only a large population of households eligible for Wx programs, but they are also likely to receive some of the greatest indirect benefits of the program such as job creation. Additionally, the high population density of urban areas allow for easier implementation of the DOE's Retrofit Ramp Up program, which aims to fund programs that can reach entire neighborhoods (Chu 2009). Some states have enacted legislation for the purpose of promoting weatherization programs in urban areas, such as the Urban Weatherization Initiative Act in Illinois (Illinois General Assembly 2009). Given the DOE's objectives, it seems likely other states will choose to focus weatherization assistance efforts in urban areas.

Towards fulfilling this purpose, our research objective research was twofold. Our first objective was to evaluate how readily available energy modeling software can: a.) accurately model low-income urban housing energy usage and b.) realistically project energy savings gained from retrofits. Our second objective was to develop a framework for determining where weatherization in urban areas would be most cost-effective. To meet these objectives, we used the Home Energy Saver model driven with housing information from the American Housing Survey to project expected energy savings from weatherizing the low-income urban housing stock in widely different geographical regions. We compared the results of this approach to measured energy savings achieved in an urban Wx program. We then applied our approach to the analyses of the cost-effectiveness of retrofitting low-income housing stock in cities from different Census regions and climate zones.

2 RESEARCH METHODS

This chapter describes our project's approach to modeling expected energy savings and reductions in carbon emissions from various weatherization retrofits. The approach consisted of extracting data from the American Housing Survey (AHS) to drive the Home Energy Saver (HES) model. HES calculated energy consumption for individual houses, energy savings achieved with specific weatherization treatments, and the installation costs of the weatherization treatments. With energy price and carbon intensity information published by the EIA and Environmental Protection Agency (EPA), respectively, we determined the cost-effectiveness of energy abatement and carbon abatement for each weatherization treatment. Figure 2.1 illustrates this process.

Each section within this chapter describes each component of the approach in more detail. The first section describes the energy modeling software used to project retrofit costs and resulting energy savings. The second section describes the data selected to drive the model and evaluate the validity of our modeling approach. The final section describes how we selected the urban areas to model and how we applied our model.

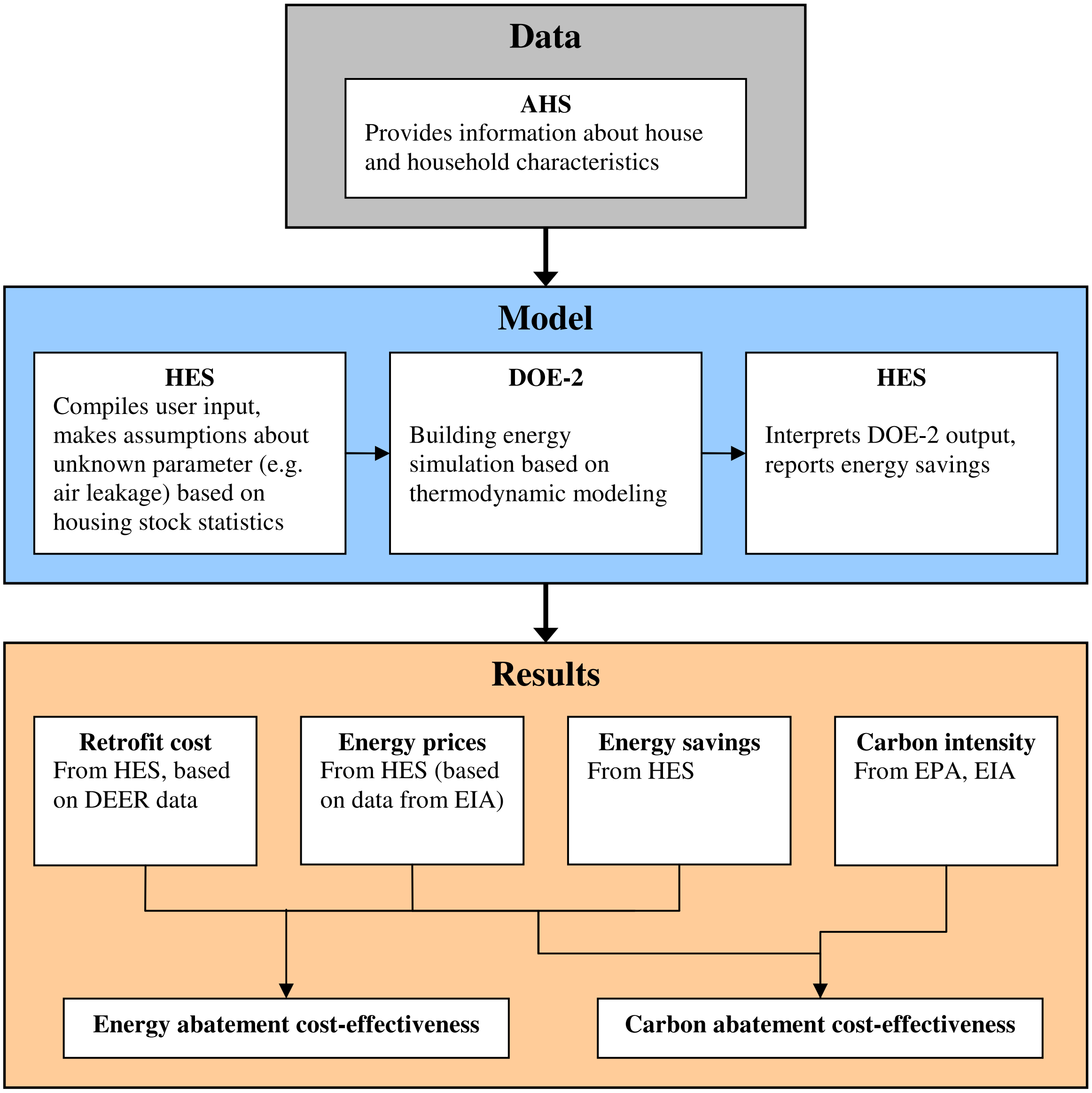

Figure 2.1. Approach Flow Chart for Calculating the Cost-effectiveness of Energy and Carbon Efficiency from Weatherization Treatments.

2.1 *ENERGY AND RETROFIT MODELING*

This project used the Home Energy Saver (HES) software to model both expected energy consumption and savings gained from retrofitting treatments with publicly available technology. HES (http://hes.lbl.gov) is a freely available web-based residential energy audit tool developed and maintained by Lawrence Berkeley National Laboratory (LBNL). HES relies on user input, housing stock statistics, and the building simulation DOE-2 engine to approximate whole house energy consumption, potential energy savings with various retrofit treatments and the costs of such treatments. We selected HES over other models because it is readily available, comprehensive, and user-friendly. In an evaluation of three top house energy modeling softwares—SIMPLE, REM/Rate, and HES—HES required the fewest data inputs and the least time for data entry: to model a single house, HES required only 24 inputs and an average of 11 minutes for data entry, while the only other presently available software evaluated[viii], REM/Rate, required 100 inputs and an average of 45 minutes for data entry (Earth Advantage Institute and Conservation Services Group 2009). We also judged HES an appropriate choice for this project choice given that past McKinsey & Co. analyses (Creyts et al. 2007; Granade et al. 2009) have used HES to estimate the energy consumption and possible savings from retrofit treatments in the residential sector. Because our project only considers energy consumed for space conditioning, we limit this discussion of HES to those parts related to space conditioning.

[viii] SIMPLE is still in development and not readily available (Blasnik 2009b).

2.1.1 Energy consumption and savings

HES calculates and reports end-use energy savings expected for the modeled house with prescribed retrofitting treatments. HES reports these savings both by end-use category (i.e. space heating, space cooling, water heating, appliances, lighting) and by fuel (i.e. gas, fuel oil, or electricity). Space conditioning energy consumption depends on a significant number of factors including, but not limited to: geographic location; house construction and foundation type; appliance use; the quality, quantity, and location of windows; building orientation; HVAC equipment type and efficiency; insulation levels in the floors, walls, and ceilings; air-tightness of the house envelope; and residents' energy-consumption behavior. The following discussion will describe how HES models the major components of space conditioning that weatherization assistance (Wx) programs frequently address: namely, building envelope insulation and air-tightness, HVAC equipment type and efficiency, and residents' energy-consumption behavior.

Based on the HES documentation files (Mills 2008), each subsection below briefly describes how HES determines the effect of each major component and how it calculates expected values to the extent necessary for this project. In all cases, HES sends the relevant equipment and house envelope information to DOE-2 software (version 2.1E) that performs the thermodynamic modeling required to determine hourly space conditioning energy consumption. DOE-2 (http://www.doe2.com) is a widely used and accepted building simulation program developed as a joint-project between James J. Hirsch & Associates and LBNL. The U.S. and other countries have developed building standards on the basis of DOE-2, and many design and consulting firms use DOE-2 as the main engine for energy modeling (Ellington 2010). Building information modeling software, such as the popular Green Building Studio, use the DOE-2 engine to perform a whole building energy analysis (Autodesk 2010).

Building envelope insulation and air-tightness

HES sends the building material and insulation information to DOE-2, which uses a table of typical material insulating properties to model the conductive losses through the building envelope. DOE-2 also models foundation heat transfer according to the methods developed by Huang et al (Huang et al. 1988) and updated by Winkelmann (1998) and Huang (Huang 2003)[ix]. These methods use effective foundation U-factors and typical soil insulating values to model conductive heat transfer between the foundation and the ground.

To determine building infiltration, HES uses the empirical equation for fractional leakage area that Sherman and Matson (1997) developed from analysis of LBNL's national leakage database. The national leakage database contains normalized leakage (NL) values and some basic building descriptions for over 12,000 single-family houses nationwide (Sherman and Dickerhoff 1998). The empirical equation for fractional leakage derived from this database is

$$FLA = \frac{NL/1000}{\left(\frac{8*0.3048*stories}{2.5}\right)^{0.3}}$$

where
FLA = Fractional leakage area, the ratio of effective envelope leakage area to floor area
NL = Normalized leakage (sq. ft total leakage area/sq. ft conditioned floor area)
stories = 1 if single-story house, 2 if multi-story
8 = assumed house ceiling height (feet)
0.3048 = converstion factor for feet to meters
(Sherman and Matson 1997)

[ix] Cited in (Warner 2005)

If the user does not provide leakage information for a house, HES selects a normalized leakage value from the national leakage database based on house vintage (pre-1980s, 1980 or later), stories (1, more than 1), foundation type, presence of a ducted heating or cooling system and shell condition (whether or not there had been previous air sealing). For houses built after 1990, HES assumes an *NL* value of 0.5, a typical *NL* value in new construction.

HES passes fractional leakage area, house vintage, and number of stories to DOE-2, which calculates infiltration according to the Sherman-Grimsrud Method (Sherman and Matson 1997). Because DOE-2 calculates hourly energy consumption, it can account for the change in infiltration resulting from open windows: DOE-2 simulates windows opening for natural ventilation whenever the outside temperature and humidity would result in a cooling effect outside of the heating season.

HVAC equipment type and efficiency

HES passes HVAC equipment type (e.g. central gas furnace, oil boiler, electric baseboard heater) and efficiency ratings to DOE-2, which calculates hourly energy consumption. DO2-E uses unpublished LBNL performance data to determine equipment capacity curves and efficiency as a function of outdoor temperature. DOE-2 uses high resolution weather data to model hourly energy consumption necessary to maintain prescribed indoor temperatures. HES converts energy consumption into the relevant units of fuel according to standard conversion factors. If the user does not prescribe the efficiency of the heating system, HES assumes a default efficiency value based on typical efficiency of the heating equipment type.

Residents' energy-consumption behavior

HES models the energy savings gained from replacing a standard thermostat with a programmable thermostat. Unless the user specifies otherwise, HES assumes that the switch from a standard to programmable thermostat changes the number of heating and cooling demand from 15 hours to 7 hours. DOE-2 uses this schedule to calculate hourly heating and cooling energy consumption.

2.2 *DATA*

This section describes the data used to drive the Home Energy Saver and the observation data we used to evaluate the validity of our modeling approach.

2.2.1 American Housing Survey

For this project, we used 2007 American Housing Survey (AHS) national microdata to drive the Home Energy Saver software (US Census Bureau and HUD/U.S. 2008). The U.S. Census Bureau and the Department of Housing and Urban Development (HUD) has conducted the American Housing Survey every odd-numbered year since 1981. The survey collects data from a fixed sample of roughly 55,000 houses selected in 1985 using cluster sampling. In each iteration of the survey, the Census Bureaus adds to the sample some newly constructed houses and removes houses from the sample if they no longer exist. AHS reports not only house characteristics—such as house vintage, conditioned floor area, number of floors, and space conditioning equipment—but also household characteristics—such as household size and income.

While AHS has less energy-related data than the Energy Information Administration's (EIA's) Residential Energy Consumption Survey (RECS), AHS is more useful for this project because it contains more specific location information for each house in the sample. The only information RECS provides that could be used to determine houses' location is census region, census division, and heating and cooling degree-days [x]. At best, this information allows the user to identify a climate contour along which the house exists within a census division. AHS, on the other hand, reports if a

[x] Heating and cooling degree days are quantitative indices that reflect the demand for space conditioning. A degree day is defined as the difference in temperature between outside and inside a building, assuming that the inside is a constant room temperature, typically 65 °F. These heating and cooling degree days are usually summed and reported for a heating and cooling season, respectively.

house is within a standard metropolitan statistical area (SMSA), defined by the Census Bureau as a metropolitan area of over 100,000 people. AHS also reports if the house exists in an urban or rural area within the SMSA. AHS uses the 1980 Census definition of an urban area as an incorporated place with a densely settled area (1000+ people per square mile) totaling at least 50,000 people. This resolution of AHS allows us to isolate low-income urban homes within a specific metropolitan area

2.2.2 Philadelphia observation data

To evaluate the accuracy of our model, we compared modeled energy savings with observed energy savings resulting from retrofits of similar housing stock. Observed energy savings data came from an impact evaluation of Philadelphia Gas Works' Conservation Works Program (CWP), a Wx program in Philadephia (M. Blasnik & Associates 2008). In this report, Michael Blasnik, of the energy performance consulting firm M. Blasnik & Associates, evaluated the effectiveness of two contractors within CWP, the non-profit Energy Coordinating Agency (ECA) of Philadelphia and the for-profit Honeywell. Using the same methods as PRISM, Blasnik analyzed pre- and post-treatment energy bills to calculate weather-normalized energy consumption in houses that received treatment to determine gross energy savings. To account for any non-program related trends in energy consumption, Blasnik also examined energy bills from a comparison group—a group of houses similar to those treated, but that did not receive treatment. Blasnik calculated the net energy savings as the gross savings within the treatment group minus the average change in consumption within the non-treatment comparison group.

Of the two contractors Blasnik evaluated, we chose to compare our modeling estimates with the data from Honeywell's for two reasons. The first reason is that ECA targeted high energy users and Honeywell did not. Many evaluations show that retrofits in high-user houses are substantially more cost-effective than average-use houses (Blasnik 2009a). This relationship certainly has meaningful implications for designing weatherization strategies, but it is problematic for this project—which aims to quantify average energy savings from retrofitting low-income houses—since by definition high users are not representative of this population. We also selected to emulate Honeywell's result because HES can model each of its main retrofitting treatments—programmable thermostat, roof insulation and blower-door guided air sealing—whereas ECA did not use air sealing and installed under-porch partitions, which HES could not model. Due to HES limitations, however, we could not model roof insulation retrofits, so we instead chose to model roof insulation as attic insulation. With three different treatment elements, there are seven different treatment scenarios of a single treatment or combination of multiple treatments. Figure 2.2 shows Blasnik's calculated energy savings for each treatment scenario in the Honeywell population. Table 2.1 lists each treatment scenario's symbol abbreviation used throughout this report, along with the number of houses that received that treatment according to Blasnik's evaluation. These savings, as a percentage of pre-retrofit space conditioning energy consumption, are roughly consistent with those reported for ECA and in impact evaluations of other Wx programs in colder (i.e. coldest, cold, and cool) climate zones (APPRISE 2006; Blasnik 2009a; Khawaja et al. 2006; M. Blasnik & Associates 2004, 2007, 2009).

The error bars seen in Figure 2.2 (indicating a 90% confidence interval) suggest the wide variability of energy savings for each treatment scenario. While there is almost certainly some error associated with the energy savings calculation process, these error bars demonstrate that treatment effectiveness can vary from house-to-house. Such variation occurs because the sample—the Philadelphia housing stock—is heterogeneous. Houses can vary by many physical factors including shape, size, materials, construction type and many other factors. Over their lifetimes, the physical characteristics of houses will change depending on local weather conditions and resident wear-and-tear. And beyond the physical characteristics of the house, there is a behavioral component to energy usage that will cause energy consumption to vary from person-to-person, and as discussed in Subsection 1.2.2, take-back may skew the measure of energy savings.

Table 2.1. Treatment Scenarios, Corresponding Symbols, and Number of Houses Receiving that Treatment. ***Data source:*** **(M. Blasnik & Associates 2008).**

Treatment scenario	Symbol	Number of units
Thermostat only	T	205
Roof/attic insulation only	A	14
Air sealing only	S	155
Air sealing and thermostat	S & T	345
Roof/attic insulation and thermostat	A & T	38
Roof/attic insulation and air sealing	A & S	95
Attic insulation, air sealing and thermostat	A & S & T	279

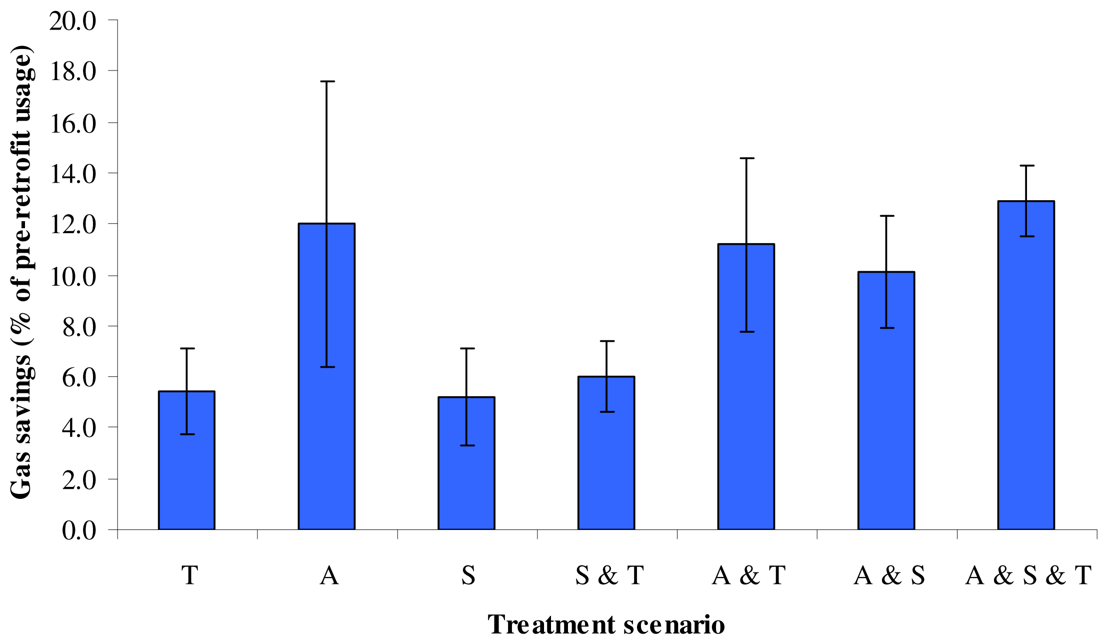

Figure 2.2. Net Natural Gas Savings Observed for Different Treatment Scenarios. ***Savings are relative to pre-retrofit consumption. Error bars represent a 90% confidence interval. Data source:*** **(M. Blasnik & Associates 2008).**

2.3 ANALYSIS SUMMARY

The following section describes in more detail some of the specifics of our modeling choices and applications.

2.3.1 Analysis methods

For this project, we restricted our analysis to occupied, low-income, one-unit buildings within the urban areas of an SMSA. One-unit buildings include both attached and detached housing units, but exclude mobile homes and buildings with more than one unit such as apartments or multi-family houses. In this analysis, a household income of 150% of the federal poverty line classified a household as low-income. The federal government uses this income level to determine eligibility for many assistance programs, including LIHEAP, a federal heating and cooling assistance program.

Because our reference data—Blasnik's Honeywell evaluation—contains combinations of only three treatments, we will only consider treatments that are combinations of programmable thermostats, air sealing and attic insulation. Specifically, we modeled that air-sealing would reduce infiltration 25% and installing attic insulation would increase attic insulation from R-0 to R-38 [xi]. For treatment scenarios that did not include attic insulation, we assumed the HES default for attic insulation, R-11. The 25% infiltration reduction is consistent with average reductions measured by ECA and some specific contractors in Pennsylvania Wx programs, but this reduction estimate is conservative compared to the 40% reductions delivered by contractors in other Wx

[xi] R-values are measures of thermal resistance, defined as the temperature difference across an insulator divided by the heat flux through it. Bigger R-values indicate more effective insulation. Typical residential insulation levels range from R-values of 0 (no insulation) to 60, with 38 as a typical moderately efficient level (Mills 2008).

programs in Pennsylvania (M. Blasnik & Associates 2007) or the roughly 27-39% infiltration reduction found in Ohio Wx programs (Khawaja et al. 2006).

For this project, we used AHS to provide input to HES for house vintage; conditioned floor area; number of floors; if a house were attached or detached; foundation type; heating equipment fuel and type; air conditioning type; and number of residents in the house. Based on these inputs, HES determined typical values for the remaining variables based on expected parameters for single family detached houses described in RECS.

To determine the average energy consumption and energy savings for a housing stock, we calculated the expected value of energy consumption and energy savings for each treatment among the houses modeled in a city. In calculating these expected values, we weighted the results of each model run according to the weights provided in AHS, which indicates how many houses in the population each house in the sample represents. We used average energy consumption and average energy savings to describe the results of our analysis. Many of this report's plots feature error bars indicating 90% confidence intervals. Blasnik's analysis included calculating these error bars assuming a Student's t-distribution. For the modeled energy savings, we also assumed that the average energy savings followed the Student's t-distribution, and we calculated 90% confidence intervals accordingly with sample size equal to the number of houses modeled.

2.3.2 City selection

As discussed in Subsection 1.2.3, energy consumption data demonstrate that consumption varies with Census region and climate zone because of housing stock trends and different weather-driven space conditioning demands. In order to investigate how potential energy savings varied among geographical and climatic regions, we selected cities to analyze based on census region, climate zone, and data availability.

With the goal of selecting cities representative of their region's housing stock, we analyzed AHS data to compare the vintage of each SMSA's urban housing stock to the vintage of regional urban housing stock. We selected vintage to describe housing stock because factors important to space conditioning (e.g. insulation levels, air-tightness) depend on the building technology available and building practices followed when the house was built: new houses are generally tighter and better insulated than older houses because of improvements in building materials and practices. Regression analysis of a national residential leakage database identified age as one the most significant building characteristic relevant to its leakage, with leakage increasing 1% per year since a house was built (McWilliams and Jung 2006).

To measure regional representativeness, we formed a cumulative distribution function (CDF) for vintage in each city and compared it to the regional urban housing stock CDF. We calculated representativeness as the sum of absolute deviation from the regional CDF, where most representative cities were those with the lowest sum. Figure 2.3 through Figure 2.6 show how the housing stocks of a sampling of cities compare to the regional urban housing stock.

To the extent possible, we selected cities to model based on this measure of representativeness. In all cases, however, the most representative cities yielded a very small sample size of low-income household. In the South census region, for instance, the urban housing stock in the Fort Worth-Arlington, TX metropolitan area was most representative of the region's urban housing stock, but the query for low-income houses in Fort Worth-Arlington identified only one house. Mindful of both sample size and regional representativeness, for modeling purposes we selected the low-income housing stock in Orlando, FL; Los Angeles-Long Beach, CA; Seattle, WA; Philadelphia, PA; Detroit, MI; and Milwaukee, MI. Figure 2.7 shows the CDF for vintage in each of these selected metropolitan areas.

Table 2.2 summarizes the major building characteristics of the low-income urban housing stock for each of the cities we modeled. Among the major differences within building characteristics are foundation type, vintage, space conditioning equipment and number of floors.

Basements dominate the foundation type in northern cities, while cities in the south are predominantly built on concrete slabs. Foundation type may be relevant as houses with crawlspaces or unconditioned basements are statistically on average 8% leakier than comparable houses with conditioned basements or concrete slab foundations (McWilliams and Jung 2006).

The summary of house vintages indicates that Orlando and Los Angeles-Long Beach have newer housing stock than the other cities, suggesting that these houses may initially be better insulated and more tightly sealed.

The Orlando housing stock relies entirely on electric heating, but most houses in the other cities use natural gas. As discussed in the next subsection, this has implications for both the cost and carbon intensity of space conditioning in these areas. Additionally, different HVAC equipment types typically have different efficiencies. In general, electric furnaces are more efficient by end-use than natural gas furnaces, but they tend to have much larger carbon footprints as electricity is typically more carbon intensive than natural gas or fuel oil.

Orlando is also the only city with universal air conditioning. Air conditioning ownership in other cities varies tremendously and somewhat surprisingly: Milwaukee, the coldest of the cities we examined, has the second highest ownership rate of air conditioners after Orlando. Although natural gas-powered air conditioning units exists, all air conditioning units in the modeled sample contain either an electric room air conditioner or electric central air conditioning system. The combination of climate and air conditioning ownership will cause the contribution of space cooling to total space energy consumption to vary significantly across the cities we model.

For this project's purposes, the number of floors was relevant for multiple reasons. Statistically, leakage is 16% greater in multi-story houses compared to single-story houses of comparable floor area (McWilliams and Jung 2006). The number of floors was also important in conjunction with average floor area to determine the Floor Area Ratio (FAR). The FAR is defined as the ratio of a building's total floor area to the building's footprint. Table 2.2 shows that, with the exception of Milwaukee housing, the low-income housing stock floor area does not vary much between cities—only from 1514 ft^2 to 1699 ft^2. But because the number of floors—or stories—vary, the FAR must also vary: houses with fewer floors but the same floor area must have a lower FAR, and therefore more floor area per story. The FAR was relevant to this thesis because of the implications on attic size. Houses in Orlando, where most housing is single-story, will on average have larger attics than houses in Detroit, where most low-income houses have three floors. The likely implications are that homes in Orlando would lose a greater percentage of their space conditioning through uninsulated attics than houses in Detroit would, and it would likely cost more to insulate attic in Orlando than Detroit because larger attics require more insulation material and labor.

Table 2.2. Building Characteristic Summary of Low-Income Housing Stock by SMSA.

Parameter		Orlando	Los Angeles-Long Beach	Seattle	Philadelphia	Detroit	Milwaukee
Census region		South	West	West	Northeast	Midwest	Midwest
Region representativeness rank		6 of 48	27 of 30	23 of 30	11 of 33	8 of 34	17 of 34
Climate zone		Hot	Mild	Cool	Cool	Cold	Coldest
HDD65 (1971-2000 average)		580	1274	4615	4759	6422	7087
CDD65 (1971-2000 average)		3428	679	192	1235	736	616
Sample size		4	14	4	11	13	8
Number of households		9225	41597	13798	37398	41789	24651
Average floor area (ft^2)		1657	1688	1669	1562	1514	1945
House type	**Attached**	0%	17%	0%	57%	0%	0%
	Detached	100%	83%	100%	43%	100%	100%
Foundation type	**Basement**	0%	0%	81%	92%	93%	100%
	Crawlspace	0%	35%	0%	8%	7%	0%
	Concrete slab	100%	65%	19%	0%	0%	0%
Number of floors	**1**	74%	69%	0%	0%	0%	0%
	2	26%	24%	100%	36%	15%	37%
	3	0%	0%	0%	64%	85%	63%
	4	0%	7%	0%	0%	0%	0%
Vintage	**< 1920**	0%	0%	0%	35%	15%	42%
	1920-1939	0%	0%	57%	14%	40%	0%
	1940-1959	26%	50%	24%	30%	41%	45%
	1960-1979	74%	27%	19%	21%	0%	13%
	>= 1980	0%	23%	0%	0%	4%	0%
Heating equipment	**Central gas furnace**	0%	37%	81%	42%	74%	72%
	Room gas furnace	0%	43%	0%	10%	8%	0%
	Gas burner	0%	0%	0%	19%	18%	28%
	Oil burner	0%	0%	0%	29%	0%	0%
	Electric furnace	100%	13%	19%	0%	0%	0%
	Electric baseboard heater	0%	8%	0%	0%	0%	0%
Air conditioning	**Room A/C**	0%	0%	24%	34%	36%	28%
	Central A/C	100%	44%	0%	35%	11%	59%
	No A/C	0%	56%	76%	31%	54%	13%

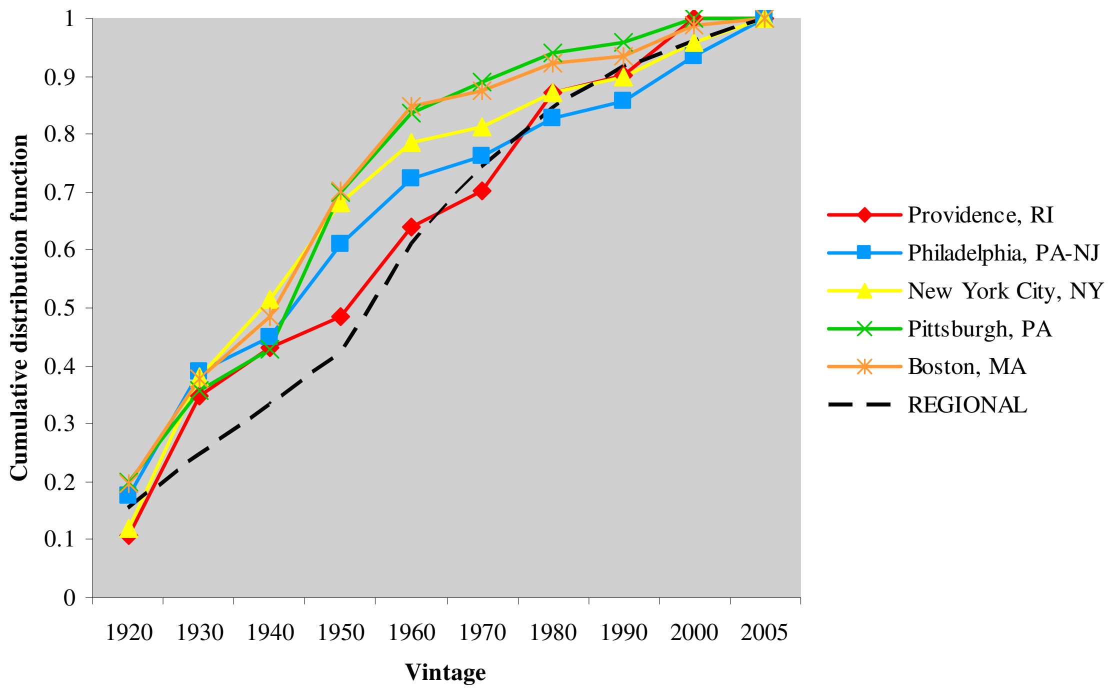

Figure 2.3. Cumulative Distribution Function for Urban Housing Stock Vintage in the Northeast.

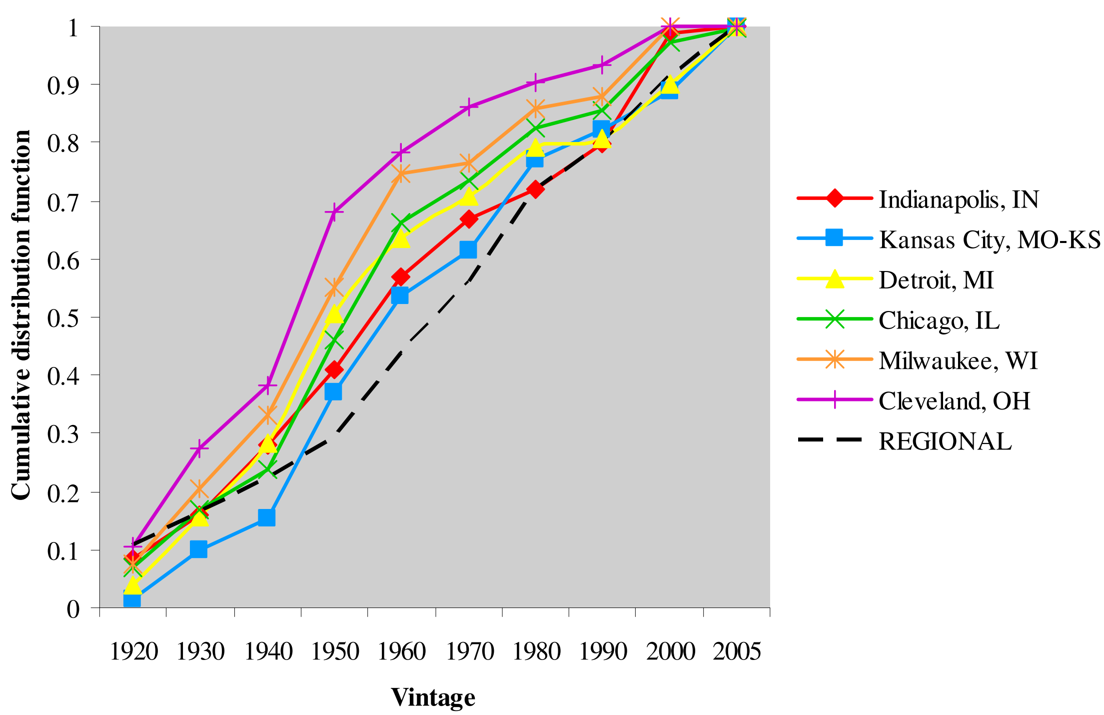

Figure 2.4. Cumulative Distribution Function for Urban Housing Stock Vintage in the Midwest.

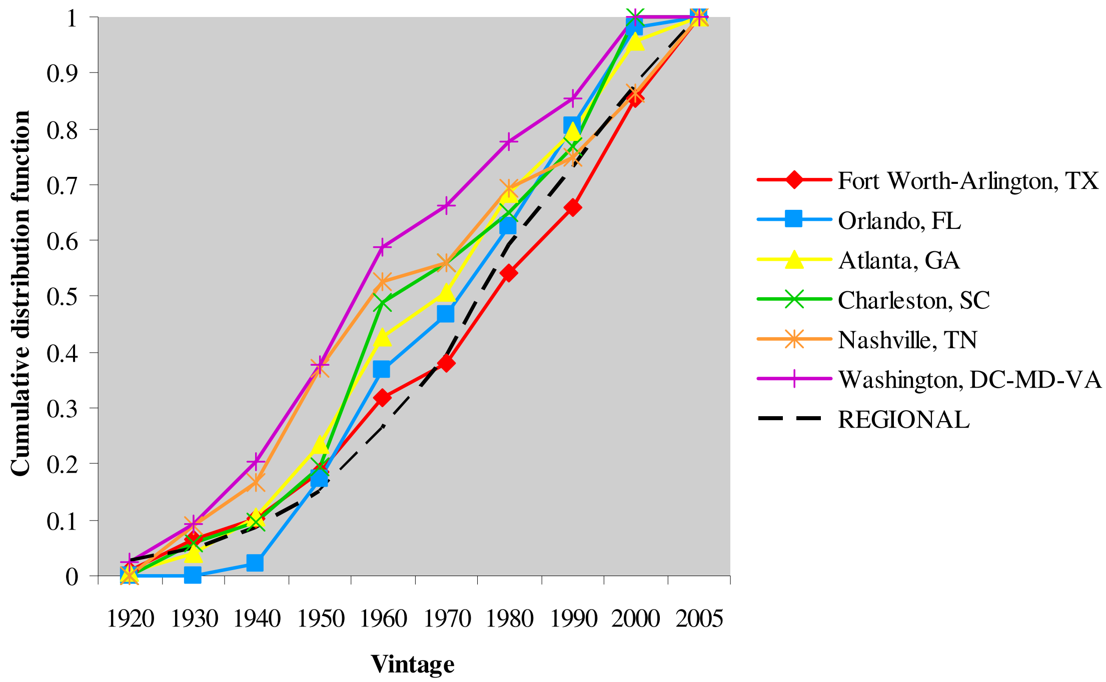

Figure 2.5. Cumulative Distribution Function for Urban Housing Stock Vintage in the South.

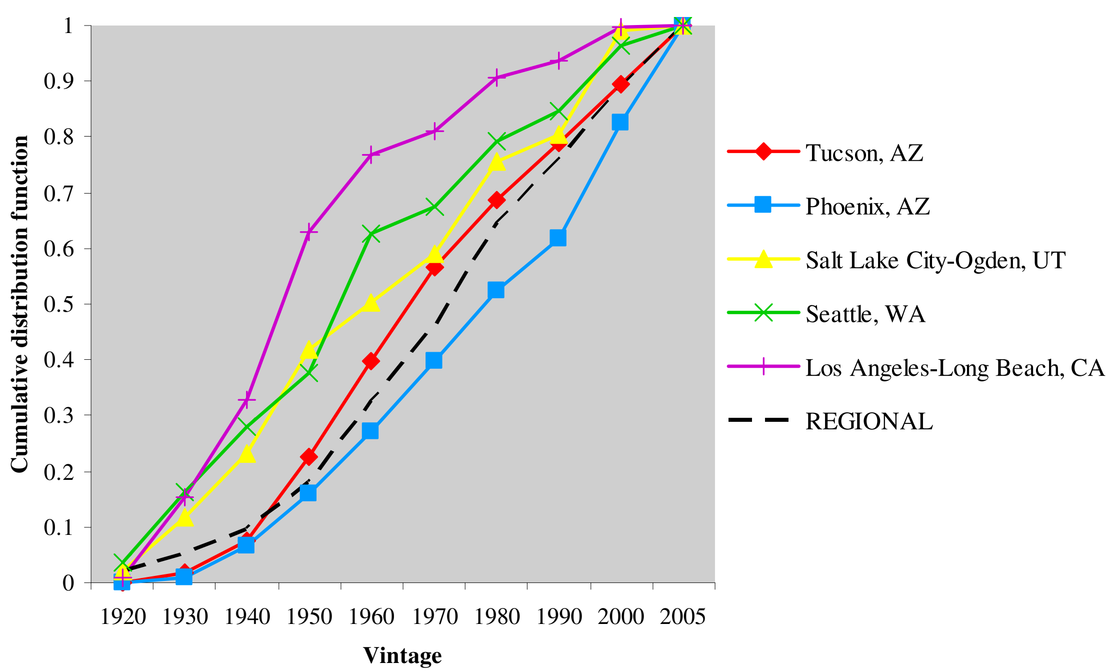

Figure 2.6. Cumulative Distribution Function for Urban Housing Stock Vintage in the West.

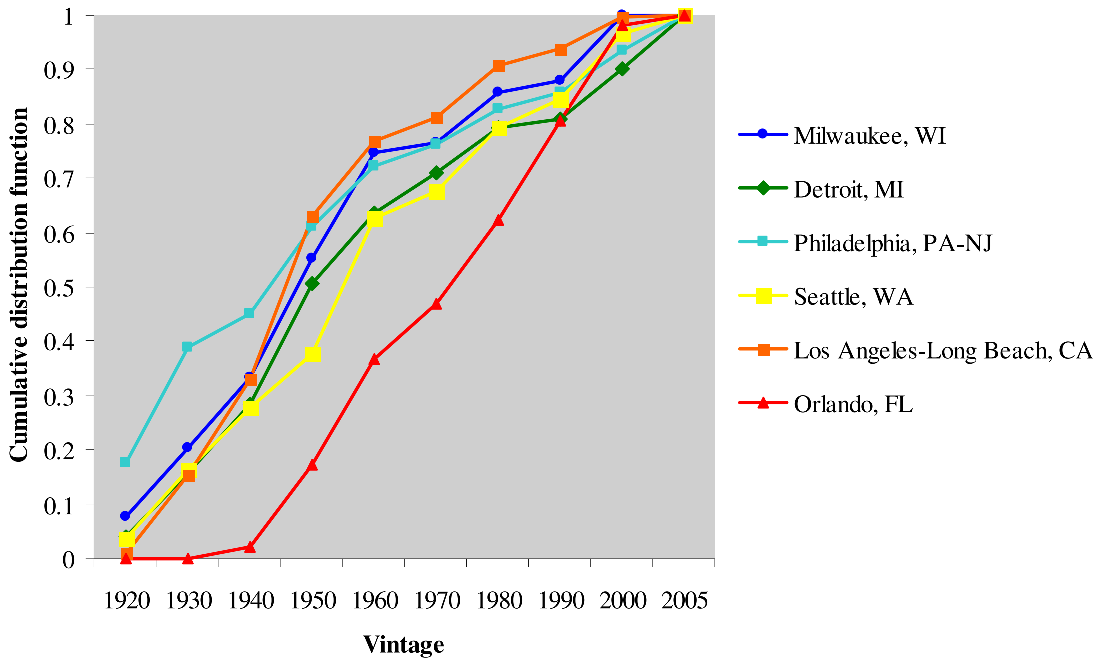

Figure 2.7. Cumulative Distribution Function for Urban Housing Stock Vintage of the Selected Metropolitan Areas.

2.3.3 Value of energy savings

To quantify the value of the energy saved by retrofitting treatments, we found information that allows us to convert from energy savings to both monetary savings and carbon savings.

The direct monetary value of energy savings is the avoided cost of energy consumption, and is therefore equal to the energy saved multiplied by the energy price. HES's default energy prices are the EIA's reported average statewide energy prices from 2004 for natural gas and electricity and from 2000 for fuel oil (Mills 2008). Figure 2.8 shows how energy prices for each fuel vary across the states that encompass the cities we selected to model. We decided to use these energy prices rather than more recent prices because the global economic downturn has caused energy prices to be uncharacteristically low. In contrast, as seen in Figure 1.1 (pg. 6), national average energy prices from 2004 for natural gas and electricity are representative of EIA-projected energy prices in the coming years. If the price of fuel oil closely follows the price of crude oil, however, these EIA projections indicate that fuel oil prices from 2000 are much below prices likely in the near future.

The effectiveness of a retrofitting treatment to reduce carbon emissions depends on the carbon intensity of the energy saved. In conventional space conditioning systems, there are three primary energy sources: natural gas, fuel oil, and electricity. Carbon intensity is a chemical property of the fuel used and the physical process used to convert the fuel into energy. In the cases of natural gas and fuel oil, carbon intensity is a chemical property that will vary slightly depending on the quality of the fuel, but it is generally constant. The carbon intensity of electricity, however, varies significantly depending on the process that produced it. Wind, solar, and hydropower are all electricity-generating processes with negligible carbon emissions, but coal-fired power plants generally create electricity in a very carbon intensive way, in part because coal has the highest carbon content of any fossil fuel, and in part because coal-fired power plants are frequently not very efficient: the national average thermal efficiency of coal-fired power plants in 1999 was 33.5% (US DOE and EPA 2000) compared to efficiencies of roughly 40% and 60% for simple and combined cycle gas turbines, respectively (Unger and Herzog 1998). The power generation equipment available in each state depends on many factors, including fuel availability and state policy and regulations, and therefore the carbon intensity of electricity can vary significantly among states. Figure 2.9 illustrates the energy consumption mix for several states, including those states to which the cities analyzed here belong. West Virginia and New Jersey appear in the figures for points of reference. Figure 2.10 shows how each state's energy mix translates into carbon emissions per MMBTU of electricity.

2.3.4 Retrofit costs

In addition to estimating the energy saved from a treatment scenario, HES also estimates the cost of treatment, taking into account not only the cost of purchasing treatment materials but also the cost of installation. HES takes its cost estimates from the California Public Utilities Commission's Database of Energy Efficient Resources (DEER) (Horman 2010). DEER provides estimates of energy savings, treatment costs, and effective useful life for a large variety of residential energy-efficient technologies and measures. HES does not vary costs by location, an assumption justified by a 1990 evaluation of WAP programs that reported installation costs do not vary much between climate regions (Brown and Berry 1993). Of the three treatments examined—programmable thermostat, blower-door guided air-sealing and attic insulation—HES estimates that attic insulation is the only treatment with a cost that varies by house. Attic insulation depends on size of the attic. Installing insulation in larger attics is not only more expensive because it requires more insulation materials, but also because of the greater labor requirement. Unfortunately, there are not many evaluations of Wx programs, and of those that exist, few of them list the cost of each measure. To evaluate the validity of these cost estimates, we examined several other Wx impact evaluations that show the DEER estimated costs are relatively representative of reality. Table 2.3 summarizes these findings, showing that HES's cost estimates for programmable thermostats and blower-door guided air sealing are conservative compared to observed costs. Observed costs also show a wide range of attic insulation costs, roughly consistent with HES estimates.

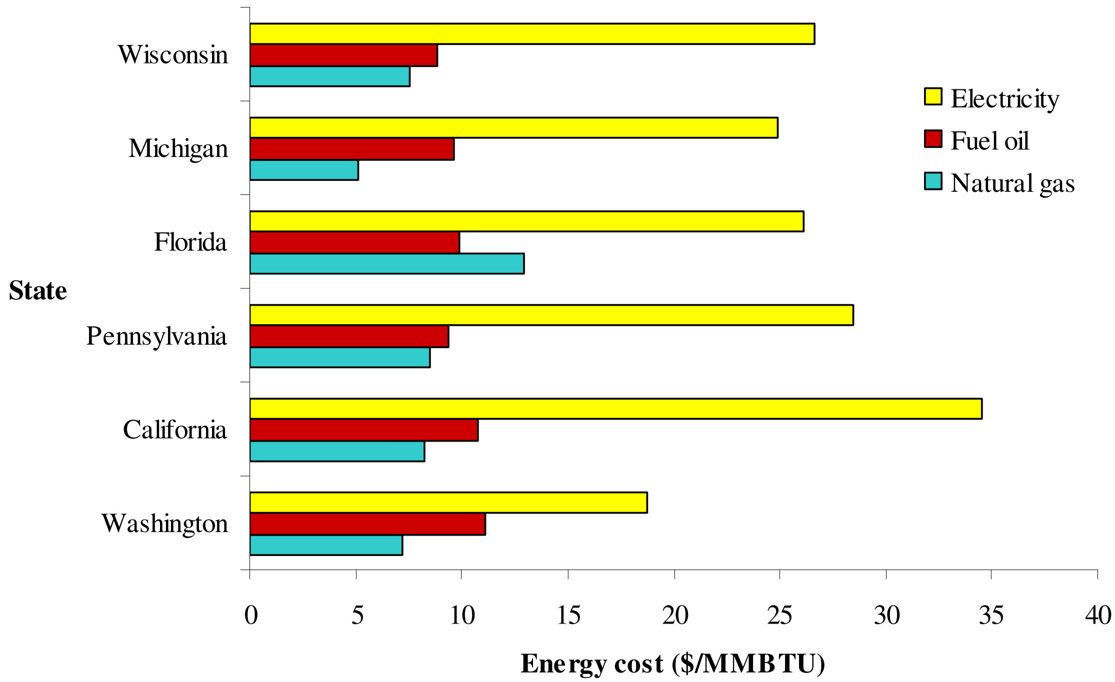

Figure 2.8. Energy Costs for Selected States. ***Data source:*** **(Mills 2008).**

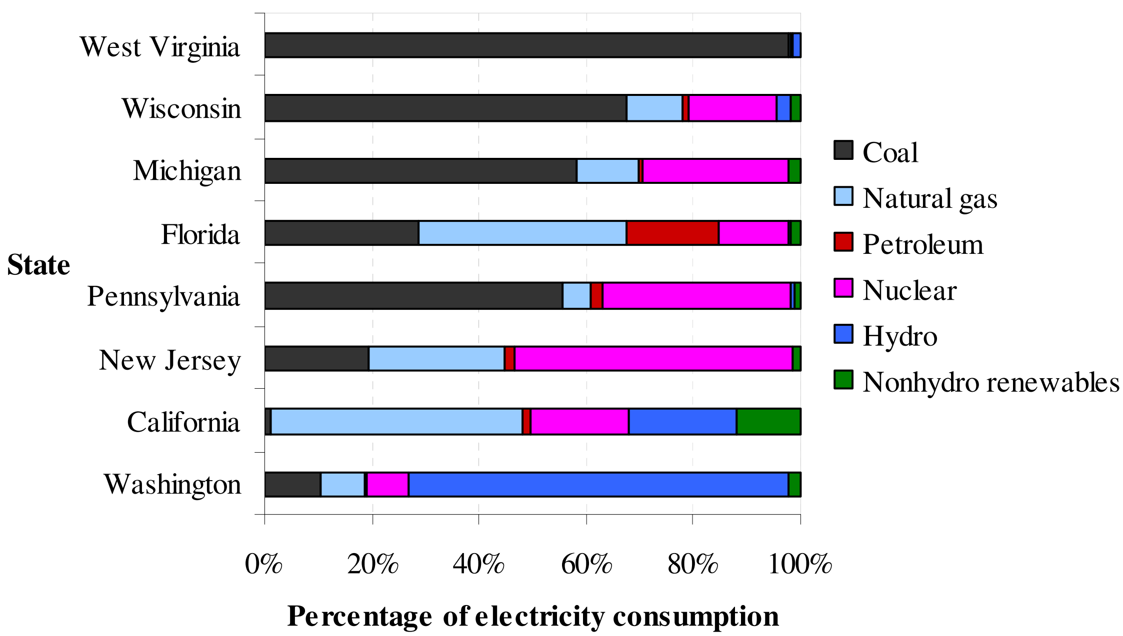

Figure 2.9. Electricity Consumption by Fuel for Selected States. ***Data source:*** **(EPA 2010).**

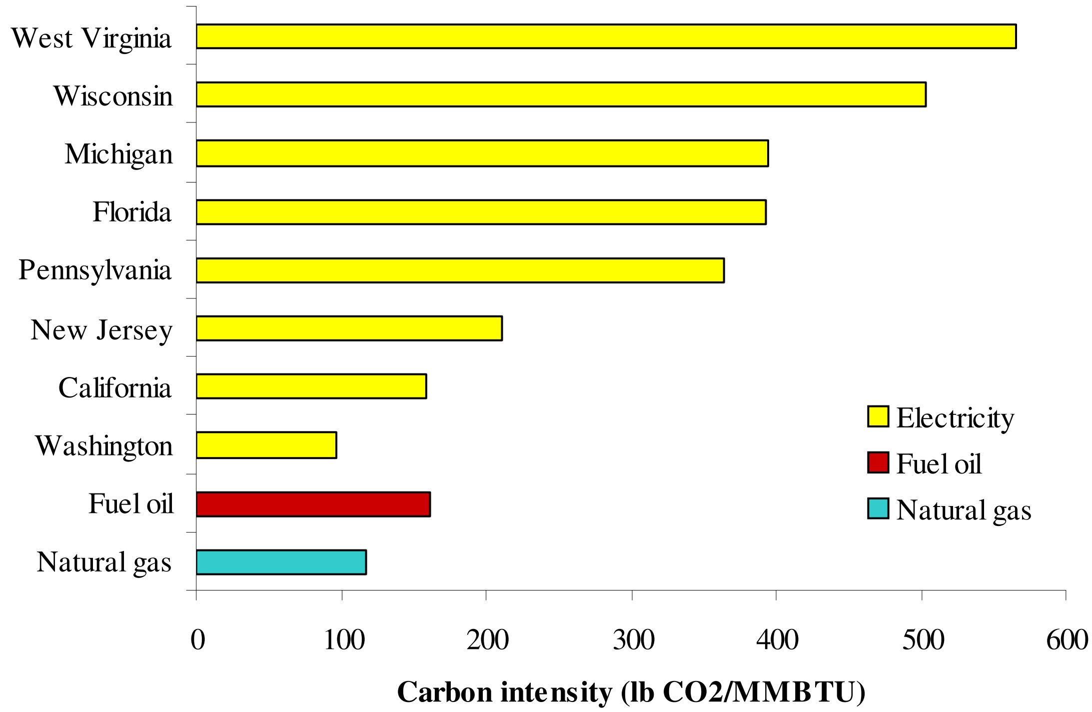

Figure 2.10. Carbon Intensity of Retail Electricity for Selected States, Fuel Oil, and Natural Gas. ***Data source:*** **(EIA 2009c; EPA 2010).**

Table 2.3. Summary of retrofitting costs reported for different Wx programs.
**** indicates that cost is for roof insulation***

Location	Thermostat	Attic insulation	Blower-door guided air sealing	Study
Pennsylvania	38-48	209-288	153	(M. Blasnik & Associates 2008)
	n/a	882	288	(APPRISE 2006)
	0	1659	228	(M. Blasnik & Associates 2007)
Ohio	n/a	610-980	209	(Khawaja et al. 2006)
Colorado	n/a	300	n/a	(M. Blasnik & Associates 2009)
	n/a	300	n/a	(M. Blasnik & Associates 2006)
New Jersey	57	583	286	(M. Blasnik & Associates 2004)
Mean across programs	**36**	**657**	**247**	
HES estimate	**70**	**172-1547**	**400**	

3 RESULTS AND DISCUSSION

This chapter presents and discusses our project's main results. The first section evaluates how accurately our model emulates average energy savings possible through retrofitting low-income houses. The second section presents and contrasts the our model estimates of the cost-effectiveness of three common retrofitting treatments in the low income housing stock of six different metropolitan areas spanning each census region and climate zone.

3.1 *Model evaluation*

As discussed in Chapter 2, our proposed model consisted of driving the Home Energy Saver with American Housing Survey data in order to predict energy savings for low-income housing stock. To test the accuracy of this approach, we compared modeled energy savings with actual energy savings measured by the Philadelphia Gas Works' Conservation Works Program (CWP), a weatherization assistance program for low-income households in Philadelphia, PA (M. Blasnik & Associates 2008). Specifically, we analyzed the energy savings achieved by the CWP contractor Honeywell, and used our model to emulate their achieved results. Emulating Honeywell's results included first analyzing how accurately our model estimated pre-retrofit energy consumption and secondly analyzing how accurately our model estimated the effectiveness of different retrofitting treatments.

3.1.1 Pre-weatherization energy consumption

We first examined how well our model simulated pre-retrofit energy consumption for space conditioning. The information available in the CWP evaluation limited this analysis in two respects. First, the CWP evaluation includes information on natural gas pre- and post- weatherization consumption, which provides us information about space heating energy, but the evaluation does not include information about the pre- or post-weatherization electricity consumption, so we have no information about the space cooling energy demand or how it changes after weatherization. The CWP evaluation use energy bills to determine natural gas consumption, but because energy bills do not itemize consumption by end-use, we could not precisely isolate natural gas consumption for the space heating end-use. Because we could not compare observed to modeled space heating energy consumption, we instead chose to compare observed to modeled total natural gas consumption. HES provides individual energy end-use estimates for the two major natural gas end-uses—space heating and water heating—and we calculated the total natural gas consumption as the sum of the these two end-uses. Figure 3.1 shows that our approach models the average natural gas consumption reasonably well: the mean observed natural gas consumption was 126.4 ± 1.5 MMBTU, and the mean modeled natural gas consumption was 132.6 ± 24.3 MMBTU. This modeled consumption is certainly within range of the observed mean. In previous years' evaluations, the average household pre-weatherization natural gas consumption ranged from 122.0 MMBTU to 187.3 MMBTU (M. Blasnik & Associates 2008 p. 4).

3.1.2 Energy savings

We considered natural gas consumption to be a good proxy for space heating energy consumption, so establishing that the model accurately emulates natural gas consumption suggests HES accurately describes thermal exchanges and heating loads when driven with AHS data. After validating the model's ability to emulate energy consumption, we analyzed how well the model emulated post-retrofit energy savings. Figure 3.2 shows how average retrofit effectiveness compares between observed and modeled results. The CWP evaluation indicates that gas savings range from a minimum of 5% for air sealing and programmable thermostat installation to a maximum of 13% for all of the treatments—programmable thermostats, attic insulation and air sealing. Compared to the observed savings, the model fairly accurately predicted savings when the only treatment was a programmable thermostat (5.4% observed vs. 4.5% modeled) or attic insulation (12.0% observed vs. 10.7% modeled). For each of the other treatment scenarios, the modeled energy savings were much more inaccurate (e.g. 6.0% observed vs. 13.3% modeled for the combination of air sealing and thermostat). As discussed in Subsection 1.2.2, discrepancies between observed and modeled energy savings fall under the category of shortfall and take-back. Take-back, a behavioral change towards consuming more energy, is possible in all scenarios, and addressing it is beyond the scope of our research. We did, however, identify two likely sources of technical estimation, or shortfall. These sources were inaccurate leakage modeling and unrealistic modeling of combined effects of multiple treatments.

Perhaps the most obvious error apparent from Figure 3.2 is that the model significantly overestimates energy savings for treatments scenarios that include air sealing. As discussed in Subsection 2.3.1, the modeled 25% leakage reduction expected from air sealing is comparable to leakage reductions observed from air sealing in other retrofitting programs in Pennsylvania. If we are willing to accept that the 25% leakage reduction represents the actual leakage reductions Honeywell achieved, then the model overestimated either pre-retrofit leakage, energy losses due to leakage, or both. It is also possible that improper air sealing resulted in the lower than expected energy savings. An impact evaluation of the Ohio Weatherization Assistance Program identified improper or inadequate air sealing as the most frequent source of lower-than-expected energy savings (Khawaja et al. 2006 p. 53). This evaluation found that inadequate air sealing typically around the chimney, plumbing bypasses, wall tops, windows and kneewall bottoms resulted in 30% less reduction in leakage than expected.

The second error Figure 3.2 suggests is that the model does not accurately estimate savings for combination treatment scenarios—that is, scenarios that consist of more than one treatment. The interaction between different treatments is complicated, especially those treatments which address different types of energy losses, such as air sealing—which addresses convective losses—and insulation, which reduces predominantly conductive losses. Indeed, these complicated relationships are significant contributors to the difficulty of accurate building energy modeling, and our results lead us to believe our approach insufficiently models them.

While modeling these complicated relationships is certainly a source of uncertainty, the largest discrepancies between observed and modeled energy savings arose when the treatment scenarios included air sealing. The only treatment scenario not to include air sealing—the scenario with attic insulation and thermostats installed—features a discrepancy that is relatively small (11.2% observed vs. 14.8% modeled) compared to the other combination treatment scenarios (e.g. 10.1% observed vs. 18.6% modeled for the combination of attic insulation and air sealing). This relationship may suggest that while the model may not accurately calculate the interaction between individual treatments, this shortcoming may be exaggerated in Figure 3.2, in which more than half of the treatment scenarios include air sealing, which, as we discussed above, was a treatment vastly overestimated.

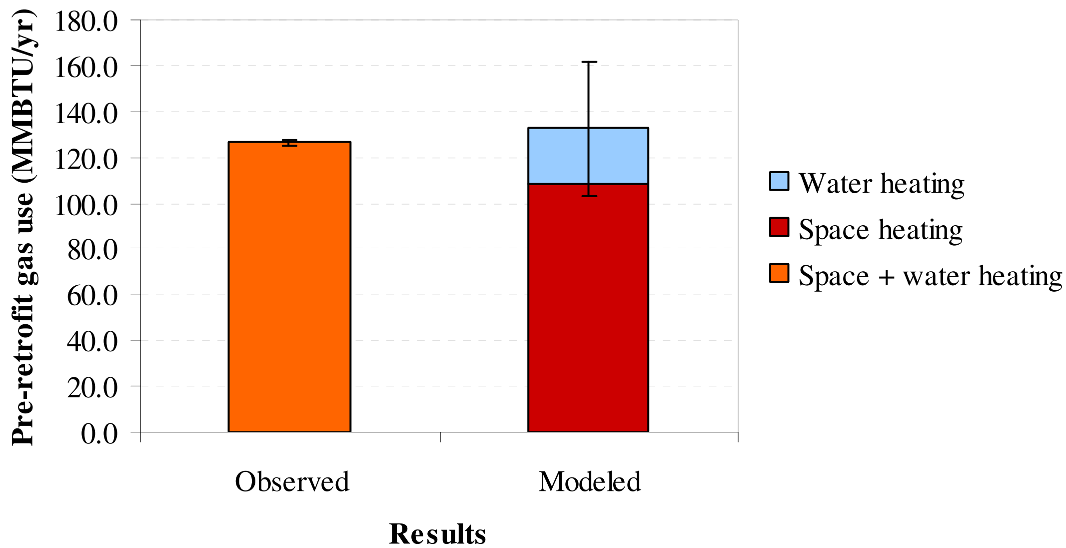

Figure 3.1. Average Observed and Modeled Pre-retrofit Natural Gas Use for Low-income Homes in Philadelphia. ***The values inside each column indicate column height Error bars indicate a 90% confidence interval.***

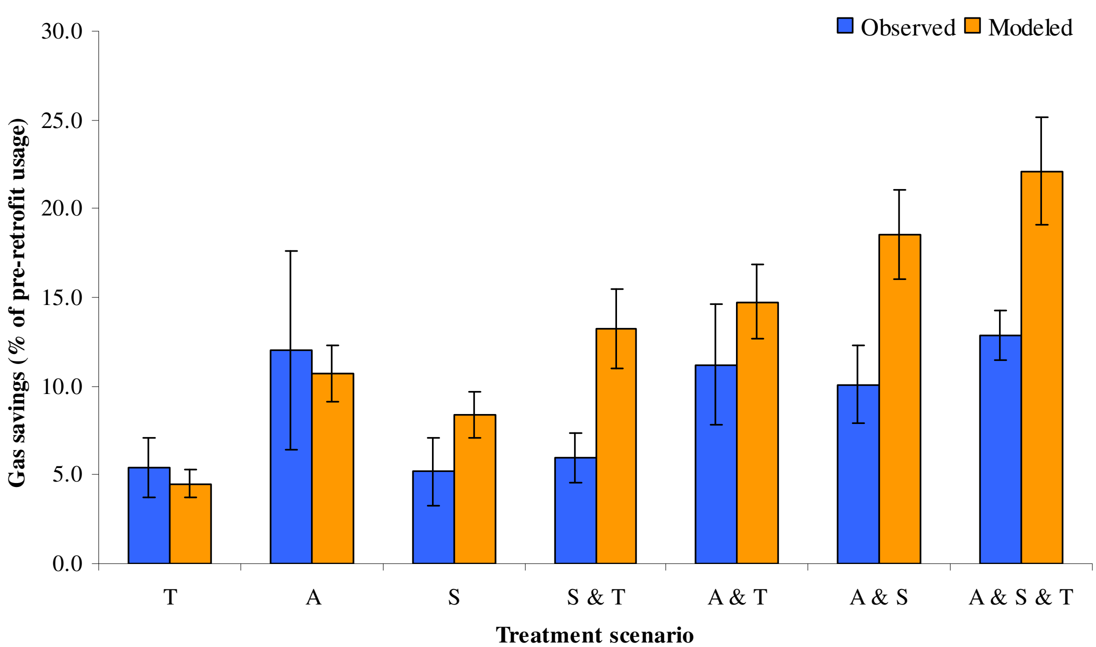

Figure 3.2. Observed and Modeled Energy Savings for Low-income Housing in Philadelphia. ***Savings are relative to pre-retrofit gas usage. The values inside each column indicate column height. Error bars indicate a 90% confidence interval.***

3.2 *CITY ANALYSIS*

This section presents and discusses the results of our modeling analysis of low-income housing stock in Milwaukee, Detroit, Philadelphia, Seattle, Los Angeles-Long Beach and Orlando.

3.2.1 Pre-weatherization energy consumption

As discussed in Subsection 2.3.2, for the purposes of analyzing the cost-effectiveness of retrofit treatments varied for different regions, we modeled the energy use and energy savings for low-income urban housing stock in six different metropolitan areas: Milwaukee, Detroit, Philadelphia, Seattle, Los-Angeles-Long Beach, and Orlando. Figure 3.3 shows the modeled average household space conditioning energy consumption for each of the six cities we examined. Figure 3.3 also displays the heating and cooling degree days, from which we can see that that energy consumption is generally driven by heating demand, measured by heating degree day (HDD). This trend confirms our expectations that the housing stock in colder climates consumes more energy than the housing stock in warmer climates. Among the cities we analyzed, Orlando is the only city that does not follow this trend. Despite the fact that Orlando has the fewest HDDs of any of the cities we modeled, average energy consumption for space conditioning is higher in Orlando than in Los Angeles, a city with more than twice as many HDDs than Orlando. This anomaly exists because of the difference between the two cities' space cooling loads. Orlando has five times as many cooling degree days as Los Angeles, and space cooling constitutes roughly half its space conditioning loads (Figure 3.4), meaning the difference in cooling demands greatly exceeds the difference in the two cities' heating demand. Additionally though less significantly, while all of the Orlando sample has air conditioning, only 44% of the Los Angeles sample had any air conditioning, making space cooling's contribution to Los Angeles' energy consumption even smaller than it would be if 100% of the housing stock had air conditioning.

Using the energy conversion methods described in Subsection 2.3.3, we calculated the average carbon emissions associated with space conditioning. Figure 3.5 shows the relationship between energy consumption and carbon emissions for the six cities we modeled. As expected, we see a general trend of carbon increasing with energy consumption. Orlando, however, is again the exception. Orlando's carbon footprint is disproportionately large relative to its energy consumption because the energy mix for space conditioning is entirely electricity, while in every other city we examined, natural gas was the predominant fuel and source of the majority of space conditioning-related carbon emissions (Figure 3.6). This difference in fuel source is significant as Florida's electricity is among the most carbon-intensive we examined and is more than three times as carbon-intensive as natural gas (Figure 2.9).

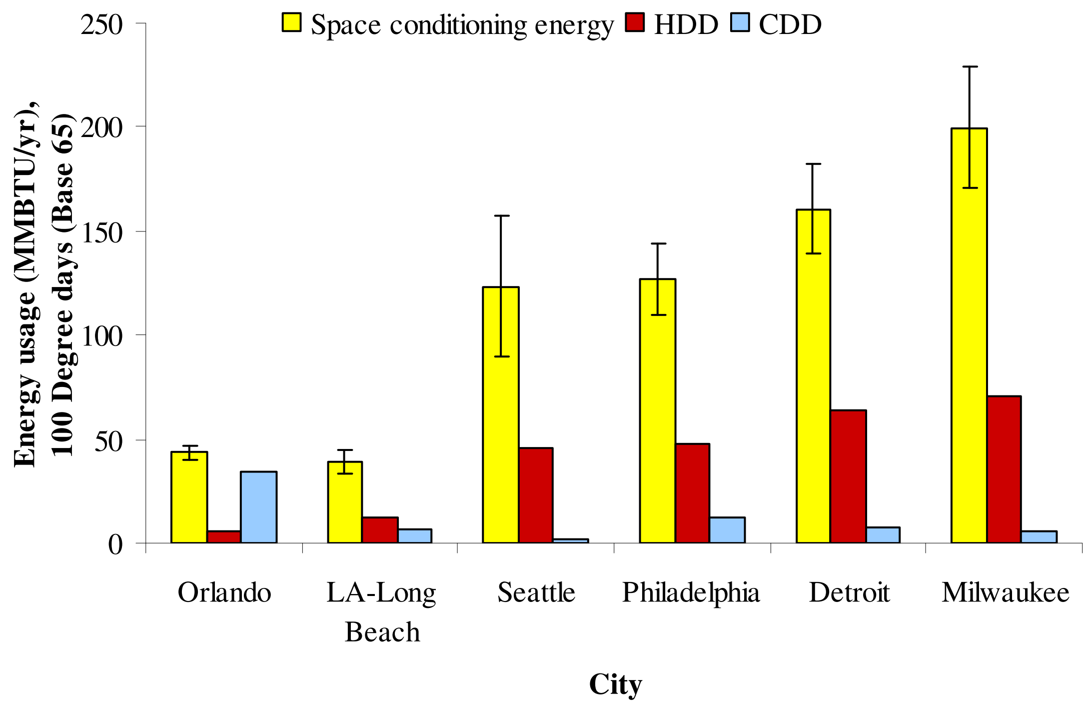

Figure 3.3. Average Space Conditioning End-use Energy Consumption in Low-income Houses for Selected Cities with Heating and Cooling Degree Days (HDD and CDD, respectively). ***Error bars represent a 90% confidence interval.***

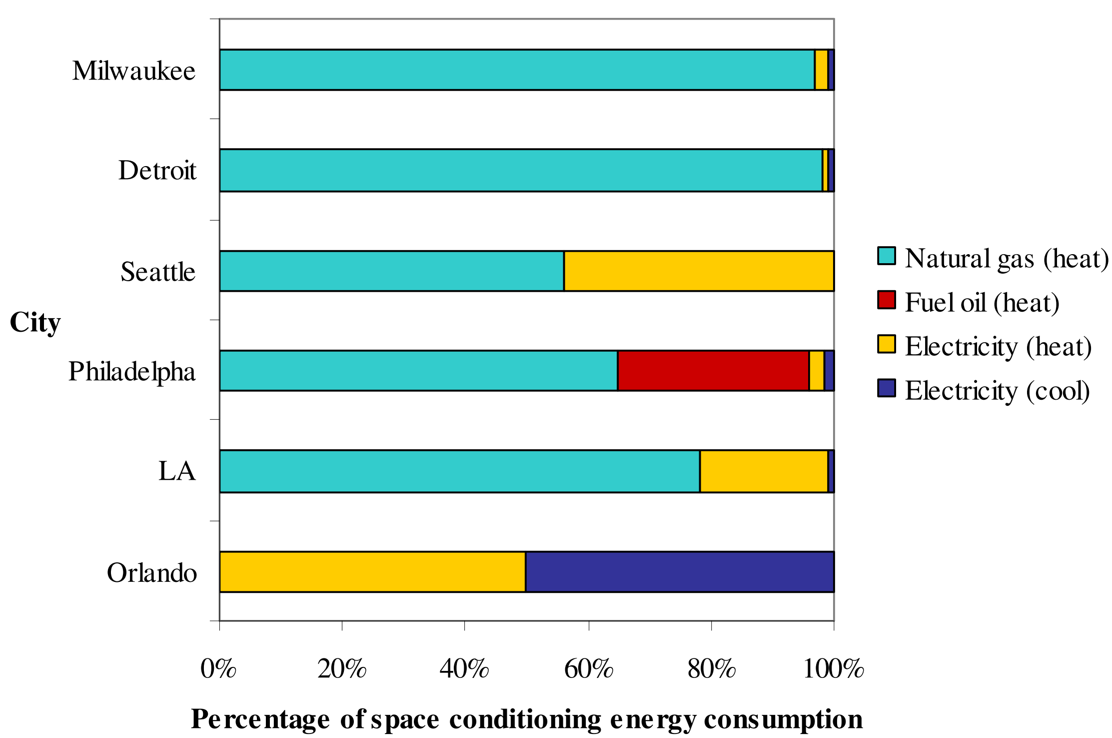

Figure 3.4. Energy Mix for Space Conditioning in Low-income Houses by City.

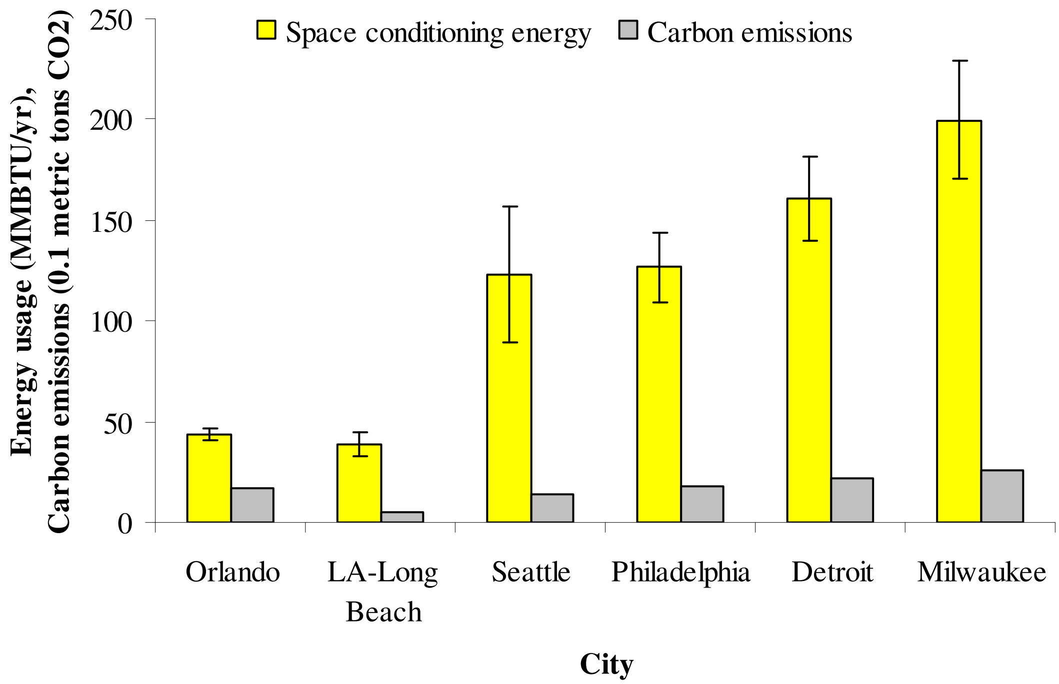

Figure 3.5. Average Annual End-use Energy Consumption and Carbon Emissions for Space Conditioning in Low-income Houses for Selected Cities. ***Error bars represent a 90% confidence interval.***

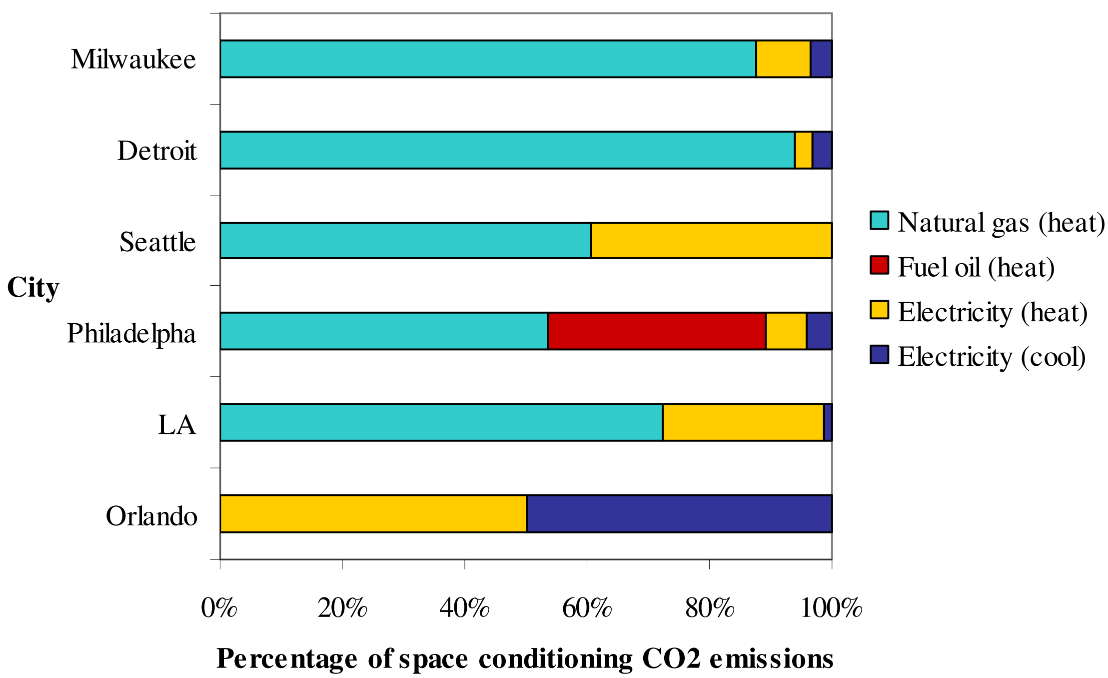

Figure 3.6. Carbon Dioxide Emissions Associated with Energy Mix for Space Conditioning in Low-income Houses by City.

3.2.2 Energy savings

After examining what the model describes as the current status of space conditioning in these cities, we then analyzed the projected cost-effectiveness of the six treatment scenarios. Figure 3.7 through Figure 3.17 [xii] illustrate the results of our cost-effectiveness analysis, described here in a step-by-step process. Figure 3.7 displays the average annual energy savings for a low-income house in each of the cities and for each of the treatment scenarios we considered. This figure shows that, generally, energy savings from retrofitting treatments increase with colder climates. As observed and discussed earlier, houses in cities in colder climates generally consume more energy for space conditioning than cities in warmer climates, so we would expect that there is a greater potential for energy savings in houses that initially consume more energy for space conditioning. Somewhat unexpectedly, this figure shows that inter-city savings do not remain constant or proportional for different treatment scenarios. For example, attic insulation saves the average Milwaukee house about twice as much energy as it saves the average Orlando house, but air sealing saves the average Milwaukee house about ten times as much energy as the average Orlando house. Such a variation may be unrealistic and attributable to a modeling error, but our model validation in Section 3.1 suggests the model is capable of estimating energy consumption and savings within reasonable accuracy. The modeled geographic differences in energy consumption are instead likely due to differences in climate, housing stock, and space conditioning equipment. These results, therefore, are an indication that our approach could be useful for determining how the effectiveness of treatments vary geographically.

[xii] Refer to Table 2.1 on page 33 for a key describing of the treatment scenario symbols

In determining the cost-effectiveness of energy-saving projects, it is essential to consider the value of the avoided energy consumption—that is, the value of energy savings. As mentioned in Chapter 1, there are many benefits of energy conservation unrelated to energy cost savings, such as job creation, reduced air pollution, and reduced dependence on foreign energy sources. Many studies have researched and quantified these indirect benefits, but these estimates vary widely from study-to-study, so our analysis is based only on the direct, energy cost-related benefits. The value of the energy savings, therefore, is equal to the energy savings multiplied by energy cost. Figure 3.8 shows the value of the annual energy savings resulting from each treatment scenario. As described in Subsection 2.3.3, energy prices vary by location; for our analysis, we assumed each city's energy costs were equal to its average state energy prices [xiii].

After quantifying the benefits, the next step in calculating cost-effectiveness is to consider costs. Figure 3.9 shows how the cost of each treatment scenario varies for different cities. As described in Subsection 2.3.4, HES assumes a constant cost for thermostat installation and air-sealing, but the cost of attic insulation varies. The cost of attic installation is a function of material and labor costs, which in turn is a function of attic size. According to calculations based on HES estimates, average attic insulation installation costs are roughly equal in Philadelphia, Detroit and Milwaukee, but are significantly higher in Orlando, Los Angeles-Long Beach and Seattle. These variations in attic cost are because the housing stock in these cities has larger attics than do Philadelphia, Detroit, and Milwaukee and therefore require not only more insulating material but also more labor to install it.

[xiii] Refer to Figure 1.6 on page 18 to see how these prices vary for each state

Once the costs and benefits have been quantified, there are several different methods to weigh their values. One basic method is to calculate the simple payback period, which is the time required for the benefits of a project to equal or fully compensate for the costs without accounting for the time value of money. We calculated simple payback period as the cost of treatment scenario divided by the annual energy savings resulting from the treatment scenario. Figure 3.10 illustrates the simple payback period for each treatment scenario. It is, effectively, Figure 3.9 divided by Figure 3.8. The simple payback period is an indication of how profitable each treatment is in each city. While air sealing in Los Angeles-Long Beach has a ten year payback period, the same treatment has a three year payback period in Milwaukee. This means that over the ten year period it takes to recover the attic insulation investment in Los Angeles-Long Beach, we could say that the attic insulation in Milwaukee paid for itself roughly three times. From Figure 3.10, we can discern that for all treatment scenarios except for thermostat installation, Los Angeles-Long Beach has the longest payback of any city. By reexamining Figure 3.8 and Figure 3.9, we can see that these long payback periods result from comparatively low energy cost savings and comparatively high treatment costs.

The simple payback period is useful measure of profitability when the project consists of one upfront cost and then constant benefits over time, but it is limited by an inability to account for a varying series of future cash flows. For example, A more refined and realistic approach for determining a project's feasibility is to calculate its Net Present Value (NPV), which allows us incorporate future cash flows and discount those flows to account for time preferences and opportunity costs. Figure 3.11 shows the seven year Net Present Value (NPV) of different treatment scenarios. The NPV is calculated by summing all discounted cash flows within the prescribed payback period . Here, we selected a period of seven years, a typical payback period in the building industry. The NPV can be interpreted as the real financial value of a project, where a positive NPV indicates that a project is profitable and a negative NPV indicates that a project loses money. In our analysis, we discounted future money flows by 7%, the rate the federal government suggests applying to public projects because it approximates average private sector rate of returns (Office of Management and Budget 1992). Based on EIA projections, we also assumed that the price of electricity and natural gas would approximately remain constant relative to the 2004 costs we used in our analysis (EIA 2009e).

Figure 3.11 shows that except for Orlando and Los Angeles-Long Beach, every treatment scenario is profitable in each of the cities we modeled. For the Orlando housing stock, only air sealing is NPV-negative, but for the Los Angeles-Long Beach housing stock, attic insulation, air sealing, the combination of the two, and the combination of all three treatments are NPV-negative. The negative NPV for these scenarios indicates that the treatment options do not save enough energy to earn back the money invested in the treatment scenario. From Figure 3.11, we can see that installing thermostats is the only treatment that is NPV-positive for every city, and all of the other treatment scenarios are particularly profitable for Philadelphia and Milwaukee due to significant energy savings and relatively high energy prices.

The NPV as calculated above is useful for estimating a project's financial feasibility assuming that there are no other costs associated with energy consumption, such as an energy tax. To account for an energy tax, such as the so-called BTU tax

President Clinton proposed in 1993 (Greenhouse 1993), it is more appropriate to consider the NPV per unit energy saved over the project's lifetime. Any project that costs less than the tax rate per unit energy saved is profitable, while any project that costs more than the tax rate loses money. Figure 3.12 is an energy abatement cost graph, modeled after McKinsey & Co.'s greenhouse gas abatement curves that show the cost of abating greenhouse gases associated with different activities. Figure 3.12 shows the NPV of projected energy savings divided by the total energy saved over the payback period. We selected a 15 year payback period based on the expected lifetime of the thermostat, the shortest-lived of the treatments we considered (M. Blasnik & Associates 2008). Although we did discount energy cost savings to account for time preferences and opportunity costs, we did not discount future energy savings. Applying no discount to future energy savings means that the value of energy saved in the future is the same as the value energy saved in the present. This principle is not only logical, as there is no convincing reason to discount future energy savings, but it is also common practice: McKinsey & Co. used in their analyses. Figure 3.12 illustrates that most measures, except for air sealing and the combination of attic insulation and air sealing in Los Angeles-Long Beach actually saves money per MMBTU abated, meaning that each of them is a profitable energy-saving measure. Despite Orlando being among the lowest savers of end-use energy, because Orlando uses electricity for space conditioning, whereas each of the other cities uses mostly comparatively inexpensive natural gas, the high cost of electricity makes weatherization in Orlando among the most profitable modeled. Oppositely, weatherization in Detroit, where there is high energy savings potential but low energy prices, is among the less profitable modeled.

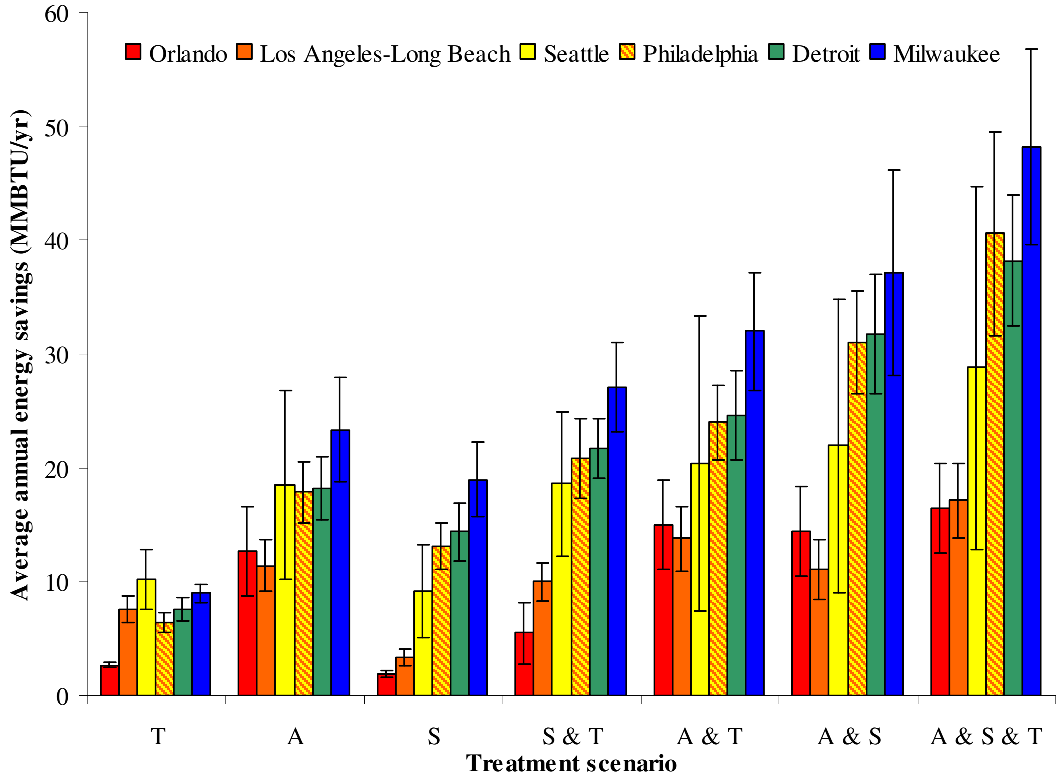

Figure 3.7. Average Annual Low-income Household End-use Energy Savings by City and Treatment Scenario. ***Error bars represent a 90% confidence interval.***

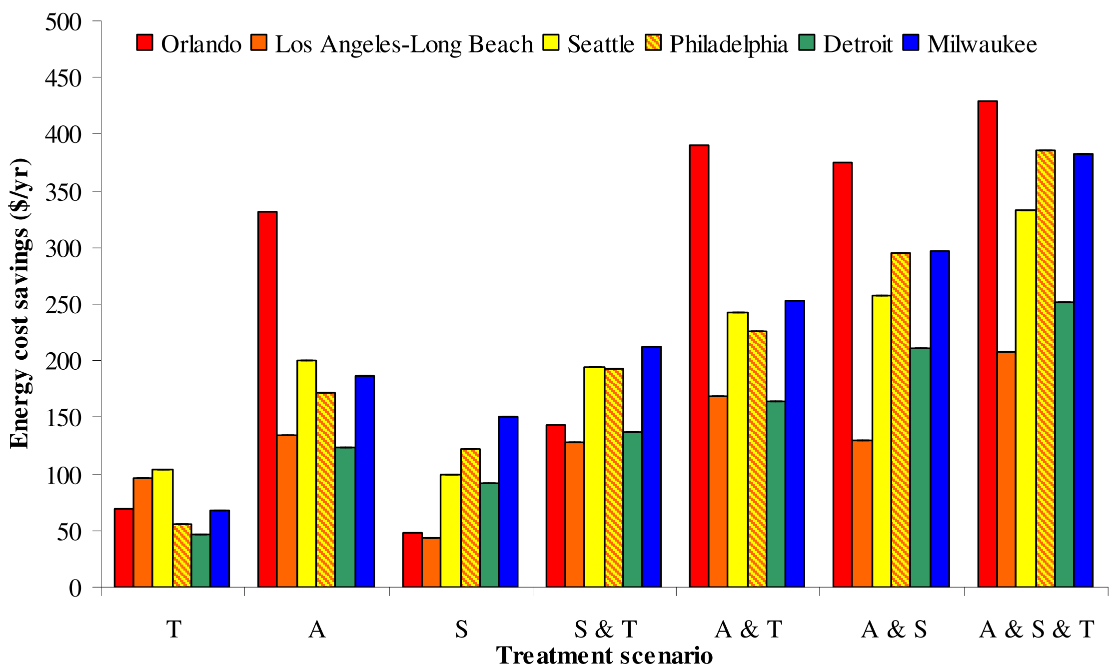

Figure 3.8. Average Low-income Household Annual End-use Energy Cost Savings by City and Treatment Scenario.

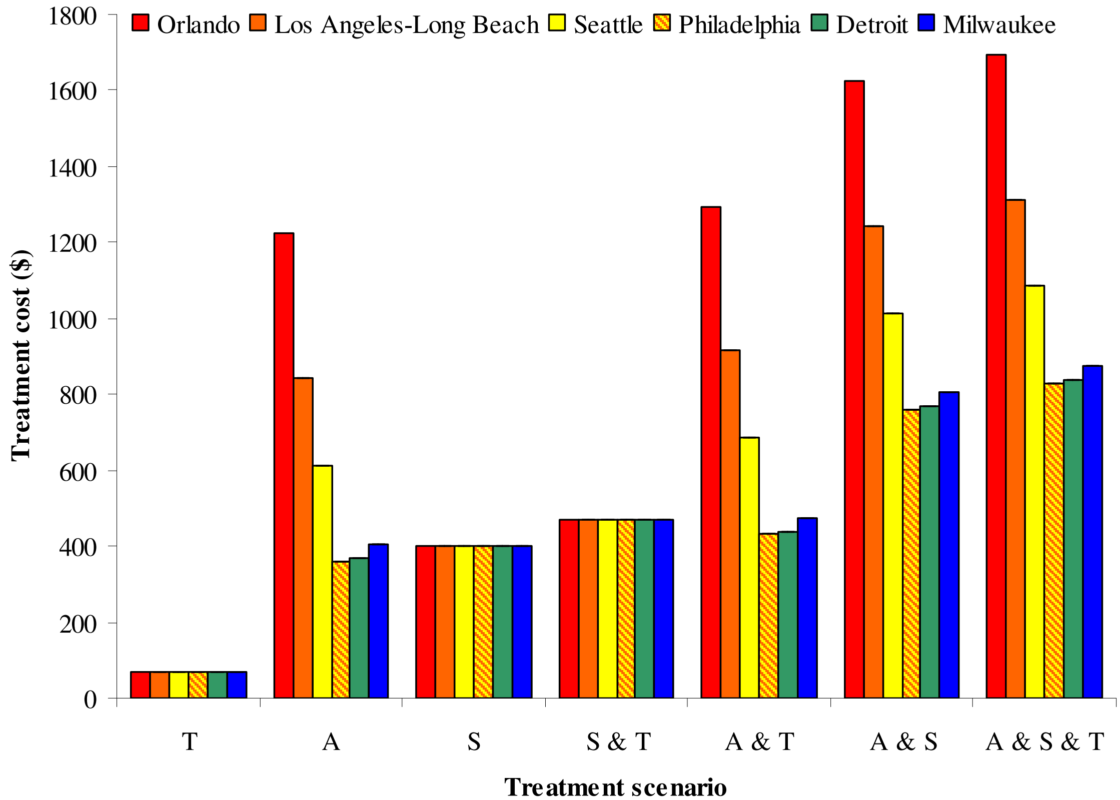

Figure 3.9. Average Cost of Weatherizing a Low-income House by City and Treatment Scenario.

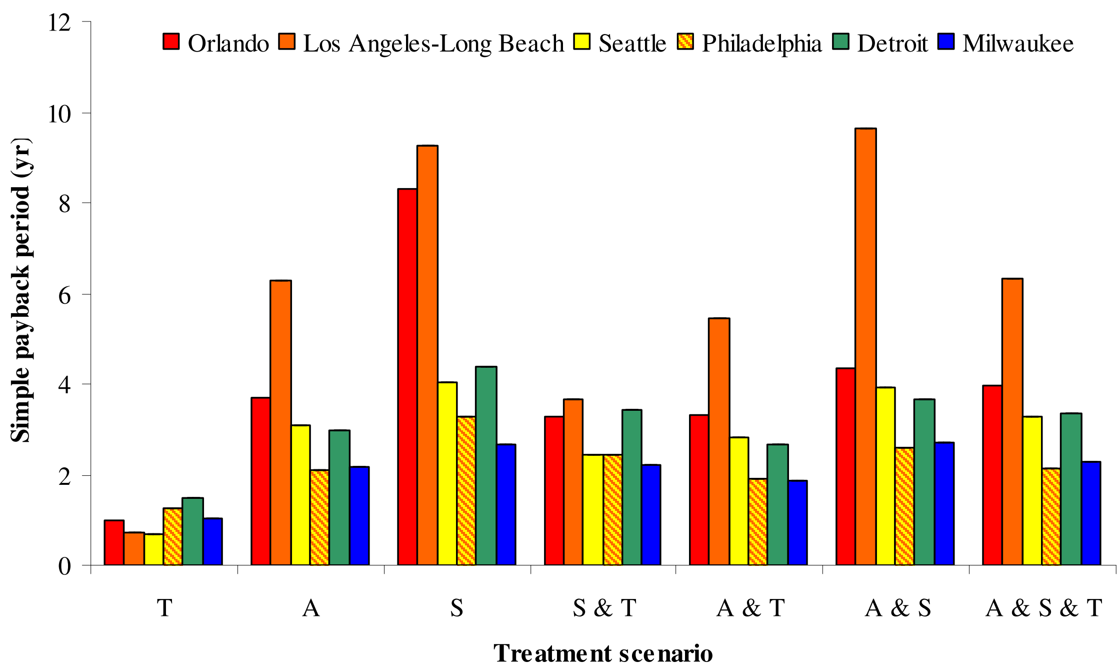

Figure 3.10 Average Simple Payback Period for Weatherizing a Low-income House by City and Treatment Scenario.

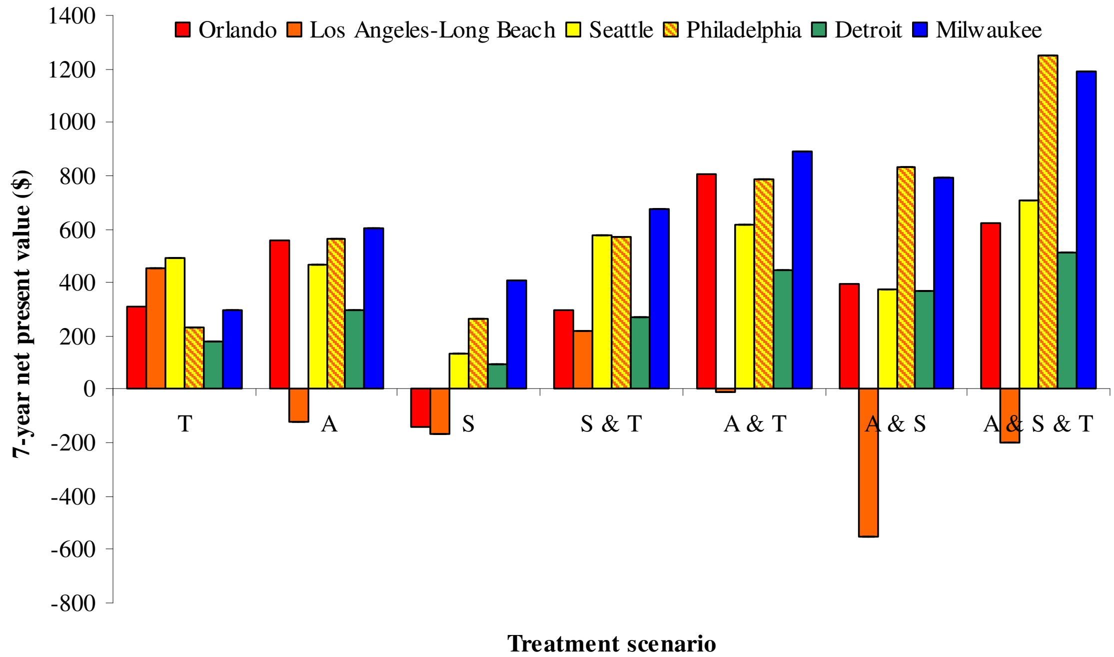

Figure 3.11. Average Net Present Value of Weatherizing a Low-income House by City and Treatment Scenario.

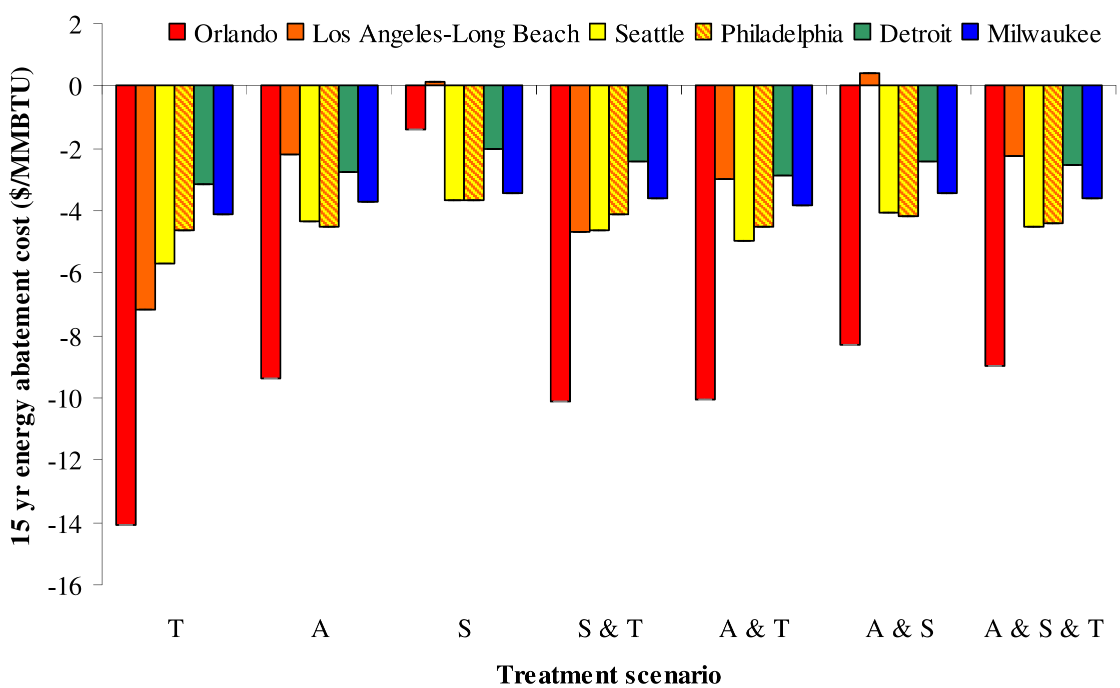

Figure 3.12. Average End-use Energy Abatement Cost for Weatherizing a Low-income House by City and Treatment Scenario.

3.2.3 Carbon savings

It is useful to estimate how the energy savings shown in Figure 3.7 translate into carbon abatement. As discussed in Chapter 1, scientists and policy-makers addressing climate change are interested in the carbon savings potential of energy reduction measures, such as weatherization. We calculated carbon saving by translating the energy savings and their associated energy mix into its associated CO_2 emissions. Figure 3.13 illustrates our carbon savings estimates. This graph in many ways looks similar to Figure 3.7, with colder climates generally saving more carbon than warmer climates, but noticeably Orlando, which was among the lowest energy savers, is among the highest carbon savers. As previously discussed, whereas all the other cities' housing stock rely on natural gas for most of its space conditioning energy, the Orlando housing stock uses electricity exclusively. As presented in Figure 2.10 (p. 47), Florida's electricity, which emits 393 lbs CO_2 per MMBTU (EPA 2010), is more than three times as carbon intensive as natural gas, which emits 117 lbs CO_2 per MMBTU (EIA 2009c).

There are a few different ways to consider measuring the carbon abatement cost-effectiveness of weatherization treatments. While a comprehensive, all-inclusive, NPV analysis is valuable to consider the full direct benefits of weatherization (as we do below), the cost of carbon abatement without counting the value of energy savings is a useful measure for weatherization funders (e.g. government agency, non-profit, or private company). In most, if not all instances of weatherization assistance, the residents—not the weatherization funder—reap the direct monetary value of any achieved energy savings. Without the monetary incentive of energy savings, the funder may instead be motivated to achieve the most cost-effectiveness carbon abatement. Figure 3.14 illustrates this cost-effectiveness by displaying the cost of each treatment scenario per ton of carbon abated per year over the lifetime of treatment scenario. This graph is effectively Figure 3.9 divided by Figure 3.13. From this graph, we infer that installing thermostats is similarly cost-effective in each of the cities examined. There is a clear pattern across the rest of the treatment scenarios that Los Angeles is the least cost-effective (due to very low carbon savings) followed by Orlando (due to high attic insulation costs and low carbon savings from air sealing) and Seattle (due to relatively low carbon savings). The remaining cities—Philadelphia, Detroit, and Milwaukee—are all similarly cost-effective across all treatment scenarios because they share both common treatment costs and carbon savings.

As discussed above, a more comprehensive cost-effectiveness analysis looks at the NPV of weatherization, which is the metric we used to more thoroughly examine how the feasibility of weatherization varied by city. Just as an energy abatement cost graph (Figure 3.12) is useful in determining the financial feasibility of a project when there exists an energy tax, a carbon abatement curve (Figure 3.15) is useful for considering the financial feasibility of a project when there exists a carbon tax. But unlike the energy tax, which has received little mention or major consideration in many years, the idea of a carbon tax, or at least a carbon price, is incredibly relevant. In the face of worsening climate change, many policy-makers seek to curb climate change through use of price-instruments, either through a cap-and-trade system or a carbon tax. This carbon abatement graph is especially relevant among discussions of a carbon tax as a price-instrument to reduce carbon emissions in order to curb climate change. Although it has been proposed in many pieces of recent legislation, the US is yet to establish a nationwide carbon pricing system. The cap-and-trade system proposed by the American Clean Energy and Security Act (HR 2454) would set a minimum price of \$10/ton C, or \$2.73/ton CO_2, in 2012, and this price floor would increase at a annual rate of 5% plus inflation (111th United States Congress 2009b sec. 791). Economic models suggest that limiting atmospheric concentration of CO_2 to two times pre-industrial levels and limiting average global warming to 2.5°C required a carbon price in 2005 of about \$30/ton C, or \$8.18/ton CO_2, increasing linearly to \$85/ton C, or \$23.20/ton CO_2 by the middle of the century (Nordhaus 2007).

We recall from Section 3.1 that our model exhibited significant error for some treatment scenarios when compared to observed energy savings. As a first-order error correction method, we multiplied the expected energy savings in each treatment scenario by a correction factor derived from our model evaluation in Section 3.1. We developed two different correction factors for each treatment scenario to account for different levels of model error. We defined the mean error correction factor as the ratio of the observed energy savings from the CWP evaluation to the modeled energy savings for Philadelphia's low-income housing stock. We defined the extreme error correction factor as the ratio of upper 90% confidence limit for the modeled results and the lower 90% confidence limit of the observed results. By its definition, the extreme error correction factor is greater than the mean correction factor, and so the extreme error correction factor provides a more conservative energy savings estimate as it implies greater model error. This extreme correction factor corresponds to a very low confidence in our results and could be interpreted as a worst-case scenario factor. For treatment scenarios in which modeled savings exceeded observed savings, we set the correction coefficient to 1, leaving the energy savings estimate unaltered. Table 3.1 presents both the mean error and extreme error correction factors for each treatment scenario. Figure 3.16 and Figure 3.17 illustrate the carbon abatement costs when adjusting for the mean model error and extreme model error, respectively.

To express some of the uncertainty surrounding treatment costs, these figures also include error bars to illustrate 50% of the expected treatment scenario cost. From this, we can identify which measures' abatement costs are more elastic than others. The abatement cost of thermostats in all cities, for instance, does not vary significantly with price, in part because they are very inexpensive. The abatement cost of attic insulation, however, is much more elastic, because installation costs and energy cost savings vary significantly among the cities modeled.

The effect of the correction factor is noticeable. Before applying a correction factor (Figure 3.15), our analysis suggested that all treatment scenarios were profitable, with the exception of two treatment scenarios for Los Angeles-Long Beach. After applying the mean error correction factor (Figure 3.16), most treatment scenarios in most cities still remain profitable or at least less than \$20/ton CO_2, even with a 50% treatment cost inflation. Applying the extreme error correction factor (Figure 3.17) brings the abatement costs of most treatment scenarios in most of the cities within a range 0 ± \$20/ton CO_2, and most still remain around or below the American Clean Energy and Security Act proposed initial carbon price floor of \$8.18/ton CO_2**.** Thermostats remain significantly profitable throughout any correction scenario, demonstrating that thermostats are a reliable and profitable investment in any of the cities modeled.

Table 3.1. Treatment Scenario Correction Factors Applied to Figure 3.16 and Figure 3.17.

Treatment scenario	T	A	S	S & T	A & T	A & S
Mean error correction factor (Figure 3.16)	1*	1*	0.62	0.45	0.76	0.54
Extreme error correction factor (Figure 3.17)	0.66	0.50	0.32	0.28	0.44	0.36
* indicates that observed savings exceeded modeled savings						

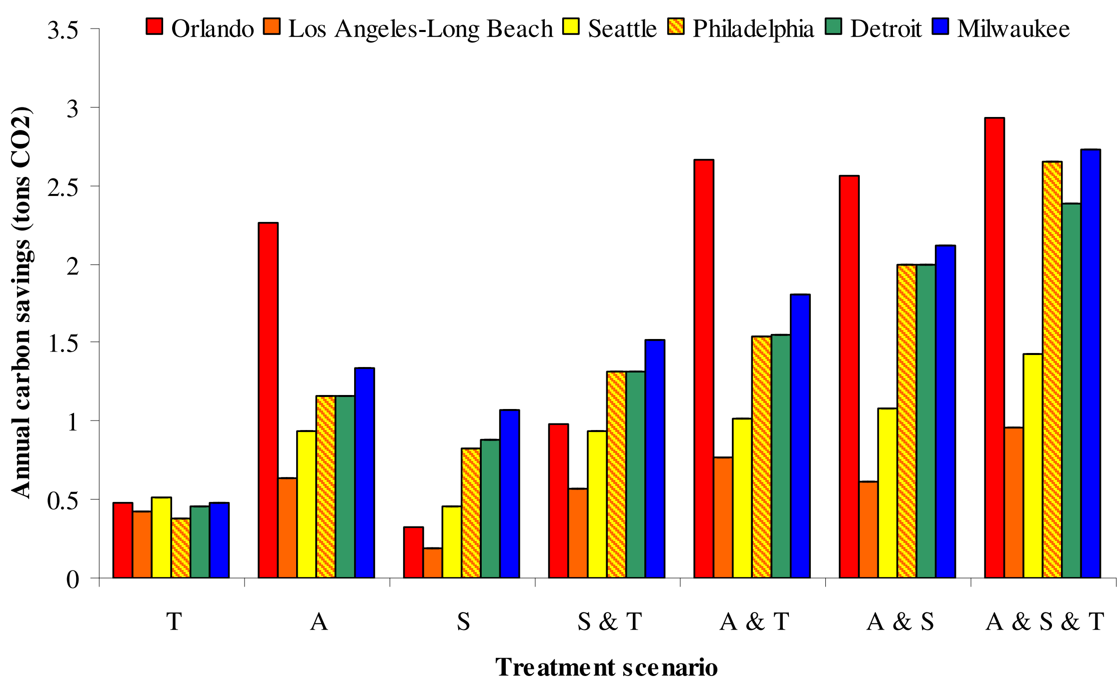

Figure 3.13. Average Annual Carbon Savings from Weatherizing a Low-income House by City and Treatment Scenario.

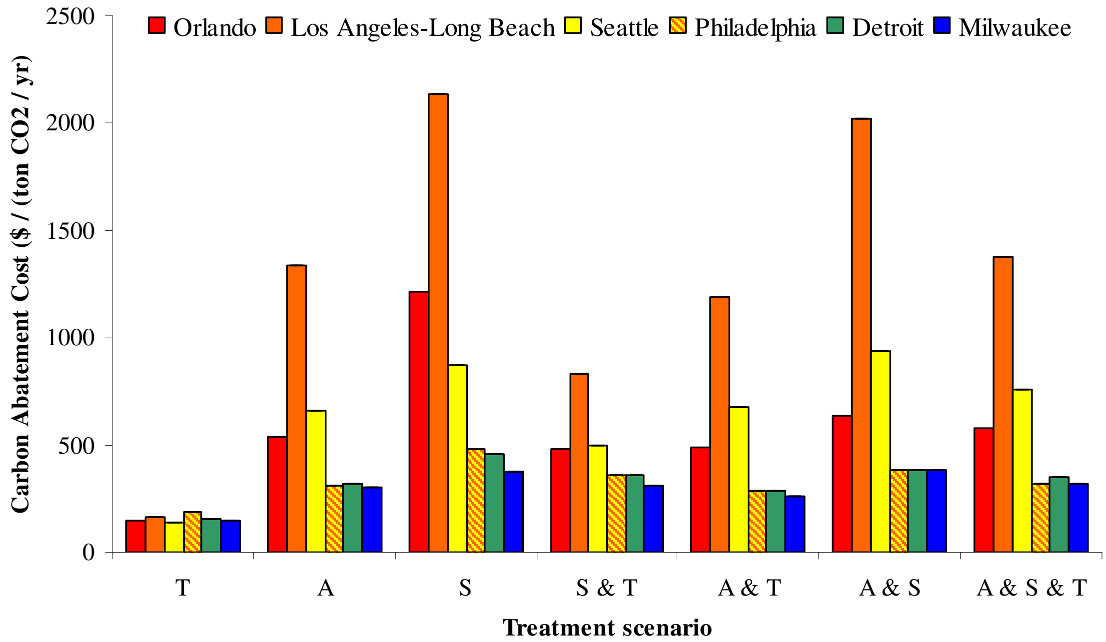

Figure 3.14. Average Carbon Abatement Cost for Weatherizing a Low-income House by City and Treatment Scenario, Omitting the Value of Energy Savings.

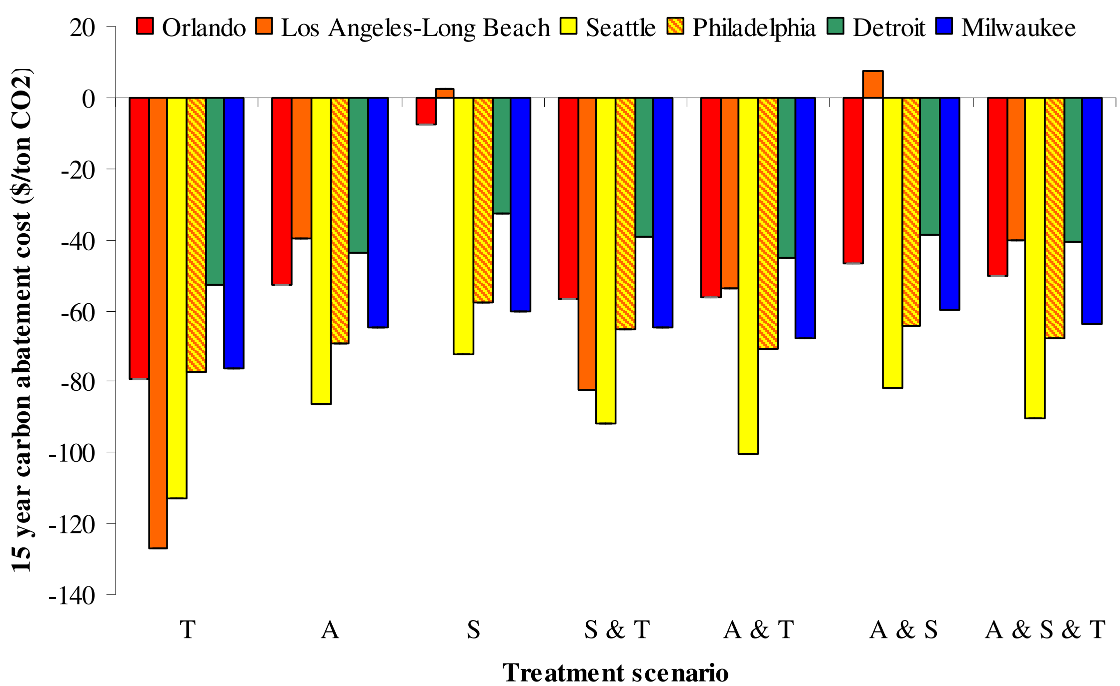

Figure 3.15. Average Carbon Abatement Cost for Weatherizing a Low-income House by City and Treatment Scenario.

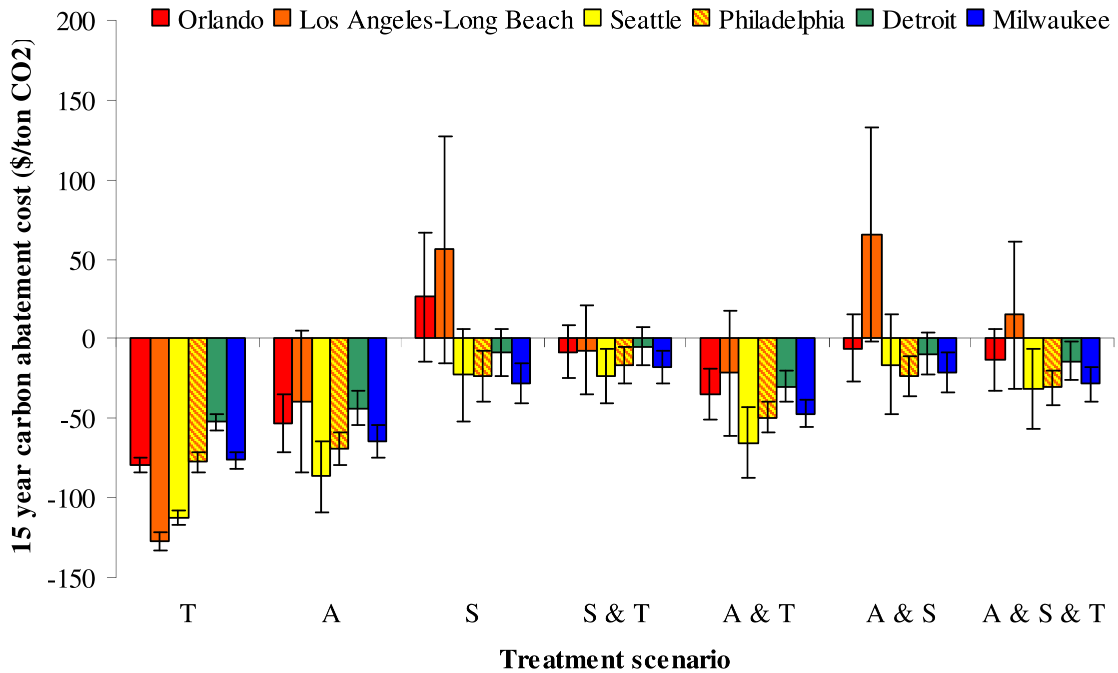

Figure 3.16. Average Carbon Abatement Costs for Weatherizing a Low-income House by City and Treatment Scenario, Adjusted for Mean Model Error. ***Error bars indicate range of abatement costs for treatment costs ± 50%.***

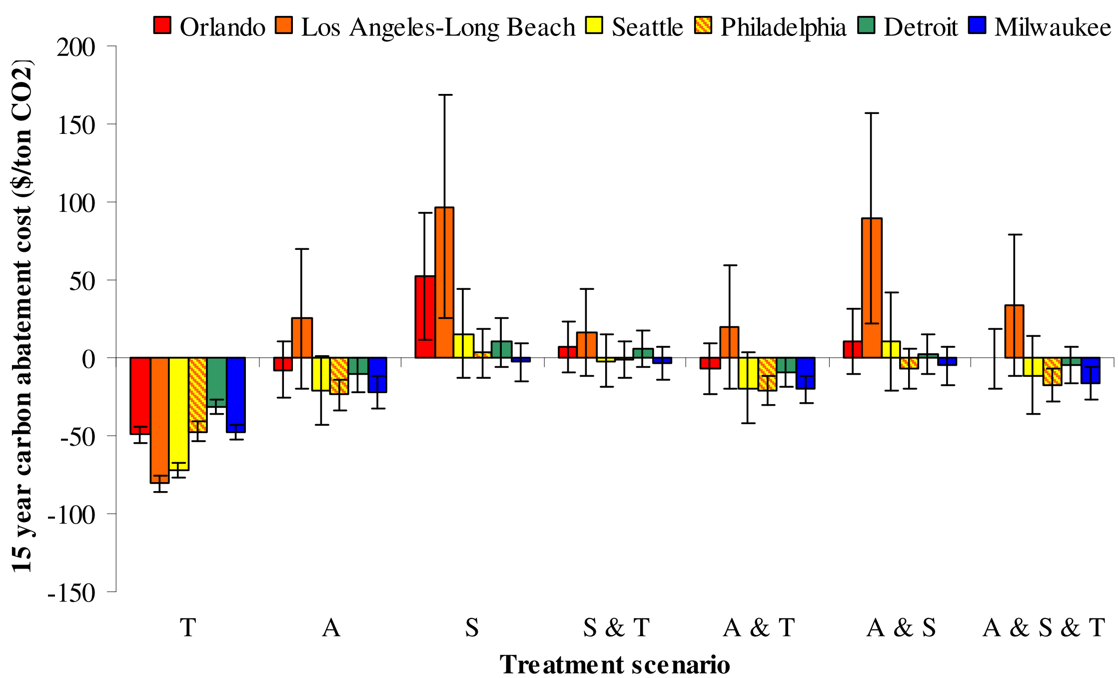

Figure 3.17. Average Carbon Abatement Cost for Weatherizing a Low-income House by Treatment Scenario and City, Adjusted for Extreme Model Error. ***Error bars indicate range of abatement costs for treatment costs ± 50%.***

4 CONCLUSIONS

The Obama Administration has placed energy efficiency at the core of its energy policies, and it has emphasized residential weatherization as a particularly advantageous means of achieving energy efficiency. In addition to reducing household energy consumption and lowering energy bills, weatherization also carries the benefits of reducing dependence on foreign energy sources and lowering residential greenhouse gas emissions while creating jobs and improving outdoor air quality. Past studies have estimated the cost-effectiveness of weatherization programs at a national scale, but have not examined how cost-effectiveness varies geographically due to differences in climate, housing stock, and energy prices. The purpose of our research was to develop an approach that could model the cost-effectiveness of weatherization programs in urban areas across the U.S. and to verify this model by comparing model estimates to observed energy savings from various retrofit treatments in one urban area. This chapter discusses our conclusions and our recommendations for future work in the area of housing stock energy modeling.

4.1 ANALYSIS

Our findings demonstrated that the concept of city-level weatherization cost-effectiveness analysis is not only possible, but also valuable in determining where weatherization programs could have the greatest impact. Based on these results, we can refine conclusions about the potential cost-effectiveness of weatherization for low-income urban housing that other studies made using national data.

Most weatherization treatments examined are profitable

Although cost-effectiveness varies significantly between cities and treatment scenarios, almost all treatments in the cities examined were NPV-positive over either a 7 or 15 year period. These results indicate that we would expect the present value of energy savings earned through weatherization to exceed weatherization installation costs for programmable thermostats, attic insulation, and air sealing.

Greater energy efficiency will be realized by retrofitting houses in colder climates

Following trends predicted from national data, urban houses in colder climates consume more energy for space conditioning than houses in warmer climates. Furthermore, many of the cities in these cold climates are located in the Northeast and Midwest Census regions, which have leakier and older housing stock than the South or West. Older houses tend to be less energy-efficient than newer houses, and our analysis suggests that older urban housing stock in cold climate zones may have the greatest potential for saving energy by weatherization retrofitting.

Regional variations in energy prices significantly affect the cost-effectiveness of weatherization retrofits

As exemplified in Orlando and Detroit, differences in energy prices can outweigh differences in energy savings in a cost-effectiveness analysis. Although retrofits saved less energy in Orlando than in Detroit, because Orlando had the most expensive and Detroit had the least expensive energy prices, Orlando's low-income housing stock was among the most profitable to retrofit, as measured by NPV, and Detroit's was among the least profitable.

Greater carbon efficiency can be realized by retrofitting houses with electric space conditioning compared to oil or natural gas

Relatively low-carbon natural gas provided most of the space conditioning energy in five of the six cities examined, but carbon-intensive electricity provided all of the space conditioning energy in Orlando, making the city's low-income housing stock a consistent top carbon saver across all weatherization treatments despite it being one of the lowest end-use energy savers. Until houses can access electricity from cleaner energy sources—either from cleaner energy on the electrical grid or from onsite renewable technologies such as photovoltaic solar panels—houses that rely on conventional electric heating and cooling systems will continue to be the largest source of potential carbon savings from retrofits.

Weatherization strategies aimed at energy savings, carbon savings, and cost-effectiveness may not lead to the same conclusion

Because average energy consumption, carbon intensity of energy consumed, and energy prices all vary geographically and largely independently, energy savings, carbon savings, and cost-effectiveness are not necessarily aligned. Weatherization strategies that seek to minimize residential energy use may not be the same strategies that seek to minimize residential carbon emissions. Additionally, there are different ways to consider cost-effectiveness, including net present value or by abatement cost for energy or carbon. In evaluating existing and designing new weatherization programs, it will be important for policy-makers to recognize these differences and decide the priorities of weatherization programs.

Programmable thermostats provide cost-effective savings in any setting

Of the weatherization treatments examined, replacing standard thermostats with programmable thermostats were a consistent source of carbon and energy savings across all cities. In the comparison between modeled and observed energy savings, which may indicate that thermostats are among the treatments least susceptible to shortfall and take-back. Installing programmable thermostats requires minimal training, so the likelihood of improper installation is small. Additionally, since programmable thermostats are automatic, as long as residents do not interfere with set heating and cooling schedules, there is minimal opportunity for behavioral changes to alter the thermostat's effectiveness.

4.2 *LIMITATIONS AND AREAS FOR FUTURE WORK*

The approach developed for the research is useful for comparing how the average cost-effectiveness of different retrofitting treatments will vary geographically due to differences in climate, housing stock, and energy prices. There are, however, several limitations to this approach.

First, there are occasionally large discrepancies between modeled and observed energy savings. This does not necessarily indicate that the HES model is incorrect, only that modeled energy results do not reflect observed results. Energy modeling literature attributes this primarily to modeling errors, improper retrofitting installation errors, or changes in resident's energy consumption behavior. Because the model determines energy savings using DOE-2, a comprehensive physical model—as opposed to statistical models, for instance—it seems unlikely that the model itself is a primary source of error. The model's usefulness, however, hinges upon the data used to drive it, so modeling error can be minimized by driving HES with more detailed information than AHS provides. We expect that these errors are systematic and affect each modeling run similarly, so it is unlikely that any such error would significantly change the qualitative results of our analysis (e.g. which housing stocks are more cost-effective to weatherize), but it would affect the quantitative details of the results (e.g. the exact quantities of energy saved). As such, our approach is still useful for comparing weatherization cost-effectiveness among different housing stocks.

It is important to emphasize that this approach should only be used to examine the average cost-effectiveness of a specific housing stock. Because the physical characteristics of houses vary depending on design, construction methods, and use, any housing stock will be heterogeneous, so even if weatherization treatments were applied uniformly—which evaluations show they are not—the actual energy savings and retrofitting costs can vary widely even within a designated housing stock. While our approach may poorly model any one house, we expect that it reasonably models the average energy consumption and savings from many houses.

Errors in this assumption could be decreased by calculating average energy consumption and savings from larger sample sizes. The AHS National microdata we used may not provide the larger sample size required for a more thorough analysis, but data in the AHS Metropolitan supplement might. This supplement provides the same information as the National microdata we used, except for a larger sample size in 41 metropolitan areas. Using HES for such modeling is presently time-consuming as it requires inputting data one value at a time. Thus, the future completion of a batch capability will facilitate the process of modeling many houses, which would be required for analysis using data from the AHS Metropolitan supplement.

In addition to potential data and modeling shortcomings, there is substantial uncertainty surrounding our energy and retrofit cost estimates, and more specifically how these costs will change in the future. Our cost analysis assumed that energy and retrofit prices remained constant. We employed a discount rate of 7% for all future money flows, but this rate could fluctuate depending on future energy and retrofit cost prices relative to the rate of inflation. We expect that the cost of implementing the weatherization treatments we examined would not increase, but it may decrease as technological advancements lower weatherization installation costs, making retrofits more cost-effective than we modeled. It is much more difficult to predict the future behavior of energy prices, as there are occasionally major market perturbations. For example, recent advancements in natural gas recovery technology have significantly increased domestic gas reserves. Energy analysts forecast the resulting increase in gas supply with keep prices uncharacteristically low in the next few years as the price of other forms of energy continue to grow (Schlesinger 2010). Unusually low gas prices decrease the value of energy savings and the cost-effectiveness of weatherization in houses that use gas for space conditioning, making houses that rely on other energy sources like fuel oil and electricity comparatively more cost-effective.

Although this project was designed to model the low-income urban housing stock, our approach is not limited to this application. Our approach could be extended to model the cost-effectiveness of weatherization treatments on housing stocks on any level, including upper-income stock and non-urban housing stock, although the usefulness of the average energy consumption and savings determined from such modeling will depend on how the housing stock is defined.

REFERENCES

111th United States Congress. (2009a). *American Recovery and Reinvestment Act of 2009*. *H.R.*

111th United States Congress. (2009b). *American Clean Energy and Security Act*. *H.R.*

APPRISE. (2006). *PPL Electric Utilities Winter Relief Assistance Program*. Princeton.

Autodesk. (2010). "Autodesk Green Building Studio - Questions and Answers." <http://usa.autodesk.com/adsk/servlet/pc/index?siteID=123112&id=11179514> (Mar. 30, 2010).

Berger, J., and Carroll, D. (2007). "Measures that Save the Most Energy."

Blasnik, M. (2009a). "What Saves Energy & Why: US Program Measured Results." Toronto.

Blasnik, M. (2009b). "RE: Energy Conservation Agency evaluation."

Brown, M., and Berry, L. (1993). "Weatherization Assistance: The Single-Family Study." *Home Energy Magazine Online*.

Brownsberger, W. (2008). "How much energy does the United States import?." <http://willbrownsberger.com/index.php/archives/656> (Mar. 1, 2010).

Charles, D. (2009). "Leaping the Efficiency Gap." *Science*, 325(5942), 804-811.

Chu, S. (2009). "Weatherization: Saving Money by Saving Energy." *The Huffington Post*, <http://www.huffingtonpost.com/steven-chu/weatherization-saving-mon_b_339935.html?&just_reloaded=1> (Feb. 2, 2010).

Close, P. D. (1947). *Thermal Insulation of Buildings*. New York.

Creyts, J., Derkach, A., Nyquist, S., Ostrowski, K., and Stephenson, J. (2007). *Reducing U.S. Greenhouse Gas Emissions: How Much at What Cost? U.S. Greenhouse Gas Abatement Mapping Initiative*. McKinsey & Company.

D&R International, Ltd. (2009). *2008 Buildings Energy Data book*. US Department of Energy, Washington, D.C.

Earth Advantage Institute, and Conservation Services Group. (2009). *Energy Performance Score 2008 Pilot: Finding & Recommendations Report*.

EIA. (2000). "U.S. Census Regions and Divisions." Energy Information Administration.

EIA. (2002). "Residential Energy Usage by Origin of Householder." *Energy Information Administration*, <http://www.eia.doe.gov/emeu/recs/origin/origin_householder.html> (Feb. 6, 2010).

EIA. (2009a). *2005 Residential Energy Consumer Survey*. Energy Information Administration, Washington, D.C.

EIA. (2009b). *Annual Energy Outlook 2009: With Projections to 2030*. Energy Information Administration, Washington, D.C.

EIA. (2009c). "Fuel and Energy Source Codes and Emission Coefficients." *Voluntary Reporting Greenhouse Gases Program*, <http://www.eia.doe.gov/oiaf/1605/coefficients.html> (Mar. 15, 2010).

EIA. (2009d). *International Energy Outlook 2009*. Energy Information Administration, Washington, D.C.

EIA. (2009e). *Annual Energy Outlook 2010: Early Release with Projections to 2035*. Energy Information Administration, Washington, D.C.

EIA. (2010). "Real Petroleum Prices." *Short-term Energy Outlook*, <http://www.eia.doe.gov/emeu/steo/pub/fsheets/real_prices.html> (Apr. 9, 2010).

Ellington, K. (2010). "DOE-2 : Software : Resources : Environmental Energy Technologies Division." *Lawrence Berekely National Laboratory*, <http://eetd.lbl.gov/eetd-software-doe2.html> (Mar. 30, 2010).

Energy Information Administration. (2008). *Housing Unit Characteristics by Household Income, 2005*. 2005 Residential Energy Consumption Survey--Detailed Tables, US Department of Energy, Washington, D.C.

EPA. (2010). "Emissions & Generation Resource Integrated Database." *eGRID*, <http://cfpub.epa.gov/egridweb/> (Mar. 17, 2010).

EPRI. (2009). *Assessment of Achievable Potential from Energy Efficiency and Demand Response Programs in the U.S.: (2010-2030)*. Electric Power Research Institute, Palo Alto.

Fels, M. (1986). "PRISM: An Introduction." *Energy and Buildings*, 9(1-2).

Granade, H. C., Creyts, J., Derkach, A., Farese, P., Nyquist, S., and Ostrowski, K. (2009). *Unlocking Energy Efficiency in the U.S. Economy*. McKinsey & Company.

Greenhouse, S. (1993). "Clinton's Economic Plan: The Energy Plan; Fuels Tax: Spreading The Burden." *The New York Times*, New York.

Hendricks, B., Goldstein, B., Detchon, R., and Shickman, K. (2009). *Rebuilding America: A National Policy Framework for Investment in Energy Efficiency Retrofits*. Center for American Progress.

Horman, G. (2010). "HES question."

Huang, Y. J. (2003). "In preparation." Building Energy Simulation User News.

Huang, Y. J., Shen, L. S., Bull, J. C., and Goldberg, L. F. (1988). "Whole-House Simulation of Foundation
Heat Flows Using the DOE-2.1C Program.." *ASHRAE Transactions*, 94(2), 936-944.

Illinois General Assembly. (2009). *Urban Weatherizatin Initiative Act*.

IPCC. (2007). *Synthesis Report*. Fourth Assessment Report, Intergovernmental Panel on Climate Change, Geneva.

John Horowitz, J. G. (2009). "Global Climate Change: Background." *USDA Economic Research Service*, <http://www.ers.usda.gov/Briefing/GlobalClimate/Background.htm> (Feb. 9, 2010).

Khawaja, M. S., Lee, A., Perussi, M., and Morris, E. (2006). *Ohio Home Weatherization Assistance Program Impact Evaluation*. Quantec, LLC.

Levy, J. I., Nishioka, Y., and Spengler, J. D. (2003). "The public health benefits of insulation retrofits in existing housing in the United States." *Environmental Health*, 2, 4-4.

Longstreth, M., and Topliff, M. (1990). "Determinants of energy savings and increases after installing energy-conserving devices." *Energy*, 15(6), 523-537.

Lotz, B. (2006). "A Brief History of Thermal Insulation." *Roofing/Siding/Insulation Magazine*.

M. Blasnik & Associates. (2004). *NJ Comfort Partners Impact Evaluation Report*. M. Blasnik & Associates, Boston.

M. Blasnik & Associates. (2006). *Colorado Energy $avings Partners Impact Evaluation*

Report. M. Blasnik & Associates, Boston.
M. Blasnik & Associates. (2007). *Impact Evaluation of Columbia Gas of Pennsylvania's Warm Choice Program Calendar Year 2005*. M. Blasnik & Associates, Boston.
M. Blasnik & Associates. (2008). *Impact Evaluation of Philadelphia Gas Works' Conservation Works Program Calendar Year 2006 and Comprehensive Treatment Pilot*. Boston.
M. Blasnik & Associates. (2009). *Colorado Low Income Energy Efficiency Retrofit Program Energy Impacts: First Response and Energy Savings Partners*. M. Blasnik & Associates, Boston.
Martin, C., and Watson, M. (2006). *Measurement of energy savings and comfort levels in houses receiving insulation upgrades*. Energy Saving Trust, June 2006.
McWilliams, J., and Jung, M. (2006). *Development of a Mathematical Air-Leakage Model from Measured Data*. Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley, 50.
Mills, E. (2008). *The Home Energy Saver: Documentation of Calculation Methodology, Input Data, and Infrastructure*. Lawrence Berkeley National Laboratory, Berkeley.
Nevin, R. (2010). "Energy-efficient housing stimulus that pays for itself." *ENERGY POLICY*, 38(1), 4-11.
Nordhaus, W. D. (2007). *The Challenge of Global Warming: Economic Models and Environmental Policy*. Yale University, New Haven.
Office of Energy Efficiency and Renewable Energy. (2008). "Non-Energy Benefits of Weatherization." *Weatherization Assistance Program*, <http://apps1.eere.energy.gov/weatherization/ne_benefits.cfm> (Mar. 28, 2009).
Office of Management and Budget. (1992). *Circular No. A-94 -- Guidelines and Discount Rates for Benefit-Cost Analysis of Federal Programs*. Transmittal Memo No. 64, Office of the President of the United States, Washington, D.C.
Office of the Press Secretary. (2010). "Fact Sheet: Homestar Energy Efficiency Retrofit Program." The White House.
Pacala, S., and Socolow, R. H. (2004). "Stablization Wedges: Solving the Climate Problem
for the Next 50 Years with Current Technologies." *Science Magazine*, (305), 968-972.
Recovery Accountability and Transparency Board. (2009). "Where is Your Money Going?." *Recovery.gov*, <http://www.recovery.gov/?q=content/investments> (Mar. 28, 2009).
Rios, R. V. (1981). "Preface." *Optimal Weatherization: Proceedings of the National Conference on Optimal Weatherization, December, 1980*, Information Dynamics, Silver Spring, Md, v-vi.
Schlesinger, B. (2010). "Global Implications of LNG and Unconventional Natural Gas: The Coming "Double Hit"." Washington, D.C.
Schweitzer, M., and Tonn, B. (2002). *Nonenergy Benefts from the Weatherization Assistance Program--A Summary of Findings from Recent Literature*. Oak Ridge National Laboratory, Oak Ridge, TN.
Sherman, M., and Dickerhoff, D. (1998). "Air-tightness of US dwellings." *ASHRAE Transactions*, 104, 1359.

Sherman, M. H., and Matson, N. E. (1997). "Residential Ventilation and Energy Characteristics." *ASHRAE Transactions*, 103(1), 717-730.

Sorrell, S. (2007). *The Rebound Effect: An Assessment of the Evidence for Economy-wide Energy Savings from Improved Energy Efficiency*. UK Energy Research Centre.

Unger, D., and Herzog, H. (1998). *Comparative Study on Energy R&D Performance: Gas Turbine Case Study*. Massachusetts Institute of Technology, Cambridge, Mass.

US Census Bureau, and HUD/U.S. (2008). *2007 American Housing Survey*. US Census Bureau & Department of Housing and Urban Development, Washington, D.C.

US DOE. (2008). "History of the Weatherization Assistance Program." *DOE Weatherization Assistance Program*, <http://apps1.eere.energy.gov/weatherization/history.cfm> (Feb. 8, 2010).

US DOE. (2009). "About the Weatherization Assistance Program." *DOE Weatherization Assistance Program*, <http://apps1.eere.energy.gov/weatherization/about.cfm> (Feb. 8, 2010).

US DOE. (2010). *Department of Energy FY 2011 Congressional Budget Request: Budget Highlights*. US Department of Energy, Washington, D.C.

US DOE, and EPA. (2000). *CO2 Emissions Report from the Generation of Electric Power in the United States*. United States Department of Energy and Environmental Protection Agency, Washington, D.C.

Warner, J. L. (2005). *The Use of DOE-2 in the Home Energy Saver*. Lawrence Berkeley National Laboratory, Berkeley.

Weissinger, E., Choi, J., Clark, L., Johns, K., Liang, Y., Yang, J., Peters, C., Harris, R., and Ellis, B. (2009). *Energy Investigation of the Smith House*. Princeton University, Princeton, N.J.

Winkelmann, F. C. (1998). "Underground Surfaces: How to Get a Better Underground Surface Heat Transfer Calculation in DOE-2.1E." *Building Energy Simulation User News*, 19(3), 6-13.

APPENDIX A: RESEARCH METHODS DETAILS

This Appendix discusses this thesis's research methods in greater detail . The first section specifies which AHS data we used to drive HES. The second section provides details about how we drove HES with AHS data to model house's energy consumption and expected savings from weatherization treatments. The third section demonstrates how we calculated the expected values of energy consumption and energy savings from modeled results of individual houses. The final section describes how we used AHS and HES to calculate the expected contribution of water heating to houses' natural gas energy consumption.

A.1 AMERICAN HOUSING SURVEY

In its raw form, American Housing Survey public microdata are divided into six different files. In this project, we used the datasheets called NEWHOUSE. NEWHOUSE contains data at the household level and includes information about the housing unit. Table A-1 lists the variables used for this project.

Table A-1. List of American Housing Survey Variables Used.

Variable name	Definition
WEIGHT	Final weight
VACANCY	Vacancy status
TYPE	Housing unit type
UNITSF	Square footage of unit *(conditioned only)*
NUNIT2	Are these living quarters in a…
HEQUIP	Main heating equipment
HFUEL	Fuel used most for heating unit
AIR	Room air conditioner
AIRSYS	Central air conditioner
AFUEL	Type of fuel used for air conditioners
FLOORS	Number of stories in building
SMSA	1980 design PMSA code
METRO3	Central city / suburban status
BUILT	Year unit was built
DEGREE	Average heating/cooling degree days
ZINC2	Household income
PER	# of persons in household
POOR	Household income as percentage of poverty line
CELLAR	Unit has a basement

A.2 HOME ENERGY SAVER

To begin a session, HES requires the input of the ZIP code within which the house is located. HES uses the ZIP code to locate the city where the house is for purposes of estimating the climate conditions and housing characteristics typical for that area. For all houses within a city, we used the same zip code. Table A-2 lists the zip codes used for each city.

Table A-2. ZIP codes used for HES modeling.

City	ZIP code
Milwaukee	53201
Detroit	48201
Seattle	98101
Philadelphia	19019
Los Angeles-Long Beach	90001
Orlando	32801

HES initially asks nineteen questions for a "simple" level of calculation. These questions provide the most basic level of information required for HES to model energy consumption. Below are the questions that we answered with AHS data, along with specific instructions how we used AHS data to answer it. All other questions were left blank, in which case HES inserts a default value pre-determined from RECS for a typical single-family, detached house in the appropriate Census region.

2. Which city has the most similar climate to your house?

From the ZIP code, HES identifies several cities closet to the zip code in terms of location and climate based on several different sources of historical weather information. HES included each of the cities we modeled as an option, so in each instance we selected that city.

3. Year your house was built

AHS provides this information in the BUILT variable. AHS indicates if a house was built by decade for 1920-1969, by half-decade for 1970-1999, and by year for 2000-2005. AHS also indicates if the house was built before 1920. We input the year built as the beginning of the period that AHS indicates. For example, if AHS lists the house vintage as 1920-1929, we input the house age as 1920. For houses built before 1920, we input that they were built in 1919.

4. What is the conditioned floor area?

AHS provides this information in the UNITSF variable. In a small number of samples, this parameter was blank in the AHS data. When this happened, we left this parameter blank and AHS inserts the appropriate default parameter.

5. How many stories above ground level are there?

AHS provides this information in the FLOORS variable.

7. What type of foundation does your house have?

AHS provides this information in the CELLAR variable.

15. What kind of heating equipment do you have?

AHS provides this information in the HEQUIP and HFUEL variables, which indicate the house's main heating equipment and fuel, respectively.

16. What kind of cooling equipment do you have?

AHS provides this information in the AIR and AIRSYS variables. HES does not provide the option to select natural gas as the cooling energy source, but this was not an issue in our study since the variable AFUEL indicated all houses we modeled had electric air conditioning.

19. Please tell us how many people living in your house fall into the following groups.

AHS provides the number of residents in the PER variable. This specific question asks how many residents fall with four different age brackets: 0 to 5 years, 6 to 13 years, 14 to 64 years, and 65 years and older. Since AHS does not provide the age composition of the residents, we assumed an age composition for each of the PER values observed in this study. Table A-3 lists our assumed age compositions.

Table A-3. Assumed Resident Age Composition Corresponding to AHS PER Variable.

PER	6 to13 years	14 to 64 years
1	0	1
2	0	2
3	1	2
4	2	2
5	3	2
6	4	2

Among the many other parameters HES allows users to specify, one is house shape. In this study, we modeled both attached and detached single-unit houses. AHS indicates which houses are attached and which houses are detached in the NUNIT2 variable. To model detached houses, we used AHS's default house geometry of a "rectangle," detached house. To model attached houses, AHS allows users to select "townhouse" or shape and indicate whether the house is in the end or middle of the row. To calculate the average energy consumption of an attached house, we calculated the expected value of energy consumption applying a weight of 5 middle per 1 end townhouse.

After entering as much data as the user desires, HES calculates expected energy consumption and allows the user to model different retrofit treatments. Figure A-1 is a screenshot from HES's retrofit selection page displaying the different retrofit options.

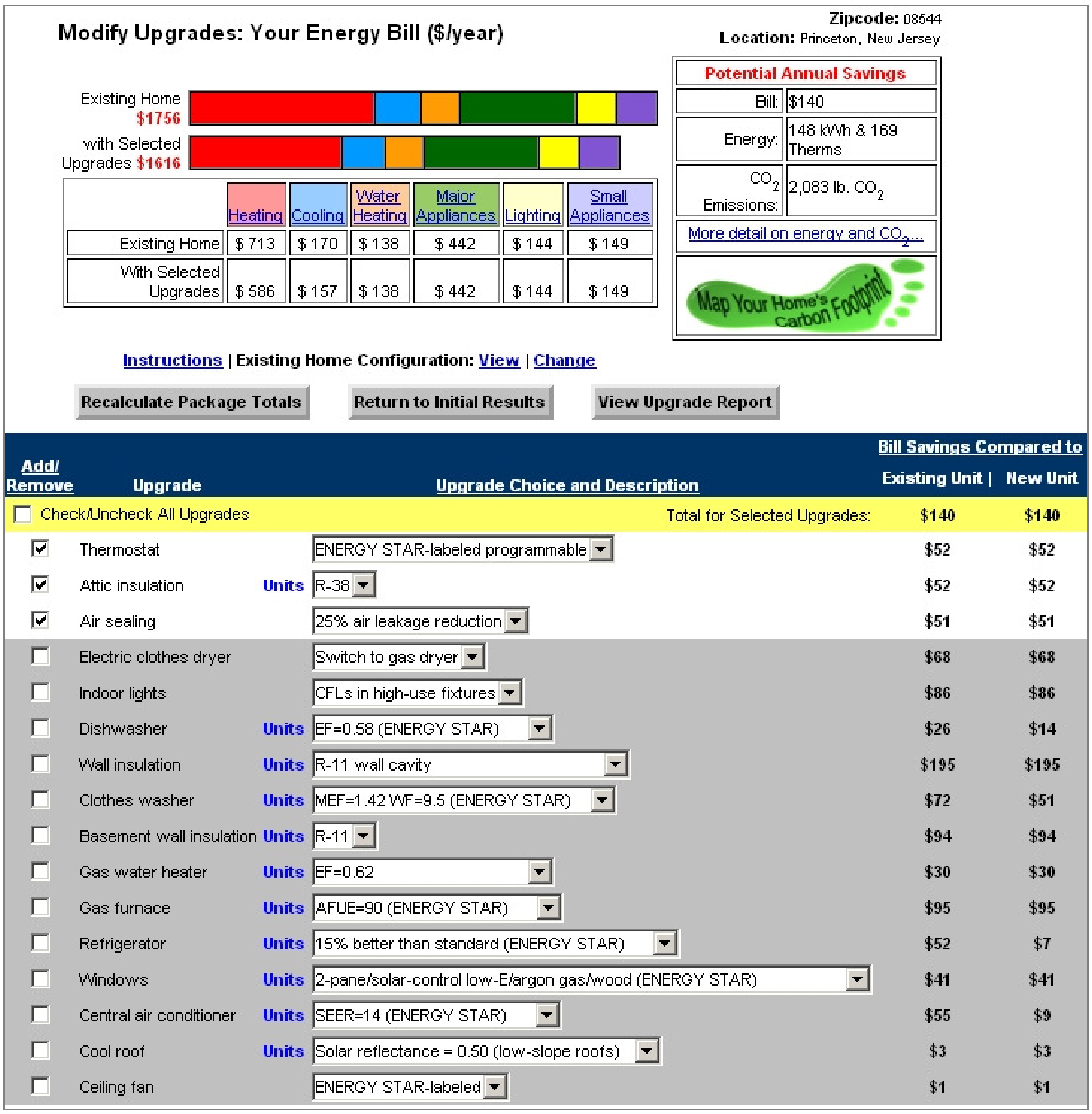

Figure A-1. Screenshot of Home Energy Saver Retrofit Selection Page.

After selecting which retrofit treatments to model, HES will calculate expected energy savings and report these savings by end-use and fuel (when applicable). Figure A-2} is a screenshot of one of the result pages. From these result pages, we read the modeled space heating and cooling energy consumptions and savings. Since the interaction between retrofit treatments is complex, each treatment scenario was modeled individually for each house.

Home Energy Saver Making It Happen

About HES What's New Energy Librarian Glossary FAQ Search E-mail Help

Detail of Whole House Annual Energy Use

		Your House	With Selected Upgrades	Savings
Whole House	$	$1,648	$1,450	**$198**
	Energy	6,457 kWh & 2,153 Therms	6,399 kWh & 1,776 Therms	**58 kWh & 377 Therms**
	Emissions	35,257 lb. CO_2	30,762 lb. CO_2	**4,495 lb. CO_2**
Heating	$	$1,000	$802	**$198**
	Energy	586 kWh & 1,859 Therms	528 kWh & 1,482 Therms	**58 kWh & 377 Therms**
	Emissions	22,636 lb. CO_2	18,140 lb. CO_2	**4,495 lb. CO_2**
Cooling	$	$6	$6	**$0**
	Energy	75 kWh	75 kWh	**0 kWh**
	Emissions	117 lb. CO_2	117 lb. CO_2	**0 lb. CO_2**
Hot Water	$	$85	$85	**$0**
	Energy	294 Therms	294 Therms	
	Emissions	3,435 lb. CO_2	3,435 lb. CO_2	**0 lb. CO_2**
Major Appliances	$	$335	$335	**$0**
	Energy	3,178 kWh	3,178 kWh	
	Emissions	4,973 lb. CO_2	4,973 lb. CO_2	**0 lb. CO_2**
Lighting	$	$109	$109	**$0**
	Energy	1,286 kWh	1,286 kWh	**0 kWh**
	Emissions	2,012 lb. CO_2	2,012 lb. CO_2	**0 lb. CO_2**
Misc.	$	$113	$113	**$0**
	Energy	1,332 kWh	1,332 kWh	**0 kWh**
	Emissions	2,084 lb. CO_2	2,084 lb. CO_2	**0 lb. CO_2**

Figure A-2. Screenshot of Home Energy Saver Results Page.

A.3 SAMPLE SPACE CONDITIONING EXPECTED VALUE CALCULATIONS

For each of the six cities we modeled, we calculated the average energy consumed for space conditioning and saved for each weatherization treatment. In some instances, such as houses that have gas space heating and electric space cooling, it was necessary to converted the reported energy values (therms for gas, kWh for electricity, gallons for fuel oil) to a common unit. MMBTU is a standard unit for space conditioning, so we converted to MMBTU using common conversion factors (0.1 therm/MMBTU, 293 kWh/MMBTU, 0.072 fuel oil gallons/MMBTU), and then summed each energy source and end-use to calculate the total space conditioning energy consumption for each house modeled. Figure A-3 displays the results of this model and calculation for the 7 houses modeled for the comparison of observed to modeled energy savings. We calculated the expected value of energy consumption (or savings) using the quantity of energy consumption (or savings) modeled and the weights AHS calculated and indicated in the WEIGHT variable.

While AHS indicates there are 11 low-income urban houses in the Philadelphia metropolitan region included 11 units, for our comparison of observed to modeled results we only considered the 7 units identified as AHS as existing in the center city of the metropolitan area, indicated in the SMSA variable. We did, however, consider all 11 low-income urban units for purposes of modeling how the cost and effect of retrofits varied among metropolitan areas.

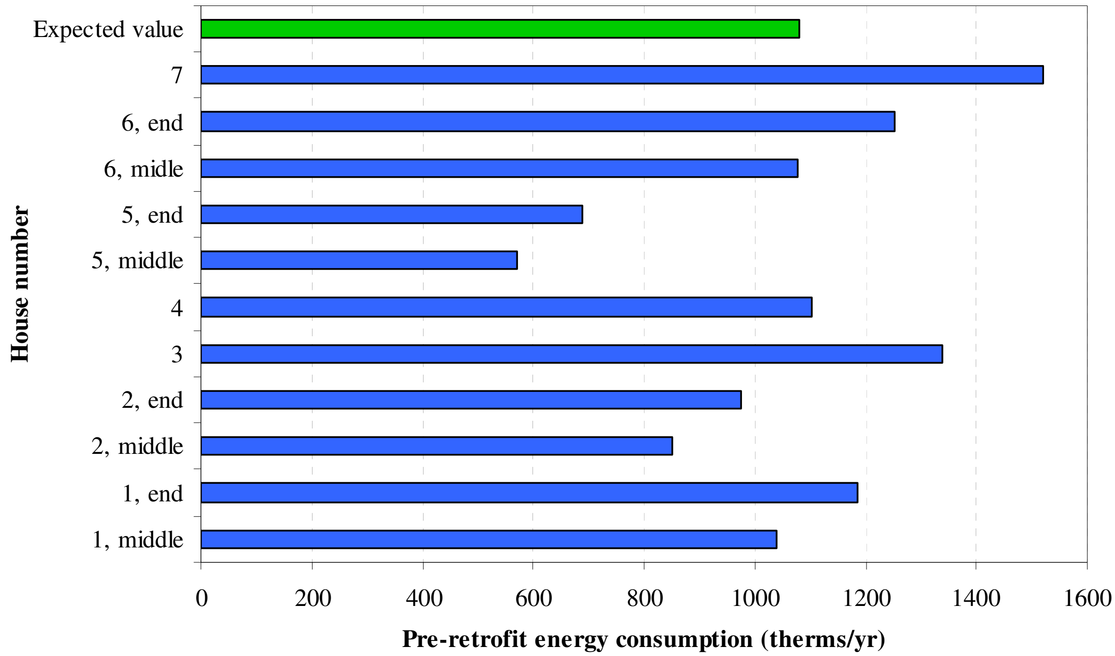

Figure A-3. Modeled Pre-retrofit Space Conditioning Energy Consumption. ***Houses numbered 1, 2, 5, and 6 were attached houses. "Expected value" is the weighted average of the houses' space conditioning energy consumption.***

Similar to Figure A-3, Figure A-4 shows how the modeled energy savings varied for each of the different houses modeled under each of the different treatment scenarios.

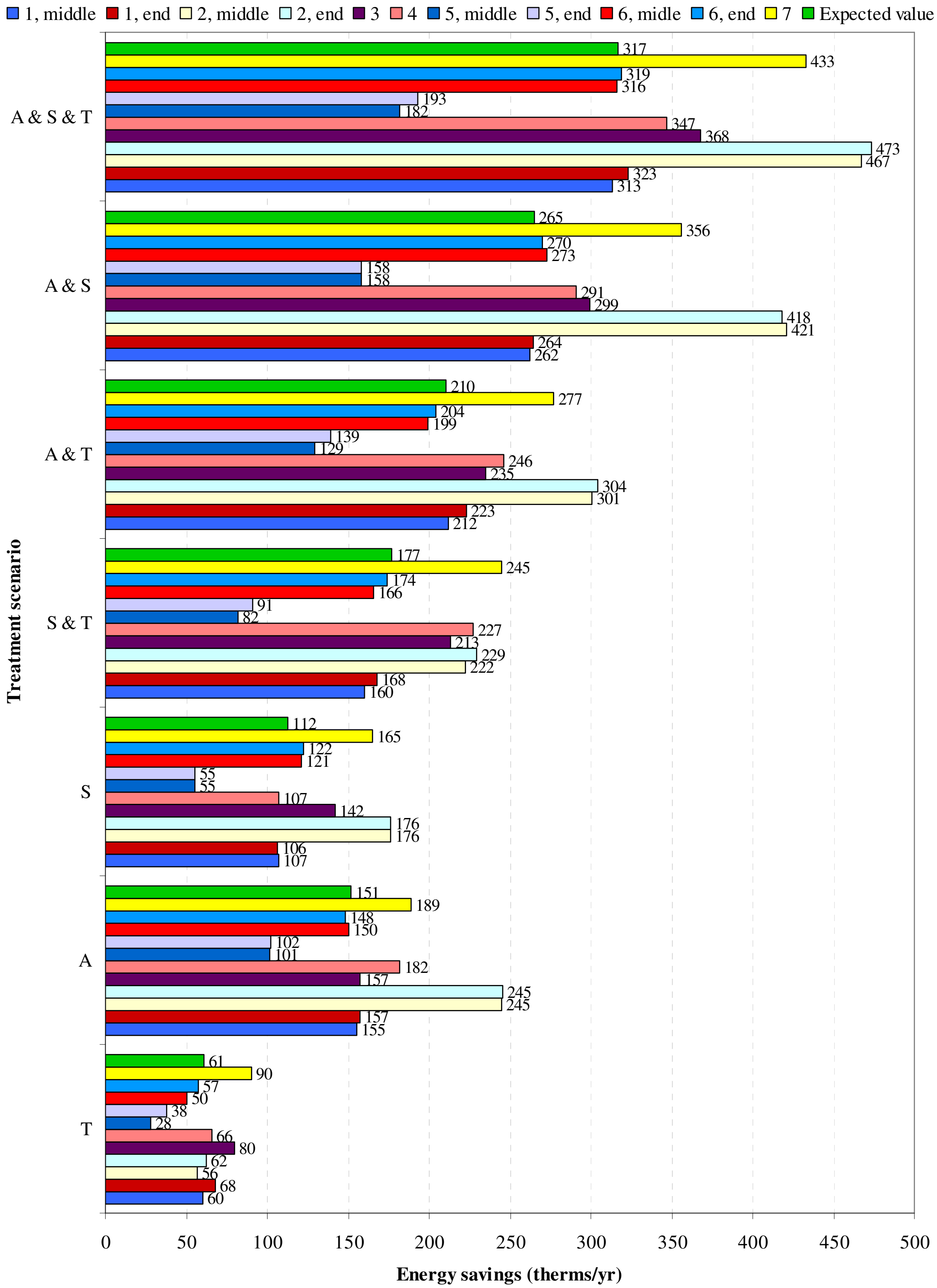

Figure A-4. Energy Savings for Different Treatment Scenarios. ***Houses numbered 1, 2, 5, and 6 were attached houses. "Expected value" is the weighted average of the houses' space conditioning energy savings.***

A.4 Water heating calculations

Within our AHS subset of low-income houses in the central city of the Philadelphia metropolitan area, all 7 of the samples use natural gas water heaters, as indicated in the survey's WFUEL variable. Therefore, rather than compare observed to modeled space heating energy consumption, we measured natural gas consumption, which we calculated from HES as the sum of space heating and water heating consumption.

HES divides water heating into three end-uses: taps and faucets, dishwashers, and clothes washers. HES allows users to indicate whether or not a house has a dishwasher and clothes washer, and we used AHS to determine if each house we modeled had these appliances. AHS indicates in the DISH variable that only two of the samples, representing 35% of the population, have dishwashers. AHS also indicates in the DRY variable that 82% of these homes have clothes dryers, from which we inferred that these homes also had clothes washers. According to the HES results, clothes washers, dishwashers, and taps and faucets consume an average of 9.7, 2.8, and 15.5 MMBTU/yr in houses that have all of those features.