Designing building energy efficiency programs for greenhouse gas reductions

Michael Blackhurst a,*, Inês Lima Azevedo b, H. Scott Matthews b,c, Chris T. Hendrickson c

a Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, 1 University Station C1752, Austin, TX 78712, USA
b Department of Engineering and Public Policy, Carnegie Mellon University, 119 Porter Hall, Pittsburgh, PA 15213, USA
c Department of Civil and Environmental Engineering, Carnegie Mellon University, 119 Porter Hall, Pittsburgh, PA 15213, USA

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A B S T R A C T

Costs and benefits of building energy efficiency are estimated as a means of reducing greenhouse gas emissions in Pittsburgh, PA and Austin, TX. The analysis includes electricity and natural gas consumption, covering 75% of building energy consumption in Pittsburgh and 85% in Austin. Two policy objectives were evaluated: maximize GHG reductions given initial budget constraints or maximize social savings given target GHG reductions. This approach evaluates the trade-offs between three primary and often conflicting program design parameters: initial capital constraints, social savings, and GHG reductions. Results suggest uncertainty in local stocks, demands, and efficiency of building operations. The analysis indicates that benefits of energy efficiency investment strategies for some end uses vary significantly (in excess of 100%) between Pittsburgh and Austin, suggesting that resources and guidance may not adequately represent such factors, leading to program

1. Introduction

Energy demand from commercial and residential buildings accounts for 40% of greenhouse gas emissions in the United States (EPA, 2009). Electricity generation constitutes 70% of GHG emissions; the remaining from on-site natural gas combustion (EPA, 2009).

Policy analysts, researchers, and government agencies have demonstrated the potential of energy efficiency to combat climate change, promote sustainability, enhance energy independence, and generate social savings (IEA, 2009; EPA, 2008, NRC, 2009; ILG, 1997; Azevedo, 2009).

'Social savings' in this study refers to discounted costs of energy efficient technologies and customer-based savings realized through reductions in energy use, expressed as net present value (NPV). Positive NPVs represent social savings. Social savings do not reflect externalities here.

The EPA estimates that energy efficiency measures can generate up to $500B in social savings by 2025 (EPA, 2008). The NRC (2009) finds that 12 residential energy efficiency interventions alone can save 15% of electricity use and generate social savings. Similar research suggests that 16–40% of baseline energy use can be reduced with no total social costs (ILG, 1997; Koomey et al., 1991). More recently, energy efficiency has been proposed as a cost-effective means for reducing greenhouse gas (GHG) emissions from fossil fuel combustion (Richter et al., 2008; Creyts et al., 2007).

Funding for energy efficiency programs appears to be increasing and is mostly administered at the state and local level. As part of the American Recovery and Reinvestment Act of 2009, the Federal government has appropriated nearly $12B for energy efficiency programs, with over $8B for states and $3B in grants for State and local authorities (DOE, 2009). Loper (2010) reports utility rate-payers spent $4.4B for efficiency in 2009, a $1B increase from 2008. Some state proceeds from the Regional Greenhouse Gas Initiative (RGGI), a regional cap-and-trade market for power sector emissions, are being spent on energy efficiency (Environmental Protection, 2010). Local and municipal expenditures are less certain.

Cities are making aggressive voluntary commitments to GHG reductions without supporting analysis of costs and benefits (see many profiled climate action plans at EPA, 2010). Kousky and Schneider (2003) surveyed 23 municipalities with formal GHG reduction programs. Most programs were motivated by internal cost savings, with little to no recognition of social costs or benefits.

Many local factors influence energy markets: resource pricing, electricity grid mix, climate, character of building stock, economic activity, and organizational capacity. Decision support resources may not adequately represent such factors, leading to program
inefficiencies and ineffectiveness. Public stakeholders in Austin, TX – often cited as an aggressive leader in local environmental and sustainability initiatives – have expressed skepticism towards performance of the City’s Climate Protection Program (Gregor, 2010).

Improved efficiency program design decision support is needed, particularly with regard to GHG impacts and social costs and benefits. As Kousky and Schneider (2003) suggests, local agencies are currently ill-equipped – in both staff and finances – to broaden their jurisdiction into climate protection. Pennsylvania’s Act 129 – which requires major electric utilities to reduce energy consumption – leaves program design to the electric utilities, which has resulting in unusual program designs (for example, see Duquesne Light Company, 2009).

This study examines local building energy efficiency program trade-offs between critical but oft-conflicting program design parameters: maximizing social savings, minimizing capital costs, and maximizing total GHG reductions. We focus on reducing GHG’s from energy efficiency, but the methods also apply to energy consumption. The data estimation techniques used here apply generally to program evaluation and reflect the major sources of uncertainty influencing decision-making.

2. Materials and methods

2.1. Scope of analysis

This study evaluates the costs and benefits of existing local residential and commercial building energy efficiency policies aimed at reducing greenhouse gases (GHGs) from fossil fuel combustion. Costs (capital and labor) include replacing inefficient stock of building-related equipment that uses energy (such as a furnace) or indirectly affects energy consumption (such as insulation). Costs could be private (spent by property owners) or social (paid by government). Net benefits are consumer savings from using less energy and potable water. Net social savings is thus the net present value (NPV) of the costs of energy efficient stock and consumer savings from energy and water reductions, discounted to 2009$. Additional social benefits of energy efficiency – such as offsetting new generation and transmission infrastructure, health benefits from reduced fossil fuel combustion, and reduced climate change impacts – are not within the scope of this study.

Two case studies are examined: Pittsburgh, PA and Austin, TX. Modeling is conducted at the local level to reflect current program administration and to identify potentially influential regional factors, such as climate, urban form, electricity grid emission, and resource pricing (electricity, natural gas, and water).

The scope of the analysis is limited to primary heating and cooling, lighting, residential water fixtures, and major residential appliances. Residential appliances in scope include refrigerators, freezers, water heaters, and clothes washers and dryers. Less pervasive equipment, such as space heaters, were not included in the analysis. Only electricity and natural gas consumption is included in the analysis. GHG’s were estimated using emissions factors reported by the EPA (2010) in units of CO₂ equivalents (“CO₂ eq”).

The scope of analysis includes only existing building stock, representing approximately 75% and 85% of current commercial energy use in Austin and Pittsburgh, respectively, and approximately 90% and 70% of current residential energy use in Austin and Pittsburgh, respectively (DOE, 2005; DOE, 2008).

2.2. Climate comparisons

The primary sources of data used to estimate stocks of end-use equipment and demands (the energy consumption of each stock) are the US Department of Energy’s Commercial Buildings Energy Consumption Survey (CBECS) for 2003 (DOE, 2005) and the Residential Energy Consumption Survey (RECS) for 2005 (DOE, 2008). In the present study we assume that CBECs and RECS are representative of 2009 conditions.

The primary source of efficiency data used in this study is the Database For Energy Efficient Resources (DEER) published by the California Public Utilities Commission (2009). DEER has been used to guide California’s state energy efficiency program. DEER reports efficiency impacts for California’s 16 climate zones. California’s diverse climate zones are fairly representative of climates in other US locales (see PGE (2006) for a characterization of California’s climate zones). Thus the energy use and efficiency impacts in DEER may characterize building energy use and efficiency impacts elsewhere. To this end, DEER efficiency measures were selected to best match the climate and energy use patterns of the case studies (Pittsburgh and Austin). Table 1 shows the California climate zones matched to each case study for efficiency modeling. Table 1 demonstrates seasonal heating and cooling variation. Such seasonal variation was not explicitly modeled; Table 1 is only provided for context.

2.3. End-use equipment stocks and demands

The US Department of Energy’s Residential Energy Consumption Survey (RECS) was used to estimate city-level stocks. Residential stocks (e.g., number of appliances, numbers of heating equipment) are estimated by proportioning the RECS Census Division inventories of stock to the city level according to Eq. (1). The most recent publication, the 2005 benchmark, consists of approximately 4400 household surveys of household energy use equipment, demands, and sources of fuel used. The Energy Information Administration (EIA) uses the survey responses to estimate and report stocks and demands by the 9 US Census Divisions. Only existing stock is considered for replacement with efficient technology. Service area growth – increases equipment stock that results from new construction – is

<table>
<thead>
<tr>
<th>Heating degree days</th>
<th>Cooling degree days</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pittsburgh, PA</strong></td>
<td><strong>Mt Shasta, CA</strong></td>
</tr>
<tr>
<td>Average</td>
<td>2110</td>
</tr>
<tr>
<td>Median</td>
<td>2050</td>
</tr>
<tr>
<td>Max</td>
<td>2560</td>
</tr>
<tr>
<td>Min</td>
<td>1840</td>
</tr>
<tr>
<td><strong>Pittsburgh, PA</strong></td>
<td><strong>Mt Shasta, CA</strong></td>
</tr>
<tr>
<td>Average</td>
<td>725</td>
</tr>
<tr>
<td>Median</td>
<td>678</td>
</tr>
<tr>
<td>Max</td>
<td>1030</td>
</tr>
<tr>
<td>Min</td>
<td>529</td>
</tr>
</tbody>
</table>

Table 1: Climate comparisons for case studies (Pittsburgh, PA and Austin, TX) and similar California climate zones (Mt. Shasta for Pittsburgh and Red Bluff for Austin). For example, Austin’s winter climate (heating degree days, HDD) is matched to California climate zone 11 (NOAA, 2009).

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outside the scope of the analysis:

\[
\text{Stock} \quad \text{Household (or Person)} \quad \text{Census Division}
\]

(1) Individual survey responses or
(2) Census Division totals

\[
\times \quad \text{City Households (or Population)} = \text{City Stock Estimate}
\]

From American Community Survey [US Census 2009]

For each city, the RECS data for the respective Census Division was used to prepare four distinct city-level stock estimates: two RECS datasets (the individual survey responses and the Census Division totals) were proportioned by either households or population (US Census Bureau, 2008a, 2008b, 2008c). When defining modeling ranges, preference was given to the estimates derived from individual survey responses because stocks for urban geographies could be isolated, whereas the Division totals do not isolate urban conditions for each stock. For example, it is less likely urban areas are served by point-of-use heating fuels, such as kerosene. Judgment was used to adjust modeling ranges for urban conditions. For each stock item (e.g., gas water heaters), a maximum, minimum, and base-case estimate was selected for modeling from these four point estimates. The maximum and minimum residential stock estimates are generally within 30% of the median estimate, with all estimates being within a factor of 2 of the median estimate. Residential insulation assumptions follow Wenzel et al. (1997). Appendix A in the Supplemental information shows residential stock estimates and related assumptions.

Similarly, commercial building stocks were estimated by proportioning the US DOE's CBCES Census Division inventories of stock to the city level according to Eq. (2). The most CBCES recent publication, the 2003 benchmark, consists of approximately 5200 surveys of commercial building energy use equipment, demands, and sources of fuel used. For each Division, individual survey responses were normalized by square foot of commercial building space:

\[
\text{Stock} \quad \text{Square Foot} \quad \text{Census Division}
\]

(1) City Commercial Square Feet

from CBES [DOE 2005]

\[
\times \quad \text{City Commercial Square Feet} = \text{City Stock Estimate}
\]

from either (1) County Real Estate Tax Roll
(2) GIS Data or
(3) Proportioned by Residential Floor Space within Census Division

City-level commercial floorspace was estimated using (1) county real estate tax databases, (2) geographic information systems data, and (3) ratios of commercial to residential floor-space at the Census Division level. These three estimates of commercial square footage lead to three distinct estimates of city-level commercial stocks, which define minimum, maximum, and base-case modeling scenarios. The maximum and minimum ranges for commercial stock estimates are within 40% of the base-case estimates.

The floorspace without adequate insulation or weatherization was assumed to be half of the city total. No reference was found to support this assumption, though it is consistent with residential

Fig. 1. DOE end use demands for Census Division 2 (DOE 2005, 2008) shown as shaded box plots. Demands for California climate zone 16 (CPUC, 2009, “DEER”) are shown as open box plots. The box plots show the median, 25% quartile, 75% quartile, maximum, and minimum.

The stock estimation method assumes that residential stocks are uniformly distributed by population or household within a Census Division and commercial stocks are uniformly distributed by floorspace within a Census Division. This is clearly not the case. The ability to isolate urban geographies for residential stock improves the estimates. Ranges are modeled in attempt to test the validity of this assumption.

End use demands (consumption of electricity, gas, and water) were primarily estimated from RECS and CBECs. City-level unit demands (energy use per floorspace, energy use per appliance, or energy use per household) were assumed to match those reported for their surrounding Census division.

Commercial and residential lighting demands were estimated from Navigant Consulting (2002). Navigant Consulting (2002) specifies total commercial lighting demand variability by building activity for all lighting technologies. Variability for individual lighting technologies is not reported. As the variability in demand stems mostly from different use patterns, the variability reported for all lighting technologies is used as a proxy for each individual lighting technology.

Demands for residential clothes washers were taken from DOE (2004). Natural gas clothes dryer demands were estimated from Wenzel et al. (1997), who reports that residential natural gas dryers consume approximately 10% energy than electric dryers. Residential water use demands – including water heating, treatment, and distribution energy requirements – were estimated from engineering fundamentals, manufacturers’ specifications, and an assumed duration of daily use. Water use assumptions and the energy used for water heating are summarized in Appendix D in the Supplemental information.

Probability distributions for unit heating and cooling energy demands were prepared from the individual survey responses in RECS and CBECs. Figs. 1 and 2 show box plots of the local stock demands modeled as part of this study. These data represent demand distributions from DOE survey responses and (DOE, 2005, 2008) and simulated demands from California climate zones that best approximate the case studies (CPUC, 2009). DOE data distributions reflect variations in individual survey responses by Census Division. CPUC (“DEER”) data reflect variations in primary building activity, vintage, and size for buildings in by California climate zone.

With the exception of a few end uses (residential heat pumps, central air conditioning), Figs. 1 and 2 indicate that median demands simulated in California are within a factor of two of those estimated from survey responses with no over- or under-prediction bias. Reported demands typically depict more spread, indicating that the variation in building prototypes or weather used to simulate demands in California may not be representative of buildings in similar climates at the Census Division level. Census Division data represent larger geographic areas and may capture more variation in building prototypes. These results suggest that, absent improved local building metering, modeling tools such as DEER (CPUC, 2009) can be useful for efficiency policy decision-making.

Figs. 1 and 2 also show that larger demands typically demonstrate more spread, with some buildings demonstrating extreme demands relative to their peers. These results highlight end-uses prime for energy efficiency, such natural gas heating and traditional electric cooling end uses.

Ranges in demands were only prepared for heating, cooling, and commercial lighting. The means, 25% quartiles (“Q25”), and 75% quartiles (“Q75”) shown in Figs. 1 and 2 were used to define ranges for modeling. These end uses constitute approximately 55% and 35% of the total energy consumed in Pittsburgh and Austin, respectively.
Heating, cooling, and commercial lighting likely demonstrate the most significant variability across building type, vintage, and primary activity. Point estimates were prepared for appliances, water heating, and residential lighting. The end use demands and estimation assumptions are summarized in the Supplemental information (Appendices A and B).

2.4. Efficiency measures

Energy efficiency measures can be characterized by their initial cost, operating and maintenance costs, service life, and effectiveness (impact on energy use). The impact on energy use can vary significantly by climate and building activity.

California’s DEER database (CPUC, 2009) consists of approximately 130,000 building energy consumption model simulations. Each simulation tests the impacts of an efficiency intervention. Simulations vary by building size, activity, vintage, California climate zone, and the stock being replaced or modified. Simulations use the DOE-2 software (www.doe2.com). Itron, Inc. (2005) contains more details on DEER.

Some efficiency measures – such as heating and ventilation retrofits – impact both heating and cooling as well as both natural gas and electricity use. This approach accounts for the potential unintended negative technical impact of efficiency interventions. Heating and cooling stocks and demands were combined when modeling these efficiency measures. Existing control technologies (such as thermostats) were averaged across the heating and cooling stocks to model their impacts. For these measures, CPUC (2009) does not report heating and cooling impacts separately. The impacts associated with such measures cannot be reported separately for heating and cooling.

DEER reports efficiency data for only five vintages: pre 1978, 1978–1992, 1992–2001, 2002–2005, and post 2005. Thus it was not possible to rigorously align the vintage of building stock in the case studies with the DEER data. Appendix H in the Supplemental information compares DEER building vintages to those for the case studies. For Pittsburgh, only simulations for buildings built before 1992 were selected when defining efficiency measures. For Austin, all building vintages in the DEER database were considered. These vintages are reasonably consistent with household ages in Pittsburgh and Austin (US Census Bureau, 2009a, 2009b, 2009c).

DEER reports energy efficiency impacts in absolute terms (e.g., “kWh reduced”). These values were converted to percent reductions from baseline when modeling. This approach moderates climate differences in baseline energy use. Absolute demand reductions are modeled for end uses not affected by climate. Compounding efficiency impacts associated with efficiency measures – such as combining insulation with an efficient furnace – were not modeled. As a result, the heating and cooling impacts may be overestimated.

We assume cooling efficiency measures reported for central cooling apply to district cooling systems. Efficiency measure costs, effectiveness, assumptions, and other efficiency data sources are summarized in Appendices E and F in the Supplemental information.

2.5. Modeling scenarios

All models assume a 2009 baseline, a 4% discount rate, and a 20-yr planning horizon. The OMB (2009) recommends a 4.4% nominal rate for 20-yr horizon federal cost effectiveness analysis. However, municipal bonds have higher interest rates. Here, 4% is used for base-case analysis. Model sensitivity to discount rates is discussed in Section 3. All costs and benefits are discounted to 2009$. Eqs. (1)–(4) show the costs and benefits for each stock replacement scenario. Eqs. (1)–(4) specify a linear programming optimization system where the stock replaced (“no. of stock”) is the decision variable and the costs, benefits, and energy and water savings become either constraints or objectives.

Immediate replacement of end-use equipment:

\[
\text{Cost NPV}_{\text{End-Use Stock}} = \sum_{n=0}^{\text{Planning Horizon}} \text{Capital Cost of End-of-Service-Life Replacement} \times \left( \frac{\text{No. of Stock}}{(1+i)^n} \right)
\]

\[
\text{Benefit NPV}_{\text{End-Use Stock}} = \sum_{n=0}^{\text{Planning Horizon}} \text{Net Energy & Water Savings} \times \left( \frac{\text{No. of Stock}}{(1+i)^n} \right)
\]

Replacement of stock as it retires

\[
\text{Cost NPV}_{\text{End-Use Stock}} = \sum_{n=0}^{\text{Planning Horizon}} \text{Capital Cost of End-of-Service-Life Replacement} \times \left( \frac{\text{No. of Stock}}{(1+i)^n} \right)
\]

\[
\text{Benefit NPV}_{\text{End-Use Stock}} = \sum_{n=0}^{\text{Planning Horizon}} \text{Net Energy & Water Savings} \times \left( \frac{\text{No. of Stock}}{(1+i)^n} \right)
\]

where UAE is the uniform annual equivalent of a time series of cash flows.

Electricity, natural gas, and water prices are shown in Appendix G in the Supplemental information. The GHG impacts of efficiency interventions are compared to the case in which no efficiency program is implemented, i.e., the impacts of efficiency policies are evaluated relative to current demands.

Two modeling scenarios are conducted for each case study.

(1) Efficiency Potential: All baseline end-use stock is replaced immediately with efficient stock. Consumers immediately incur the full cost of efficient technologies. Savings and GHG reductions start immediately and continue throughout the planning horizon. The marginal cost to replace efficient stock as it retires throughout the planning horizon is included. This scenario defines the maximum GHG reduction potential for energy efficiency. The reference case (the case against which efficiency performance is evaluated) assumes consumers would use existing stock at current levels until retired, then utilize “standard-code” equipment for future replacements at current “standard-code” equipment cost and performance.

(2) Efficiency Standards for New Equipment: Stock that has reached its service life is replaced with more efficient technology. A fraction (1/stock service life) of the “old” stock is replaced annually with efficient stock, e.g., for equipment with a 10-yr service life, 1/10th of the stock is replaced each year. The energy and cost savings cumulatively increase each year (e.g., 1/10 in year 1; 2/10 in year 2, etc.). Once the old stock is completely turned over, the annual energy and cost savings peak, but the cost to maintain the efficient stock is incurred.
The reference case assumes retired stock is replaced by “standard” technologies, as defined by current technology cost and performance. Future changes to standard and efficient technology cost and performance are not modeled.

For each scenario, two distinct policy objectives are tested: (1) maximize GHG reductions (tons) given an initial budget constraint or (2) to maximize the net social present value given a reduction target. This modeling architecture allows for comparative analysis of the trade-offs between the initial cost, consumer savings, and GHGs mitigated. The model scenarios are summarized in Table 2. Traditional engineering economic analysis was combined with the constrained optimization tool Solver (Flystra et al., 1998) in Microsoft Excel® to evaluate the modeling scenarios.

<table>
<thead>
<tr>
<th>Case studies</th>
<th>Efficiency scenario</th>
<th>Scenario objectives</th>
<th>Inputs with ranges</th>
<th>Point inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pittsburgh, PA</td>
<td><strong>Efficiency potential:</strong> Immediately replace current stock with efficient stock</td>
<td>Max GHG reductions given current budget constraint</td>
<td>Stocks, demands, and efficiency impacts weather sensitive equipment. Ranges designated as “low,” “med,” and “high.”</td>
<td></td>
</tr>
<tr>
<td>Austin, TX</td>
<td><strong>Efficiency Standards for New Equipment:</strong> Annually replace retired stock with efficient technology</td>
<td>Max GHG reductions given annual budget constraint</td>
<td>Stocks, demands, and efficiency impacts for non-weather sensitive equipment</td>
<td></td>
</tr>
</tbody>
</table>

2.6. Variability and uncertainty

Three major sources of unknown variability are modeled: unknown quantities of end use stock, unknown demands for weather-sensitive end uses, and unknown impacts of efficiency interventions. Ranges in demands and efficiency impacts were not modeled for non-weather sensitive end uses.

The unknown variability stems from not having data to represent stocks, demands, and efficiency impacts at the local level. This unknown variability is therefore represented by ranges in stock estimates (Section 2.2) and building-to-building variation in demands and efficiency impacts (Section 2.3).

To address this variability in the context of an optimization model, a low, median, high simulation was modeled. The low scenarios represent aligning the low stock estimate (Appendices A and B), the 25th percentile demand (Appendices A and B), and the 25th percentile efficiency impacts. The median and high scenarios follow, with the high scenario representing 75th percentile estimates. As building-to-building variation represents extreme potential variation when scaled up to the municipal level, the low and high modeling scenarios likely represent extreme conditions.

3. Results

Results are discussed from a social perspective. Social savings refer to the discounted cost of energy efficient technologies and the customer-based savings realized through reductions in energy use, expressed at net present value (NPV). Costs include the capital and labor costs of energy efficient technologies.

While some efficiency program administrators plan programs on a basis of per building (per meter) or per technology (e.g., per refrigerator), our results are presented on a per capita basis for comparison across sectors and case studies and to inform broader decision-making.

Fig. 3 shows the initial marginal capital costs, GHG reduction, and social savings for replacing stock as it retires in Pittsburgh, PA. Capital costs (budget constraints) shown in Fig. 3 reflect the incremental cost between efficient and “average” technologies. Fig. 3 shows maximum GHG reductions given increasing initial annual budget (capital and labor) constraints ranging from almost no increase ($0.05/capita) in the marginal cost of replacing stock with efficient equipment to spending around $25/capita/yr, or around $10 M/yr for all of Pittsburgh. Fig. 3 indicates that an annual budget of approximately $1 per capita could result in annual GHG reductions of 0.5–3 tons per capita and generate social savings of $1000–$6000 per capita.

Fig. 3 shows that commercial lighting and HVAC efficiency interventions are relatively affordable and effective, mitigating up to near 3 tons of CO₂ eq/capita/yr at less than $1 per capita per year and generating up to $6000/capita in present value savings over a 20-yr period. As the budgetary constraint increases, additional technologies – e.g., residential lighting and commercial cooling – become “affordable” and are selected as part of the optimization routine specifying that GHG reductions are maximized given a budget constraint.

Fig. 3 demonstrates that unknown variability in stocks, demands, and efficiency impacts at the municipal level is significant. For example, an annual GHG reduction of 1 ton/capita/yr could cost from $1 per capita to $10 per capita annually. The optimal sectors and end uses for investment – the investment strategy – differ as well (compare results for the median inputs for $1/capita budget to the low inputs for the $20/capita budget). Such uncertainty may undermine capital planning for local climate policies and highlights the need to carefully perform rigorous benefit–cost analysis when committing to GHG reductions.

Fig. 4 shows similar results for Austin, TX. Fig. 4 demonstrates that unknown variability in stocks, demands, and efficiency impacts is less significant in the Austin case study than the Pittsburgh case study. For example, the annual capital budget required to reduce emissions by 1 ton/capita/yr emissions reduction ranges from $1 to $5/capita/yr and returns approximately $2000/capita in savings over a 20-yr period. A $5/capita capital budget investment in Pittsburgh results in GHG reductions on the order of 1–4 CO₂ eq per capita, whereas expected reductions in Austin are 1–2 CO₂ eq per capita. On a percent basis (relative to total building emissions), a $5/capita

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Fig. 3. Maximum GHG reductions and potential social savings (NPV) given annual budget constraints in Pittsburgh, PA. Note there are 2 y-axes: one for GHG reductions and one for NPV. Each group of three bar charts corresponds to increasing annual budgetary constraints, with the right-most group corresponding to implementing all measures. The bar charts show CO₂ eq reductions by efficiency category. The line charts show the total net present value per capita from the indicated efficiency categories. Ranges (low, med, and high) reflect ranges in model inputs as discussed in Section 2.6.

Fig. 4. Maximum GHG reductions and potential social savings (NPV) given annual budget constraints in Austin, TX. Note there are 2 y-axes: one for GHG reductions and one for NPV. Each group of three bar charts corresponds to increasing annual budgetary constraints, with the right-most group corresponding to implementing all measures. The bar charts show CO₂ eq reductions by efficiency category. The line charts show the total net present value per capita from the indicated efficiency categories. Ranges (low, med, and high) reflect ranges in model inputs as discussed in Section 2.6.
marginal capital budget investment result in reductions on the order of 20–40% in Austin and 5–20% in Pittsburgh. Expected social savings associated with these investments range from $2000–$8000 for Pittsburgh and $2000–$4000 in Austin.

Fig. 5 compares expected emissions reductions for increasing efficiency investment levels for weather sensitive end-uses in Austin and Pittsburgh. Results in Fig. 5 reflect median inputs for replacing retired stock. Fig. 5 indicates that emission reductions for heating, HVAC retrofits, and commercial lighting are generally much higher (50–200%) in Pittsburgh than Austin. This is likely due to cost efficiencies associated Pittsburgh’s more intense heating season, an approximately 10% higher electricity emissions factor, and older building stock and end-use equipment. As expected, cooling end-uses demonstrate more potential in Austin. While not shown here, a comparison of expected social savings is very similar.

Fig. 6 shows the potential 20-yr social savings (net present value) associated with each simulated energy efficiency policy objective in Pittsburgh. Consider mitigating 1.4 tons of CO₂eq/capita/yr in Fig. 6. Replacing stock as it retires (shown by bar charts not bounded by black line) will generate approximately $2500–$3000/capita of savings over a 20-yr period. The specific amount depends on whether the policy is cost constrained by a budget (indicated by “C”) or is designed to maximize social savings (indicated by “NPV”). Fig. 6 demonstrates that some efficiency measures (e.g., residential heating) must be implemented as stock retires to generate positive social savings. Some strategies, such as commercial HVAC retrofits, perform well under all scenarios.

The policy objectives, constraints, and replacement timing evaluated here have little effect on the expected social savings with the exception of implementing all efficiency measures, which corresponds to the far right set of bar charts ( > 2.6 CO₂ eq mitigated per capita). At lower values of GHGs mitigated, maximizing social savings (indicated by “NPV” on the x-axis) can increase social savings slightly, on the order of a $100–$200 per capita over the 20-yr planning horizon. However, these margins decrease to near nothing at higher GHG mitigation targets.

Immediate replacement leads to a social loss (negative social savings) for many end uses. This social loss results from immediately paying the total cost (capital and labor) for efficiency technology, as opposed to paying the incremental cost (the difference between “average” and efficient equipment) as stock retires. Not only is the incremental cost of efficient technologies often much less than the total cost, the incremental cost is discounted, which increases potential social savings.

Fig. 6 also highlights that different policy objectives and equipment replacement timing can also lead to different optimal investment strategies across efficiency technologies. For example, residential appliances, cooling, and water heating perform better when stock is replaced as it retires.

Fig. 7 shows the cost effectiveness of annually replacing retired stock with efficient stock in Pittsburgh and Austin. As expected, policies that maximize net present value (shown by solid symbols) are more cost effective. When maximizing net present value, the cost effectiveness decreases as the amount of GHG mitigated increases.

This trend follows from the optimization routine: the most cost effective policies are implemented first. Policies constrained by initial budget demonstrate an irregular pattern of cost effectiveness with increasing GHGs mitigated. This is because affordable efficiency measures may or may not be cost effective. For Pittsburgh, the cost effectiveness varies from around $40 to $60/ton depending on the objective, constraint, and GHG reduction target. For Austin, the cost effectiveness varies from around $100 to $140/ton.

Fig. 7 also indicates that commercial sector efficiency measures are generally more cost effective across the full range of GHG mitigation potential and given system uncertainty, particularly in Austin. Residential measures are generally more cost effective when assuming relatively low values for model inputs; however, commercial sectors investments prove more cost effective for nearly all other model assumptions.

An analysis of model sensitivity to expected total GHG reductions and social savings (20-yr NPV) indicates that model is particularly sensitive to changes in the demand for commercial space conditioning (a 50% change in demand results in a 50% on GHG reductions and NPV), the discount rate (a 50% in discount rate results in 20% change in NPV), and electricity emissions factor (a 40% change in emissions factor results in s 20% change in GHG reductions). Assuming reasonable ranges, sensitivity to the remaining input parameters is generally less than 10%.

4. Discussion

Results highlight opportunities for improving the design of energy efficiency policies aimed at reducing GHGs. Effective
efficiency investment strategies are a function of the capital cost of efficient technologies, the marginal cost of efficient technologies relative to “standard” technologies, and the marginal performance of efficient technologies relative to “standard” technologies, which are all influenced by the local market for energy services and efficiency opportunities. In other words, there are trade-offs among capital costs, social savings, and the target GHG reductions, which differ from region to region.

This work uses simple engineering and optimization models to demonstrate potential trade-offs associated with different energy efficiency program objectives and constraints. There are several limitations to this work that offer useful insights into the unique challenges of designing energy efficiency programs.

Typical incentive-based efficiency programs require necessary but voluntary participation. While the cost-effectiveness of energy efficiency programs rests on the vintage, activity, and size of participating buildings, participation across these building characteristics is uncertain. The approach to modeling uncertain self-selection here is to establish ranges in efficient technology costs and benefits estimated for different building vintages, sizes, and activities, then assume each building owner is willing to participate in efficiency programs that meet the modeled objectives and constraints. This “willingness to participate” assumption does not reflect reality and creates and upper bound for estimated GHG reductions and social savings. These issues are difficult to integrate into program design and may not be recognized by program administrators.

As a result of uncertain participation, some public program administrators may be hesitant to promote energy efficiency despite the opportunities for social savings or they may only be comfortable focusing on internal operations or familiar programs (e.g., new construction through buildings codes), even though more effective opportunities exist in the community at large in existing building stock. This may partially explain a lack of consideration of social benefits when developing climate action policies (Kousky and Schneider, 2003) and the disparate program designs and successes associated with public efficiency programs.

Despite these limitations, the methods and results profiled herein can help narrow and prioritize the end uses that support program objectives and plan appropriate (and realistic) capital budgets. For example, commercial HVAC retrofits performed robustly across the program objectives, constraints, and ranges of uncertainty modeled. When combined with other data sources that highlight targeted building activities – sources such as local tax assessment data or the Commercial Buildings Energy Consumption Survey (DOE, 2005) – efficiency program design strategies may become more focused and effective. Robust performance assessment is particularly helpful given limited available capital.

Of course, a narrowing of efficiency investment strategies may not meet other public sector goals, such as equity. For example, many public efficiency programs have focused on weatherizing low-income households to reduce household operating costs. DSIRE (2009a) reports that 20 states have low-income efficiency programs and a total of about 100 low-income efficiency programs nationwide.

Efficiency program administrators commonly design and administer separate programs for different sectors. For example, DSIRE (2009b) reports that over half of domestic efficiency programs target just one end use sector. However, our results indicate that program objectives may be better met by collectively evaluating end-use sectors, allocating efficiency investments to sectors and end uses that best meet program objectives.

Our reference case assumptions (see Section 2.5) also limit model results. The reference case refers to the uncertain future

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**Fig. 6.** Social savings (NPV) associated with building energy efficiency policies in Pittsburgh. Results shown for median simulations only. Results show for four potential policy objectives: (1) immediately replace all stock given a budget constraint; (2) immediately replace all stock maximizing social savings; (3) annually replace retired stock given a budget constraint; and (4) annually replace retiring stock maximizing social savings. Each set of four bar charts refers to a different target GHG reduction. The right-most bar chart reflects implementation of all efficiency measures. For example, consider mitigated 1 ton CO₂ eq/capita/yr. Replacing stock as it retires (shown by bar charts not bounded by black line) will generate approximately $900–$1200 of savings per capita over a 20-yr period. The specific amount depends on whether the policy is cost constrained (indicated by “C”) or is designed to maximize social savings (indicated by “NPV”). At 1 ton CO₂ eq/capita/yr mitigated, more savings can be generated by replacing stock immediately (indicated by bar charts outlined in black).
portfolio of energy technologies available and purchased absent any policy intervention, influenced by future changes to energy prices, GHG markets, standard-code technology, efficiency technology, and many other factors. For example, future increases to energy prices or accounting for climate change impacts would increase the social savings associated with efficiency. These limitations are likely low in the short-run; as stocks will continue retiring and pricing and technology performance is likely stable.

Finally, our representation of consumer behavior with respect to increased efficiency is likely inadequate. Rebound effects occur when consumers erode predicted energy savings through re-spending. Rebound can be significant, potentially eroding all planned savings (Sorrell et al., 2009; Greening et al., 2000). Future work on efficiency program design should integrate rebound effects.

This work has identified the following guidelines for energy efficiency program design:

1. Consider your market for energy efficiency. The local market for energy efficiency is influenced by climate; the portfolio of building quality, vintage, and primary activity; the demands of existing end-use equipment; price of fuels, water, and labor; growth; and the types fuels used to produce locally consumed energy. Fuel sources (e.g., natural gas and those used to produce electricity) will significantly influence the potential for GHG reductions. The optimal bundle of technologies and end uses prime for GHG reduction investments vary significantly between Austin and Pittsburgh, and technologies demonstrate more than 100% difference in performance at similar capital investments. While the 20-yr effectiveness of GHG reductions in Pittsburgh is about half of that in Austin, higher per capita GHG reductions are expected in Pittsburgh at similar capital investments.

2. Narrow and prioritize end uses for potential investment. Some end uses, sectors, and building activities demonstrate relatively more robust socially efficient GHG reduction opportunities than others given system uncertainty and trade-offs amongst program constraints. The results here suggest commercial HVAC retrofits demonstrate robust performance given system constraints, uncertainty, and trade-offs amongst varying program objectives, especially in Pittsburgh. Analytical methods like the optimization modeling conducted here can be used to scope relatively more effective local GHG reduction opportunities and direct incentives as appropriate.

3. Develop a strategy to promote effective and ample self-selection. If the efficiency program requires self-selection (such as rebates and similar incentive programs), identify strategies to promote ample self-selection. Given the commercial sector results demonstrated herein, effective strategies may include targeting centralized commercial decision-makers, such as large institutions.

4. Be proactive in reducing the uncertainty in local stocks, demands, and efficiency impacts. Such uncertainty undermines opportunities for financial planning, program design, and performance monitoring. The capital costs required to meet target GHG reductions

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Fig. 7. (a) (Pittsburgh) and (b) (Austin): The cost effectiveness of greenhouse gas reductions associated with replacing retired stock with efficient stock. Cost-effectiveness is measured as the uniform annual equivalent of capital costs and savings divided by annual greenhouse reductions. The labels “R” and “C” denote end-uses and technologies in the residential and commercial sectors, respectively.
and/or generate a specific amount of social savings vary by a factor of about 5.

(a) Include major energy end uses in routine property tax data collection: Counties, with jurisdiction over property taxes, may be best suited to reduce the uncertainty in equipment stocks.

(b) Require energy audits to receive a transfer of title: Audits could be incorporated into property inspections during negotiation of sale. For example, energy audits cost approximately $400 per household (less than $200 per capita) and $0.10–$0.15 per ft² of commercial space (EAU 2009). These one-time costs are certainly within the range of potential savings generated by energy efficiency.

(c) Encourage voluntary reporting of energy use: Most energy utility data is private, making estimating current demands difficult. Local authorities could encourage anonymous on-line reporting of energy use, potentially providing small tax breaks for participation.

(5) Allocate appropriate resources to energy efficiency programs.

This work indicates that achieving meaningful GHG reductions will take considerable capital investment, strategic planning, and careful program design, requiring new skill sets and resources. Given the potential public value of efficiency, public agencies will likely need to continue supporting efficiency markets through carefully planned capital investments and improved decision support resources.

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Appendix A. Supplementary information

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