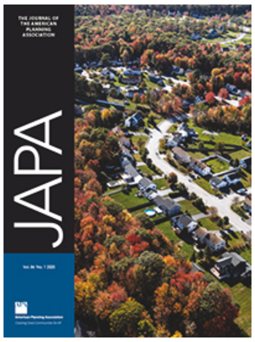

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Energy Cost Burdens for Low-Income and Minority Households

Evidence From Energy Benchmarking and Audit Data in Five U.S. Cities

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ABSTRACT

Problem, research strategy, and findings: Of the three primary components of housing affordability measures—rent, transportation, and utilities—utility costs are the least understood yet are the one area where the cost burden can be reduced without household relocation. Existing data sources to estimate energy costs are limited to surveys with small samples and low spatial and temporal resolution, such as the American Housing Survey and the Residential Energy Consumption Survey. In this study, we present a new method for small-area estimates of household energy cost burdens (ECBs) that leverages actual building energy use data for approximately 13,000 multifamily properties across five U.S. cities and links energy costs to savings opportunities by analyzing 3,000 energy audit reports. We examine differentials in cost burdens across household demographic and socioeconomic characteristics and analyze spatial, regional, and building-level variations in energy use and expenditures. Our results show the average low-income household has an ECB of 7%, whereas higher income households have an average burden of 2%. Notably, even within defined income bands, minority households experience higher ECBs than non-Hispanic White households. For lower income households, low-cost energy improvements could reduce energy costs by as much as $1,500 per year.

Takeaway for practice: In this study we attempt to shift the focus of energy efficiency investments to their impact on household cost burdens and overall housing affordability. Our analysis explores new and unique data generated from measurement-driven urban energy policies and shows low-income households disproportionately bear the burden of poor-quality and energy-inefficient housing. Cities can use these new data resources and methods to develop equity-based energy policies that treat energy efficiency and climate mitigation as issues of environmental justice and that apply data-driven, targeted policies to improve quality of life for the most vulnerable urban residents.

Keywords: big data, energy cost burden, energy efficiency, environmental justice, housing affordability

Of the three primary components of housing affordability—rent, transportation, and utilities—utility costs are the least understood, despite representing a significant opportunity to improve overall affordability without the need for household relocation (Stone, 2006). Excessive utility expenditures fall disproportionately to the lowest income households, who are least able to make energy efficiency investments, thus raising important social and environmental justice concerns that require policymakers and planners to act (Jenkins, McCauley, Heffron, Stephan, & Rehner, 2016). The slow pace of energy retrofits in existing multifamily buildings highlights the systemic investment constraints that result in an underallocation of energy-efficient technologies in housing (Pivo, 2014). Beyond the potential financial benefits for low-income households, energy-efficient investments can reduce carbon emissions and improve occupant health while achieving long-term sustainability goals (Nevin & Jacobs, 2006; Pearsall & Pierce, 2010). Researchers have made important strides in quantifying the magnitude of energy cost burdens (ECBs) on macro and regional levels, but policymakers and planners lack the granular, high-spatial- and temporal-resolution data needed to develop targeted and proactive policies and programs to directly address this issue. Such policies include incentives and mandates for energy efficiency improvements based on measured energy performance, subsidies for specific energy retrofits tied to building characteristics, and affordable

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housing programs that integrate rental subsidy amounts with ECB estimates.

In this study we present a new methodology to model household ECBs based on actual energy use data for individual buildings across five major U.S. cities and link energy costs to savings opportunities based on specific residential building types and characteristics. Specifically, we a) use high-resolution data to develop small-area estimates (at the level of individual buildings) of ECBs, b) analyze how ECBs vary by building across demographic and income groups, and c) assess the implications of energy retrofit investments on housing affordability. We examine differentials in ECBs across neighborhoods and socioeconomic groups, comparing lower income and wealthier neighborhoods and analyzing racial disparities within income groups. The data we use in this study consist of actual annual building energy consumption for approximately 13,000 multifamily buildings in New York City (NY), Boston (MA), Cambridge (MA), Seattle (WA), and Washington (DC) reported through city energy disclosure laws. We integrate these data with building and land use characteristics, housing subsidy program information, and socioeconomic characteristics to develop a comprehensive building-level data set of energy use and resident attributes. To analyze the potential financial implications of energy retrofit investments for low-income households, we use a unique data set of energy audit reports for approximately 3,000 residential buildings in New York City to estimate economically and technically feasible energy retrofit opportunities and their impact on ECBs. Although the data we use in this study represent a nonrandom sample of buildings and cities, they nonetheless provide a unique opportunity to develop and demonstrate a new method for planners to leverage large energy data sets to more fully understand household cost burdens at higher spatial and temporal resolutions than are currently possible.

Housing Affordability and Energy Efficiency

There is an abundance of evidence demonstrating a growing national housing affordability crisis, yet little attention is given to one of its main components: energy costs (Rohe, 2017; Routhier, 2018). Most studies that report on housing affordability measures do not account for energy costs at all in their cost burden measurements because actual utility consumption and associated expenses are difficult to estimate (Haffner & Boumeester, 2015). In the context of rising energy costs and growing calls for climate action, this lack of data represents a key challenge for planners looking to create programs that address the ECBs that disproportionately fall on low-income households.

The U.S. Department of Housing and Urban Development considers a household rent burdened if more than 30% of gross income is spent on rent (Collinson, 2011). Rent increases drastically outpaced income growth in almost all of the 238 largest metropolitan statistical areas (MSAs) between 2000 and 2010 (Schwartz et al., 2016), and the resulting rent burdens have failed to decline since then, particularly for the lowest income households (Turner, 2018). Of the 44 million renter households in the United States, 47% are rent burdened (Landis & Reina, 2019). Of greater concern, 89% of households with incomes less than $20,000 are rent burdened (Landis & Reina, 2019). One limitation of the studies documenting this steady increase in rent burdens is the research rarely disaggregates energy and housing costs and thus obscures the complete picture of rent burdens. Where utility costs are included in rents because a unit is master metered (meaning the landlord, not the tenant, pays the utility bills), these costs could be an important factor contributing to increasing rents. More commonly, utility costs are not included in the rents for low-income households, which means existing rent estimates represent a lower bound of housing-related cost burdens.

Energy Justice

Previous research demonstrates ECBs disproportionately affect lower income households, largely because they are most at risk for living in substandard and inefficient housing (Hernández & Phillips, 2015). From the widely held concept of filtering in housing markets, low-income households are more likely to rent units of lower quality in less accessible areas because these units become the only affordable option (Baer & Williamson, 1988; Galster & Rothenberg, 1991; Ohls, 1975). As a result, low-income households will typically inhabit the poorest quality housing units, which are often in the least efficient buildings (Lowry, 1960; Reina & Kontokosta, 2017). This means that even with behavioral adjustments to reduce energy consumption, low-income households typically face higher utility costs to achieve a basic comfort level in their homes.

There is evidence that even affordable units developed through low-income housing programs, which theoretically should have a higher level of quality due to government supervision and subsidy, are less energy efficient than similar unsubsidized properties (Dastrup, McDonnell, & Reina, 2012; Pazuniak, Reina, & Willis, 2015; Reina & Kontokosta, 2017). Despite the potential to reduce energy use through better quality housing and by retrofitting the existing stock (Dall'O, Galante, & Pasetti, 2012; Hsu, Meng, Han, & Suh, 2017), lower income households continue to face the economic and health impacts associated with poorly constructed and managed buildings with little recourse from landlords, which further compounds inequality and injustice (Jain, Moura, & Kontokosta, 2014; Kheirbek et al., 2014; Walker, 2015). Energy costs highlight persistent racial injustice in housing markets, with evidence that minority households may experience greater ECBs (Bednar, Reames, & Keoleian, 2017; Reames, 2016). This is particularly concerning when placed in the context of the long history of discriminatory housing policies, lending practices, and owner behaviors that have systemically limited housing options, neighborhood access, and ownership and wealth-building opportunities for minority households across the United States. Although residential heating and cooling demand is steadily increasing regardless of housing quality (Hernández, 2016), understanding how these increases affect households differently and vary with housing quality and household socioeconomic characteristics is important for more effective and equitable housing policy. For instance, qualitative studies show that low-income households are sometimes forced to make a tradeoff between energy use at home and other basic needs (Hernández, 2016), and households with high ECBs are more likely to report issues of food insecurity and housing instability (Hernández & Bird, 2010). Despite the implications of utility costs on housing affordability and household outcomes, the levels, drivers, and variation of these burdens across income and racial groups is not well understood. Such knowledge is particularly important for planners seeking to address housing affordability challenges and those concerned with how energy cost savings can be leveraged to develop equity-based programs that simultaneously reduce greenhouse gas emissions and housing cost burdens.

Only a few studies attempt to quantify utility cost levels and burdens, and fewer still estimate energy cost differentials for minority households. One national study finds households that made $15,000 or less per year on average spent 21% of their income on utilities (Carliner, 2013). In New York State, low-income households face average ECBs of 12.9% (New York State Energy Research and Development Authority, 2017). A report by the American Council for an Energy-Efficient Economy illustrates that low-income households, measured as those earning less than 80% of area median income, have a median ECB of 7.2%, with some households paying up to 25% of their annual gross income on utilities (Drehobl & Ross, 2016). It also finds African American and Latino households face higher energy costs, on average, than White households, but the study does not control for income differences between racial groups.

These estimates are valuable but are constrained by the reliance on U.S. Census American Housing Survey (AHS) and U.S. Department of Energy Residential Energy Consumption Survey (RECS) data. The AHS collects data on household energy use and self-reported measures of cost, but these data are available only at the MSA or regional/national geographies (U.S. Census Bureau 2018a). The self-reported nature of the survey is problematic (Dastrup et al., 2012; Drehobl & Ross, 2016). One concern is reported data represent a smoothed estimate and are likely rounded and approximated by the households reporting them. Therefore, a small over- or underestimation of monthly costs is magnified when looking at annual costs. More important, self-reported estimates for the lowest income households could reflect how much they actually paid, rather than a larger amount that was due on their bill (Hernández, 2016).

RECS reports detailed energy use and building characteristics information for a selected sample of residential buildings across the United States; however, it consisted of only 5,686 housing units in 2015, which represents a negligible fraction of the more than 130 million housing units nationwide, even after accounting for survey weights. Although these data provide useful reference points for energy use and expenditures, the surveys rely on aggregated measures that limit their application for targeted, local policymaking (Pivo, 2014). The small sample size results in higher standard errors that undermine confidence in the resulting estimates, an error that increases with geographic resolution. Data on energy conservation measures or retrofit savings opportunities for specific building types and individual buildings are also limited, which prevents any connection between reported energy use, retrofit costs, and potential savings. Combined, this means current methods to understand household cost burdens are limited in their temporal and spatial granularity, which undermines policymakers' access to localized estimates and the ability to understand social–spatial variations within cities and across neighborhoods.

Data and Methods

In this study we analyze the spatial and socioeconomic patterns, by building and census block group geographies, of ECBs in multifamily housing across five major cities in the United States using a unique set of building-level consumption data for almost 13,000 buildings and completed energy audit reports for approximately 3,000 buildings. Specifically, we a) analyze the distribution and magnitude of the burden for individual

Table 1

Summary of disclosure ordinances and data.

City	Year of adoption[a]	Building size[a]	No. buildings reported[b]	Total floor area (ft^2)
Boston (MA)	2013	≥50 units	365	64,571,156
Cambridge (MA)	2014	≥50 units	362	46,927,944
New York City (NY)	2009	≥50,000 ft^2	9,104	1,279,586,655
Seattle (WA)	2012	≥20,000 ft^2	2,413	185,786,358
Washington (DC)	2008	≥50,000 ft^2	461	75,633,051

Notes:
a. Source: Institute for Market Transformation, 2018.
b. Sources: City of Boston, 2018a; City of Cambridge, 2018a; City of New York, 2018a; City of Seattle, 2018b; Washington, DC, Department of Energy & Environment, 2018.

households by building, b) identify spatial clusters of energy cost–burdened buildings and their relationship to low-income and minority communities, and c) evaluate the financial impact of energy retrofit investments in energy-inefficient buildings where residents face high cost burdens. Our goal with this analysis is to enable more informed and effective government interventions that specifically address the implications of energy costs on the welfare of low-income households.

High-Resolution Data to Estimate Localized ECBs

We extracted the primary data from publicly available energy disclosure, or benchmarking, policies from the cities of Boston (MA), Cambridge (MA), New York City (NY), Seattle (WA), and Washington (DC). Disclosure laws require buildings of certain size thresholds to report their energy consumption and other relevant building attributes each year (Hsu, 2015; Kontokosta, 2013, 2015; Kontokosta, Bonczak, & Duer-Balkind, 2016; Palmer & Walls, 2017). More than 20 cities and 10 states have adopted some form of energy disclosure, and these data have been well studied within specific cities, particularly New York City (Hsu, 2015; Institute for Market Transformation, 2017; Kontokosta & Jain, 2015; Kontokosta & Tull, 2017; Marasco & Kontokosta, 2016; Papadopoulos, Bonczak, & Kontokosta, 2017, 2018). Although similar, each city has developed its own policy requirements (as shown in Table 1) to reflect the nature of the local building stock and the political context (and appetite) for the adoption of mandatory reporting. We selected these five cities based on the availability of public disclosure data on multifamily buildings that also contained information on relevant building attributes, such as building size, energy consumption by fuel type, and property geolocation. The analysis period is calendar year 2015, when consistent data were available from each of the selected cities. We generated disclosure data sets using the Energy Star Portfolio Manager tool, which ensures the reported data are in a relatively standardized format, although data cleaning remains an important data processing step (ENERGY STAR, 2018; Institute for Market Transformation, 2018). Energy use is measured as weather-normalized site energy use intensity (EUI) in thousands of British thermal units (kBtu) per square foot. The weather normalization process accounts for variations in regional climate based on differences in measured heating degree days and cooling degree days (Eto, 1988).

Energy disclosure data are integrated with city-specific administrative records for parcel-level land use and property characteristics (City of Boston, 2018c; City of Cambridge, 2018c; City of New York, 2018d; City of Seattle, 2018c; Washington, DC, 2018b) and building footprints (City of Boston, 2018b; City of Cambridge, 2018b; City of New York, 2018b; City of Seattle, 2018a; Washington, DC, 2018a). These data are publicly available through the respective city's official open data portal and contain information on the specific location and geometry of each property and its footprint, as well as land use type, floor area, number of units, building age, height, shape, and land/building value, among other features. Details on each of the data sets used are presented in Table A-1 of the Technical Appendix.

We use the U.S. Census American Community Survey data (ACS), specifically TIGER/Line with the Selected Demographic and Economic Data product (U.S. Census Bureau, 2018c), to measure local demographic and socioeconomic characteristics. These data contain sampled information on population demographics, employment, education, household income, and housing expenditures. The analysis is at the census block group (CBG) level because it is the smallest areal unit for which the U.S. Census Bureau publishes survey data to maximize spatial granularity. ACS data are also used to estimate median household income for the principal city in each MSA represented in the study.

Electricity and natural gas prices data are extracted from the U.S. Energy Information Administration (EIA), which is responsible for publishing national energy statistics. We use the average annual residential energy prices for 2015 for each state for electricity (EIA, 2018a) and natural gas (EIA, 2018b).

We investigate the potential household financial impact of energy retrofit investments in buildings with high ECBs. To do so, we incorporate New York City's Local Law 87 Energy Audit data (LL87), provided by the New York City Mayor's Office of Sustainability (City of New York, 2018c), and subsidized housing data maintained by the NYU Furman Center for Real Estate and Urban Policy. LL87 requires all properties covered by New York City's energy disclosure ordinance (locally called LL84) to conduct an energy audit once every 10 years and report the findings. In addition to energy consumption data, energy audits collect detailed information on building systems, energy end uses, and metering configuration, as well as provide recommendations for potential energy conservation measures (ECMs) and their associated energy and cost savings. The 2015 LL87 data consist of completed audit reports for more than 3,000 properties, accounting for approximately 20,000 individual ECMs. The subsidized housing database combines more than 50 government databases and provides detailed information on the characteristics of nearly 235,000 units of privately owned and publicly subsidized properties in New York City.

Methodology for Estimating Household ECBs

Estimating ECBs for households in individual multifamily buildings requires significant data processing as illustrated by the methodology flowchart shown in Figure A-1 in the Technical Appendix. In the first step, disclosure data for each city are standardized by 1) filtering for only residential properties, 2) creating common field definitions for variable inputs across all city data sets, 3) converting units as needed (e.g., from kilowatt-hours into thousands of British thermal units), and 4) removing or converting nonnumeric values to numeric values as needed. We then georeferenced the data to spatially join individual buildings with administrative (parcel and building footprint) records and sociodemographic (ACS) data. The final, clean data set consists of a total of 7,841 properties across the five studied cities. A summary of the cleaning steps is presented in Table A-3 of the Technical Appendix.

Equation 1 presents the calculation for the average household ECB for each individual building in the sample.[1] We extract building-level annual energy consumption data by energy source (natural gas, *G*, and electricity, *E*, because these were consistently reported in all of the studied cities and represent most total energy use) and apply the regional retail cost per energy unit (β_g and β_e, respectively) to calculate the total annual energy cost for the whole building. We divide this figure by the number of units in the building (*U*) to estimate the annual household energy cost. ECB is then calculated as the total household energy cost divided by the median household income (Inc) for the CBG in which the household and building are located.

We merged both the LL87 energy audit and subsidized housing data with the cleaned New York City disclosure data set (LL84) based on the unique borough-block-lot parcel identifier for the retrofit and cost savings analysis. The merged disclosure and audit data consist of approximately 1,000 properties, including 85 subsidized buildings. These properties account for more than 6,000 ECM recommendations in total. We estimated the aggregate potential cost savings for each ECM, grouped by expected payback period, based on the audit-reported values for annual energy savings of electricity and natural gas.

Results

The building stock we analyzed in each city varies significantly, which is a function not only of topological, economic, and regulatory differences of the studied cities but also of the specific requirements of their respective disclosure laws. Figure 1 illustrates median values for several building characteristics by city.[2] The Seattle sample contains the smallest buildings, with an average size of 48,863 ft^2, and the most efficient properties, with median site EUI of 31 kBtu/ft^2 and median Energy Star Score of 74. New York City has the largest household size (on average 2.35 persons) compared with the lowest of 1.83 in Seattle. There is also an observable trend where household size is negatively correlated with median household income, as in DC, which has relatively small households with a high median income of $84,000.

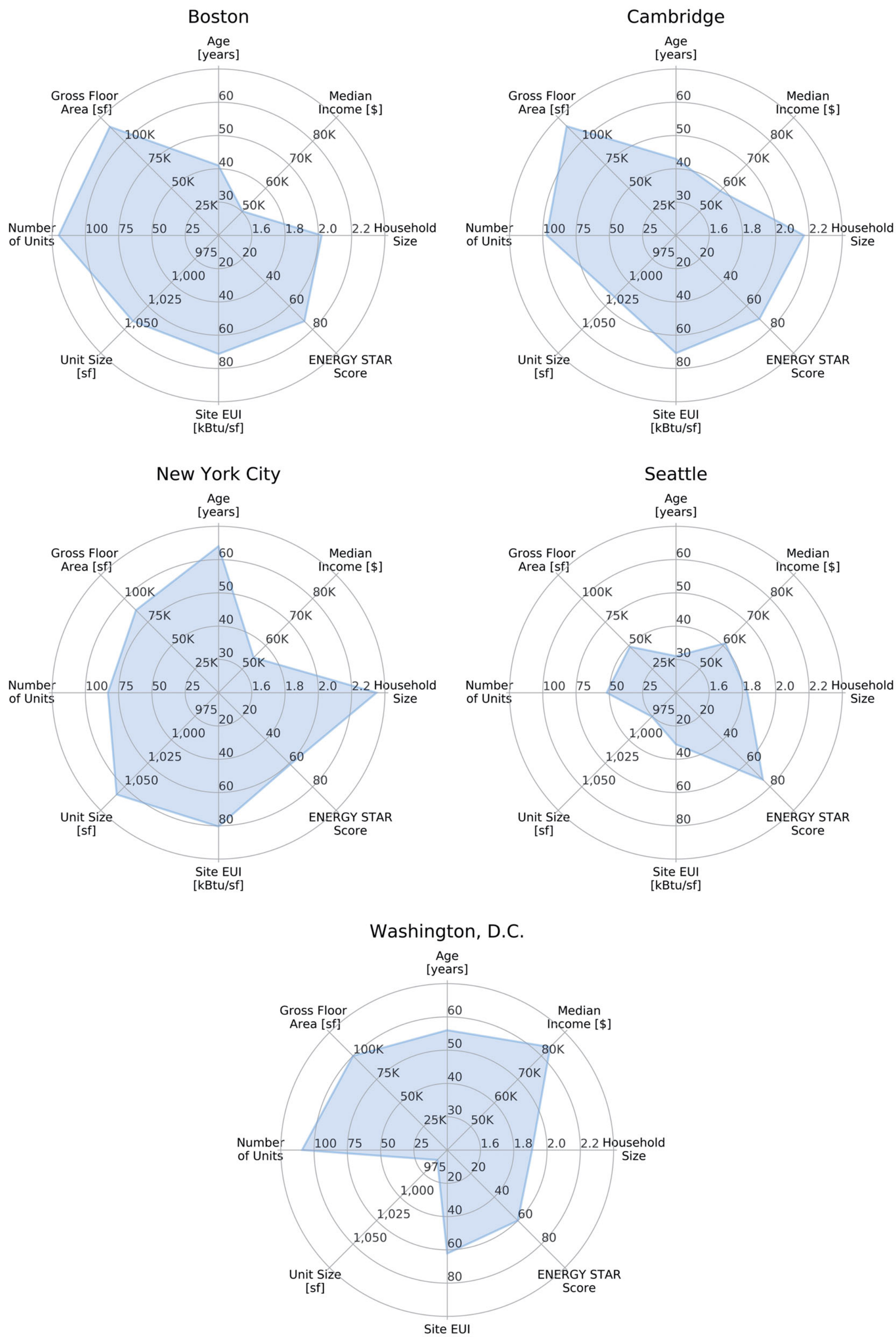

Figure 1. Radar plots of housing, energy efficiency, and socioeconomic characteristics by city (median values), 2015. Note: Income is household income for 2015.

Household Characteristics by Income

Energy costs are a function of housing quality (energy-efficient design and systems) and consumption behavior (occupant usage patterns and building management quality). A lower household income is associated with living in poor-quality, less energy-efficient housing, which has implications for energy use behaviors (Abrahamse & Steg, 2011; Poortinga, Steg, & Vlek, 2004). Because ECBs are a function of consumption levels and household income, a poor household will face a higher ECB, holding energy consumption constant.

As expected, we find higher income households tend to occupy newer properties with larger units.[3] On average, unit sizes for higher income households are 13% larger than those of the lowest income households (1,125 ft^2 versus 995 ft^2). At the same time, the highest income households consist of only 2.0 persons on average, whereas households earning up to 120% of area median income (AMI) have, on average, 2.3 persons. Both of these characteristics directly affect household-level energy consumption.

Using EUI as a proxy for a property's energy performance, we find a quadratic relationship between EUI and income, where the lowest and highest income households exhibit the highest EUIs. We use a pairwise non-parametric Mann-Whitney *U* test (Mann & Whitney, 1947) to statistically compare the distributions of EUI values for each income band. Consistent with the observational assessment above, the middle income ranges differ significantly from the lowest and the highest income households, whereas there is no significant difference found between the latter two groups. The lowest and highest income groups are shown to have higher total consumption levels by housing unit than do households with incomes between 50% and 150% of AMI. For the lowest income households, higher consumption can be attributed, in part, to higher occupant densities and equipment and systems inefficiencies. Consumption by high-income households can be explained by larger unit sizes, as well as occupant behavior (for example, more amenities or additional plug loads from personal electronics). Confirmation of both trends is found in the Energy Star Score estimates, which are derived from a linear regression model that attempts to normalize energy use by controlling for selected building characteristics and weather conditions (although this approach is not without its statistical limitations; see Hsu, 2015; Kontokosta, 2015; Papadopoulos & Kontokosta, 2019).

ECB Analysis

Figure 2 illustrates the median values of energy cost per square foot (expressed in dollars per square foot) and ECBs by income band for each city. Seattle, which has both the most energy-efficient properties and the lowest electricity prices (and relatively limited use of natural gas), has the lowest energy costs, estimated below \$1.00 per square foot. On the other hand, Boston and Cambridge have median energy costs between \$1.50 and \$2.00 per square foot. These costs can be partially attributed to the significantly higher prices of electricity and natural gas recorded in Massachusetts in 2015, which were 36% and 16% higher, respectively, than the average of the other study cities. At the same time, we observe multiple examples of properties where energy costs exceed \$5.00 per square foot, mostly in New York City.

ECBs follow a decreasing exponential function as shown in Figure 2. As expected, lower income households are the most exposed to high ECBs, which reach, on average, approximately 10% of gross income and up to 20% for some households. The ECBs for all other income bands in the analyzed population do not exceed 10% of annual gross income and typically range between 1.5% and 3% of annual gross household income. Variations in ECBs across cities reflect differences in energy prices and socioeconomic diversity. The lowest ECBs can be observed among the wealthiest households in Seattle and DC, where energy costs are less than 5% of annual household income.

We find significant differences in ECBs by race and ethnicity when comparing within specific household income bands. As shown in Table 2, each property is assigned to its respective CBG, which is then classified as "predominantly minority" if the proportion of non-Hispanic White population in the CBG is lower than the citywide average. Buildings in the five cities span a total of 3,122 CBGs, of which 42% are classified as predominantly minority neighborhoods. For the three lowest income groups (≤50%, 51%–80%, and 81%–120% AMI), we find statistically significant differences in ECBs between the two neighborhood classifications based on the results of *t* tests between the two neighborhood types stratified by income. Very-low-income residents (≤50% AMI) in predominantly minority neighborhoods experience a 1.56-percentage-point higher ECB than do low-income residents in predominantly non-Hispanic White communities, which equates to a 27% greater ECB on average. This difference persists in the two other lower income groups (51%–80% AMI and 81%–120% AMI), and although the magnitude of the gap falls to approximately 0.60 percentage points, this reflects as much as a 24% greater ECB in minority neighborhoods. Why minority communities experience higher ECBs, after accounting for income differentials, is unclear, but our finding provides additional evidence for the

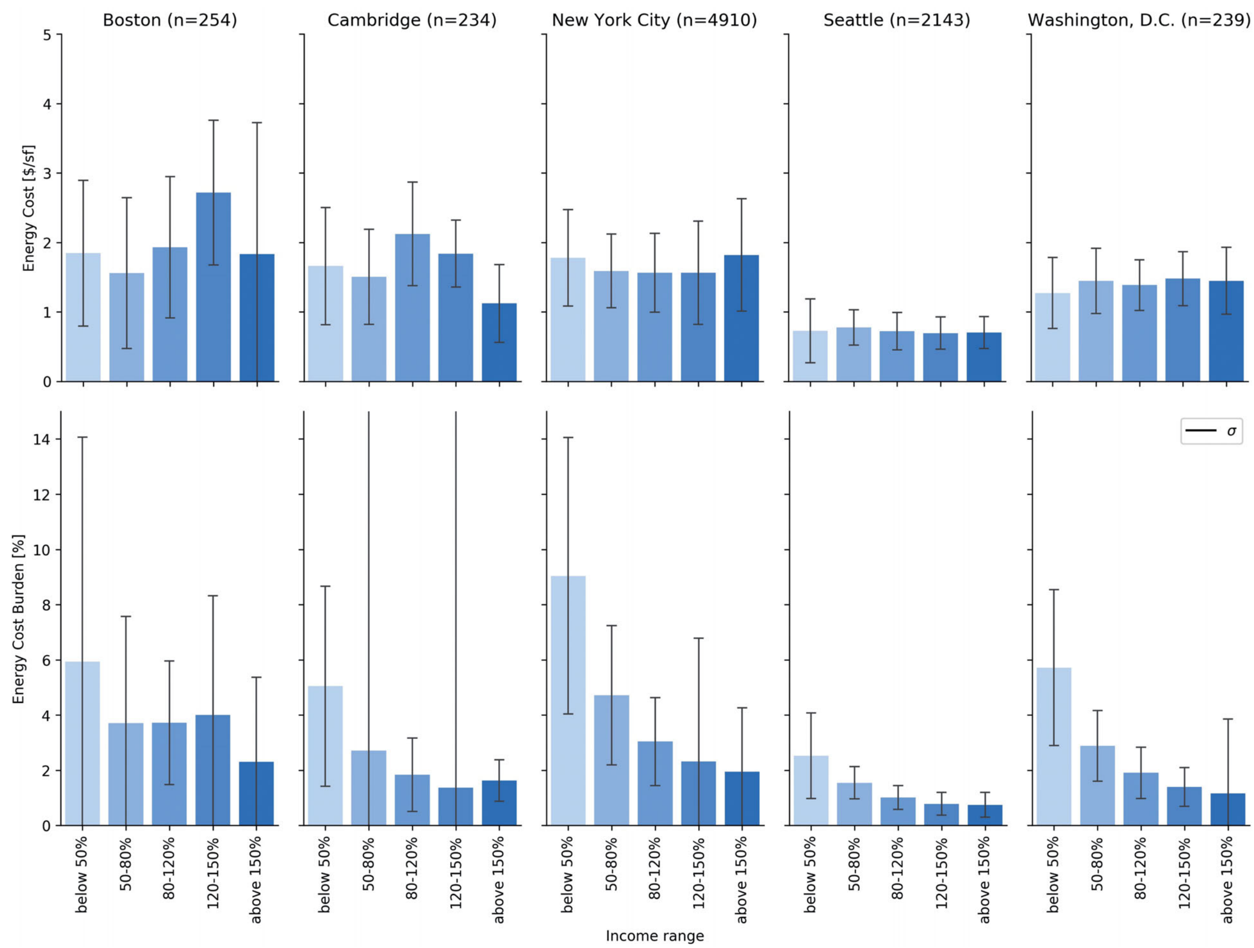

Figure 2. Bar plots of median annual energy cost per square foot and energy cost burden by city and income band, 2015. Note: Income percentiles are based on median household income for 2015. Bars indicate one standard deviation.

growing concern for equity and fairness in the distribution of energy-efficient and better quality housing.

Given the potential geospatial relationships between income, race, and energy efficiency, we examine the extent of spatial clustering of buildings by ECBs because this information can be used to develop integrated place- and need-based energy policies. The visualizations in Figure 3 show the locations of all analyzed properties across the five cities. Each dot represents a specific property, with shaded areas indicating predominantly minority census block groups. Concentrations of high ECBs by building are shown as a heat map overlay. The results of a Moran's *I* test for global spatial autocorrelation (Mitchell, 2005) show that properties in all cities except Cambridge are not randomly distributed within the city boundaries but rather are defined by spatial clusters. Given that energy disclosure laws cover larger, higher density, multifamily properties, we observe concentrations around the city center (Boston) and along major boulevards (New York City, Seattle). CBGs with minority population higher than the city average are represented by highlighted areas, revealing associations between higher ECBs and neighborhoods identified as predominantly minority.

Energy Cost Savings Potential by Income and Building Characteristics

Building on the analysis of the localized spatial and socioeconomic patterns of ECBs, we seek to understand the potential of building energy retrofits to reduce these burdens for lower income households. New York City's LL87 energy audit data set provides a comprehensive resource to identify economically and technically feasible energy retrofit opportunities at the building scale. After significant data cleaning and preprocessing, we link energy audit data with energy consumption data to estimate the impact of ECMs on energy costs and cost burdens.[4]

Table 2

ECBs by income group and neighborhood racial/ethnic composition.

	Minority		Median ECB									
			≤50%		51%–80%		81%–120%		121%–150%		>150%	
City	CBG	*n*	*n*	ECB	*n*	ECB	*n*	ECB	*n*	ECB	*n*	ECB
Boston	No	161	23	6.50	22	3.52	23	3.15**	13	4.36	80	2.31
	Yes	93	40	4.83	29	4.24	22	4.43**	1	2.17	1	2.09
Cambridge	No	58	1	2.76	8	3.58	20	1.70	10	20.38	19	1.63
	Yes	176	108	5.05	4	2.42	43	1.84	21	0.92		
New York City	No	2,898	135	7.13***	320	4.19***	612	2.92***	406	2.27*	1425	1.96*
	Yes	2,012	532	9.33***	772	5.02***	535	3.18***	135	2.5*	38	1.74*
Seattle	No	1,178	71	2.11***	214	1.34***	463	0.99***	271	0.79**	159	0.84***
	Yes	965	217	2.67***	415	1.62***	219	1.07***	82	0.7**	32	0.66***
Washington, DC	No	175	2	6.11	16	2.44**	42	1.88	58	1.38	57	1.17
	Yes	64	15	5.69	38	2.97**	9	2.13	2	1.59		
Total	No	4,470	232	5.87***	580	3.22***	1,160	2.08***	758	1.74	1,740	1.82***
	Yes	3,310	912	7.43***	1,258	3.78***	828	2.73***	241	1.68	71	1.23***

Note: Statistical significance of group differences based on independent samples *t* tests: *$p < .05$; **$p < .01$; ***$p < .001$.

Table 3 presents the 10 most common ECM recommendations we identified by analyzing individual audit reports for all multifamily properties contained in the LL87 data. Approximately 40% of all recommendations are related to lighting, particularly upgrading existing lamps to light-emitting diode (LED; 1,321 occurrences), which tends to have a short payback period. Although lighting upgrades are relatively high-return investments, their annual cost savings potential is modest, ranging on average between $8 and $50 per housing unit per year when accounting for improvements to building common areas only. Retrofits related to domestic hot water (DHW) systems, such as installing low-flow aerators or separating DHW from the heating system, constitute approximately 10% of all ECMs and have an average cost savings ranging from $47 to $117 per unit per year. The most cost-effective ECM opportunity, based on the analyzed data, is installing a building management system, with an average cost savings reaching $118 per unit. It is important to note these recommendations relate to central systems or, as in the case of lighting, common areas only. Therefore, these cost savings estimates represent a lower bound of savings potential.

Table 4 presents the potential aggregate energy cost savings per household for all audit-recommended

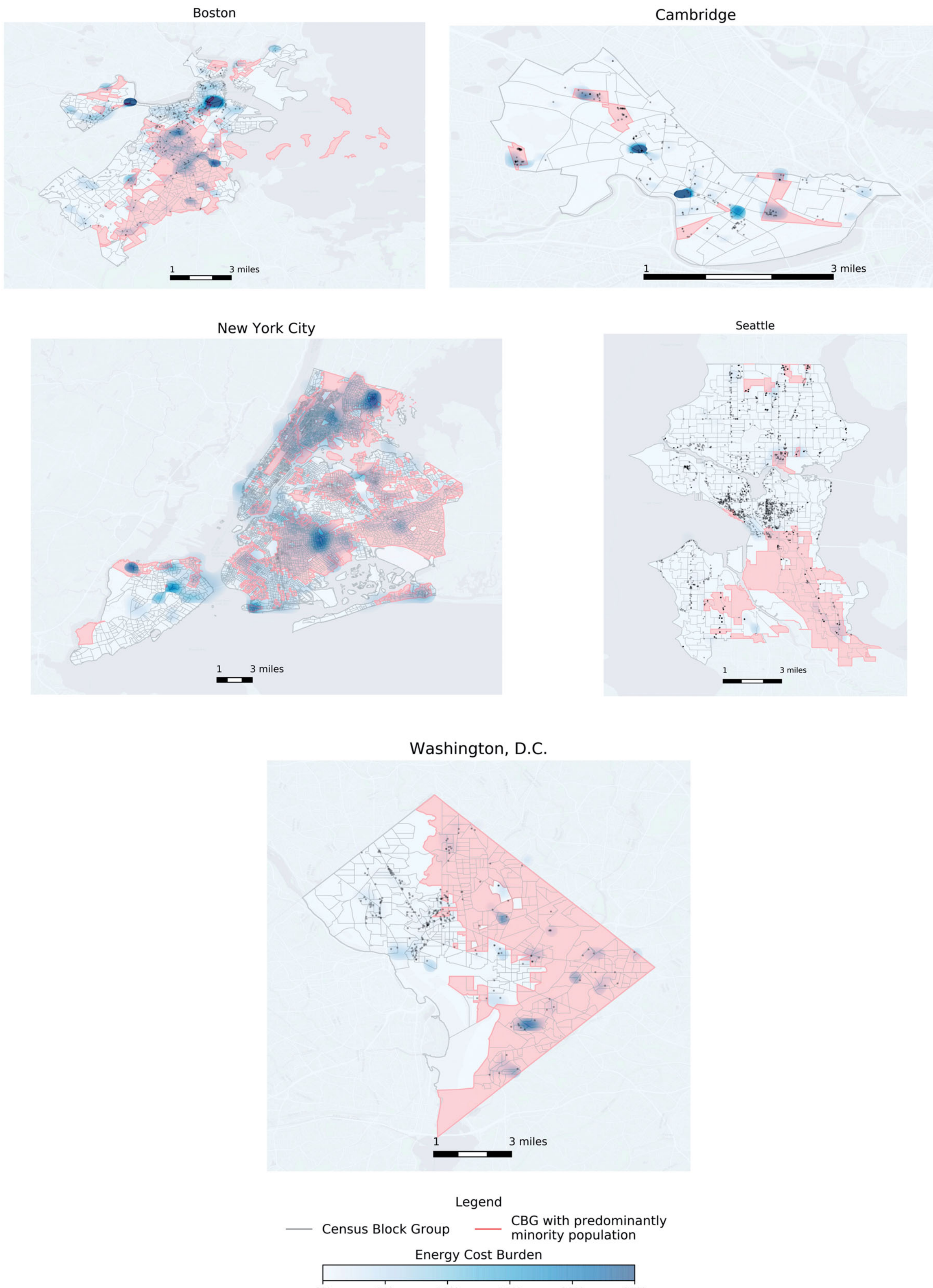

Figure 3. Spatial dispersion of energy cost burdens (blue heat map), properties (in black), and neighborhood classification (predominantly minority census block groups in red) in selected cities, 2015. (Color version of figure available online.)

Table 3

Most common ECM recommendations and expected cost savings.

		ECM occurrence				Median annual cost savings[a] ($)	
Category	**Measure**	**2-Year payback**	**5-Year payback**	**10-Year payback**	**Total**	**Whole building**	**Per unit**
Lighting	Upgrade to LED	608	547	166	1,321	2,655.39	23.14
DHW	Install low-flow aerators	159	120	94	373	5,138.66	46.99
Distribution system	Insulate pipes	159	129	71	359	1,184.63	14.85
Lighting	Upgrade to fluorescent	149	102	61	312	1,533.32	17.31
HVAC controls and sensors	Install or upgrade energy management system (EMS)/ building management system (BMS)	113	65	86	264	11,601.33	118.33
DHW	Separate DHW from heating	25	90	137	252	15,738.41	116.52
Lighting	Other	45	129	52	226	5,691.10	49.57
Lighting	Upgrade exterior lighting	95	68	59	222	1,568.82	8.74
Envelope	Sealing: door	87	70	44	201	1,276.56	14.90
Lighting	Install occupancy/ vacancy sensors	40	51	50	141	1,308.74	15.12

Note: DHW = domestic hot water; EMS = emergency management system; HVAC = heating, ventilation, and air conditioning; LED = light-emitting diode.
a. ECM estimations provided for central systems or common areas only.

ECMs with payback periods of less than 2, 5, and 10 years, respectively, based on specific building types and characteristics. The potential energy cost reductions for ECMs with the shortest payback period fall between approximately $32 (first quartile) and $266 (third quartile) per unit per year, with a median of $112 and reaching as high as $800 per unit per year. Including ECMs with longer payback periods results in higher potential cost savings, with median values increasing to $298 for upgrades with a 10-year payback. Of course, longer payback periods equate to a lower expected return on investment; therefore, the financial viability of longer payback period investments may be a constraint for building owners without subsidies to reduce initial costs or other incentives to reduce energy use.

Figure 4 shows the potential impact of adopting ECMs with each payback period duration on the estimated ECB for households by income range. Box plots labeled “None” represent the “business-as-usual” scenario, whereas the others show the expected ECB after implementation of the recommended retrofits by payback period. ECM adoption for low- and very-low-income households demonstrates nontrivial reductions in cost burdens of 2% of annual household income, on average.

To highlight the opportunity for cost savings in subsidized properties in New York City, Figure 5 illustrates the potential ECB reductions after implementation of all ECMs with a 10-year (or less) payback period specifically in government-subsidized buildings. The average savings is estimated to be approximately 2%, and the savings potential in several buildings exceeds 5% of annual household income.

Table 4

Potential reductions of annual energy costs after implementation of ECMs with different payback periods.

	ECM payback period		
Measure	**2 Years**	**5 Years**	**10 Years**
Count	742	948	976
Mean	$225.36	$361.52	$426.94
SD	$364.09	$455.87	$490.82
25th	$32.53	$97.91	$139.20
50th	$112.44	$235.62	$298.64
75th	$266.66	$447.30	$525.82
95th	$804.99	$1,114.05	$1,197.83

Discussion and Implications for Planning

Housing affordability measures have consistently omitted utility and energy expenses in overall household cost burden calculations, thereby underestimating the significance of energy costs for lower income households. Using newly available energy data for individual residential buildings in five cities, combined with property characteristics, energy audit reports, and socioeconomic data, we develop small-area estimates of ECBs for households in multifamily buildings within and across neighborhoods. High energy costs caused by inefficient housing disproportionately affect low-income households. ECBs approach 7%, on average, for very-low-income households, but this figure can reach as high as 20% of annual household income. Because these costs are largely driven by housing quality, cost burdens can only be meaningfully reduced by improving the efficiency of the building and housing unit. Although upper income households also experience significant energy costs, with energy expenditures per square foot of approximately $1.80, this does not create a high burden because of their income level. In addition, energy costs for higher income households are driven in part by high-intensity energy use behaviors, which means modifying consumption behavior alone can meaningfully reduce energy costs for this group. There is also significant variation in ECBs across cities and regions. Boston and New York City exhibit the highest average burden of approximately 3%, whereas the

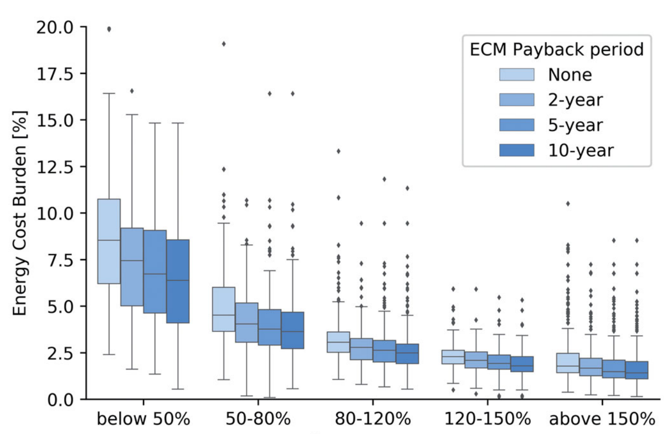

Figure 4. Energy cost burdens after implementation of ECMs by payback period.

Color version available at ***tandfonline.com/rjpa***

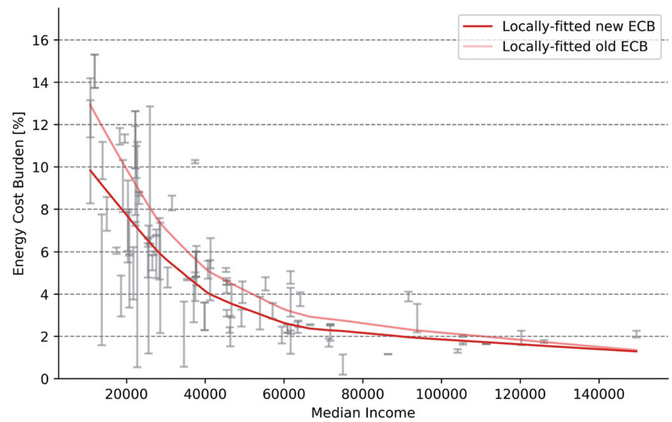

Figure 5. Potential energy cost burden reductions in subsidized properties in New York City after implementation of recommended energy conservation measures.

typical household in Seattle and Washington (DC) pays less than 2% of gross income for energy. This range is driven by differences in the efficiency of the local housing stock, the distribution of household income in each city, and regional energy prices.

Our findings largely confirm what other aggregate studies of energy costs have shown, which is an important validation of this method to generate small-area estimates of housing cost burdens. These data and building-level energy cost estimates allow planners to leverage more frequently updated information at smaller geographies, particularly when compared with current survey alternatives such as AHS and RECS, and highlight the applications of expanding energy disclosure mandates across additional cities and regions.

In addition to providing high-frequency, small-area estimates of ECBs, the method we describe here enables the study of energy efficiency from a social justice perspective. Specifically, we analyze the distribution of energy costs for racial and ethnic minority groups. ECBs for households in "predominantly minority" neighborhoods (defined here as those CBGs where the percentage of non-Hispanic White population is less than the respective citywide average) are higher for all low-income groups—by as much as 27%—than for households with similar incomes in predominantly non-Hispanic White communities. This sociodemographic analysis does have a number of constraints, including the lack of building- and household-specific demographic data and the unavailability of utility subsidy program data at the building level. However, our findings highlight significant variations in cost burdens across low-income households that raise new concerns about energy justice and warrant further exploration.

The potential benefits of energy-efficient investments for low-income, cost-burdened households are a viable pathway to reduce overall housing affordability challenges. On average, energy retrofits with payback periods of less than 2 years could result in an annual savings of approximately $112 per household. By including ECMs with payback periods of up to 10 years, the estimated annual household savings could increase to almost $300 per year and, in some cases, as much as $1,200 per year. These savings figures represent lower bound estimates because reported energy audit ECM recommendations focus on "whole building" efficiency opportunities rather than individual apartments, and thus the financial implications for low-income households could be even greater.

Given the significance of energy costs for the overall welfare of low-income households and the favorable rates of return for building energy efficiency investments, planners can use these findings and data to justify both incentives and mandates for energy upgrades in energy-inefficient buildings housing low-income residents. Building on existing energy disclosure policies enacted in our study cities, the next step is to develop effective peer performance measures to openly and rigorously compare the energy use profiles of similar buildings (Burr, Keicher, & Lawrence, 2013; Papadopoulos & Kontokosta, 2019). This can be operationalized as a building energy "grade," similar to what has been adopted for fuel efficiency in the auto industry and cleanliness scores in the food service industry. Although Energy Star and, to a lesser extent, the U.S. Green Building Council Leadership in Energy and Environmental Design (LEED) rating systems attempt to provide such a measure, these labels have been criticized for relying on misspecified models, small-sample data, and lack of transparency. City-specific initiatives, such as new building energy grading laws adopted in Chicago (IL) and New York, create localized performance measures that can more reliably account for regional variations in building stock, household behavior, and weather.

These grading systems, however, are essentially "need blind." Cities have limited resources, whether in financial or political capital, to motivate building owners to reduce their energy consumption. Thus, targeting the allocation of these resources to those most in need should be the foundation for city energy policy. Planners can identify buildings where residents experience high ECBs and the specific, economically viable energy upgrades that can reduce these costs by using the method we present here. In particular, by linking subsidized housing data with energy performance data, cities can both identify high-need buildings and develop tools to support cost-effective energy retrofits in these properties. These data could be coupled with existing programs, such as the U.S. Department of Health and Human Services' Low Income Home Energy Assistance Program, to identify retrofit opportunities and promote investments that enable Low Income Home Energy Assistance Program resources to be more efficiently and equitably allocated.

Planners should expand the data collection efforts of current energy disclosure ordinances to improve household cost burden estimates and provide a foundation for need-based energy incentives and performance standards. These ordinances, including LL84 in New York City, are generating significant new streams of data to allow for peer-to-peer building comparisons, longitudinal studies of energy use, and empirical evaluations of energy efficiency and carbon reduction policies. However, the data reporting requirements currently focus on physical aspects of the building and its energy use profile. Household income or demographic data, aggregated to the whole building to protect confidentiality, could be a valuable resource for research at the intersection of energy efficiency, behavioral economics, and urban planning. This information would also complement census data by generating an annual source of high-spatial-resolution socioeconomic data. Given that tenant rental applications for multifamily buildings typically require income reporting, it would be possible for building owners to aggregate these data and report medians and averages for buildings of certain size and unit number thresholds. Although there are significant privacy concerns to consider, the implications of such data disclosure would be an important resource for researchers and policymakers, and energy reporting mandates provide a viable mechanism for additional data collection at the building level that could support a variety of policy goals.

Conclusion

Energy efficiency and urban climate action have taken on a new significance with the growing recognition that cities must take the lead in reducing consumption and carbon emissions. Although the building sector has been the primary focus of urban sustainability initiatives, attention has been focused on the physical asset rather than the household. Our study shifts the focus of energy efficiency investment to its impact on household cost burdens and overall housing affordability. We use new and unique data generated from measurement-driven urban energy policies and find low-income households disproportionately bear the burden of poor-quality and energy-inefficient housing. This translates to ECBs for the lowest income households of more than three times those of higher income households. Households in predominantly minority communities face even higher cost burdens, even after accounting for income differences. Cost-effective ECMs have the potential to reduce this cost burden by as much as half for low-income households, representing a potentially significant reduction in overall housing cost burdens without the need to relocate. In this study we validate small-area estimates against currently available regional and national data and highlight how cities can use new localized data resources and methods to develop place-based and equity-focused energy policies.
Our research demonstrates that building energy efficiency and climate mitigation should be considered issues of environmental justice and that data-driven approaches can be leveraged to improve housing affordability and quality of life for the most vulnerable urban residents.

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SUPPLEMENTAL MATERIAL

Supplemental data for this article can be found on the publisher's website.

NOTES

1. The formula is $\mathrm{ECB} = \frac{\mathrm{E} \times \beta_e + \mathrm{G} \times \beta_g}{\mathrm{U}} \div \mathrm{Inc.}$

2. Figure 1 illustrates median values for several building characteristics by city. Disclosure data provide information on gross floor area, age, and number of units, which we supplement with calculations of average unit size.

3. Income group thresholds are defined by percentage AMI for each MSA. This commonly used normalization approach allows for direct comparison across different regions (Linneman & Megbolugbe, 1992; U.S. Census Bureau 2018b).

4. The payback period is calculated by dividing the implementation (first) cost of the ECM by its expected annual cost savings. Although other investment metrics, such as net present value and internal rate of return, provide risk-adjusted measures of financial returns, the payback period method is a widely used approach for comparing alternative investments and identifying higher-return ECMs. We focus on audit-recommended energy conservation measures with payback periods less than 10 years.

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