

Data-Driven, Equity-Centered Energy Efficiency for Multifamily Complexes

Hal Nelson, Ph.D., Res-Intel (lead author)

Hunter Johnson, Ph.D., Res-Intel

Alex Brey, Res-Intel

ABSTRACT

Multiple studies show that historically marginalized and low-income multifamily (MF) households are the most energy and housing insecure (Wilson et al. 2013). The majority of these households reside in “naturally occurring affordable housing” (NOAH); low-income MF housing without government subsidies. Yet, little is known about the MF-NOAH sector's buildings and energy use. Full stop. In order to measure MF-NOAH energy use, 62,000 MF property databases in California were aggregated using artificial intelligence and spatial analytics. Utility meter metadata and daily energy consumption were pulled from tens of thousands of MF complexes across California. Next, building energy benchmarking and load disaggregation techniques identified properties with cost-effective energy efficiency (EE) supplies. Utility EE program data were used in machine learning models to predict existing equipment at each property. Finally, up to 22 EE measures in the California eTRM database were selected for each property based on energy-use intensity, building age, and other factors.

The results show that site-level energy use intensity (EUI) is lower for government subsidized low-income properties than other MF properties. The EUI for NOAH properties with the highest share of low-income residents is statistically significant, and 20% higher than other MF properties. The highest share of low-income residents live in Garden and Low-Rise style properties that are more likely to be tenant-metered for electricity. The discussion includes recommendations for specific retrofit measures. The conclusion includes calls for deep engagement with affected stakeholders on what type of energy services they want and how this can improve their lives.

Introduction

Multiple studies have shown show that historically marginalized and low-income multifamily (MF) households are the most energy and housing insecure. The majority of these households reside in “naturally occurring affordable housing” (NOAH); low-income MF housing stock not associated with government rent subsidies. While the conventional wisdom is that NOAH properties are older and smaller than government subsidized, low-income properties, very little if anything is known about MF-NOAH whole building energy use and efficiency opportunities. This is because most MF energy studies rely on data from large properties that are 1) either required to comply with building energy benchmarking ordinances that typically have a minimum property size of 25,000-50,000 square feet (i.e Hsu, 2014) or 2) lessons learned from government subsidized property retrofits (Bright Power/SAHF, 2014). This research sheds new light on NOAH building attributes and energy use for over 60,000 MF complexes in California.

Literature Review

In order to understand NOAH energy, several approaches have been used. In an effort to identify how low-income households interact with energy services, Dreihobl, Ross, and Ayala (2020) define energy burden as energy spending as a percentage of household income. An energy burden of greater than 6 percent is considered high, and greater than 10 percent is considered severe (p. 1). Using U.S. Census data, the authors find that more than a quarter of all households endure high energy burden, and half of those have severe energy burden (p. iii). Multifamily energy burden is highly segmented by income. The overall multifamily energy burden is at 2.4 percent, which is below the residential median of 3.1 percent; but low-income multifamily is well above the median at 5.6 percent.(p. iv). Renter energy burden is 13 percent greater than owner energy burden, at above the median at 3.4 percent (p. iii).

Dreihobl et al (2020) and (Wilson et al. 2013) also find that Black, Indigenous and People of Color (BIPOC), low-income, and elderly people experience disproportionately high energy burdens. Black and Hispanic households face energy burdens 43 percent and 20 percent greater than non-Hispanic white households respectively. Finally, the authors note that, “many highly burdened groups are intersectional—that is, they face compounding, intersecting causes of inequality and injustice” (Dreihobl et al., 2020, 11). Using utility meter data, Nelson & Gebbia (2018) found that low-income, single-family renters in inland California annual energy burden is about 34% higher than that of comparable homeowners, controlling for income, house age, house size, weather, and other variables. These disparities highlight the need for energy policy to be informed by an energy justice perspective.

Our understanding of energy justice is still nascent. The energy burden metric ignores that low-income households can experience worse thermal comfort than higher-income households. Energy limiting behavior occurs when households choose not to operate heating or cooling equipment in order to limit utility bill impacts. Cong, et al (2022) find that low-income households suffer with summer temperatures 4.7–7.5 °F (2.6–4.2 °C) higher than higher income households. There is little overlap in the households experiencing the energy equity (temperature) gap and households experiencing high energy burdens in the Cong et al (2022) sample. This indicates that the energy equity gap metric compliments existing the energy burden metric, which is often difficult to estimate due to a lack of household income data.

This discussion of the attributes of energy justice metrics points towards Baker, Devar, and Prakash (2019) discussion of the context and importance of energy justice. They argue that the urgent need to transition away from fossil fuels presents opportunities to “reshape socio-economic relationships created by energy policy choices” (p. 8). The concept of energy justice implies striving for social and economic fairness in current policies, addressing past harms, and elevating the voices of marginalized communities. It is an outgrowth of the environmental and climate justice movements that specifically focuses on the costs and benefits of energy as well as decision making influence. The authors note that environment, climate, and energy often intersect, requiring “an exploration of these multiple layers of burden faced by frontline communities” (p. 20). The authors propose an energy justice framework that examines both procedural and distributional justice. It dictates that any policy should be examined in terms of, 1) meaningful participation, 2) restoration of past harms, 3) decision-making influence, 4) distribution of benefits, and 5) access to energy (p. 23).

Developing EE programs with strong energy justice elements is not easy. The California Energy Commission (2016) discusses some of the barriers to increasing access to energy efficiency, weatherization and renewables in low-income communities. Structural issues include the split incentive problem, a risk of high retrofit costs in older buildings, and financing challenges. The report notes that multifamily building characteristics vary across markets, making it challenging to design a comprehensive program that works well for all properties. Affordable multifamily properties may struggle to fund retrofits due to tight margins, and tax-credit financed properties are often limited in their ability to take out additional loans.

One of the reasons that so little is known about NOAH building attributes and energy use is a lack of available data. Nelson (2020) highlights the data issues just discussed by pointing out several flaws in existing inventories of multifamily properties. One problem is that the Census data after 2017 seems to have been compromised by respondent confusion over the detached housing categories (American Housing Survey, 2020, 3). County assessor data often lists individual parcels as opposed to whole multifamily complexes and must be aggregated to correct for this. Address data makes it challenging to determine if the presence of multiple address lines indicate a condo, duplex, or apartment. These issues in matching energy consumption to building characteristics have complicated utilities' attempts to determine MF energy-use intensity.

Data and Methods

The sample in this study are about 62,000 MF properties across California representing over 700,000 housing units. In order to validly identify multifamily NOAH building attributes, energy use, and EE opportunities, vast amounts of missing property information had to be overcome. First, multiple multifamily property databases, such as tax assessor records and CoStar's property database were aggregated into MF complexes using artificial intelligence and spatial analytics as shown in the left box of the Figure 1.

Figure 1: Aggregation of MF complexes using artificial intelligence and spatial analytics



Next, LiDAR and building footprint data were integrated into predictive models for building-level and site-level attributes as seen on the right panel in the above Figure. The LiDAR and building outline data provide building-level area and unit-count estimates to perform building energy benchmarking on these properties that would otherwise be unavailable. The Residential Characterization Tool predicts several key attributes of multifamily properties including:

1. Conditioned living space
2. Number of units
3. Number of buildings
4. Number of floors
5. Style (garden/low-rise/mid-rise/high-rise)
6. Presence of a swimming pool

In the next step, utility meter metadata were matched onto all relevant properties in the utilities' service territory. Utility metadata was used to match the utility meters to properties using three sophisticated matching methods. Typically, over 97% of meters were matched to residential or commercial buildings. Once all the meter metadata had been matched to all relevant properties, energy consumption data for MF properties were joined into the analysis. Next, sophisticated geolocation and other tools were used to assign meters to specific buildings on MF properties. One example is shown in Figure 2 below. The blue balloons represent MF service addresses and the red dots represent the geolocation of nearby gas or electric meters.

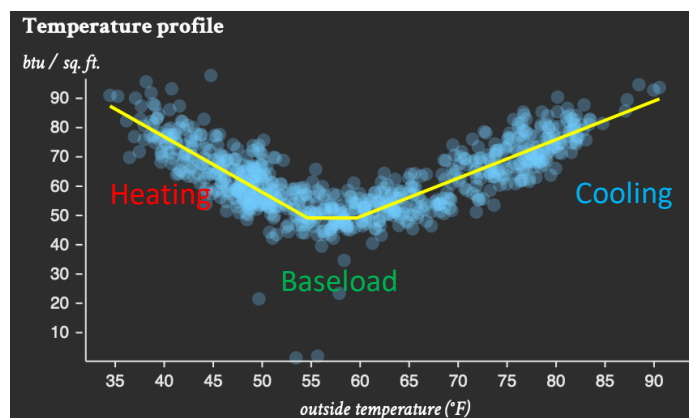
Figure 2: Matching MF complexes to utility meters



The analysis also identified properties with the greatest share of low-income residents using utility customer metadata. California Alternative Rates for Energy (CARE) is a means-tested electric and gas discount program targeting households with income less than 200% of the Federal poverty level. This allows CARE enrollment to be treated as an approximation of the incidence of the share of low-income households in an MF complex.

Next, building energy benchmarking and load disaggregation techniques were performed to identify properties with cost-effective EE and demand response supplies. Energy use intensity (EUI) serves as the main measure of energy consumption and efficiency. EUI is simply a building's combined gas and electric energy use, measured in kBtu per square foot of conditioned living area per year at each site. A property's benchmark score was determined by comparing its energy efficiency ratio (EER) to the distribution of EERs across the entire California portfolio. A property's EER is calculated by taking the ratio of its actual EUI to its predicted EUI. As part of the benchmarking process, energy decomposition models were developed to break out heating, cooling, and baseload energy based on daily temperature. This process is illustrated in Figure 3.

Figure 3: Energy decomposition model



Next, for a subset of about 30,000 MF properties, a series of classification models were developed to detect each meter's end-use based on its energy consumption pattern, or loadpath signature. We evaluated loadpath signatures at the 24-hour interval (hourly) and daily interval within each week (weekly) and across the entire year (seasonal). The end-use classification models use these load signatures to assign one of five different end-uses to the meter:

1. **Tenant** meters track electricity or gas consumption of apartment residents,
2. **Lighting** meters track electricity consumption of common-area lighting fixtures,
3. **Laundry** meters track electricity or gas consumption of common-area appliances and lighting located in laundry facilities,
4. **Pool** meters track electricity consumption of common-area equipment connected to a swimming pool,
5. **Water Heater** meters track gas consumption of common-area boilers and water heaters

Next, utility EE program and other data were used in machine learning models to predict existing equipment at each property including: central water heat, central air conditioning, electric space heat, in-unit laundry, as well as the presence of attic and wall insulation. Identifying baseline equipment at each property entails finding data sources that provide information on MF properties end use equipment. Statistical matching techniques were used to identify the properties most similar to the ground truth data sets to maximize the reliability of predictions. Out-of-sample predictive accuracy ranged from 65%-95% depending on the end use.

Finally, up to 22 energy-efficiency measures in the California eTRM database were selected for each property based on its heating, cooling, and baseload energy use, building age, and other factors. Using this data, the total labor and measure costs, peak kW demand savings, as well as annual deemed kWh and therm savings for each measure are calculated at each property for each measure. The measures included in this version of the Residential Characterization Tool are [here](#).

Results

The main NOAH energy outcome we analyze here are energy use intensities. Table 1 shows average EUI as well as average baseload, heating and cooling EUIs broken out in quintiles for the percent of CARE enrolled units as a share of total unit count at each MF property. Recall that the CARE data is available for only about 30,000 MF properties. The second row for each quintile is the standard error of the average. Table 1 indicates that the two top quintiles of CARE share of units (NOAH properties) have statistically higher total EUI, driven primarily by higher baseload and cooling EUIs. The top CARE quintile has EUI's about 20% higher than the lowest three quintiles. This is incredibly important because energy burdens (utility bill spending/total household income) increase dramatically in the high CARE quintiles as incomes are lower, and energy use intensities are higher at these properties as shown in Table 1.

Table 1: Average total, baseload, heating, and cooling EUI

care5	eui	baseload	cooling	heating
1	41.17253 .2192397	29.68287 .1661593	.3472683 .0134366	11.14239 .1081346
2	41.10752 .286429	30.49858 .2115864	.1639033 .0106038	10.44505 .1388503
3	40.90241 .2121898	30.89012 .1655872	.3072176 .0124623	9.705075 .0908583
4	44.56118 .2270329	34.65127 .1842536	1.031253 .0272763	8.878659 .0824239
5	49.64732 .2482707	38.6445 .1949909	2.331976 .0412536	8.670851 .081921
Total	43.35753 .1072707	32.70685 .0838671	.8200342 .011428	9.830641 .0457362

Table 2 examines some of the attributes CARE enrollment and master meter configurations for different property types:

1. Garden-style properties (Style1) defined as four or more low-rise (1-3 stories) buildings per property have a mean of about 43% CARE-eligible units as a share of total units.
2. High rise properties (Style2) have a mean of about only about 5.6% CARE units.
3. Low-rise properties (Style3) are similar to Garden style but with 1-3 low rise buildings per property have about a 30% CARE penetration.
4. Mid-rise (Style4) defined as 4-9 stories buildings mean share is about 15% CARE penetration.

These results indicate that Garden and Low-Rise properties consist of the bulk of NOAH properties.

We also investigate master-meter configurations. We classify a property as master-metered if there are less than half as many meters as apartment units. The Garden and Low-Rise NOAH properties are also much less likely to have master-metered electricity configurations than other building types. The prevalence of master metered gas is more ubiquitous across building types except High-Rises. High Rise buildings in this population have the highest share of master-metered properties. This meter configuration analysis confirms that the landlord-tenant market failure is more prevalent for a typical NOAH property (Garden and Low-Rise) than for higher income property types (Mid-Rise, High-Rise).

Table 2: CARE and master metering in Garden, High-Rise, Low-Rise, and Mid-Rise properties

style1	CARE%	Master Electric	Master Gas
Garden	.4287918	.2572473	.0791717
High-Rise	.0563504	.9615385	.1923077
Low-Rise	.3033578	.1906516	.0583661
Mid-Rise	.1529133	.3773737	.0787879
Total	.3077439	.2149945	.0628584

Given this analysis of building type and meter configuration, we now turn to examining energy use by fuel. Table 3 below shows how total EUI is broken out by fuel for the lowest three CARE penetration quintiles in the row, the top two quintiles (NOAH) in the second row, and overall the third row. Electricity has about an 8% higher share of total energy use in the NOAH properties, represented here as the top 40% CARE penetration properties. This is an issue to which we shall return below.

Table 3: EUI by fuel source by CARE penetration

top40_care_pcmt	Electric EUI Percent	Gas EUI Percent
Non-NOAH	.2805333	.7194942
NOAH	.3606165	.6394032
Total	.2957976	.704219

Next, let us examine the other predictors of site-level MF EUI (in kBTU/sqft) by turning to ordinary least squares (OLS) regression modeling to control for geography and building attributes. The F-statistics for the regressions are strongly significant (not shown). The models' coefficient of determination (R^2) indicates that the combined effects of the variables in the model explain between 13% to 62% of the variation in the different types of EUI. Robust standard errors are used in all models to mitigate the effects of heteroskedasticity. A variance inflation test showed collinearity between climate zone variables, but removing the climate zone variables had little impact on standard errors for the other variables so they remain in the results below (although they are not displayed).

Table 4 shows regression results for total EUI for the full sample, as well as total EUI, baseload, cooling and heating EUIs for the CARE-only sample. Model 1 shows the total EUI regression results for the full sample of ~62,000 MF properties, while the sample for Models 2-5 is about 30,000 properties. Model 2 is preferred over Model 1 as it includes CARE penetration and explains an additional 40% of the variation in total site-level EUI compared to Model 1 (as indicated by the R-squared of 18.2% vs 25.8% for Models 1 and 2 respectively).

The following interpretations of the regression results address Models 2-5 that include CARE penetration:

Table 4: OLS regression of total EUI, baseload, heating, and cooling EUI

VARIABLES	(1) eui-full	(2) eui-CARE only	(3) baseload	(4) heating	(5) cooling
Year built	-0.0555***	-0.0350***	0.00379	-0.0412***	0.00239***
Area (sq ft)	-0.0229***	-0.00982***	-0.00231	-0.00662***	-0.000892***
Average unit size (sq ft)	-11.90***	-20.62***	-16.64***	-3.672***	-0.304***
Pool	2.156***	1.685***	1.833***	-0.0926	-0.0554*
Master-metered electric	-1.916***	-4.553***	-3.981***	-0.188	-0.384***
Master-metered gas	-6.073***	-8.299***	-5.902***	-2.574***	0.177***
Cooling degree days	0.00537***	0.00279***	0.000730	9.13e-05	0.00197***
Heating degree days	0.00263***	0.00337***	0.00105***	0.00181***	0.000511***
High-rise properties	18.99***	22.34***	19.51***	2.204	0.627***
Low-rise properties	-0.221	-1.107***	-0.616**	-0.513***	0.0218
Mid-rise properties	3.588***	4.395***	3.107***	1.150***	0.137***
Deed-restricted properties	-0.714	-4.643***	-3.018***	-1.204***	-0.420***
Second CARE quintile		-0.420	-0.191	-0.165	-0.0641***
Third CARE quintile		-0.989***	0.285	-1.199***	-0.0753***
Fourth CARE quintile		2.329***	3.799***	-1.450***	-0.0199
Fifth CARE quintile		8.331***	8.708***	-0.774***	0.396***
Constant	159.0***	121.0***	34.80***	93.10***	-6.882***
R-squared	0.182	0.258	0.261	0.128	0.621

*** p<0.01, ** p<0.05, * p<0.1

- Newer properties (higher year built) tend to use less total energy (EUI), but more cooling-related energy because unlike older properties that lack air conditioning, newer MF construction has included space cooling.
- Larger properties (higher area) use less energy per sqft for all end-uses, *ceteris paribus*.
- Unit size is used as an indicator for occupancy where larger apartment sizes are associated with more bedrooms and thus more occupants. Each additional 1,000 sqft in the size of an apartment unit predicts an additional 20kBTU/ sqft. Note the mean unit size is ~700 sqft.
- The presence of a pool predicts an increase in total EUI of 1.67 kBTU/sqft

- The effects of the landlord-tenant market failure can be estimated from properties that are "master-metered"; defined here as having half, or less, as many meters as apartment units.
 - Master-metered electricity properties consume about 4.5 kBTU/sqft less than tenant-metered properties with nearly all of this in reduced baseload electricity.
 - Master-metered gas properties are estimated to consume 8.3 kBTU/sqft less than tenant-metered properties, consisting mostly of baseload as well as some gas for space heat.
 - Combining gas and electricity, master-metered properties are about 29% more energy efficient per sqft versus the mean EUI. These represent the independent effects of meter configuration controlling for all the other variables in the model.
- As expected, more heating degree days and cooling degree days are associated with more total EUI as well as baseload and heating EUI. Additional cooling degree days are associated with additional cooling EUI. Cooling energy use is likely understated in this analysis due to limitations in the available climate data.
- Some of California's climate zones show effects on EUI independent of climate but the effects are not terribly interesting (not shown).
- The property style affects EUI, *ceteris paribus*. The base category style in the regression are Garden-style properties with four or more low-rise (1-3 stories) buildings per property.
 - High rise properties predicted EUI is nearly 22 kBTU/sqft higher than the Garden style average EUI.
 - Low-rise properties (1-3 stories) are slightly more efficient than Garden-style
 - Mid-rise (4-14 stories) are estimated to have slightly higher EUI. These results need to be investigated further.
- The main energy equity findings from the modeling are in the 4th and 5th (highest) CARE penetration quintiles 4.care5 and 5.care5. These are the main NOAH properties:
 - These properties are expected to consume 2.3 and 8.3 kBTU/sqft more total EUI respectively than the lowest CARE penetration quintile (1.care5 not shown) which is the base category. Baseload increases are slightly higher in these groups than the lowest CARE group.
 - The impacts of income on heating and cooling EUI are mixed in this sample.
- Again, please note that increased consumption for high CARE penetration complexes controls for all the other variables in the model, including building age, size, meter configuration, climate, built environment, and building type.
- Finally, deed restricted MF properties (1.low_income) are predicted to use about 4.6 kBTU/sqft less energy than non-deed restricted properties controlling for all the other factors.

These are the first-ever (that we are aware of) analysis of a huge population of NOAH MF properties with detailed building, tenant, and energy data. The results are surprising, even to those of us who have been working in the industry for decades. These results indicate that Garden and Low-Rise properties are not inherently less energy efficient, but rather that that building vintage, meter configuration, and landlord disinvestment are likely driving the higher EUIs seen in these property types where low-income residents are more likely to live.

Energy Efficiency Savings Potentials

The methods section above describes the energy disaggregation and machine learning modeling used to predict existing equipment and normalize EE measures for each of about ~30,000 properties.

Table 5 shows the average eTRM savings estimates as a share of pre-retrofit electricity and gas. The lowest three CARE penetration quintiles in the zero row show average electricity and gas savings of about 16% and 14.7% respectively. The top two quintiles in the one row show average electricity and gas savings of 11% and 35% respectively. Overall, average electricity and gas savings in the bottom row are 15% and 18% respectively. NOAH properties have double the estimate gas savings than non-NOAH properties.

One of the reasons that electricity savings are lower than gas savings in Table 5 is due to fuel switching from gas to electricity. The Tool selects heat pump water heaters, heat pump clothes dryers, and induction cookstoves based on existing equipment predictions, energy disaggregation results, and other factors. These measures increase site-level electricity consumption which reduces overall energy savings from other electricity measures such as duct sealing and smart power strips.

Table 5: eTRM savings estimates as share of pre-retrofit electricity and gas

top40_care_pcmt	Electric Savings	Gas Savings
Non-NOAH	.1595133	.1475772
NOAH	.1093652	.3500232
Total	.1485148	.1798458

Discussion and Conclusion

The results presented here show an unprecedented view of the MF building stock over most of the state of California. The poorest performing low-income housing stock is not government subsidized housing, but rather NOAH housing. The highest penetration of low-income residents live in older, smaller Garden and Low-Rise style properties. These properties are more likely to be tenant-metered for electricity and therefore use more energy than master-metered properties.

NOAH properties use about 20% more energy than higher income MF properties, and much of this is electricity as opposed to gas. NOAH properties' higher energy consumption is independent of building vintage, building style, climate, and meter configuration. Alternative explanations that are not modeled here potentially include the effects of historical redlining, higher occupancy rates, and different behavioral patterns such as multigenerational households with higher shares of children and seniors which has been associated with higher energy use.

The program implications from the results include special attention to in-unit measures that reduce baseload electricity use. Replacing in-unit electric water heaters and electric dryers with heat pump technology is especially promising. High efficiency refrigerators should also be considered along with smart power strips. The older Garden and Low-Rise properties that make up much of the NOAH housing stock are also good candidates for building envelope upgrades including duct sealing and attic insulation.

The recommendations from these advanced analytics need to be complemented with deep engagement with affected stakeholders. These program implications point to the need to engage NOAH landlords with whole building retrofits that upgrade tenant units as well as common area measures. The EE industry can no longer afford to design and implement programs without asking residents what type of energy services they want and how this can improve their lives (Baker et al, 2019). Furthermore, landlord engagement strategies need to be designed so that they don't lead to gentrification and tenant displacement. Existing EE programs are likely not designed appropriately for anti-displacement (Nelson, et al, 2022).

These results are based on EUI and do not measure the energy equity (temperature) gap where low-income households are more likely to engage in energy limiting behavior (Cong, et al, 2022). The health impacts of energy limiting behavior are not easily estimated, however it is safe to say that these low-income households are experiencing higher levels of chronic morbidity and mortality, as well as greater absenteeism from work as a result of greater thermal stress (WHO, 2018a; WHO 2018b). It is only with participation and shared decision-making from under-represented households that the EE industry can overcome the market failures and social justice failures that have plagued us traditionally.

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