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A comparison of building system parameters between affordable and market-rate housing in New York City

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HIGHLIGHTS

- Affordable and market-rate building systems compared for 7,328 NYC multifamily buildings to examine if differences exist.
- Two-sample *t*-test, chi-squared test of independence, and multivariate regression employed to assess relationships.
- Affordable housing buildings tend to be newer, larger, and taller.
- Affordable buildings have newer & more efficient systems. This trend faded when normalizing for building characteristics.

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ABSTRACT

Low-income households in the United States experience higher than average energy burdens (defined as the proportion of household income spent on energy utilities), and many of these households struggle to simultaneously pay for rent, energy, and basic household necessities. The analysis presented here examines whether the underlying characteristics of buildings and their energy systems could contribute to this disparity for affordable housing residents in New York City. It combines an energy audit dataset of 7,328 multifamily buildings with a database of properties receiving local, state, or federal housing subsidies. The results of this analysis indicate that the building-level installed equipment in large (greater than 50,000 square feet) affordable housing buildings in New York City is more efficient than that in market-rate buildings, but this trend largely disappears when considering overall building characteristics, such as location, size, or age. Significant differences in the types of systems installed in affordable and market-rate housing are also observed, as well as the types of energy efficiency recommendations made by energy auditors. However, these latter data were not normalized by building system characteristics, as that analysis is much more difficult to interpret for categorical data such as heating system type. These findings indicate that retrofit policies and building performance standards focused on affordable housing will likely need to account for underlying differences in building characteristics between affordable and market-rate housing to achieve intended impacts.

1. Introduction

A significant number of households in the Unites States struggle to afford to pay their utility bills (gas and electric) and provide essential services, such as home heating, electricity, safe indoor air quality, and other important services. One way to measure the affordability is energy burden, which is a simple representation of the percentage of gross household income spent on energy costs. A quarter of U.S. households face a high energy burden (more than 6% of income spent on energy bills) and 13% face a severe energy burden (more than 10% of income spent on energy bills) [1]. Low-income, older adults, persons with disability, Black, Hispanic, and Native American households experience higher energy burdens, on average, a trend present in both cities and rural areas [1–4]. This study aims to investigate the underlying causes of high energy burdens for low-income populations by comparing installed building system types and efficiencies between affordable and market-

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rate multifamily housing in New York City. The results could be used to determine the types of interventions that would be most beneficial for improving the energy efficiency of multifamily affordable housing, thus alleviating energy burdens for residents of these buildings (depending on the how utility costs are factored into rent) and improving occupant health and comfort.

Significant prior research has been conducted to quantify energy burdens for different populations and explore possible causes and compounding stressors. Some communities are especially vulnerable to experiencing both high energy and rental burdens. Hernández et al. studied this double burden in low-income, renter households with children and found that different demographic groups experience these burdens in different ways, with African American households more likely than other groups to experience both burdens simultaneously [5]. Lin (2018) looks at energy burden through a household's ability to pay—that is, total income minus housing cost, showing that for low-income and renter households the high housing cost they face drastically decreases their available household budget ("residual income") to cover energy costs [6].

There are myriad drivers for energy burden inequities in the built environment. These include:

- Physical – Poorly insulated homes and inefficient appliances consume more energy.
- Socioeconomic – Existing financing and investment structures often are inaccessible to renters or low-income homeowners.
- Behavioral – Some communities, such as those with elderly occupants, may have different energy needs.
- Policy – Utility incentive programs traditionally have not been structured to reach low-income and underserved communities, and programs that are focused on low-income communities are underfunded [1].

While weatherization (e.g., WAP), bill-assistance (e.g., LIHEAP), and utility and government solar and energy storage programs exist to reduce household energy costs, current programs remain largely inaccessible to low-income households [7]. Moreover, most assistance focuses on short-term fixes rather than long-term strategies to reduce energy burden, even as studies indicate energy burden disparities between low and high-income households continue to increase [7,8]. In addition, the evaluation metrics for these programs often focus on distribution of funds or number of households assisted, rather than eventual impacts of the programs towards the stated goal of improving energy affordability [9].

While energy burdens are a direct function of a household's annual income, higher energy costs for low-income households exacerbate the energy burden disparity. Studies have shown that the highest and lowest income households tend to have higher than average energy usage per square foot (EUI), the former likely because of the presence of high-end appliances and energy-intensive occupant behavior, and the latter due to higher occupancy per square foot and energy system inefficiencies [3]. Heating and cooling EUIs are higher for regions with more low-income households, and controlling for income, non-white households experienced even higher EUIs [10].

The higher EUIs and thus higher energy burdens experienced by low-income and minority households are caused, in part, by the lower intrinsic energy efficiency of their homes and a lack of access to energy efficient appliances. Studies have shown a strong connection between building attributes and energy use [11–13]. For example, van den Brom et al found in a study of 1.4 million Dutch households that the energy-performance gap, the difference between actual and calculated energy consumption, is due to not only the occupant behavior but also the inherit building attributes [12]. In terms of access to equipment, low-income households are less likely to participate in energy efficiency programs or own energy efficient appliances, especially those with high up-front costs [14]. Low-cost appliances such as energy efficient light bulbs present their own challenges, as these technologies are less available and more expensive in high-poverty regions [15]. Rentership exacerbates these challenges, as those who do not own their homes are less likely than homeowners to have access to energy efficient appliances, even when controlling for household characteristics [16,17]. Lewis et al. show that African Americans are more likely to live in older, less energy efficient homes due to generations of structural racism, such as redlining practices that deny financial assistance to consumers based on the area where they live [18].

Beyond the physical structure of buildings and installed appliances, the energy required to maintain a livable indoor air temperature can be driven by location within a city. Urban heat islands (regions of a city with higher-than-average summer temperatures due to a higher density of heat-absorbing material such as asphalt and concrete and a lower-density of mitigating shade and green spaces) can lead to a 19% increase in cooling energy consumption [19]. Census block groups with larger populations of Black, Hispanic, and Native American populations are more likely to experience higher temperatures in summer heat waves [20]. Furthermore, Hoffman et al. (2020) examined the relationship between historically redlined neighborhoods and urban heat islands and found that for the vast majority of areas studied (94%), formerly redlined areas experience hotter summertime land surface temperatures than non-redlined areas. Hotter conditions in formerly redlined areas exacerbate cooling needs for residents, increase energy burdens for communities living in urban heat islands, and link to increased mortality from heat events [21,22]. Residency in formerly redlined neighborhoods is also associated with other health impacts, such as increased asthma-related emergency room visits [23].

Physical and mental health impacts can also be tied directly to high energy burdens. Low-income households can experience a "heat-or-eat" dilemma during periods of cold weather and have been shown to spend less on food during cold periods to account for higher energy costs [24]. One study found that 40% of surveyed low-income households had to reduce or forgo basic household needs (such as medicine and food) to pay for energy bills and that 2.1% needed to seek medical attention due to a lack of heating, while only 5.5% received assistance for bill payment or appliance repair. This "energy insecurity", defined as "… an inability to adequately meet basic household energy needs", can lead to three inter-related consequences: 1) illness and stress, 2) financial challenges, and 3) housing instability [25,26].

Energy burdens and a lack of energy efficiency in buildings are often worse for renters, particularly in multifamily housing. The "split-incentive" problem largely drives this, wherein building owners who would need to make capital investments to reduce building energy costs do not recoup any of the energy cost savings of those improvements if tenants are paying for their utilities [27]. Rental housing, especially multifamily, is associated with fewer energy efficient features than other housing types and higher energy costs per square foot [28–30].

Affordable housing program structures often exacerbate the landlord tenant split-incentive problem. For example, in project-based Section 8 and public housing, landlord subsidies are directly tied to utility costs, so landlords are effectively disincentivized from reducing energy costs [31]. Utilities are also more likely to be included in rent than for similar market-rate housing, capped at a specific level for most subsidy programs, thus providing little incentive for landlords and tenants to save energy [32]. Subsidized housing property owners generally do not have to compete for tenants as well, leaving no incentive to make units attractive to potential renters [31]. As a result, affordable housing buildings tend to consume more energy than similar market-rate buildings, with public housing consuming the most energy per square foot [33]. However, some affordable housing programs, such as the Low-Income Housing Tax Credit (LIHTC), employ different subsidy structures providing stronger incentives to increase energy efficiency [31].

A significant opportunity exists to improve energy efficiency and reduce energy burdens for low-income and minority households, particularly those residing in multifamily affordable housing. Research focused on New York City multifamily housing using energy audit data found that if energy conservation measures with a payback period of fewer than 10 years were implemented in subsidized housing energy burdens could be reduced by 2% of annual household income for the lowest income groups studied [3]. Pivo (2012) found that if the same number of energy efficiency features were installed in multifamily rental housing as other housing types, low-income rental households could save $400–600 per year on energy costs [29]. However, Kontokosta (2020) found that requiring mandatory audits, alone, does not provide a significant enough incentive for building owners to invest in energy efficiency improvements, especially beyond low-cost or *retro*-commissioning measures [34].

There is a significant push to improve energy efficiency in affordable housing, particularly in New York City, which is the focus of this paper. In "One New York: The Plan for a Strong and Just City," the New York City Mayor's Office lists affordable housing as one of the key challenges for the city and describes initiatives to improve lighting and boiler efficiency in New York City public housing [35]. In 2020, the New York State Energy Research and Development Authority and New York's investor-owned utilities committed to investing $880 million through 2025 to improve clean energy adoption for low- and middle-income households and affordable multifamily housing [36]. In 2019, the New York City council passed Local Law 97 requiring buildings over 25,000 square feet (approximately 50,000 residential and commercial properties) to meet energy efficiency and greenhouse gas limits by 2024 and 2030 [37]. The law offers alternative requirements for rent-regulated units and buildings participating in project-based federal housing programs to comply by implementing prescribed energy efficiency measures to reduce building energy consumption [38].

In light of this opportunity and a current focus on improving energy equity in buildings, this work aims to compare building system parameters between affordable and market-rate housing in New York City to uncover differences that lead to higher energy costs and worse health outcomes for residents of affordable housing. This study builds on previous research that uncovered differences in access to energy efficient appliances from survey data by analyzing detailed equipment-level inventories collected by energy auditors. The results of this work indicate that energy systems and equipment are actually newer and more efficient in affordable housing as compared with market-rate housing, but when building metadata (such as age and gross square footage) are considered, this trend largely disappears and there is not a statistically significant difference in efficiency between the two housing types based on the data included here. Further, the types of energy-serving equipment and recommended upgrades are different enough in affordable and market-rate buildings that these will need to be considered for development of affordable housing-focused energy efficiency programs. This work adds a unique contribution to the literature by analyzing detailed system-level data not present in earlier studies. Existing studies [26,27] that compare energy efficient systems between affordable and market-rate multifamily housing, while larger in geographic scope, do not contain nearly as much detail on the equipment installed in these buildings.

Section 2 describes the methodology of this analysis, including the datasets and statistical methods used; Section 3 presents the study results; Section 4 discusses implications for these findings on improving affordable housing energy efficiency; and Section 5 presents conclusions of this work.

2. Methodology

This work compares energy efficiency in affordable housing and market-rate housing in New York City based on detailed system-level (heating, ventilation, and air conditioning (HVAC); lighting; and envelope) data obtained from energy audits. It leverages a unique dataset of energy audits from New York City's Local Law 87 combined with publicly available affordable housing data and includes a regression analysis across many of the building system parameters. Merging these datasets enables a building-level comparison of the type of equipment and materials installed in affordable versus market-rate housing.

2.1. Data sources

2.1.1. Audit data

The energy audit dataset used in this analysis was generated from submitted Energy Efficiency Reports as part of New York City's Local Law 87, which mandates energy audits and retro-commissioning for large buildings every 10 years [39]. It includes data from reporting years 2013–2020, or roughly 80% of New York's building stock larger than 50,000 gross square feet. The first six years of data were obtained from the New York City Mayor's Office of Climate and Sustainability, while the last two years of data were entered directly into the U.S. Department of Energy's Audit Template tool by building energy consultants [40].

Out of the 10,334 total buildings included in this dataset, 7,328 were identified as multifamily buildings (defined here as buildings with more than 80% of square footage dedicated to multifamily housing use) and were included in this analysis. Other common use types include K-12 schools, offices, and warehouses.

Each audit record typically contains 368 pieces of information on a building, including overall building characteristics, envelope construction, HVAC system type and parameters, and lighting characteristics as well as a set of energy conservation measures identified and recommended by building auditors. Building inputs that were particularly useful for this study include:

- Building Use Type and associated Gross Floor Area
- Roof Type, Wall Type, Window Type, and associated thermal properties (R-Values)
- Lighting Type and Building Use Type Served
- HVAC Heating and Cooling Source and Use Type Served
- Energy Efficiency Measure (EEM) Category and Name
- Estimate EEM Cost Savings.

New York City Energy Efficiency Reports require the entry of the percentage of building-use types identified as common or tenant areas and a breakdown of the percentage of lighting types, HVAC system types, and hot water system types that serve these areas. Additional detail regarding the fields used in this analysis is provided in Section 2.2.1.

2.1.2. Demographic data

The NYU Furman Center's Subsidized Housing Database (SHIP) was used to enrich the audit data by labeling buildings as affordable or market-rate and providing information on specific subsidies associated with each building [41]. This dataset was used previously by Reina et al. (2017) to explore variation in energy consumption between subsidized and market-rate buildings and among buildings receiving different subsidy types [33]. The SHIP database combines over 50 separate datasets to track all publicly subsidized affordable rental housing properties in New York City. It includes data from the New York City Department of Finance, the New York City Department of Housing Preservation and Development, the New York City Housing Authority (NYCHA), the New York State Department of Housing and Community Renewal (HCR), and the U.S. Department of Housing and Urban Development (HUD). Note that the SHIP database includes information on a property-level (defined by the tax lot) and could consist of multiple buildings, while audit data are compiled at the building level.

SHIP includes data from seven subsidy types [42]:

1. HUD financing and incentives, including Section 202 and Section 811 programs
2. HUD project-based rental assistance
3. LIHTC
4. Public housing managed by NYCHA

Table 1
Audit metadata fields.

Field name	Number of buildings including field
Year Completed	7,328
Total Floor Area (ft^2)	7,243
Number of Floors	7,317
% Common Area (for multifamily space)	7,328
Borough	7,328
Tenants Directly Metered (Electric)	7,328
Tenants Directly Metered (Gas)	7,328

5. Mitchell-Lama program
6. New York state property tax incentive programs, including 421-a and 420-c
7. New York City housing production programs and zoning incentives and requirements.

The SHIP database does not include data on which properties include units receiving HUD voucher-based rental assistance (Section 8), as recipients can take their vouchers to any eligible building so the subsidy is not tied to the specific property. The NYU Furman Center does have additional datasets, such as the Neighborhood Indicator dataset, which includes information on the percentage of rental units occupied by housing choice voucher recipients for geographic areas down to individual neighborhoods [43].

The SHIP database includes information on 13,193 properties containing nearly 800,000 residential units, many receiving more than one subsidy [43]. However, some of the properties are no longer receiving an active subsidy, and the database also includes properties that received 421-a Tax Incentives that do not require a certain number of units to be set aside as affordable. Excluding properties that only received a 421-a Tax Incentives subsidy, 3,579 properties received an active subsidy in 2017 [42].

2.2. Analysis methodology

2.2.1. Organization of audit data

As an audit data record for a single building contains hundreds of fields on the building's systems, envelope, and condition, these fields had to be downselected to a subset for use in this analysis. Fields were chosen based on their relevance to energy equity, including system efficiency parameters that could affect residents' energy costs or air-sealing and ventilation fields that could impact the health of building occupants. Several other fields were chosen as metadata parameters to make sure any statistically significant findings were not skewed by other factors (such as building age). A complete list of the metadata and equity-related fields used in this analysis are shown in Table 1 and Table A1, respectively.

It is important to note that not all fields included in an audit report are filled in for each building record. In particular, 2019 and 2020 data were obtained through the Audit Template tool database, and therefore, data for those years were subject to data validation and completeness tests that did not apply to the 2013–2018 data. As such, several of the parameters of interest (such as heating plant efficiency) were only present in the 2019 and 2020 data and others had too few entries across the full dataset to be used in the analysis. In Table A1, parameters that are present only in 2019 and 2020 data are indicated.

As the audit data for a given building can include several different use-types and many different systems, for each of the relevant system types (e.g., HVAC, lighting, etc.), the system that serves the majority of the multifamily portion of the building was chosen in this analysis. For envelope and construction parameters and heating and cooling plants, the first component of each type that was listed was used. For most buildings, only one Roof, Window, Wall, Heating Plant, or Cooling Plant component was included in the data, but for approximately 25% of the buildings, additional Window components were included, and 17% of the buildings included an additional Heating Plant. These secondary components were not used in this analysis. For both lighting and HVAC components, the component was chosen that served the largest percentage of common area or tenant space, respectively. Common area was used for lighting because the percentage of common area space that a lighting fixture served was filled in much more frequently than the percentage of tenant space. Likewise, tenant area was used for HVAC because the percentage of space served by the system was included equally for both tenant and common area space, and it was assumed that the HVAC system corresponding to the tenant spaces would have a more significant impact on tenant energy costs, comfort, and health. Future work could expand on this analysis to analyze multiple HVAC and lighting systems for each building.

Some fields included in the audit data can be entered using a variety of different units and were therefore converted to a single consistent unit for the analysis. This includes the heating plant rated efficiency and the cooling system rated efficiency. The heating plant rated efficiency can be entered in units of either Annual Fuel Utilization Efficiency (AFUE) or Thermal Efficiency (Et), and was converted to Et using the following formula from [44]:

$$Et = (0.0051427 \times AFUE) + 0.3989 \quad (1)$$

Cooling system rated efficiency can be entered in units of Energy Efficiency Ratio (EER), Seasonal Energy Efficiency Ratio (SEER), or Coefficient of Performance (COP), and was converted from EER or SEER to COP using the following formula from [44]:

$$COP = 7.84 \times 10^{-8} \times EER \times Q + 0.338 \times EER \quad (2)$$

where Q is the cooling capacity in BTU/h.

All of the fields used in the analysis were reviewed and clearly incorrect values (e.g. years with 5 digits) were removed from the dataset.

2.2.2. Organization of demographic data

Data from the SHIP database were used to label and categorize buildings from the audit dataset as affordable or market-rate housing. Two different criteria were used to generate two different sets of buildings categorized as 'subsidized' and 'affordable'. For both definitions, all other buildings from the audit dataset not falling within one of the criteria were considered market-rate housing.

The 'Subsidized' set includes any building with a record in the SHIP database, indicating that the property has received any subsidy during the data collection period (with the first subsidy from the dataset starting in 1936 and ending in 1984). There are **13,193 properties** in the first set, receiving the following subsidy types: 1) homeownership, housing stability, and quality; 2) land and financing; 3) planning and zoning; 4) rental subsidies and assistance; 5) supportive/special needs housing; and 6) tax incentives. As noted above, this includes properties that received a 421-a Tax Incentives subsidy and others that may or may not require a majority of units marked as affordable. Thus, a second, narrower definition, 'Affordable', was used to designate a second set of buildings. For this definition, a building must have received a subsidy that would make or require the majority of its units to be affordable. Because many of the properties from the SHIP database received multiple subsidies, a property must have received at least one of the subsidies identified below to fall under this second definition:

- Properties with HUD financing or insurance subsidies, including Section 221d and Section 223 subsidies (**332 properties**). HUD financed properties have a requirement to make 100% of their units affordable.
- Properties with HUD contracts, such as those receiving project-based rental assistance (**932 properties**). While some of the units in these properties may be market-rate, the NYU Furman Center estimates

Table 2
Number of SHIP properties and audit data by affordability criteria.

Selection criteria	SHIP Properties meeting criteria	Audit data buildings meeting criteria	Audit data buildings not meeting criteria (market-rate)
Subsidized	13,193	1,347	5,981
Affordable	4,839	770	6,558

that 8% of the units in properties receiving this subsidy type are affordable [42].

- Properties receiving low-income housing tax credits including the New York State Homes and Community Renewal (NYS HCR) Low Income Housing Tax Credit and the federal LIHTC (**2,527 properties**). As for the properties with HUD contracts, some of the properties receiving this subsidy type may be market-rate housing, but 75% of units receiving this subsidy type are affordable housing [42].
- Properties receiving subsidies from the Mitchell-Lama program, which includes land and property tax abatements and subsidized mortgages (**260 properties**). While all units in properties receiving these subsidizes must be affordable housing, they may be targeted toward moderate-income households.
- Properties with property tax incentives with an affordability requirement, including the 420-c and 421-a Affordable Housing Tax Incentive program (**1,988 properties**). Note that the 421-a Affordable Housing Tax Incentive program is a subset of the larger 421-a program, the latter of which includes many market-rate housing units. However, the two subsidy programs considered here have a 100% affordable unit requirement.

In total, **4,318 properties** from the SHIP database receive at least one of these subsidies. Note that only a fraction of these properties will correspond to buildings in the audit dataset as the SHIP database includes buildings of all sizes, not just large buildings required to comply with New York City's audit requirement. The number matching to the audit dataset will be discussed in the next section. It is important to note that public housing owned and managed by NYCHA is not included in this affordability criteria. While NYCHA housing has a 100% affordability requirement, no NYCHA properties were in the audit dataset obtained for this analysis. In addition, the SHIP database includes properties receiving a subsidy at any point in time, starting from 1936, and some of these subsidies are no longer in place. However, for this analysis, buildings receiving a subsidy from either of the criteria at any point in time were included, as it was assumed that the building systems considered would not change significantly once a subsidy had expired. Follow-on work could explore this assumption to determine if the expiration of a subsidy was associated with a significant difference in building and system characteristics.

2.2.3. *Joining datasets*

To compare building and system characteristics between affordable and market-rate buildings, the audit data was matched to the SHIP database using the Building Block Lot (BBL) identifier. BBLs are used to describe tax lots in New York City and can include multiple buildings on the same tax lot or property. Each property from the SHIP dataset includes a BBL identifier that may correspond to one or more buildings from the audit dataset. Therefore, it was assumed that all buildings associated with a BBL from the audit data had the same affordability status as indicated by the SHIP entry corresponding to that BBL.

As mentioned in the previous section, two different affordability criteria were used for this analysis: 1) 'Subsidized' properties, which include any property in the SHIP database, and 2) 'Affordable' properties, which are a subset of subsidized properties corresponding to subsidy programs in which the majority of units are affordable units. Any building from the audit dataset not mapping to a SHIP property for each of the criteria was considered market-rate housing. It is possible that this included many buildings with some portion of the building set aside for affordable units, but given the data used in this analysis, it was not possible to identify these buildings. However, this would only serve to dampen any relationships found in this analysis, and thus would make any trends underestimates. In addition, if the majority of the units in a building are market-rate, it was assumed that landlords would have an incentive to improve energy efficiency similarly to if the entire building was market-rate. Table 2 lists the affordability criteria with an associated number of properties and the number of matched buildings from the audit dataset. Fig. 1 depicts two Venn diagrams demonstrating how buildings were categorized according to the two definitions.

Table 3
Example contingency table for window glass type with counts of buildings with each window glass type by affordability status.

Affordability status	Double pane	Double pane with low-e	Single pane
Subsidized buildings	1,111	121	86
Non-subsidized buildings	4,746	517	368

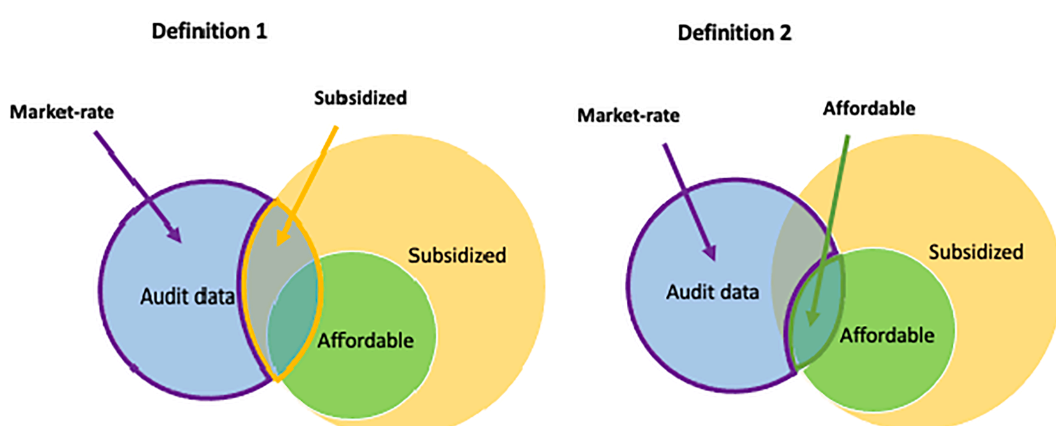

Fig. 1. Venn diagrams describing how buildings from the audit dataset were categorized as affordable or market-rate according to the two definitions. In both diagrams, the blue circle represents buildings from the audit dataset, the yellow circle depicts all properties in the SHIP database, and the green circle denotes properties in the SHIP database receiving subsidies deemed to correspond to properties where the majority of units are affordable. In the diagram on the left, the purple and yellow wedges represent buildings labeled as market-rate and subsidized, respectively, according to the first definition. In the diagram on the right, the purple and green wedges represent buildings labeled as market-rate and affordable, respectively, according to the second definition. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Two-sample *t*-test results for numerical building parameters using the subsidized housing definition.

Building Variable	p-value (stand. error)	$Median_{subsidized}$	$Median_{market}$	95% $CI_{subsidized}$	95% CI_{market}
Roof R-Value[1] (N = 6,620)	2.18E-24 (0.26)	15.00	12.00	(13.31, 18.68)	(10.63, 15.99)
Wall Insulation R-Value[1] (N = 1,328)	1.12E-09 (0.38)	9.10	5.00	(7.19, 12.01)	(4.78, 9.6)
Window U-Value[2] (N = 162)	4.64E-02 (0.03)	0.60	0.70	(0.67, 0.56)	(0.73, 0.62)
Window to Wall Ratio (N = 4,142)	9.81E-01 (0.01)	0.19	0.20	(0.21, 0.21)	(0.21, 0.21)
Slab Insulation (in) (N = 266)	9.90E-02 (0.35)	0	0	(0.4, 1.6)	(-0.19, 1)
Foundation R-Value[1] (N = 124)	5.96E-01 (1.21)	4	3	(5.92, 7.21)	(5.28, 6.57)
Heating System Year Installed (N = 5,176)	6.41E-52 (0.55)	2004	1989	(1990, 2008)	(1981, 1999)
Heating System Burner Year Installed (N = 4,606)	1.67E-81 (0.43)	2006	1994	(1994, 2012)	(1986, 2003)
Cooling System Approximate Year Installed (N = 1,696)	2.93E-18 (0.38)	2006	2002	(2002, 2009)	(1999, 2005)
Cooling System Rated Efficiency (unitless)[3] (N = 321)	4.27E-01 (0.16)	3.32	3.00	(3.3,3.6)	(3.2,3.5)
Heating Plant Burner Year Installed (N = 5,673)	6.01E-96 (0.39)	2006	1994	(1995, 2012)	(1986, 2003)
Heating Plant Year Installed (N = 6,298)	1.42E-65 (0.49)	2004	1989	(1991, 2008)	(1982,1999)
Heating Plant Rated Efficiency (%)[4] (N = 1,143)	5.85E-07 (0.32)	81.0	80.0	(79.29, 82.54)	(77.66, 80.91)
Cooling Plant Year Installed (N = 1,293)	1.76E-14 (0.45)	2006	2005	(2002, 2009)	(1999, 2006)

[1]R-values are entered in units of $ft^2 \times {}^oF \times h/Btu$.
[2]U-values are entered in units of $Btu/(ft^2 \times {}^oF \times h)$.
[3]Cooling system rated efficiency values are converted to COP (coefficient of performance) units as described in Section 2.2.1.
[4]Heating plant rated efficiency values are converted to Et (Thermal efficiency) units as described in Section 2.2.1.

Table 5
Two-sample *t*-test results for numerical building parameters using the affordable housing definition.

Building Variable	p-value (stand. error)	$Median_{affordable}$	$Median_{market}$	95% $CI_{affordable}$	95% CI_{market}
Roof R-Value[1] (N = 6,620)	1.83E-14 (0.31)	15.00	12.00	(13.56, 18.45)	(11.11, 16.01)
Wall Insulation R-Value[1] (N = 1,328)	1.56E-06 (0.46)	10.00	5.00	(7.39, 12.04)	(5.07, 9.71)
Window U-Value[2] (N = 162)	7.04E-01 (0.03)	0.6	0.69	(0.67, 0.56)	(0.73, 0.62)
Window to Wall Ratio (N = 4,142)	6.00E-06 (0.01)	0.18	0.20	(0.22, 0.17)	(0.24, 0.19)
Slab Insulation (in) (N = 266)	2.35E-01 (0.52)	1	0	(0.44, 1.74)	(-0.21, 1.09)
Foundation R-Value[1] (N = 124)	9.08E-01 (1.24)	6.00	6.14	(6.14, 5.86)	(6.29, 6)
Heating System Year Installed (N = 5,176)	3.03E-31 (0.72)	2004	1989	(1991, 2008)	(1982, 2000)
Heating System Burner Year Installed (N = 4,606)	9.77E-60 (0.50)	2006	1994	(1995, 2013)	(1986, 2004)
Cooling System Approximate Year Installed (N = 1,696)	1.02E-06 (0.55)	2005	2003	(2003, 2008)	(2000, 2005)
Cooling System Rated Efficiency (unitless)[3] (N = 321)	2.03E-01- (0.10)	3.37	3.00	(3.3, 3.6)	(3.2, 3.4)
Heating Plant Burner Year Installed (N = 5,673)	2.57E-73 (0.46)	2006	1995	(1995, 2014)	(1986, 2004)
Heating Plant Year Installed (N = 6,298)	2.18E-40 (0.64)	2004	1989	(1991, 2009)	(1982. 2000)
Heating Plant Rated Efficiency (%)[4] (N = 1,143)	3.76E-05 (0.44)	81.0	80.0	(79.40, 83.15)	(77.52,81.28)
Cooling Plant Year Installed (N = 1,293)	2.00E-05 (0.61)	2005	2005	(2003, 2008)	(2000, 2005)

[1]R-values are entered in units of $ft^2 \times {}^oF \times h/Btu$.
[2]U-values are entered in units of $Btu/(ft^2 \times {}^oF \times h)$.
[3]Cooling system rated efficiency values are converted to COP (coefficient of performance) units as described in Section 2.2.1.
[4]Heating plant rated efficiency values are converted to Et (Thermal efficiency) units as described in Section 2.2.1.

Table 6
Chi-squared results for categorical parameters. The enumerations for each option are shown in Figs. 2–5.

Building Variable	Subsidized z-value	Affordable z-value
Roof Type (n = 6,236)	5.76E-06	1.30E-05
Cool Roof (n = 7,117)	0.03	0.93
Green Roof (n = 7,117)	5.58E-03	4.41E-03
Wall Type (n = 6,860)	2.62E-11	4.02E-07
Window Framing Material (n = 7,048)	0.01	1.90E-04
Window Glass Type (n = 6,593)	1.17E-06	0.11
Window Operable (n = 7,145)	7.45E-03	0.03
Exterior Lighting (n = 7,305)	0.17	0.69
Lighting Fixture Type (n = 7,305)	9.59E-44	7.47E-43
Lighting Ballast Type (n = 4,552)	1.38E-15	5.77E-10
Lighting Controls (n = 7,328)	9.23E-05	3.70E-09
Heating System Type (n = 7,077)	1.15E-37	9.49E-13
Heating System Fuel Type (n = 5,941)	6.55E-61	9.65E-51
Thermal Zoning (n = 1,328)	0.36	N < 5
Cooling System Type (n = 5,472)	8.25E-04	3.87E-02
Central Distribution Type (n = 7,198)	4.05E-147	5.47E-115
Delivery Equipment Type (n = 7,158)	6.19E-163	3.02E-162
Air Supply Corridors (7,291)	2.63E-22	6.39E-10
Outdoor Air (n = 619)	5.66E-05	2.19E-04
HVAC Controls (n = 4,596)	4.11E-05	7.23E-12
Heating Plant Type (6,717)	1.25E-211	3.04E-171
Heating Plant Fuel Type (n = 7,176)	3.72E-62	1.99E-56
Heating Plant Venting Type (1,191)	5.07E-07	1.37E-03
Heating Plant BAS (n = 7,246)	4.97E-05	2.40E-05
Cooling Plant Type (n = 263)	6.05E-03	0.09
Cooling Plant BAS	N < 5	N < 5

2.2.4. Determining relationship between building characteristics and housing type

2.2.4.1. Relationship between building characteristics and affordability status. Several statistical methods were used to determine if a building's characteristics were related to its affordability status, depending on the type of building data—numerical or categorical. In both cases, an analysis was performed first to determine the presence of a strong relationship between the building parameter and affordability status. If a significant result was obtained, another analysis was performed (only for numerical parameters) to determine if the trend could be explained from any combination of the building metadata parameters. For example, if a strong relationship was found between affordability status and wall R-value, a second analysis was performed to determine if this relationship could be explained by the differences in typical building age and gross square footage between affordable and market-rate buildings. The second analysis was not performed in cases where no significant relationship was found between the parameter and affordability status. These analyses were all performed for both affordability definitions.

For numerical data (e.g., heating system efficiency), a two-sample *t*-test was performed to determine the initial relationship between each building parameter and affordability status, using the parameter values for affordable buildings and market-rate buildings as the two sample populations [45]. If the *t*-test returned a p-value less than 0.05, the relationship between the building parameter and affordability status was considered significant.

For categorical data (e.g., roofing type), a chi-squared test of independence was performed to determine the initial relationship [46]. Before performing these tests, a contingency table was constructed for each categorical variable. It recorded the number of buildings corresponding to each category for both affordable and market-rate buildings. Any category for which less than five buildings were included for either affordability status was removed from the analysis, as chi-squared tests of independence only return robust results when five or more samples are included for each cell in the contingency table [47]. Smaller sample sizes (between 5 and 30) were still included in the analysis, since the sample size assumption for the chi-squared test of independence was met. An example contingency table is shown in Table 3. If a p-value of less than 0.05 was returned, the relationship between building characteristic and affordability status was considered significant. The *t*-test and chi-squared test allow for straightforward comparison between affordable and market-rate housing stock. However, they do not allow for control of other factors that may influence the study outcomes (e.g., building age, location, size). Therefore, a regression model is used to provide more detailed analysis when a statistically significant relationship is found.

For only the numerical building parameters, if a significant relationship was found with affordability status, a multivariate regression then was performed to eliminate the effects of any metadata parameters on the initial relationship. A linear regression was performed for each numeric building parameter and affordability definition to predict the parameter's value using the affordability status and the metadata parameters as independent variables (Eqs. (3) and (4)). No scaling was performed on the parameters.

$$building\ \ parameter = \beta_0 subsidized + \beta_1 meta\ \ parameter + \varepsilon \tag{3}$$

$$building\ \ parameter = \beta_0 affordable + \beta_1 meta\ \ parameter + \varepsilon \tag{4}$$

Each model began with all metadata parameters included in the analysis (Table 1). The parameter with the highest corresponding p-value was dropped after each iteration, excluding the affordability status, until all parameters had a p-value of less than 0.05 (for numeric parameters) or a p(z-value) less than 0.05 (for categorical parameters). If all parameters but the affordability status had p-values or p(z-values) less than 0.05, the building parameter was recorded as not having a statistically significant difference between the corresponding affordability definition classifications. If the p-value of the affordability status was significant, the affordability status coefficient, p-value, $\hat{y}_{\text{affordable}}$ (or $\hat{y}_{\text{subsidized}}$), and $\hat{y}_{\text{market}}$ were recorded for numeric building parameters. These regressions were not performed for categorical parameters because interpreting the results of multiple models per parameter can be challenging and ambiguous. Performing such regressions could be an area for future study.

If a statistically significant model was found between the building parameter and affordability status, four diagnostic tests were performed on the model: 1) a linearity test, 2) a normality test, 3) a homoscedasticity test, and 4) an outlier test [48]. Models that did not pass these tests were eliminated. The multivariate regression analysis represents a more robust form of investigation than the aforementioned *t*-test and chi-squared test. By controlling for these metadata parameters, differences between affordable and market-rate housing can be isolated more accurately. However, although several building characteristics are included in the metadata, ordinary least squares regressions cannot conclusively eliminate omitted variable bias and thus prevent identification of causal relationships.

2.2.4.2. Relationship between recommended measures and affordability status. The audit dataset includes a list of auditor-recommended EEMs. This information includes the measure category, measure name, description, and cost and energy savings, among other fields. To understand how the overall condition of affordable housing buildings and systems may vary from market-rate buildings and systems, the frequency in which each EEM was recommended, the average cost savings per square foot, and the average number of recommended EEMs were compared between affordable and market-rate buildings. For this analysis, the definition of affordable was restricted to the more limited second definition described above, which only includes properties where the majority of units have an affordability requirement.

The only significant cleaning step for this analysis was to remove duplicate measures recommended for the same building. For example, many buildings will include multiple recommended measures related to lighting upgrades if, for instance, the building requires different types of lighting in different areas of the building. However, this analysis only

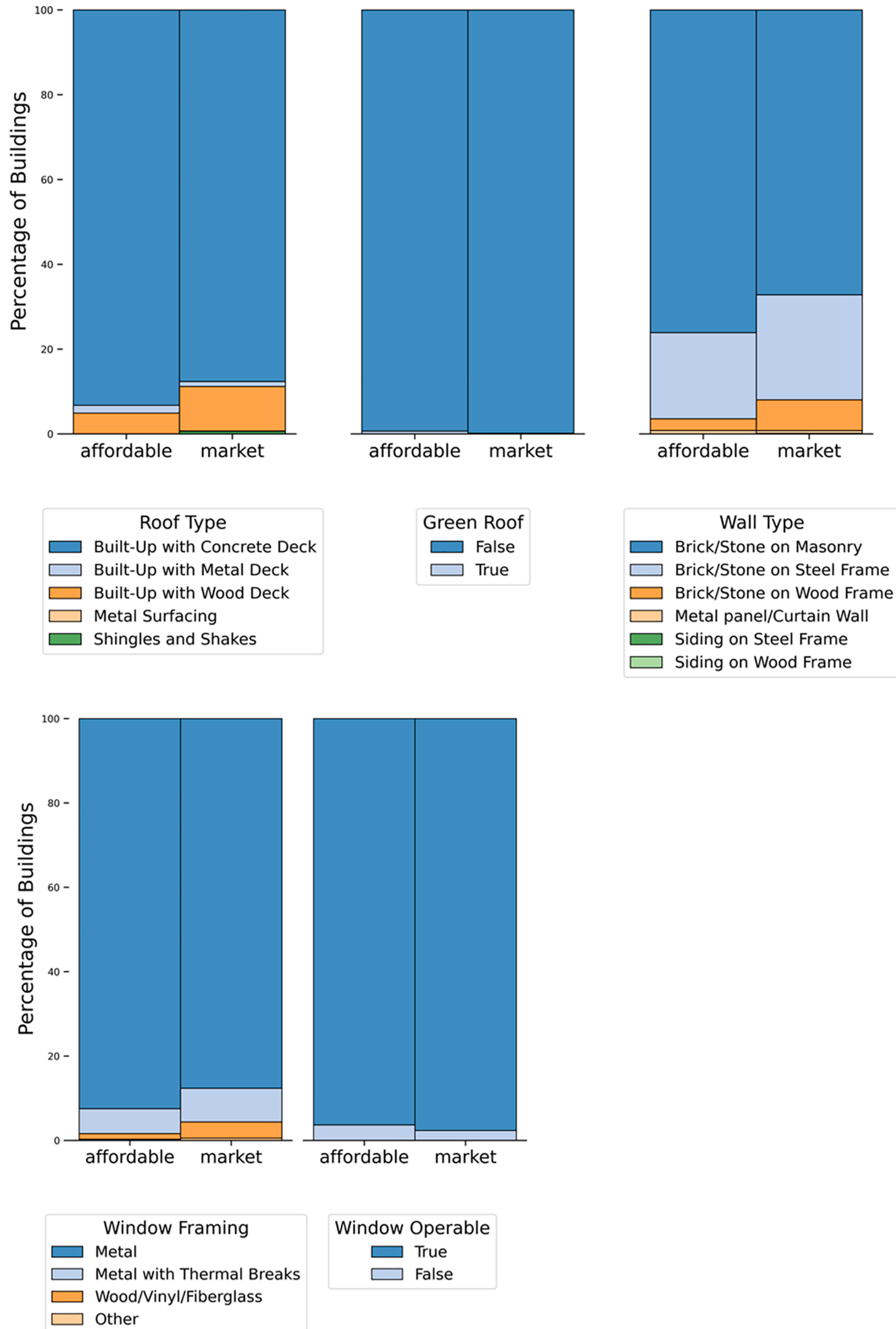

Fig. 2. The percentage of buildings with each roof type, green roof designation (True/False), wall type, window framing, and window operability designation for both affordable and market-rate buildings. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

considered unique instances of each measure type for a given building.

For the cost savings per square foot and the number of EEMs per building, the mean was calculated for each of the subgroups (affordable and market-rate) and *t*-tests were performed to determine if the differences in these parameters was significant for affordable and market-rate buildings.

To determine the most common recommended measures for the two subgroups, the number of buildings for which each measure and measure category was recommended was tabulated by affordability status, and a chi-squared test of independence was performed for each measure type and category. Before running these tests, any measure or category that was found for less than five buildings in either subgroup was removed from the analysis. Measure categories and names described as “Other” also were removed, as these are difficult to interpret. For both the *t*-tests and the chi-squared tests, if a p-value of less than 0.05 was obtained, the difference between affordable and market-rate buildings was assumed to be significant.

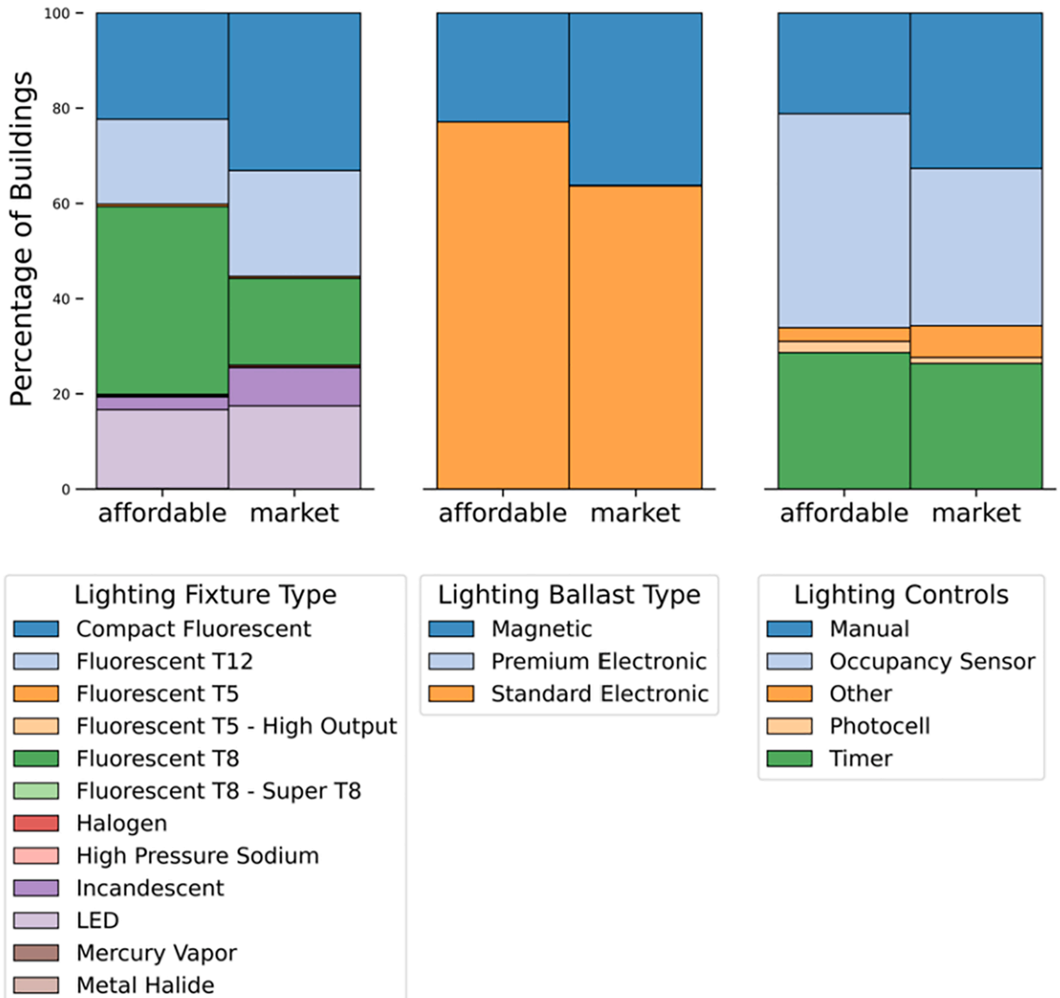

Fig. 3. The percentage of buildings with each lighting fixture type, lighting ballast type, and lighting control type for both affordable and market-rate buildings.

3. Results

3.1. Relationship between building characteristics and affordability status

3.1.1. T-tests with numerical parameters

Tables 4 and 5 show results of the two-sample *t*-tests performed on numeric parameters for the subsidized and affordable definitions, respectively. The median observed values for the subsidized or affordable and market-rate populations are shown as well as the p-value, standard error, and confidence intervals. P-values less than 0.05 are highlighted in yellow and the median values are highlighted such that the more energy efficient or more recent value (for year installed) is shown in darker green. Of the 14 numeric parameters tested, 10 show a statistically significant difference between subsidized and market-rate housing and affordable and market-rate housing, although one of the statistically significant parameters is different between the subsidized and affordable analyses.

3.1.2. Chi-squared tests with categorical parameters

Table 6 shows the results of the chi-squared tests of independence for all categorical parameters for both the subsidized and affordable definitions.

A z-value of less than 0.05 results in rejection of the null hypothesis, meaning that the two distributions of the parameter for subsidized or affordable and market-rate housing are independent (highlighted in yellow). Of the 24 parameters tested, 22 show a dependence between building parameters and the subsidy status and 19 show a dependence between building parameters and the affordable status. A few parameters did not have enough samples for all of the categories to provide a robust analysis and are indicated by 'N < 5' in the table.

Figs. 2–5 show the observed percentages of each enumeration between affordable and market-rate housing for the HVAC system, envelope, lighting, and plant parameters, respectively. Only parameters with a significant z-value (less than 0.05 are shown). The percentages for subsidized and market-rate housing are not shown for brevity, but they exhibit similar trends.

Many of the differences between building system types and characteristics observed in affordable and market-rate housing may be explained by building metadata parameters, such as building size and age. These metadata parameters will be examined between housing types in the next section.

From these figures, a few key differences are observed. For envelope parameters (Fig. 2), market-rate buildings are more likely to have roofs with wooden decks and walls constructed of wooden and steel frames than affordable buildings, although these still account for a small fraction of the total number of buildings. For lighting parameters (Fig. 3), market-rate buildings have a slightly higher occurrence of inefficient incandescent lighting, a similar occurrence of LED lighting, and are more likely to contain compact-fluorescent than fluorescent-tube lighting than affordable buildings. For HVAC and plant parameters (Figs. 4 and 5), key differences between affordable and market-rate buildings are that affordable housing is more likely to have hydronic systems with hot water baseboards and market-rate housing is more likely to include steam systems with radiator or convectors.

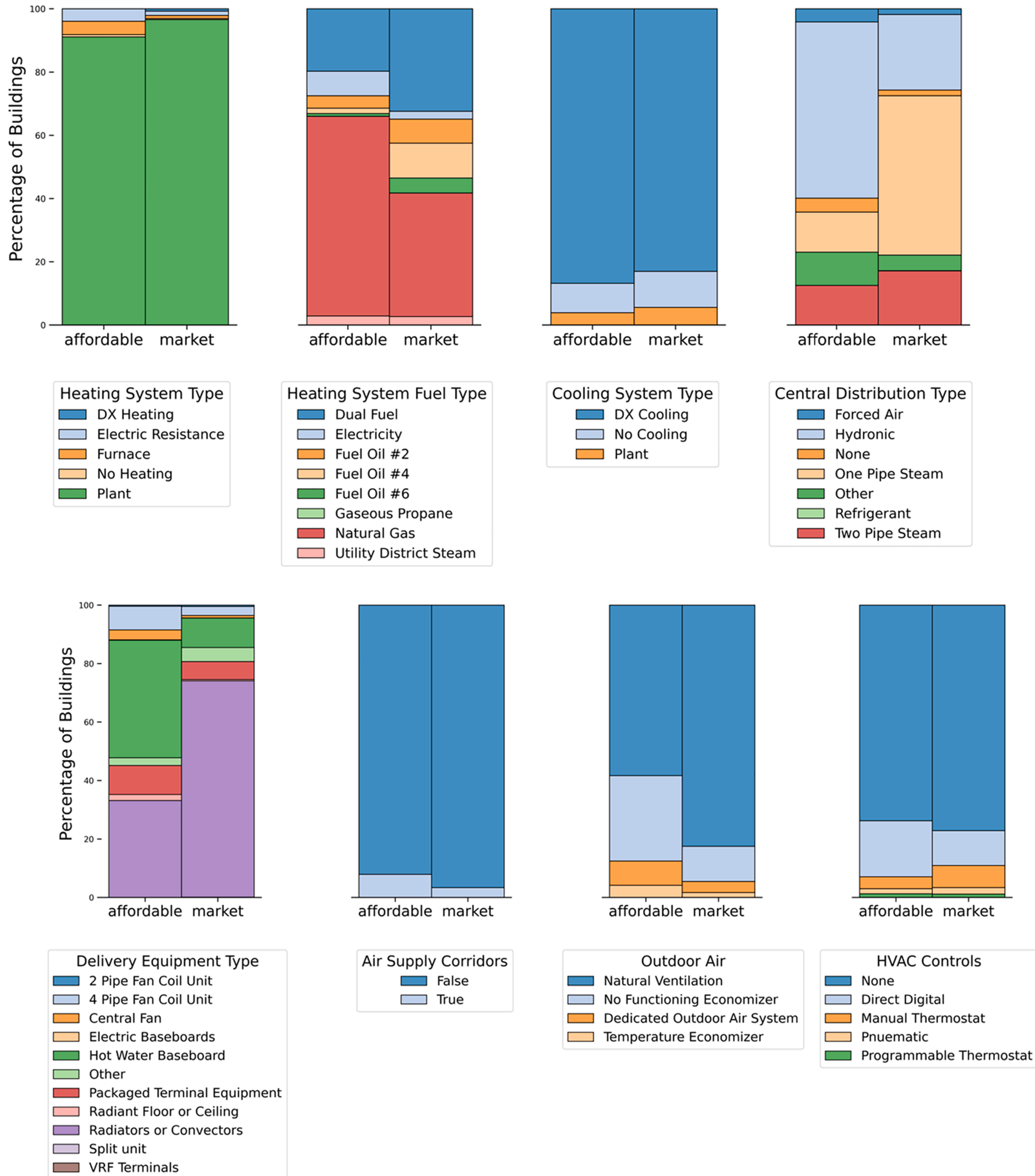

Fig. 4. The percentage of buildings with each heating system type, heating system fuel type, cooling system type, central distribution type, delivery equipment type, air supply corridors, outdoor air, and HVAC control type for both affordable and market-rate buildings.

3.1.3. *T-tests and Chi-squared tests with metadata parameters*

Tables 7 and 8 show the results of the two-sample *t*-tests performed on numeric metadata parameters and Table 9 shows the chi-squared tests of independence for categorical meta-data parameters. For the numerical parameters, the median values for each subgroup are shown, as well as the p-value and the confidence intervals. For the categorical parameters, the z-value is shown. P or z-values less than 0.05 are highlighted in yellow, and for the numerical parameters, the larger of the two medians is highlighted in darker green. Of the seven meta-data parameters tested, all show a statistically significant difference between subsidized and market-rate housing and all but common area percentage served show a statistically significant difference between affordable and market-rate housing.

Fig. 6 shows the distribution of enumerations across categorical metadata parameters and the range in values for numerical parameters for affordable and market-rate housing. Of note, many more affordable housing buildings are located in the Bronx or Brooklyn Boroughs than market-rate buildings, affordable housing buildings are less likely to meter tenants for electric and gas use, and affordable buildings are likely to be newer, larger, and taller than market-rate buildings.

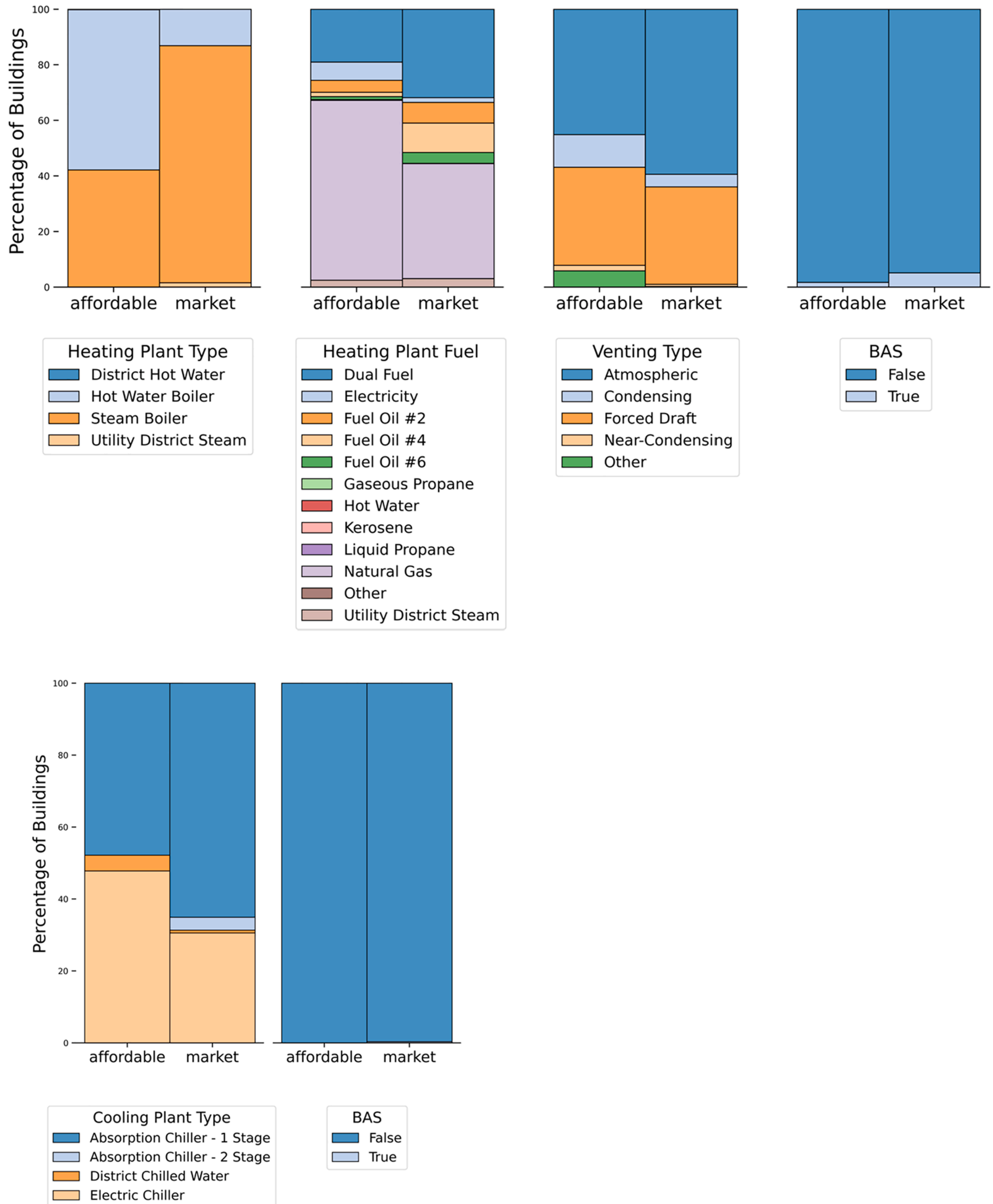

Fig. 5. The percentage of buildings with each heating plant type, heating plant fuel, venting type, heating BAS designation, cooling plant type, and cooling BAS designation for both affordable and market-rate buildings.

3.1.4. *Multivariate regressions for statistically significant numerical parameters*

Tables 10 and 11 show the linear regression results for numerical building system parameters for the subsidized and affordable definitions, respectively. Only parameters that were identified as significant from the *t*-tests were investigated in this part of the analysis. For each building parameter, the regression coefficient for the affordability status is listed with the robust standard error in parentheses and asterisks representing the statistical significance of the coefficient (see legend at bottom of Table 10). Also shown are the average predicted values for all subsidized or affordable and market-rate buildings using these linear models and the R^2 for the models. Only parameters with an affordability coefficient p-value less than 0.05 are shown in these tables. More detailed results from these models are shown in Tables B1 and B2.

While 10 numerical building system parameters showed a statistically significant relationship (p-value less than 0.05) with affordability status from the t-tests, only four were still significant (for either affordability definition) when considering metadata parameters. Even among these four parameters, all models resulted in very low R^2 values despite statistically significant coefficients. Our interpretation of these results is discussed in more detail in Section 4.

Table 7
T-test results for metadata parameters for the subsidized definition.

Building Variable	p-value (stand. error)	*Median*$_{subsidized}$	*Median*$_{market}$	*95% CI*$_{subsidized}$	*95% CI*$_{market}$
Year Completed (n = 7,328)	3.63E-105 (0.97)	1974	1949	(1947, 1992)	(1924, 1970)
Total Conditioned Floor Area (ft^2) (n = 7,243)	4.22E-13 (5,394.07)	93,000	79,460	(11,9377.66, 19,8271.63)	(79,930.67, 158,824.65)
Number of Floors (n = 7,317)	1.46E-09 (0.23)	7	6	(8.73, 11.47)	(7.36, 10.1)
Common % Area Served (n = 7,083)	2.43E-02 (0.45)	0	0	(3.23, 5.25)	(2.22, 4.24)

Table 8
T-test results for metadata parameters for the affordable definition.

Building Variable	p-value (stand. error)	*Median*$_{affordable}$	*Median*$_{marke}$	*95% CI*$_{afforrdable}$	*95% CI*$_{market}$
Year Completed (n = 7,328)	1.58E-98 (1.12)	1975	1948	(1948, 2002)	(1921, 1975)
Total Conditioned Floor Area (ft2) (n = 7,243)	3.30E-14 (8,417.95)	109,800	79,352	(11,9924.14, 25,0155.64)	(54,808.39, 185,039.89)
Number of Floors (n = 7,317)	1.07E-14 (0.31)	7	6	(8.73, 13.59)	(6.3, 11.16)
Common % Area Served (n = 7,083)	6.20E-01 (0.54)	0	0	(3.39, 3.92)	(3.12, 3.65)

Table 9
Chi-squared results for metadata parameters for both the subsidized and affordable definitions.

Building Variable	Subsidized z-value	Affordable z-value
Borough (n = 7,328)	1.65E-96	1.68E-40
Tenants Directly Metered for Electric	1.14E-05	1.56E-15
Tenants Directly Metered for Gas	3.32E-20	1.99E-36

3.2. Comparison of measure recommendation frequency

Auditor-recommended EEMs for each building were compared in aggregate between affordable and market-rate buildings to explore if auditors were more likely to recommend a different number or different types of measures for the two building types. The mean number of unique EEMs recommended per building was reasonably similar between the two types (Table 12), with a mean of 5.3 for affordable buildings and 5.6 for market-rate buildings. A *t*-test comparing the distributions for the two building types returned a p-value of 0.034, barely low enough to reject the null hypothesis that the number of EEMs for affordable and market-rate buildings were drawn from the same distribution. Histograms and smoothed kernel density estimates of the number of EEMs per building are shown in Fig. 7a, with affordable buildings shown in orange and market-rate buildings in blue, indicating different distributions for the two building types.

Interestingly, market-rate buildings are more likely to have a very low (1–4) or very high (7+) number of recommended EEMs, while affordable buildings are more likely to have a moderate number of recommended EEMs (4–7). Future work could further explore this trend to identify if the market-rate buildings with a very low or very high number of recommended EEMs differ in terms of their building or system characteristics.

The total savings of all recommended measures for each building (see Table 12) were compared between affordable and market-rate buildings. Predicted savings were normalized by square footage to account for the fact that larger buildings are likely to realize more dollar savings from the same EEMs as smaller buildings, assuming they are implemented building-wide. Savings were calculated by each individual energy auditor and do not include information on whether EEMs are targeted at owner or tenant savings. It may be possible to extrapolate who benefits from the savings based on the type of measure and the metering configuration for the building, and that could be an area for follow-on work. For affordable buildings, the average predicted savings was $0.37 per square foot, and for market-rate buildings, the average was $0.36 per square foot. A *t*-test between the two distributions returned a p-value of 0.54, which is too high to reject the null hypothesis that the variables were drawn from the same distribution. The histograms and kernel density estimates in Fig. 7b also show similar distributions.

Table 13 shows the percentage of buildings with an EEM from each of the possible categories for both affordable and market-rate buildings as well as the chi-squared test of independence p-value comparing the counts of buildings between affordable and market rate. Only EEM categories present in at least 10% of buildings for each building type were included. Cells showing the percentages of buildings are color-coded dark to light green for the highest to lowest percentage for the top five categories for each building type. P-values less than 0.05 are highlighted in yellow.

While the chi-squared p-values show that about half of the categories have statistically significant differences in counts between the two building types, both affordable and market-rate buildings have roughly the same top five EEM categories in a similar order.

The percentage of buildings with specific EEMs is shown in Table 14. Only EEMs present in more than 5% of buildings for either type are included, as well as only EEMs with chi-squared p-values less than 0.05. The top five recommended EEMs for both affordable and market-rate buildings are color-coded in green with dark to light denoting more to less frequently recommended. Among the top five recommended measures, measures more likely to be recommended in affordable buildings include Air Seal Envelope and Add VSD Motor Controller and measures that are more likely recommended in market-rate buildings include Add or Upgrade BAS/EMS/BMS, Add Pipe Insulation, Upgrade Operating Protocols, and Separate SHW from Heating. Some of the differences in recommended measures may be explained through building metadata, which is an area for future research. In addition, as some energy consulting companies are more likely to perform audits on either affordable or market-rate buildings, some bias may be introduced if some companies are more likely to recommended specific EEMs. However, the auditing company is not included for enough of the building records to perform a robust comparison here.

4. Discussion

This analysis compares building-system parameters between

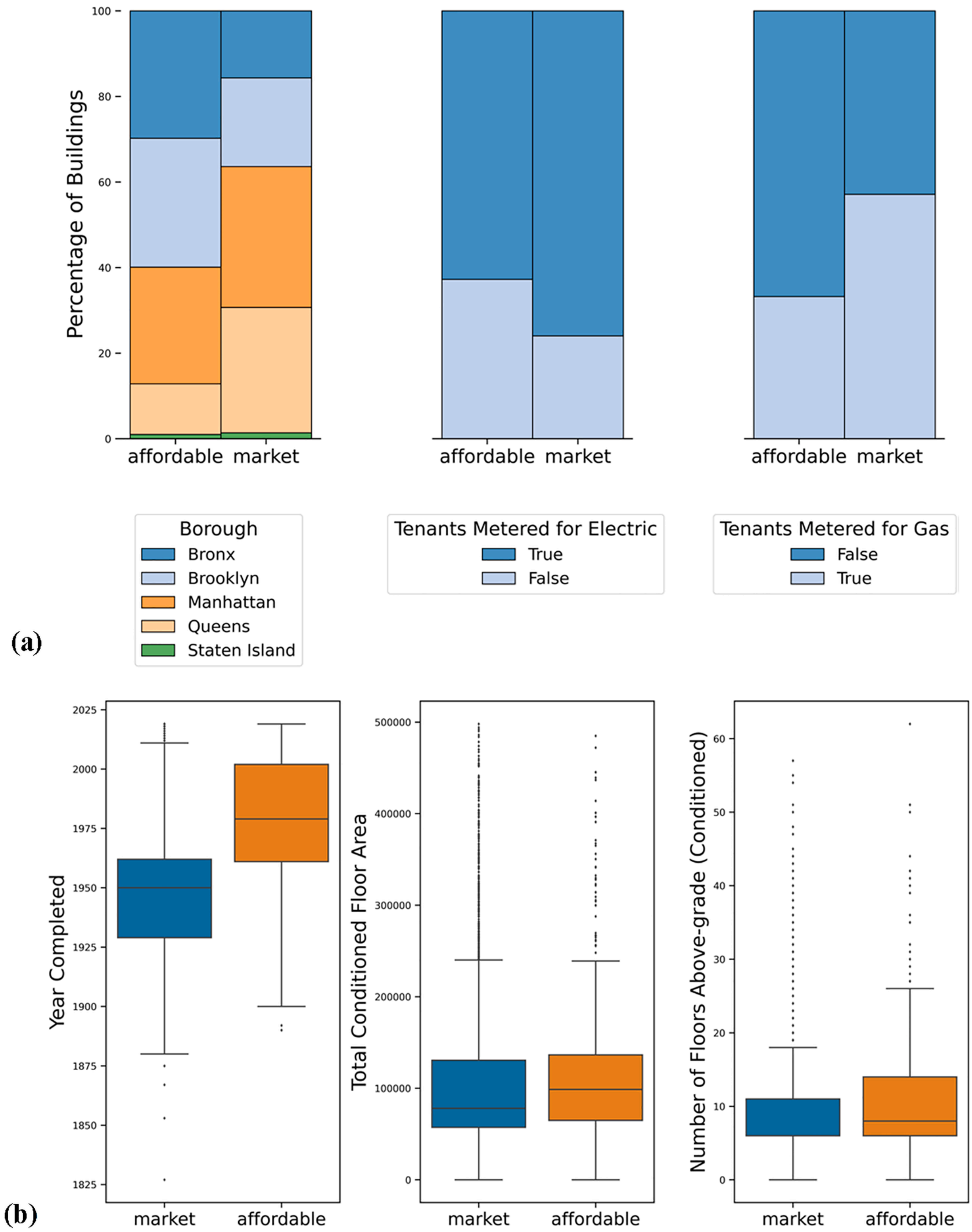

Fig. 6. Distribution of metadata parameters for the audit dataset. (a) Percentage of buildings with each categorical enumeration. (b) Distribution of each of the numerical metadata parameters, with the box showing the middle two quartiles, the whiskers showing the full range, the horizontal line inside each box showing the median, and outliers shown as points beyond the whiskers.

affordable and market-rate housing in New York City using two definitions of affordable housing—one broader definition and one that is more restrictive. Parameters were first compared to affordability status alone to determine if there was a statistically significant relationship. If one was found, a second analysis was performed to determine if that relationship could be driven by metadata parameters, such as building size or age.

A large number of the parameters considered did show a statistically significant relationship with the building's affordability status, as indicated by a p-value of less than 0.05. Interestingly, among the numerical parameters, subsidized and affordable buildings tended to have better insulation and newer and more efficient systems than market-rate housing. However, all metadata parameters also showed a significant relationship with affordability status, with affordable housing more likely to be associated with newer, larger, and taller buildings. Specifically, a typical (median) affordable housing building was built in 1979 and is 120,000 square feet and 8 stories tall, whereas a typical market-rate building was built in 1950 and is 80,000 square feet and 6 stories tall.

There was also a noticeable difference in categorical parameters between affordable and market-rate housing, especially in roof and wall construction types, lighting fixture types, and heating system types. For the latter, affordable buildings are more likely to contain hydronic systems with hot water baseboards and market-rate buildings are more likely to include steam systems with radiator or convectors. While categorical parameters such as construction and heating system type were not used as metadata for the numerical parameters in the regression analysis, it is possible that correlations exist for some parameters, such

Table 10
Regression results for numerical parameters for the subsidized definition.

Building Variable	Coefficient (robust std error)	$\hat{y}_{subsidized}$	$\hat{y}_{market}$	R^2
Roof R-value[1]	1.74*** (2.71E-01)	16.00	13.30	5.8%
Wall Insulation R-Value[1]	1.46*** (3.88E-01)	9.60	7.19	9.4%
Heating Plant Year Installed	7.94*** (5.65E-01)	1999	1991	10.8%
Heating Plant Rated Efficiency[2]	2.08*** (5.10E-01)	78.3	75.8	19.2%

[1]R-values are entered in units of $ft^2 \times {}^oF \times h/Btu$.
[2]Heating plant rated efficiency values are converted to Et (Thermal efficiency) units as described in Section 2.2.1 *Robust standard errors in* parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 11
Regression results for numerical parameters for the affordable definition.

Building Variable	Coefficient (robust std error)	$\hat{y}_{affordable}$	$\hat{y}_{market}$	R^2
Roof R-value[1]	1.00** (3.28E-01)	16.00	13.60	5.2%
Wall Insulation R-Value[1]	1.14* (4.73E-01)	9.71	7.39	8.6%
Heating Plant Year Installed	7.83*** (6.83E-01)	2000	1991	9.5%
Heating Plant Rated Efficiency[2]	2.36*** (6.60E-01)	78.3	76.0	18.6%

[1]R-values are entered in units of $ft^2 \times {}^oF \times h/Btu$.
[2]Heating plant rated efficiency values are converted to Et (Thermal efficiency) units as described in Section 2.2.1 Robust *standard errors in parentheses.*
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

Table 12
Average EEMs per building and savings per square foot for affordable and market-rate buildings.

Metric	Mean for affordable	Mean for market-rate	p-value
EEMs per building	5.3	5.6	3.40E-02
Savings per sq ft ($/sq ft)	0.37	0.36	5.36E-01

as roof construction type with roof R-value and heating system type with heating efficiency.

When regressions were performed on building parameters with statistically significant *t*-test p-values, most of the models (6 out of 10) did not have statistically significant coefficients for the affordability status parameter, indicating that building metadata characteristics (e.g., building location, age, size, etc.) were responsible for the observed relationship between affordable and market-rate buildings.

The remaining four models that had statistically significant coefficient p-values also had very low R^2 values (all less than 20%). When a multivariate regression results in statistically significant p-values for coefficients but very low overall R^2 values, this often indicates that while there is a correlation between the dependent variable (building system parameter) and independent variables (affordability status and metadata parameters), the overall trend is not strong and potentially very noisy [49]. The low R^2 values do not affect the assumptions of the multivariate regression, but could indicate that the correlation itself is weak, the dataset quality is poor, or variables that could improve the model are missing. Future work could be done to identify other variables with more explanatory power.

In the case of parameters such as roof or wall R-value, the third explanation is likely, as the roof and wall construction types could very likely help to explain differences in their R-values, but these parameters were not included as metadata. Similarly, for heating plant rated efficiency, that parameter is likely related to the heating system type and age, which were shown to have different likelihoods for affordable and market-rate housing. The fourth building system parameter with a statistically significant regression model was the year the heating system was installed. It is surprising that while this parameter shows a significant relationship with affordability status under both definitions, the age of the building has the smallest coefficient (and therefore lowest impact on the year the heating system was installed) and highest robust standard error of the models where the age of the building parameter is significant.

These analyses all indicate that affordable and market-rate housing are located in buildings with very different key characteristics and that once these characteristics are taken into account, differences among installed building system parameters such as envelope type, lighting, and HVAC systems characteristics are not significant. However, even though these differences can be explained by factors such as building

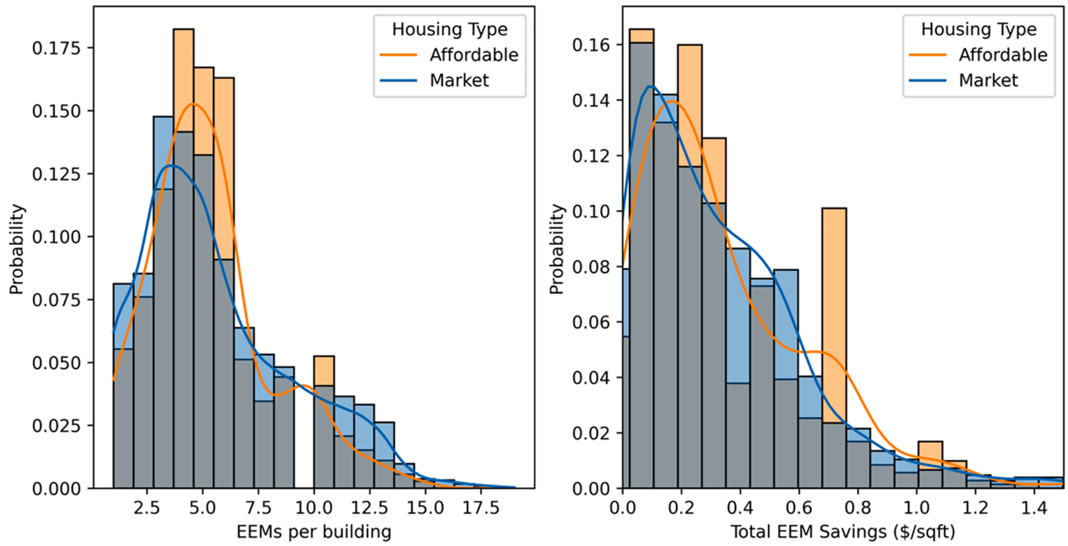

Fig. 7. Histograms (bars) and kernel density estimates (lines) for (a) the number of EEMs per building and (b) the total EEM savings per square foot for affordable buildings (orange) and market-rate buildings (blue). In both cases, the data was normalized to show probability instead of counts to make the data for the two building types more directly comparable, as the sample size for market-rate buildings is much larger than that of affordable buildings. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 13
Percentage of buildings with EEMs of each category for affordable and market-rate buildings.

EEM Category	Percent Affordable buildings with EEM category	Percent market-rate buildings with EEM category	p-value
Lighting Improvements	85.1	90.0	6.59E-05
Service Hot Water System	46.5	53.2	7.23E-04
Heating; Ventilating and Air Conditioning	45.2	43.1	3.12E-01
Building Envelope Modifications	41.9	43.8	3.28E-01
Water and Sewer Conservation Systems	38.5	40.5	3.20E-01
Chilled Water; Hot Water; and Steam Distribution Systems	31.5	42.6	9.88E-09
Control Systems	30.4	34.9	1.62E-02
Electric Motors and Drives	23.3	9.2	1.97E-31
Renewable Energy Systems	21.1	18.5	9.72E-02
Boiler Plant Improvements	17.0	19.2	1.62E-01
Distributed Generation	14.0	12.3	2.24E-01
Advanced Metering Systems	12.3	5.1	7.37E-15
Conveyance Systems	9.0	12.2	1.23E-02

age, size, location, common area percentage, and metering configuration, the intrinsic characteristics of these buildings are still significantly different, and thus the type of energy efficiency interventions that will be effective for the "typical" building may not have as large of an effect for many affordable housing buildings with different characteristics. This idea is further explored by comparing the energy efficiency recommendations across housing types.

The comparison of recommended EEMs between affordable and market-rate housing showed that the five most likely EEM categories were mostly consistent between the two housing types, although there were some statistically significant differences in the likelihood of a given category being included. In particular, while Lighting and Service Hot Water improvements were the two most likely EEM categories for both housing types, they were slightly more likely to be recommended (with a p-value <0.05) for market-rate buildings. This makes sense for lighting, as market-rate buildings are more likely to have incandescent fixture types, at least in common areas (Fig. 3).

More differences arose between affordable and market-rate housing when comparing the likelihood of specific recommended EEMs. Of note, Air Seal Envelope, the most commonly recommended measure for affordable housing, was recommended in 5% fewer market-rate buildings. This is particularly interesting given that the average insulation R-values for affordable housing are higher than those of market-rate housing. This could imply that while the structural features of buildings are perhaps more tied to their size and age, deficiencies such as those requiring air sealing, do not follow the same trend and are more dependent on how the building is maintained or the initial construction quality.

It is important to note that Add Pipe Insulation is significantly more likely to be recommended in market-rate buildings, but this is likely to be tied to the different heating system types that are more prevalent across affordable and market-rate buildings. As seen in Figs. 4 and 5, affordable housing buildings are more likely to include hydronic systems, whereas market-rate housing buildings more likely have steam systems. Because steam systems require higher temperatures than hydronic systems adding pipe insulation in buildings with steam systems likely would lead to larger cost savings, which may explain why that measure has been recommended more frequently in market-rate housing. Similarly, Add VSD Motor Controller was recommended in significantly more affordable than market-rate housing buildings. This could

Table 14
Percentage of buildings with EEMs of each type for affordable and market-rate buildings.

EEM name	% Affordable buildings with EEM	% Market-rate buildings with EEM	p-value
Air seal envelope	31.9	27.4	1.20E-02
Add or upgrade BAS/EMS/EMCS	24.7	30.5	1.37E-03
Add pipe insulation	22.8	36.6	2.13E-13
Add VSD motor controller	21.5	7.3	2.13E-37
Upgrade operating protocols, calibration, and/or sequencing	19.6	24.4	4.93E-03
Increase roof insulation	17.5	21.1	2.90E-02
Separate SHW from heating	15.2	36.5	3.63E-30
Other heating	13.7	21.4	1.61E-06
Install advanced metering systems	12.2	5.0	8.14E-15
Install SHW controls	12.2	7.3	4.83E-06
Improve ventilation fans	7.7	2.1	2.49E-18
Decrease SHW temperature	6.1	9.8	1.56E-03
Add or upgrade controls	5.1	3.4	2.30E-02
Repair or replace HVAC damper and controller	5.0	2.3	2.63E-05
Clean and/or repair	4.1	7.4	1.54E-03
Install or upgrade master venting	3.7	5.7	3.77E-02

indicate that many of the hydronic systems in affordable housing buildings are constant volume and therefore have a big opportunity for savings. This would be less applicable in market-rate buildings, which are mostly steam systems.

Differences in the prevalence of recommendations for these and other measures between affordable and market-rate buildings lend further support to the idea that the interventions commonly recommended for the majority of buildings may not be as effective for affordable housing. Thus, retrofit programs focused on affordable housing should be customized to the specific characteristics of the buildings. In addition, prescriptive paths for building performance standards, which are being implemented more-and-more, may need to consider the particular characteristics and challenges of improving affordable housing buildings, such as focusing on operations and maintenance or improving newer systems [50].

There are some limitations of the audit data used in this analysis, specifically with respect to multifamily housing. For instance, many multifamily housing buildings use window air conditioners as the primary method of cooling. Recording the incidence of in-unit appliances is not required and thus not often captured in many of the Audit Template reports [51]. Additionally, studies have shown that load shapes in ZIP codes of lower-income areas were reflective of heavy use of space heaters in the winter, and this also may not be captured in the audit data [52]. An additional limitation is that this study does not take residents' behavior, such as energy limiting behavior into account. Another caveat is that this analysis is restricted to New York City buildings subject to Local Law 87 (gross square footage greater than 50,000) and therefore does not account for differences in building conditions for residents in smaller buildings not covered by the ordinance or geographic and climate effects.

In addition, the SHIP dataset used to distinguish between affordable and market-rate housing does not include information on the percentage of units in each building set aside as affordable. To divide buildings into subgroups, the authors made assumptions as to which subsidy types were more likely to have a high percentage of affordable units, but on an individual building level, it is certainly possible that majority-affordable buildings were included in the market-rate subgroup and vice versa. Finally, NYCHA owns and manages a large percentage of the affordable housing units in New York City, and some studies (e.g., Reina, 2017 [33]) have shown that public housing consumes more energy per square foot than any other subsidized housing type in New York City. Unfortunately, none of those buildings were included in this analysis due to data unavailability, and a natural next step would be to expand this analysis to include public housing.

The overall results of this study, which indicate that large affordable housing buildings in New York City are newer and more energy-efficient than their market-rate counterparts, at first seem at odds with previous research indicating that low-income residents have less access to energy efficiency [14–18]. However, there are likely key differences in the datasets studied here and in previous work. For instance, this analysis only focuses on large buildings (greater than 50,000 square feet) and the vast majority of the audit data only includes information on building-scale systems and not in-unit appliances, the latter of which is the focus of much of the previous work on low-income access to energy efficiency. New York City may also be a unique test case, as it has one of the oldest public housing programs in the nation [53]. It is also possible that including the data from NYCHA buildings would yield a different result.

While this analysis has revealed several interesting trends, it is apparent that examining installed building characteristics may not be able to explain the differences in energy burdens and energy usage between residents of affordable and market-rate housing previously observed in other studies [26,27]. Much more could be gleaned from these datasets or new datasets in future work, however. For example, additional datasets could be used to explore differences in the prevalence and usage of in-unit appliances such as window air conditioners and space heaters between affordable and market-rate buildings or how well the buildings are maintained. The SHIP database could also be further explored, including comparing building system parameters across different subsidy types and programs. In addition, only a subset of the building system parameters from the audit data were used for this analysis, and future work could explore other parameters, or do a deeper dive into the interrelationship between building systems and recommended measures. In particular, this work only considered one HVAC system per building for simplicity, while in reality, most buildings in this dataset have multiple HVAC systems. A deeper analysis could explore how the types and percentage area served of multiple systems varies across the affordability status of the building.

Finally, this work only examined how building system parameters varied based on whether a building received subsidies and was likely to have a majority of affordable units. To more fully explore how building systems and equipment can impact energy equity, the analysis should be extended to examine differences in building systems across other demographic indicators, such as buildings in neighborhoods with a high percentage of racial minority residents, buildings primarily housing elderly or disabled residents, or buildings located in areas with higher pollution or other environmental stressors.

5. Conclusions

In this study, building system parameters from energy audit data, including envelope, lighting, and HVAC system characteristics, were compared between affordable and market-rate housing buildings to determine if differences in building characteristics could be responsible for the higher energy burdens and energy usage experienced by low-income housing residents previously observed in other studies.

The results indicate that large (greater than 50,000 square feet) affordable housing buildings in New York City tend to have more efficient and newer systems than market-rate buildings; however, this finding is explained by the tendency for affordable housing buildings to be larger, newer, and taller than their market-rate counterparts. We also found that auditor-recommended improvements were somewhat different between affordable and market-rate housing, possibly driven by the differences in energy system types between the two housing types, and a higher prevalence of air-sealing recommendations was observed for affordable housing buildings, indicating a potential disparity in building upkeep. While the results of this analysis do not indicate a linkage between building system characteristics and energy burden, especially since tenants' energy burdens will be sensitive to the specific metering configuration for the building and the requirements of the applicable subsidy programs, they do suggest that retrofit programs or building performance standards may need to consider the particular characteristics and challenges of affordable housing buildings in their policies.

CRediT authorship contribution statement

Grace Pennell: Methodology, Software, Data curation, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Sarah Newman:** Conceptualization, Methodology, Software, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Bethel Tarekegne:** Methodology, Validation, Writing – original draft. **Daniel Boff:** Methodology, Software, Investigation, Validation. **Richard Fowler:** Data curation, Writing – review & editing, Validation. **Juan Gonzalez:** Data curation, Writing – review & editing, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix. Audit data building system parameters

Table A1 shows all of the building system parameters considered for this analysis with the system type, number of buildings from the multifamily dataset that include a value for the field, and if the parameter is included in the 2013–2018 data.

Table A1
Audit building system parameters.

Field name	System Type	# of buildings including field	In 2013–2018 data?
Roof Construction Type	Envelope	6,236	Y
Roof R-value	Envelope	6,620	Y
Cool Roof	Envelope	7,117	Y
Green Roof	Envelope	7,117	Y
Wall Construction Type	Envelope	6,860	Y
Wall Insulation R-value	Envelope	1,328	N
Window Framing Type	Envelope	7,048	Y
Window Glass Type	Envelope	6,593	Y
Window Operable	Envelope	7,145	Y
Window U-value	Envelope	162	N
Window to Wall Ratio	Envelope	4,142	Y
Slab Insulation	Envelope	266	N
Foundation R-value	Envelope	124	N
Exterior Lighting	Lighting	7,305	Y
Lighting Fixture Type	Lighting	7,069	Y
Lighting Ballast Type	Lighting	4,552	Y
Lighting Controls	Lighting	7,328	Y
Heating Type	HVAC	7,077	Y
Heating Fuel	HVAC	5,941	Y
Heating Year Installed	HVAC	5,176	Y
Heating Efficiency	HVAC	34	N
Burner Year Installed	HVAC	4,606	Y
Cooling System Type	HVAC	5,742	Y
Cooling Year Installed	HVAC	1,696	Y
Cooling Efficiency	HVAC	453	N
Thermal Zoning	HVAC	1,328	N
Central Distribution Type	HVAC	7,198	Y
Delivery Equipment Type	HVAC	7,158	Y
Air Supply Corridors	HVAC	7,291	Y
Outdoor Air	HVAC	631	N
HVAC controls	HVAC	4,596	Y
Heating Plant Burner Year Installed	Plant	5,673	Y
Heating Plant Year Installed	Plant	6,298	Y
Heating Plant Rated Efficiency	Plant	1,152	N
Cooling Plant Year Installed	Plant	1,293	Y
Heating Plant Type	Plant	6,717	Y
Heating Plant Fuel Type	Plant	7,176	Y
Heating Plant Venting Type	Plant	1,191	N
Heating Plant BAS	Plant	7,246	Y
Cooling Plant Type	Plant	263	Y
Cooling Plant BAS	Plant	6,362	Y

Appendix B. Full regression results

The full model results for the numerical parameter regressions are shown in Tables B1 and B2. These include the coefficients for the affordable status parameter as well as the coefficients for each metadata

Table B1
Regression results for numerical parameters for subsidized definition.

	Subsidized	Borough (Manhattan)	Borough (Bronx)	Borough (Brooklyn)	Borough (Queens)	Borough (Staten Island)	Year Completed	Total Conditioned Floor Area	Common % Area Served	Tenants Directly Metered - Electric	Tenants Directly Metered - Gas	Number of Floors	Constant	R2 (%)
Roof R-value[1] (n = 6,620)	1.74*** (2.71E-01)						2.39E-02*** (3.83E-03)			−7.67E-01** (2.43E-01)	−2.33 (2.09E-01)		−3.12E + 01*** (7.47)	5.8
Wall R-value[1] (n = 1,328)	1.46*** (3.88E-01)						2.48E-02*** (5.61E-03)		2.48E-02*** (4.75E-03)	1.03** (3.43E-01)	−1.72*** (3.16E-01)		−4.13E + 01*** (1.09E + 01)	9.4
Heating Year Installed (n = 5,176)	7.94*** (5.65E-01)						1.06E-01*** (7.63E-03)	−3.46E-06*** (3.14E-07)	2.96E-01*** (4.99E-02)	1.73** (5.28E-01)			1.78E + 03*** (1.49E + 01)	10.8
Heating Plant Efficiency[2] (n = 1,152)	2.08*** (5.10E-01)								1.02E-01*** (7.40E-03)	4.08*** (5.04E-01)	−2.31*** (4.30E-01)	1.18E-01*** (3.03E-02)	7.27E + 01*** (5.64E-01)	18.9

[1] R-values are entered in units of $ft^2 \times {}^{o}F \times h/Btu$.
[2] Heating plant rated efficiency values are converted to Et (Thermal efficiency) units as described in Section 2.2.1.
*$p< 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table B2
Regression results for numerical parameters for affordable definition.

	Affordable	Borough (Manhattan)	Borough (Bronx)	Borough (Brooklyn)	Borough (Queens)	Borough (Staten Island)	Year Completed	Total Conditioned Floor Area	Common % Area Served	Tenants Directly Metered - Electric	Tenants Directly Metered - Gas	Number of Floors	Constant	R2 (%)
Roof R-value[1] (n = 6,620)	1.00** (3.28E-01)						2.90E-02*** (3.79E-03)		1.06–02* (5.09E-03)	−7.60E-01** (2.45E-01)	−2.32***(2.11E-01)		−4.10E + 01*** (7.40)	5.2
Wall R-value[1] (n = 1,328)	1.14* (4.73E-01)						2.71E-02* (5.65E-03)		2.65E-02*** (4.63E-03)	1.00** (3.47E-01)	−1.77*** (3.20E-01)		−4.57E + 01*** (1.10E + 01)	8.6
Heating Year Installed (n = 5,176)	7.83*** (6.83E-01)						1.14E-01*** (7.49E-03)	−3.50E-06*** (3.26E-07)	3.53E-01*** (5.71E-02)	2.03*** (5.33E-01)			1.77E + 03*** (1.47E + 01)	9.5
Heating Plant Efficiency[2] (n = 1,152)	2.36*** (6.60E-01)								1.03E-01*** (7.44E-03)	4.03*** (5.09E-01)	−2.36***(4.35E-01)	1.15E-01**(3.07E-02)	7.29E + 01***(5.62E-01)	18.6

[1] R-values are entered in units of $ft^2 \times {}^{o}F \times h/Btu$.
[2] Heating plant rated efficiency values are converted to Et (Thermal efficiency) units as described in Section 2.2.1.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

parameter. Parameters for which a coefficient are not shown were eliminated in the iterative analysis because the coefficient did not have a statistically significant p-value (less than 0.05).

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