Behavior-based Energy Savings Opportunities in Commercial Buildings: Estimates for Four U.S. Cities

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ABSTRACT

Past research has documented the large-scale, energy and carbon reductions that could be achieved in the *residential* sector by shifting everyday household behaviors, technology use patterns, and technology choices. On a national scale, estimates of achievable savings (in the short to medium-term) from these types of behavioral approaches have ranged from 20 to 30 percent of current residential energy consumption. Subsequent research at the city level has created a similar set of estimates for five U.S. cities. Until now, however, efforts to estimate the energy savings potential from behavioral initiatives have overlooked the potential energy savings that could be achieved in *commercial* buildings. This paper will share findings from a new approach aimed at providing U.S. cities with estimates of city-level, behavior-based energy savings potential. The approach is innovative in its ability to 1) estimate city-level energy consumption across nine types of commercial buildings and ten end uses, and 2) model the potential energy savings from 91 distinct behaviors that can be taken by building operators or building occupants. Building types range from office and retail to hotels, schools and hospitals and represent approximately 65% of all commercial buildings, 68% of commercial floor space, and as much as 81% of commercial building energy consumption in the four cities studied. This paper will: 1) outline the core components of the estimation model and method, 2) compare estimates across four U.S. cities, 3) compare estimates across building types and end uses, and 4) discuss the value of this information for cities, utilities, and other entities.

Introduction

As progress on national climate policy continues to be deadlocked in the United States, cities have emerged on the forefront of efforts to address energy and climate change challenges (Adler 2014, Bulkeley 2010; Rosenzweig et al. 2010). As part of their efforts, cities are increasingly recognizing the importance of engaging directly with urban residents and businesses using people-centered approaches that help households and businesses move away from wasteful energy use practices, reduce energy consumption, and lower carbon emissions (Ehrhardt-Martinez 2012). These approaches are appealing on many levels. When compared to more traditional technology-focused efforts, emerging research suggests that people-centered initiatives in the residential sector – focused on the decisions and practices of people and households – could achieve significant, short-term reductions in *residential* energy demand of 20 percent (or nine quadrillion BTUs) and reductions in carbon emissions of 7.4 percent (Dietz et al. 2009). While only a few estimates of *commercial* sector savings opportunities are available, existing studies suggest that the actions of building tenants and building operators could reduce commercial sector energy consumption by 7 to 21 percent (Ehrhardt-Martinez 2015a; Azar and Menssa 2014; Norton 2013). Given that studies of behavioral potential are necessarily focused on energy practices and decision making, they are also more likely to help households, businesses, and cities transition away from a culture of energy waste and toward a culture of more sustainable use. Notably, much of the energy savings could be achieved with relatively limited investments in new technologies.

The current roadblock for cities lies in the mismatch between *national*-level research and *city*-level sustainability initiatives as well as the unavailability of estimates for behavior-based energy savings opportunities in the commercial sector. While national-level research has provided some compelling evidence for aggregate, national-level savings opportunities in the residential sector, it has been unable to translate those findings into insights that are actionable at the commercial sector or at the city level. More specifically, national-level estimates fail to account for area-to-area variation in a wide range of important variables such as climate characteristics, building infrastructure, technology saturation and technology use patterns. Without more specialized information, cities (and states) lack the ability to effectively develop and justify behaviorally-focused policies and programs at city and state levels.

This conundrum suggests that what cities need are quantifiable estimates of potential behavior-based savings for their particular city as well as clear information concerning the sets of behaviors that promise the largest savings opportunities given their city's unique characteristics. Such information is vital to city sustainability efforts because it provides cities with the means to:

- Evaluate the relative importance of behavioral initiatives as part of a larger, city-wide sustainability, climate, and/or energy initiative,
- Prioritize investments in different types of projects and programs and focus limited resources on a more precise and promising set of interventions,
- Write more effective funding proposals, and
- Develop more targeted marketing and communications efforts,

In sum, the efforts of cities to enhance local sustainability efforts would benefit greatly from city-specific information about behavioral opportunities that recognizes local conditions and enhances the likelihood of effectively engaging city residents. Not surprisingly, however, this type of information is expensive to develop because it typically requires cities to engage in primary data collection efforts and data analysis. In response, a small group of cities decided to pursue a joint effort to explore potential means of using existing data sources to develop low-cost, city-level estimates of behavioral opportunities for reducing energy demand and carbon emissions. The goal of this effort focused on the development of an estimation model that uses existing data from a variety of existing sources to arrive at reliable measures of achievable savings. The results of each city-level assessment are summarized in a city-level Behavior Wedge Profile report, giving cities a foundation of information upon which they can be more strategic in their development of behavioral programs. The effort was initiated in 2012 by members of the Urban Sustainability Director's Network (USDN) and funding for the work was provided by several foundations. This paper provides an overview of the work and summarizes the findings, highlighting the size of behavior-based energy saving opportunities across cities, building types, and end uses.

Core Components of the Municipal Behavior Wedge Profile Model

Estimates created using the Municipal Behavior Wedge approach rely on the use of existing data sources to develop low-cost, city-specific estimates of achievable energy savings in the realms of residential and commercial buildings. This paper focuses exclusively on the development of the set of *commercial sector* estimates associated with the decisions and actions of building tenants and building operators. Information about the development of residential sector estimates can be found in Ehrhardt-Martinez (2015b and 2015c).

The Municipal Behavior Wedge Model for the commercial buildings sector creates estimates of the achievable municipal-level energy savings that can be attained through programs and projects that address the energy-related routines, actions, and decisions of building operators and building occupants in the commercial buildings sector. As with the residential model, the commercial model was developed with the expressed goals of:

- Establishing a low-cost or affordable means of developing behavior-related energy savings estimates for cities across the United States,
- Estimating measures of *achievable* savings opportunities - rather than estimates that include all of the potential savings that could come from changes in choices and actions without taking into consideration participation rates, and
- Providing information about both the overall scope of the savings opportunity and the specific types of energy saving actions that are likely to yield the largest savings (as a means of helping municipal decision makers evaluate between program alternatives and target their efforts accordingly).

Savings Estimates across Building Types. With the above stated goals in mind, the model provides each city with an aggregate, city-level estimate of the achievable energy savings opportunity (in bBtus and as a percent of current consumption), but also breaks that estimate down for nine different commercial building types as illustrated in Figure 1. These commercial building types represent approximately 65% of all commercial buildings, 68% of all commercial floor space, and between 75% and 81% of commercial energy consumption for the four cities included in this study.

Figure 1: Nine building types included in the municipal commercial behavior wedge study

Savings across Energy End Uses and Behaviors. Commercial building energy consumption is typically categorized into 10 specific end uses as illustrated in Figure 2. We use these same categories to estimate behavior-based energy savings potential for each building type.

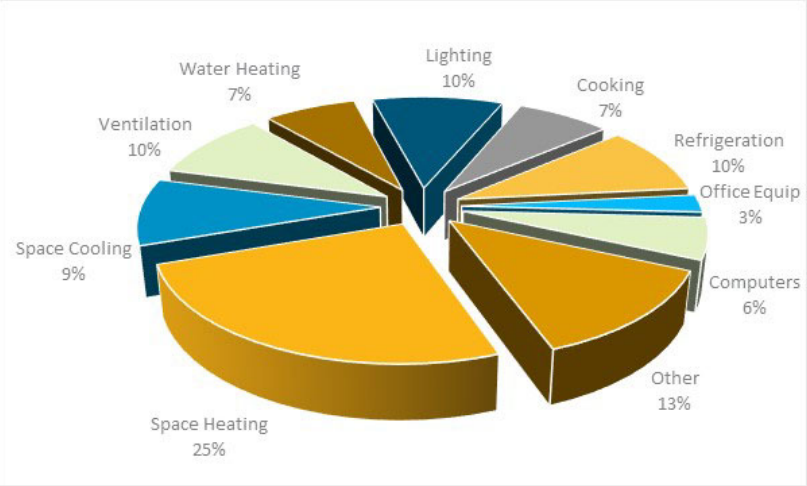

Figure 2: Energy consumption by end use in commercial buildings, 2012. *Source:* EIA 2015.

Table 1: Behaviors by end use

End Use	No. of Behaviors
Space Heating	15
Space Cooling	10
Ventilation	5
Water Heating	8
Lighting	12
Cooking	3
Refrigeration	11
Office Equip	8
Computers	7
Other	12
TOTAL	**91**

Within each of the energy end uses identified in Figure 2, the model generates estimates of the potential energy savings associated with a specified set of occupant and/or operator behaviors. Altogether, estimates are developed for a list of 91 energy-related behaviors. These behaviors are distributed across each of the end use categories as shown in Table 1. The full list of 91 behaviors is considerably longer than the list of actions used in the residential sector model and reflects the greater diversity in the types of energy-related behaviors associated with different types of commercial buildings. For example, while computer-related actions represent a key source of energy waste in office buildings, refrigerator settings and refrigerator maintenance are of much greater importance for food service and food sales. In constructing the model, our goal was to use the relevant literature to identify a subset of occupant and operator behaviors that would encompass the most significant savings opportunities across the nine types of commercial buildings included in the model. The identification of the most relevant behavioral opportunities was informed by a review of previous research, including a 2010 report on "Commercial Miscellaneous Electric Loads" (McKenney et al. 2010) and a variety of reports on commercial building plug loads written by the National Renewable Energy Lab (NREL) and the Pacific Northwest National Lab (PNNL) (NREL 2014, 2011 and PNNL 2011) among other publications listed in the References section of this report. While the commercial sector model includes a longer list of behaviors, the list is not intended to be comprehensive and the estimates that are derived from it will necessarily undercount the full range of energy savings opportunities. The full list of selected behaviors used in the Commercial Behavior Wedge model is available in Appendix B of Ehrhardt-Martinez (2015c).

Conservative Estimates of Achievable Savings Opportunities: Behaviors, Eligibility, and Participation. Similar to methodologies that have been employed in the past to create residential-sector savings estimates, the approach used to create commercial building estimates strives to establish conservative measures of the true range of potential energy/carbon savings that could be achieved through shifts in behaviors, practices and choices. The commercial sector estimates are considered to be conservative for at least three reasons: 1) the estimation model calculates estimates for only a subset of the much longer list of practices that could result in energy savings, 2) model estimates of city-wide savings associated with any given behavior are constrained by estimates of building-level eligibility for each behavior, and 3) estimates for eligible buildings are further constrained by the assumption that only 25% of eligible participants will take a particular action in the given timeframe (the model multiplies the estimated savings for eligible buildings by an assumed participation rate of 25%).[1]

As mentioned above, savings estimates are moderated by critically assessing the proportion of buildings that are eligible to participate in any particular behavior as well as their likelihood of participation. For example, buildings that are unlikely to have walk-in coolers are not eligible to reduce energy consumption by adjusting fan controls for those types of coolers. Similarly, buildings that are already turning off lights during non-operating hours are not eligible to enhance their energy savings by taking this action in the future. Estimates of eligibility for each behavior were derived from a review of CBECS data as well as information found in the commercial buildings literature. Such estimates are further moderated by applying an assumed 25% participation rate as shown in Figure 3.

$$\boxed{\textbf{Action Specific Savings} = \text{Current End Use Energy Consumption for Eligible Participants (Btu)} \times \text{Estimated Participation Rate (\%)} \times \text{Action-specific Energy Savings per Participant (\%)}}$$

Figure 3: Savings estimates as a function of eligibility and participation rate

Existing Data Sources. Estimates created using the Municipal Behavior Wedge approach use several existing data sources as a means of achieving the expressed goal of providing cities with low-cost, city-specific estimates of achievable energy savings. The primary data sources for the Commercial Behavior Wedge Model (discussed in more detail later in this paper) include the 2003 and the 2012 Commercial Building Energy Consumption Survey (CBECS) and the U.S. Census Bureau. These data sources were chosen, in part, because they provide rigorous and readily available data resources that can be used to characterize the energy consumption of different types of commercial buildings (taking into account building characteristics, technology saturation and other factors). This information is subsequently applied to the particular climate characteristics and building characteristics associated of specific cities. By using these existing data sets that provide relatively comprehensive and uniform information, the model is able to generate low-cost estimates of energy usage, patterns of usage, and energy savings opportunities for large metropolitan cities around the country.

Figure 4 provides a graphic overview of the variety of data sources that are used in the Commercial Behavior Wedge estimation model, including data from the Commercial Buildings Energy Consumption Survey (CBECS) (EIA 2015, 2008), the U.S. Census Bureau, and insights from industry experts and related literature. CBECS data provide the core set of data for the Commercial Behavior Wedge estimates. The CBECS data set includes detailed information about energy use by building type and by end use as well as building counts by building type for

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[1] Actual rates of participation in commercial sector behavioral programs are not well documented. Given that participation in behavioral programs doesn't require large up-front investments, we look to residential lighting programs and direct install programs designed for small and medium sized businesses as an indicator of potential participation. According to a recent ACEEE study (York et al. 2015), residential CFL programs have achieved socket saturations of 25 to 40% over a 10 to 20 year period. Similarly small business direct install programs have been shown to achieve participation rates of 10 to 55% over a 6 year period. Moreover, one program was able to achieve a 33% participation rate in a single year while another was successful in achieving an 85% participation rate over a period of 3 years.

each census division. They also provide critical information about the square footage and energy intensity of various types of buildings. These data play an important role is establishing estimates of baseline energy use. The U.S. Census provides population and workforce information for both cities and census districts. These data are important for understanding the local context and adjusting CBECS data to reflect city characteristics. Relevant literature and expert insights are used to assess eligibility and the likely range of savings associated with particular behaviors. Taken together, these three types of data provide the means for estimating both existing patterns of energy consumption and potential energy savings opportunities.

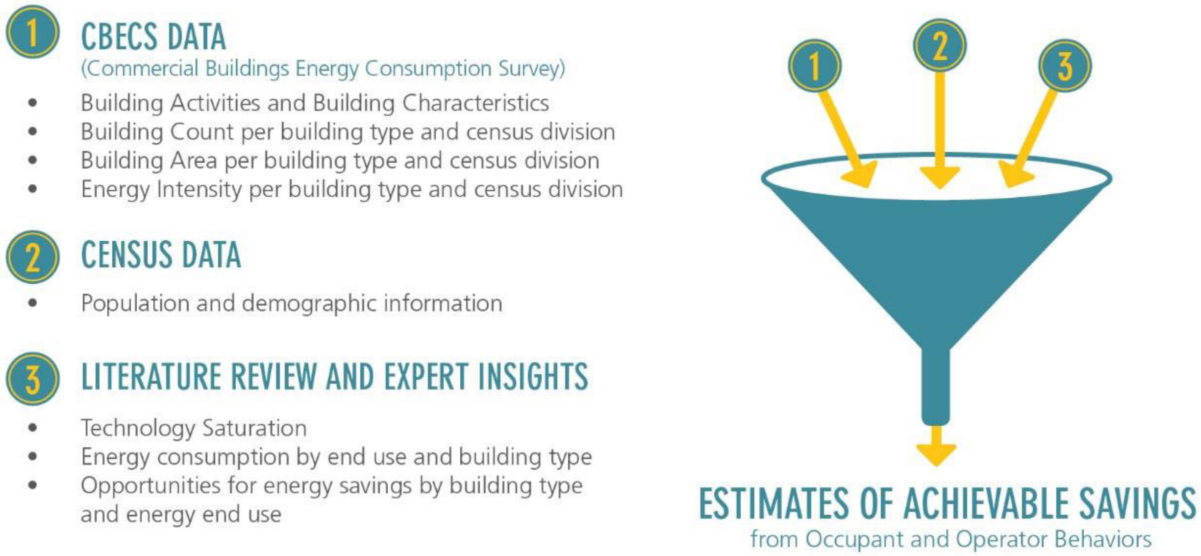


Figure 4: Data sources and inputs for the commercial municipal behavior wedge model *Source: Ehrhardt-Martinez 2015c.*

The model used to generate Behavior Wedge estimates of municipal-level savings opportunities in commercial buildings involves a two-step approach: 1) estimating municipal-level energy consumption by building type and energy end use, and 2) estimating behavior-based savings opportunities by building type and energy end use.

Estimates of Municipal-level, Commercial Building Energy Consumption. Estimates of municipal-level energy consumption were developed using data from the 2012 and 2003 CBECS (EIA 2015 and 2008) and the Annual Energy Outlook 2014. CBECS data provide information about the number of buildings and floor area by building type for the geographic region and the census division within which major metropolitan cities are located. This information is used to estimate municipal-level building counts and floor space for the cities in question by multiplying division-level building information by the proportion of the census division population living in the city. Estimates of municipal-level energy consumption are created for all end uses (other than space heating and space cooling) by taking national-level measures of energy intensity (measured as thousand Btu per square foot) for each end use and multiplying by the estimated municipal-level floor space for each building type. Estimates of municipal-level energy consumption for space heating and space cooling are created by using national-level estimates of delivered heating energy (as calculated by the EIA) and dividing by national measures of total floor space and the number of heating degree days to develop a measure of average Btus per square foot per degree day. This measure is then multiplied by municipal-level floor space estimates and municipal-level measures of heating and cooling degree days.

Estimates of Behavior-Based Savings Opportunities. Using the data sources identified in Figure 4 as data inputs, the Commercial Behavior Wedge model creates estimates of the achievable energy savings associated with 91 behavior-related measures for each of the nine types of buildings included in the model. Within the model, some estimates of savings opportunities are calculated using a top-down approach while others rely on a bottom-up approach.

The top-down estimation method is generally used for estimates of building-related technologies such as space heating, space cooling, ventilation, hot water, and lighting, whereas the bottom-up approach is used for plug-load related technologies such as cooking equipment, refrigeration equipment, office equipment, and computers. The top-down approach starts with an estimate of city-wide energy consumption for a particular energy end use in a particular building type. This consumption estimate is then multiplied by 1) a city-wide measure of eligibility to participate, 2) an estimate of the energy savings as a percent of end use demand associated with that behavior, and 3) an assumed 25% participation rate. Table 2 and Figure 5 (below) provide a more concrete example of how the formula was applied to generate an estimate of achievable savings associated with one particular behavior: limiting the hours of heating operations in office buildings.

Plug load and other estimates are calculated using a bottom-up approach that starts with estimates of city-level floor space, technology saturation (i.e. computers per square foot) and the annual energy use per device (based on information obtained through literature reviews) and then adds in the eligibility rate, participation rate and savings rate to estimate the savings that would result from consolidating equipment, powering down, and other types of actions by aggregating per unit savings. An example of this approach is provided in Figure 6 (below) which shows the estimated energy savings that could be achieved by increasing the number of computers that are turned off at the end of the day.

Table 2: Variables used to calculate energy savings opportunities from reduced hours of HVAC operations in office buildings

Variable Name	**Variable Description**	**Units**	**Value**	**Source**
Current Space Heating Demand	Total annual energy demand for space heating in office buildings at the city level	Billion Btu	827.3	Calculated
Eligibility to Participate	Proportion of office buildings that are eligible to reduce limit hours of heating operations.	Percent	38%	CBECS
Participation Rate	Proportion of eligible buildings that are likely to participate if informed and engaged.	Percent	25%	Assumed for all behaviors
Savings Rate	Proportion of heating-related energy demand that could be saved through reduced hours of operation.	Percent	20.4%	Calculated using data from literature
Savings Estimate	Total annual energy savings from	Billion Btu	16	Calculation

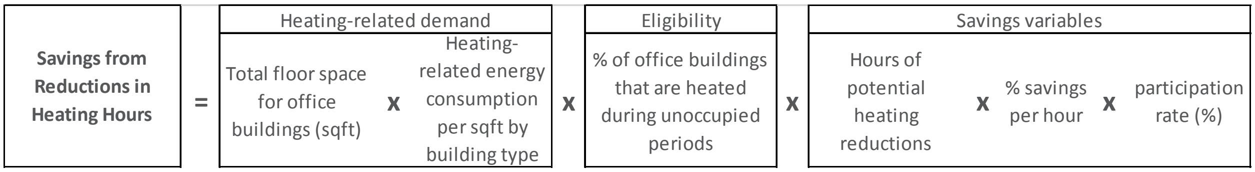


Figure 5: Top-down calculations used to derive city-level estimates of achievable energy savings in office buildings from reduced hours of heating operations

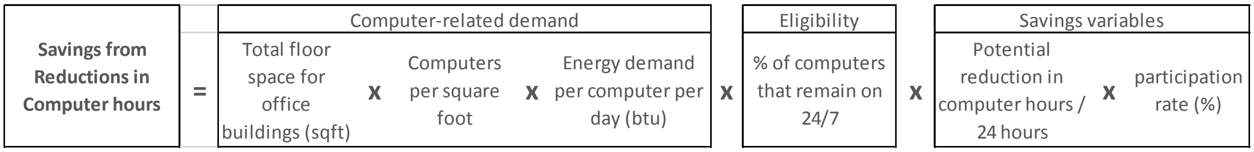


Figure 6: Bottom-up calculations used to derive city-level estimates of achievable energy savings in office buildings from turning off computers in the evenings and on weekends

Savings calculations in the model make some adjustments to reduce the likelihood of double counting savings opportunities from competing behaviors. These adjustments reduce the likelihood of inflated estimates of end-use-specific savings opportunities.

Comparison of Savings Estimates across Four U.S. Cities

The model was applied to generate savings estimates for four cities in the United States:

- Baltimore, Maryland;
- Boston, Massachusetts;
- Charlotte, North Carolina; and
- Miami, Florida.

As shown in Table 3 below, estimates of the behavior-based, energy savings opportunity were found to range from a high of 1,574 bBtu in Charlotte, North Carolina to a low of 857 bBtu in Miami, Florida. Savings opportunities in Baltimore and Boston were estimated to be 1,272 bBtu and 1,423 bBtu respectively. The size of the savings estimates is, in part, a reflection of the differences in the number of commercial buildings found in each city, the differences in total commercial square footage, and differences in estimated energy consumption.

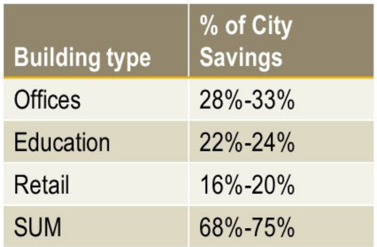
Table 3: Energy use and energy savings by city

	Baltimore, MD	**Boston, MA**	**Charlotte, NC**	**Miami, FL**
No. of Buildings	16,280	17,450	20,200	10,540
Square Feet (million)	268	250	330	173
Energy Use (bBtu)	21,940	26,500	27,210	14,400
Est. Savings Opp. (bBtu)	1,272	1,423	1,575	857
Savings Equiv.	**32,000 HHs**	**35,575 HHs**	**39,375 HHs**	**21,560 HHs**
HDD	3745	5412	3262	224
CDD	2046	903	1886	4560

Comparison of Savings Estimates across Building Types and End Uses

The distribution of behavior-based savings opportunities varies across different building types with the greatest savings coming from offices, education and retail buildings, respectively. Together these three categories of buildings represent a total of roughly 68-75% of all behavior-based savings in commercial buildings as shown in Table 9 below.

Table 4: Range of savings for top three building types



Building type	% of City Savings
Offices	28%-33%
Education	22%-24%
Retail	16%-20%
SUM	68%-75%

Below, Figure 7 illustrates that the concentration of savings in office, education and retail buildings is relatively consistent across the four cities although education and health care appear to provide a more important source of savings in Boston. Buildings focused on healthcare, lodging, food service, and service activities provide additional opportunities for behavior-based savings.

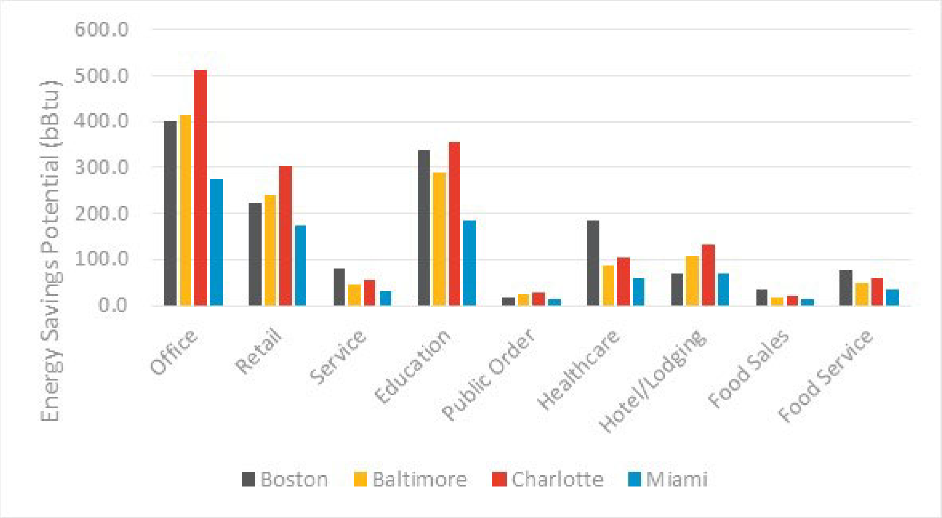


Figure 7: Behavior-based savings potential by building type and city

Not surprisingly, behavior-based savings opportunities also vary across end uses. Some of the most notable savings opportunities come from lighting as shown in Figure 8 below. The savings from lighting-related behaviors (for both tenants and operators) are estimated to exceed those of any other individual end use. However, if HVAC-related end use are taken together, the savings are roughly equivalent to those associated with lighting end uses. Water heating and computers also provide meaningful savings opportunities for all four cities. Figure 8 also shows that end-use specific savings opportunities vary across cities. Not surprisingly, space heating offers a greater proportion of savings in Boston while cooling offers a greater proportion of savings in Miami.

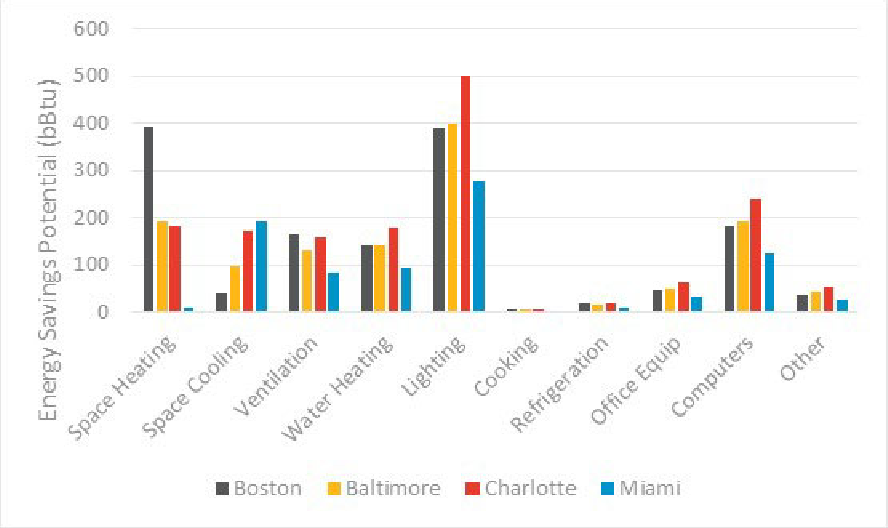


Figure 8: Behavior-based savings potential by end use and city

Finally, some cities (or other funders) might also be interested in knowing which particular end uses in which particular building types offer the largest behavior-based savings opportunities. This type of information is provided in Figure 9 which shows that in Baltimore, the top three behavior-based savings opportunities are associated with HVAC, lighting and office/computer equipment in office buildings (128, 129, and 134 bBtu, respectively). HVAC in educational buildings also represents a large savings opportunity (108 bBtu) as does lighting in retail (101 bBtu), lighting in educational buildings (83 bBtu), and HVAC in retail (73 bBtu). Other substantial savings are associated with office and computer equipment in schools (59 bBtu) and water heating in hotels, motels and other lodging facilities (40 bBtu).

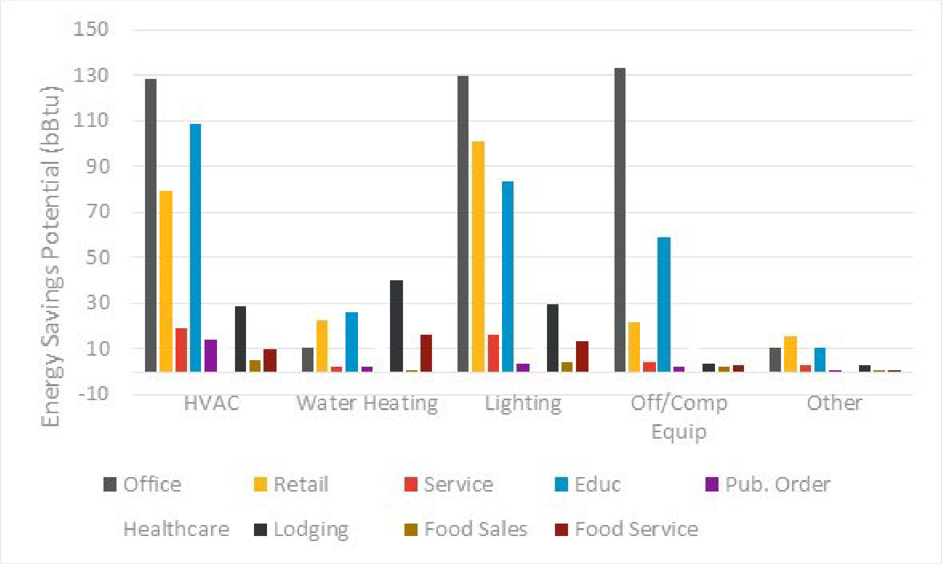


Figure 9: Behavior-based savings potential by energy end use and building type

Conclusions

City-level energy savings estimates of behavior-based opportunities can help cities and utilities determine the overall scale of savings opportunities as well as determine which end uses, building types, and behaviors matter most in reducing energy consumption. This information can help cities (and other funders and stakeholders) to target their efforts and funding toward programs focused on enhancing building operations and engaging with building tenants in ways that maximize program dollars and achieve the greatest amount of savings possible.

The estimates created through the use of the municipal behavior wedge model indicate that in three of the cities examined (Baltimore, Charlotte, and Miami) lighting-related behaviors can provide the largest behavior-based savings opportunity and in Boston, lighting-related savings are roughly on par with heating-related savings opportunities. Notably, however, if HVAC is considered as a single unit (as opposed to considering savings from heating, cooling and ventilation separately), behavior-related savings for this combined end use rival that of lighting across all four cities.

Finally, city-level estimates can also help cities and other funders and program implementers to rank the size of potential energy savings that are associated with a particular energy end use in a particular type of building. In Baltimore for example, the largest savings can be found in behaviors associated with HVAC use, lighting and office/computer equipment in office buildings, followed by HVAC in schools and lighting in retail buildings.

These types of estimates allow funders to evaluate how behavioral opportunities stack up against traditional efforts focused on generating savings through more energy efficient technologies. Because behaviors offer the opportunity to generate savings much more quickly than programs that require the purchase and installation of new technologies, having more information about behavior-based opportunities can allow funders to determine how a mix of behavioral and technological approaches might be combined to maximize both short-term and longer-term energy savings given the advantages and disadvantages of each approach. In short, policymakers, funders and implementers can use this information as a means of expanding the range of programs that can be considered and compared when designing strategies for meeting climate and energy goals at the city level.

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