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Inequalities across cooling and heating in households: Energy equity gaps

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ABSTRACT

Understanding the degree of energy limiting behavior in low-income and vulnerable households is vital to eradicating energy poverty and associated negative health effects. We estimate the outdoor temperatures at which households turn on and off their electricity-based cooling and heating units under a cold climate in northern Illinois, USA ($N = 418{,}255$ for cooling; $N = 22{,}628$ for electric heating). We find that the cooling energy equity gap between low and high income groups is 3 °F (1.7 °C), while the electric-based heating energy equity gap is 6 °F (3.3 °C). The pattern of energy limiting behavior is found to be different between the cooling season and the heating season. Our metrics contribute to the policy design of home energy bill and weatherization assistance programs to identify vulnerable households in a cold climate: Among low-to-middle-income households, our metric identifies 19,001 households (20%) in the cooling sector and 1,290 households (24%) in the heating sector who may be neglected by the traditional income-based energy poverty measure. We also find that households living in black-majority census block groups have a cooling gap that is 17% wider than households living in white-majority census block groups. Policy design should focus on addressing the income inequality and other systematic inequalities that have impacted Black American households.

1. Introduction

To achieve distributional energy justice, a society must ensure that all households are able to create a comfortable indoor environment (i.e., satisfy their cooling and heating desires; Jenkins et al., 2016, 2020). To create a comfortable indoor environment, households need sufficient access to energy services, which incurs financial cost. The differences in household spending budget among sociodemographic groups (e.g., income and race) may lead to the differences in the ability among such groups to create comfortable indoor environments. In the United States, although the federal government has been providing assistance to households to tackle energy poverty and improve energy efficiency since the 1970s, in 2017, of all U.S. households, 13% (15.9 million) endured a severe energy burden (i.e., spend more than 10% of income on energy; Drehobl et al., 2020). Also, low-income households spent three times more share of their income than the non-low-income households (Bednar and Reames, 2020; Brown et al., 2020; Drehobl et al., 2020; Eisenberg, 2014).

To tackle the problem of energy poverty and insecurity among disadvantaged groups, one needs to recognize that energy poverty is a multidimensional concept (Fizaine and Kahouli, 2019; Hernández, 2016; Meyer et al., 2018; Thomson et al., 2017), and energy poverty can appear in a person's behavior in multiple ways (Fig. 1; Barrella et al., 2022; Cong et al., 2022; Gauthier and Shipworth, 2015; Hernández, 2016; Ormandy and Ezratty, 2016). There are three major approaches to assessing energy poverty and insecurity. Under the first category (see Meyer et al., 2018 and Thomson et al., 2017 for a critical review), previous studies have developed various metrics based on objective indicators such as energy consumption, energy expenditure, energy efficiency, and income, among which the simplest metric is the ratio of energy cost over income (income-based metric of energy burden); second, one can also use self-reported subjective indicators to assess energy poverty and insecurity. These first two approaches fail to consider an important behavior-based dimension of energy poverty: the amount of energy services a household may forgo to reduce financial stress (Charlier and Legendre, 2016; Fizaine and Kahouli, 2019; Kelly et al., 2020). We define this phenomenon as displaying energy limiting behavior, where a household is unable or unwilling to consume

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sufficient energy to reach their desired level of comfort (Cong et al., 2022). The policy impact of neglecting energy limiting behavior in the assessment of energy poverty and insecurity is significant: In the U.S., roughly 25 million homes forwent energy consumption to reduce their bills so that financial resources could go to other basic necessities in 2015 (Graff and Carley, 2020). This situation is far from ideal given the negative health impacts of thermal discomfort (see Fig. 1). In addition, given that more time is spent on working from home since the COVID-19 pandemic, reducing the comfort of the indoor environment reduces the economic and health productivity of workers (Fisk and Rosenfeld, 1997).

Although recent studies have made progress in studying energy limiting behavior (Barrella et al., 2022; Berger and Höltl, 2019; Charlier and Legendre, 2016; Cong et al., 2022; Meyer et al., 2018; Santamouris et al., 2014; Vecellio et al., 2022), our study addresses two gaps in the extant literature. First, unlike a key previous study that identify households who under-consume energy to save money using economic-based measures (Barrella et al., 2022), our study takes a direct approach that examines household behaviors related to electricity consumption as a function of temperature, which has rarely been conducted under the context of energy poverty and insecurity (Thomson et al., 2017), especially in the U.S. except a very recent work (Cong et al., 2022). Second, in the U.S., recent work (Cong et al., 2022) has been conducted to capture energy limiting behavior via the estimation of outdoor temperature at which households turn on cooling units (e.g., air conditioning; AC hereafter) in Arizona. In the high-heat climate the gaps in AC turn on points between low-income and high-income households were found to range between 4.7 and 7.5 °F. This research indicated that low-income households endured hotter indoor environments in the cooling season when compared to their higher-income counterparts (Cong et al., 2022). However, this Arizona study only estimated a single outdoor temperature at which households turn on cooling units, missing the energy limiting behavior that may occur in the heating season. Thus, a current gap in the literature is to quantitatively distinguish between differences in cooling and heating usage inequalities in different geographical regions. A review of the heating literature in England found that the recommended heating set point in homes was 65 °F in the heating season (Jevons et al., 2016), yet there is uncertainty regarding whether low-income households are achieving this level of comfort.

In the current study, we build on previous work by estimating the differences in cooling and heating ability in the northern Illinois region (see Fig. A1 in Appendix A) that has a cold climate (Pacific Northwest National Laboratory, 2015) with longer and colder heating seasons (see Fig. A2 in Appendix A). This allows us to examine energy limiting behavior in both cooling and heating scenarios. It is important to understand how energy usage varies by climate zone and temporal patterns because households will face different weather risks, which can be mitigated with indoor energy use. We illustrate the effectiveness of using energy equity gaps for identifying households at risk for inability to reach comfortable indoor temperatures, and possibly cold- and heat-related illnesses (Fig. 1). Between 2011 and 2018, the State of Illinois had more reported cold-related deaths (1,935) compared to heat-related deaths (70; Friedman et al., 2020). Meanwhile, the numbers of people affected by cold-related illness (23,834) and heat-related illness (24,233) were similar. Therefore, with climate change increasing the number of heatwaves in northern Illinois (Hayhoe et al., 2010) and in the U.S. (Shindell et al., 2020), we focus our energy-limiting behavior analysis on both the cooling and heating sector. Here energy limiting behavior is defined as the inability or unwillingness to consume enough energy to reach a desired level of comfort. To ensure an equitable and just energy transition, regions must identify disparities in heating and cooling system use, and then use this to reallocate a fairer distribution of benefits for a clean energy transition (García-Muros et al., 2022; Jenkins et al., 2020; Wang and Lo, 2021).

We estimate two separate temperatures using a large electricity consumption dataset for one year (June 2020–May 2021): one at which households start or end using cooling units (cooling balance point) in the cooling season, and one at which households start or end using heating units (heating balance point) in the heating season. The estimated temperatures were then compared among income groups and used to calculate the energy equity gaps. The energy equity gap is defined as the difference (in outdoor temperature) between the maximum and minimum of the median cooling balance points across the best off and worst-off economic groups (see the formal definitions in Section 2). In light of previous studies on race and energy poverty (Adua et al., 2022; Dogan et al., 2022; Goldstein et al., 2022; Wang et al., 2021), we also contribute to this literature by examining energy equity gaps within each racial group.

The first key assumption in this analysis is that there is no difference in comfort preference or need across demographic groups. This assumption stems from (1) heating and AC systems being the largest electricity consumer within a household (Do and Cetin, 2019), and (2) our study region having a climate that has significant cooling and heating demands (Fig. A2). The balance points of a household (Fig. 2)

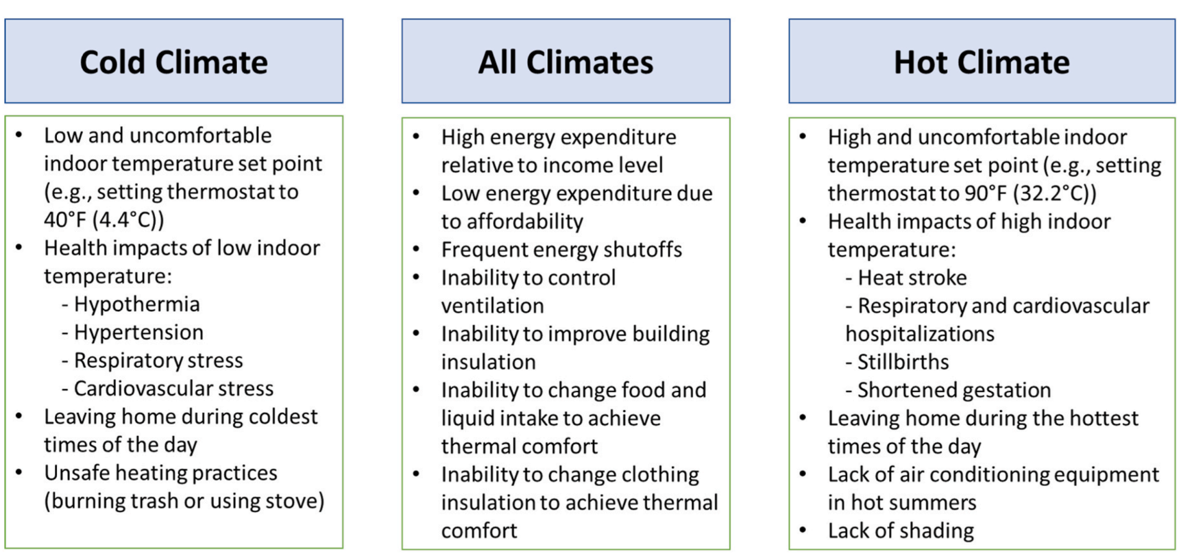

Fig. 1. Behavioral signs of energy poverty (Barrella et al., 2022; Cong et al., 2022; Gauthier and Shipworth, 2015; Hernández, 2016; Ormandy and Ezratty, 2016; Vecellio et al., 2022).

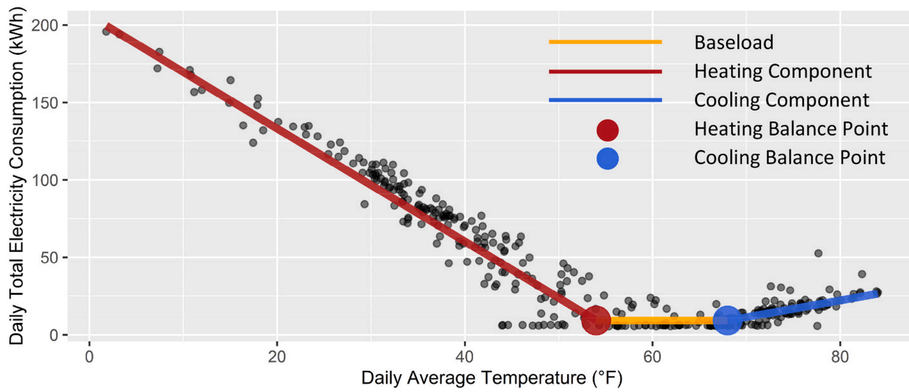

Fig. 2. Illustration of balance points. *Each data point represents one day. Data chosen from a household that uses electric heating and cooling for illustration purpose. For this household, the estimated heating balance point and cooling balance point are 54 °F and 68 °F, respectively.*

are calculated based on a five-parameter linear regression that models the relationship between daily outdoor average temperature and daily total electricity consumption (see Section 2). The second key assumption we make is that the estimated balance point represents the outdoor daily average temperature when a household turns on and turns off cooling or heating units. For example, in Fig. 2, the heating balance point (54 °F) can be an outdoor daily average temperature commonly found in October when the heating season starts and in April when the heating season ends (see Fig. A3 for a monthly fluctuation of outdoor daily average temperature in northern Illinois).

The current study aims to contribute to the existing and new policies and programs that address energy poverty in Illinois and beyond. In Illinois, the Energy Assistance Act authorizes utilities to collect a surcharge to fund energy assistance programs (Illinois Commerce Commission, 2022). The main existing programs at the state level include the Low Income Home Energy Assistance Program (LIHEAP; with both federal and state funding) where participants receive a one-time bill credit, the Percentage of Income Payment Plan (PIPP; with state funding only) where participants pay 6 percent of their monthly income for gas and electricity combined and make even monthly payments, the Illinois Home Weatherization Assistance Program (IHWAP; with both federal and state funding) where participants receive funding to improve home insulation, to repair or upgrade to more energy-efficient heating or cooling equipment, or for moisture control, and the arrearage reduction programs (with state funding only) where the amount of unpaid past bills can be offset with dollar credits (ComEd, 2022; Illinois Commerce Commission, 2022). A new program where low-income households receive tiered discount rate has been approved by the Illinois Commerce Commission (Illinois Commerce Commission, 2022). For all the mentioned programs above, the eligibility standard is solely based on income. We hope that the method we developed based on energy limiting behavior in this study can help assist those vulnerable households who may be neglected by solely income-based measures.

2. Data and methodology

Here we describe the data used in our analysis, our definition of energy equity gap, and our methods for determining the ability of a household to create a comfortable and safe indoor environment (i.e., energy limiting behavior) using piecewise linear regression (often referred to as a change point model; Perez et al., 2017).

2.1. Data

The residential electricity consumption dataset is provided by the Anonymous Data Service (ADS) at Commonwealth Edison (ComEd), an electric utility company in Illinois (ComEd, n.d.). ComEd is the sole electric provider in Chicago and the surrounding areas in northern Illinois. The timeframe of our analysis is a 12-month period (June 1, 2020–May 31, 2021).

For each household, the data includes a nine-digit ZIP Code, a delivery class (indicating whether electricity is used for heating), and the daily total electricity usage (kWh) for the household. The delivery class variable has four residential classes: single-family with or without electric heating, and multi-family with or without electric heating. Furthermore, we included only those households with electric heating when we examined the energy equity gaps in the heating scenario. The full sample sizes were 418,255 and 22,628 for the cooling case and the heating case, respectively. Other data sources and the procedures of preparing temperature data (via the eeweather Python package),

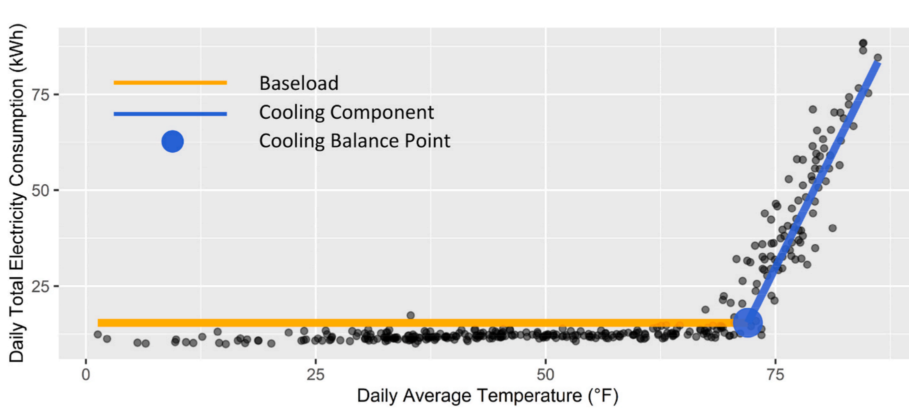

Fig. 3. Illustration of balance point in the cooling only case. *Each data point represents one day. Data chosen from one household that had a significant demand for cooling only for illustration purpose. For this household, the estimated cooling balance point is 72 °F.*

demographics like income and race (U.S. Census and American Community Survey), and residential building performance data (U.S. Building Performance Database) were reported in Appendix A. We assigned a race label to a household based on the U.S. Census data at the block group level. If a block group has the white population exceeding 50% in composition, the households residing in this block group is considered as white-majority; the same applies to black or other single race households; if no racial group exceeds 50% in composition of a block group, the households residing in this block group is considered multi-race. The residential building performance data (Lawrence Berkeley National Laboratory, n.d.) provided the electric energy use intensity (calculated as amount of electricity consumption divided by building area) data at the five-digit ZIP Code level, which was used to examine electricity consumption after controlling for home size in the main analysis, and used as a proxy variable for energy efficiency in our additional analysis (Appendix C).

2.2. *Energy equity gap, cooling, and heating balance points*

We define energy inequity in a region as a difference between different social group's ability to create a comfortable indoor environment (i.e., the energy equity gap; Cong et al., 2022). The energy equity gaps (i.e., G_C and G_H) are defined in Equation (1) (for cooling balance point, T_C) and Equation (2) (heating balance point, T_H).

$$G_C = \max(T_{C,\ MDN}) - \min(T_{C,\ MDN}), \quad (1)$$

$$G_H = \max(T_{H,\ MDN}) - \min(T_{H,\ MDN}), \quad (2)$$

Where the cooling balance point (T_C) is defined as the outdoor temperature at which a household switches on its cooling units in cooling season; the heating balance point (T_H) is defined as the outdoor temperature at which a household switches on its heating units in heating season. $T_{C,\ MDN}$ ($T_{H,\ MDN}$) represents the median of cooling (heating) balance point among households in an income group (Cong et al., 2022).

2.3. *Finding cooling and heating balance points using regression analysis*

For some households, electricity usage can be divided into three components: a base load, a cooling component, and a heating component (Fig. 2). However, there are other cases (i.e., houses with oil or natural gas heating) where a household's electricity consumption pattern is different. Using two other households as examples, Figs. 3 and 4 illustrate a pattern without a heating component and a pattern without a cooling component, respectively.

We use piecewise linear regression, implemented in an iterative multiple linear regression analysis, to identify the cooling balance point, T_C, and the heating balance point, T_H. This method originated from ASHRAE's inverse modeling (Lovvorn et al., 2002; Perez et al., 2017) and the CalTRACK method (Golden et al., 2019; Plagge et al., 2017). The cooling and heating balance points for each household, are derived using the concepts of cooling demand and heating demand. Cooling demand (*CD*) and heating demand (*HD*) are very similar to cooling degree day and heating degree day–measures of how relatively warm or cold a day is from a reference point (i.e., the temperature balance point). We further assume that for cooling, if the daily outside average temperature is below a balance point, there would be no cooling demand; and likewise for heating. Another key assumption is that daily total electricity consumption increases linearly as *CD* and *HD* increases (Lovvorn et al., 2002; Perez et al., 2017; Plagge et al., 2017). In other words, we assume linearity in the relationship between electricity consumption and variation in temperature: As cooling or heating demand increases, the electricity consumption increases by a constant—kWh/°F. This linearity assumption can be justified by its physical significance to how energy use responds to cooling and heating demand in most buildings and its ease of interpretation (Lovvorn et al., 2002), as well as by the empirical evidence found regarding the linearity (Perez et al., 2017; Plagge et al., 2017).

Given that there are three major patterns (Figs. 2–4), we specify three linear regression models with the daily electricity consumption (E_i) as the dependent variable, and cooling demand (*CD*) and heating demand (*HD*) as the main predictors in concern (Cong et al., 2022; Lovvorn et al., 2002; Perez et al., 2017; Plagge et al., 2017; Equations (3)–(5)). In addition, we added several weather-related control variables based on a study that analyzed electricity consumption using a similar dataset (Lou et al., 2021). Equations (3)–(5) are referred to as temperature response functions hereafter, each of which corresponds to one of the patterns shown in Figs. 2–4. Let E_i be the daily total electricity consumption of day *i*.

$$E_i = \mu + \beta_C CD_i + \beta_H HD_i + \beta_W W_i + \beta_{HL} HL_i + \delta_i + \theta_i + M_i + \varepsilon_i, \quad (3)$$

$$E_i = \mu + \beta_C CD_i + \beta_W W_i + \beta_{HL} HL_i + \delta_i + \theta_i + M_i + \varepsilon_i, \quad (4)$$

$$E_i = \mu + \beta_H HD_i + \beta_W W_i + \beta_{HL} HL_i + \delta_i + \theta_i + M_i + \varepsilon_i, \quad (5)$$

where μ represents baseload (i.e., baseline energy use), W_i and HL_i are the weekend and holiday dummy variables of day *i*, δ_i represents the day-of-the-week fixed effects, θ_i represents the month-of-the-year fixed effects, M_i is a vector of weather-related covariates (including a linear and a quadratic term of daily average precipitation, a linear term of daily average wind speed, and a linear term of daily average relative humidity; see Lou et al., 2021), ε_i is the error term, cooling demand (*CD*) and heating demand (*HD*) are further defined in Equations (6) and (7).

$$CD_i = \max(T_i - T_C, 0), \quad (6)$$

$$HD_i = \max(T_H - T_i, 0),\text{w} \quad (7)$$

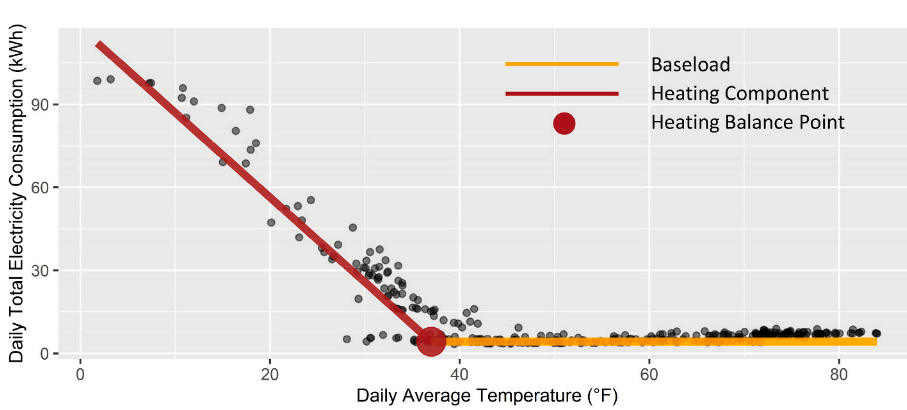

Fig. 4. Illustration of balance point in the heating only case. *Each data point represents one day. Data chosen from one household that had a significant demand for heating only for illustration purpose. For this household, the estimated heating balance point is 37 °F.*

where T_i is the outdoor daily average temperature, T_C is the cooling balance point, and T_H is the heating balance point.

Here we describe how we find the optimal balance points using the regression models. The optimal cooling balance point and heating balance point for a household are chosen from a range of degrees for both T_C (cooling balance point) and T_H (heating balance point). We followed the range used in the OpenEEmeter method (Plagge et al., 2017): 30–90 °F (integer only). Then, using Equations (6) and (7), we prepared a series of *CD* variables and *HD* variables for the regression analysis. For the regression model in Equation (3), each combination of the *CD* and the *HD*, where $T_C > T_H$, based on the above range is used to fit the regression model; for the regression models in Equations (4) and (5), each temperature (in integer) in the above range is used to calculate the *CD* or the *HD* to fit the regression model. Two additional restrictions for a cooling balance point and a heating balance point to qualify after the above calculations are: (1) that the number of calculated non-zero *CD*s or *HD*s must be greater than 10; and (2) that the sum of the calculated *CD*s or *HD*s must be at least 20 (Plagge et al., 2017).

Because we do not know a priori which of the three patterns (Figs. 2–4) would be the best case for a household, we fit all three temperature response functions for each household, using ordinary least squares (OLS). The complete set of regression models with different *CD* and *HD* variables are defined as candidate models.

Among all candidate models, the one that has positive and significant ($p < 0.1$) β_C (slope of *CD*) and β_H (slope of *HD*), a nonnegative intercept, and the largest adjusted R^2 is selected as the best-fit model. If the best-fit model is the CD-HD model (Equation (3); Fig. 2), both the optimal cooling balance point and the optimal heating balance points are found, and these balance points are the ones used to calculate *CD* and *HD* in that best-fit model. If the best-fit model is a CD-only model (Equation (4); see also Fig. 3), the optimal cooling balance point is the temperature used to calculate the *CD* in that model, whereas the optimal heating balance point is missing. Lastly, if the best-fit model is an HD-only model (Equation (5); see also Fig. 4), the optimal heating balance point is the temperature used to calculate the *HD* in that model, whereas the optimal cooling balance point is missing. If the energy consumption pattern as a function of outdoor daily average temperature is inconsistent with either of the three patterns, neither cooling balance point nor heating balance point could be found and the household is omitted from further analysis. We describe in Appendix B a sensitivity analysis on the model specification in Equations (3)–(5).

We then used Equations (1) and (2) to calculate the energy equity gap. We used the Kruskal-Wallis test (two-tailed) to examine whether differences in group medians were significant. We report the *H* statistics (approximately chi-squared distributed), degree of freedom (number of groups minus one), and the *p* values from the Kruskal-Wallis test in the results section. The null hypothesis in the Kruskal-Wallis test is that the population medians of groups are equal.

3. Results and discussion

3.1. Distributions of balance points by income and energy equity gaps

The distributions of cooling balance points across income groups are shown in Fig. 5 (Panel a). For each household, income was determined by the median income of the U.S. Census block group that this household belongs to (see also Appendix A). All households were then divided into eight income groups (see legend in Fig. 5; same method was applied to other figures in Section 3 where appropriate). As expected, we found a negative relationship between income and cooling balance point. The medians across income groups were significantly different ($H[7] = 10{,}650$, $p < 0.001$; Kruskal-Wallis test, see Section 2), with the lowest-income group having the highest median cooling balance point (68 °F) and the two highest-income groups having the lowest median cooling

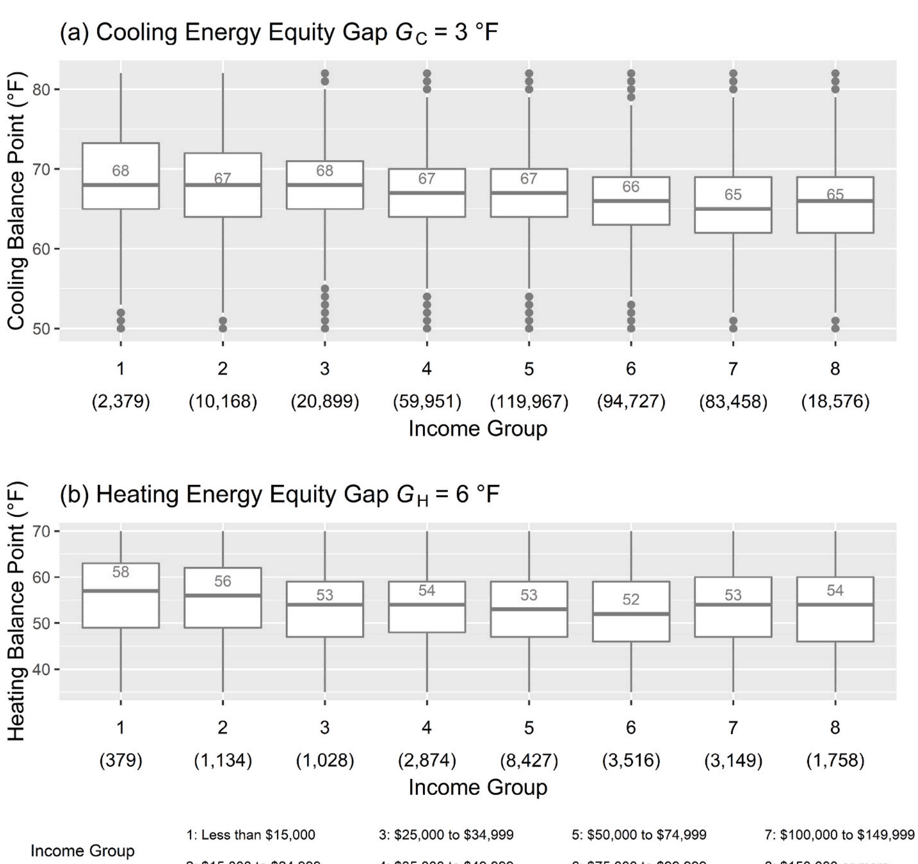

Fig. 5. Energy equity gaps across income groups. *Cooling energy equity gap (G_C) is shown in Panel a; heating energy equity gap (G_H) is shown in Panel b. The energy equity gap is calculated as the difference between the highest and lowest median balance point (indicated by the middle bar and number) among all income groups. Each box and whiskers plot indicates the minima and maxima of balance points of one income group (the lower and upper bound of the whiskers), the first and third quantiles (the lower and upper bound of the box), and the median (the middle line). The outliers are shown as dots on either side of the whiskers; same extreme outliers are omitted to save space for plotting. The sample size for each income group is shown under the x-axis in parentheses.*

balance point (65 °F). The cooling energy equity gap, G_C, is 3 °F.

For heating balance points by income (Fig. 5, Panel b), the energy equity gap in heating is 6 °F. The medians across income groups were significantly different ($H[7] = 168.67, p < 0.001$). However, the effect is counterintuitive to our assumption that low-income groups would turn on or off their heating systems at lower outdoor temperatures than high-income groups. In fact, the lower-income groups had the highest median heating balance point (56–58 °F), whereas the higher-income groups' heating balance points ranged from 52 to 54 °F. Higher-income groups in general had lower median balance points than lower-income groups (further supported partially in our additional analysis; see Table C3, Appendix C), which seems to contradict our assumption of energy limiting behavior. If our assumption about energy limiting behavior due to financial stress is plausible, lower-income households should have lower heating balance points. However, energy limiting behavior can also be identified by examining the overall electricity consumption level during a heating season. That is, due to financial stress, the overall electricity consumption level of the lower-income groups is expected to be lower than that of the higher-income groups. Furthermore, the energy limiting behavior in heating season can be identified in the heating slope: Low-income households are expected to consume less electricity per unit decrease in outdoor temperature (kWh/°F) than high-income households. These expected patterns regarding overall electricity consumption and heating slopes turned out to be true, which is presented in the next section.

3.2. Balance point, energy consumption, and energy burden

To further examine energy limiting behavior, we examined the relationships among the estimated balance points, energy burden, and electricity consumption. For cooling (Fig. 6), as expected, low-income households consumed less electricity than middle-income and high-income households (see also Fig. C1a). The median cooling season electricity consumption of the highest-income group (3,158 kWh) was 164% greater than that of the lowest-income group (1,197 kWh). Also, we found more households who had *high energy burden* (i.e., spending between 6% and 10% of income on electricity bills) and *severe energy burden* (e.g., spending more than 10% of income on electricity bills; thresholds defined by American Council for an Energy-Efficient Economy; Drehobl et al., 2020) among the four lower-income groups (Fig. 6., upper panels) than higher-income groups (Fig. 6., lower panels).

For heating, we note that in the previous section (Fig. 7, Panel b), we find lower-income households turned on and off heating units at higher outdoor temperatures than higher-income households in the heating season. However, we find that while lower income groups turn on their heating systems earlier when heating season starts and turn off later when heating season ends, their overall electricity consumption level was lower than high-income households throughout the heating season. As shown in Fig. 7, lower-income households consume much less electricity than higher-income households in the heating season (see also Fig. C1b). The median consumption of the highest-income group (7,593 kWh) was 64% greater than the median consumption of the lowest-income group (4,616 kWh). As expected, and consistent with the cooling case, we found more households who had high energy burden and severe energy burden among the four lower-income groups.

Regarding electricity consumption by income, we also examined whether high-income households consumed more electricity than low-income households after controlling for home size. Although the home size data was not available at the household level, we used the residential building performance dataset (Lawrence Berkeley National Laboratory, n.d.) to examine the electric energy use intensity by income for the cooling case and the heating case combined (Chicago only for Year 2017). We found a similar pattern after controlling for building area: The median electric energy use intensity of the highest-income group (29.5 kBtu/sqft/year) was 52% greater than that of the lowest-income group (19.4 kBtu/sqft/year).

Next, we explore how income groups differ regarding electricity use behavior in the cooling season and in the heating season. We chose three income groups (the lowest, a middle-income group, and the highest) to highlight disparities. As shown in Fig. 8, in both the cooling case (Panel a) and the heating case (Panel b), we found that the lowest-income group (green line) had the smallest absolute slope (0.29 kWh/°F for cooling and 0.99 kWh/°F for heating) of electricity consumption and the smallest baseload (5.92 kWh for cooling and 5.95 kWh for heating). In contrast, the highest-income group had the largest absolute slope (0.73 kWh/°F for cooling and 1.74 kWh/°F for heating) and the greatest baseload (14.7 kWh for cooling and 9.04 kWh for heating). The flatter slope (see also Fig. C2) and lower usage among low-income households indicate long-term energy limiting behavior across the entire cooling or heating season. Remarkably we find that in the heating case, the lowest-

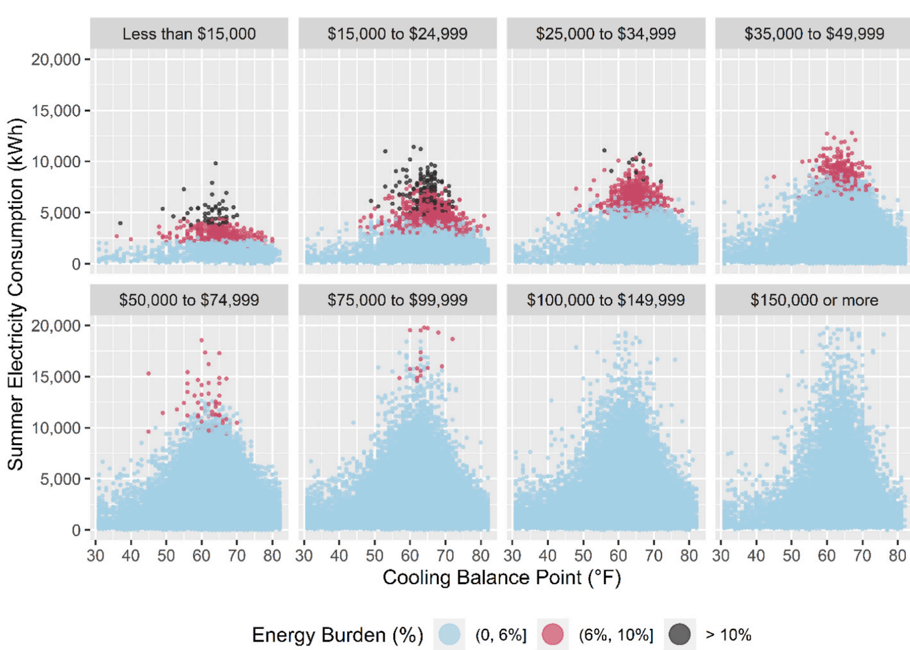

Fig. 6. Relationships among cooling balance point, cooling season electricity consumption, and energy burden by income groups. *Each data point represents one household. Each panel corresponds to one income group. Electricity consumption is calculated as the sum of electricity consumption in four cooling season months (see Fig. A2). Energy burden is calculated as the ratio of electricity bill over the median income of the Census block group that a household belongs to. The blue, red, and black dots represent energy burden levels of 6% or below (low energy burden), between 6% and 10% (high energy burden), and higher than 10% (severe energy burden), respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)*

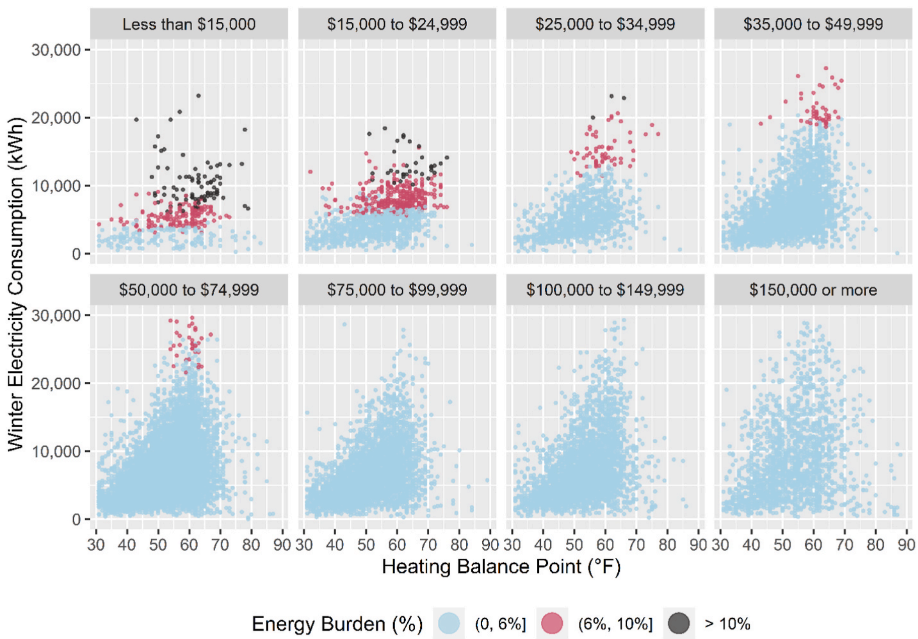

Fig. 7. Relationships among heating balance point, electricity consumption in heating season, and energy burden by income groups. *Each data point represents one household. Each panel corresponds to one income group. Electricity consumption is calculated as the sum of electricity consumption in heating season (eight months; see Fig. A2). Energy burden is calculated as the ratio of electricity bill over the median income of the Census block group that a household belongs to. The blue, red, and black dots represent energy burden levels of 6% or below (low energy burden), between 6% and 10% (high energy burden), and higher than 10% (severe energy burden), respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)*

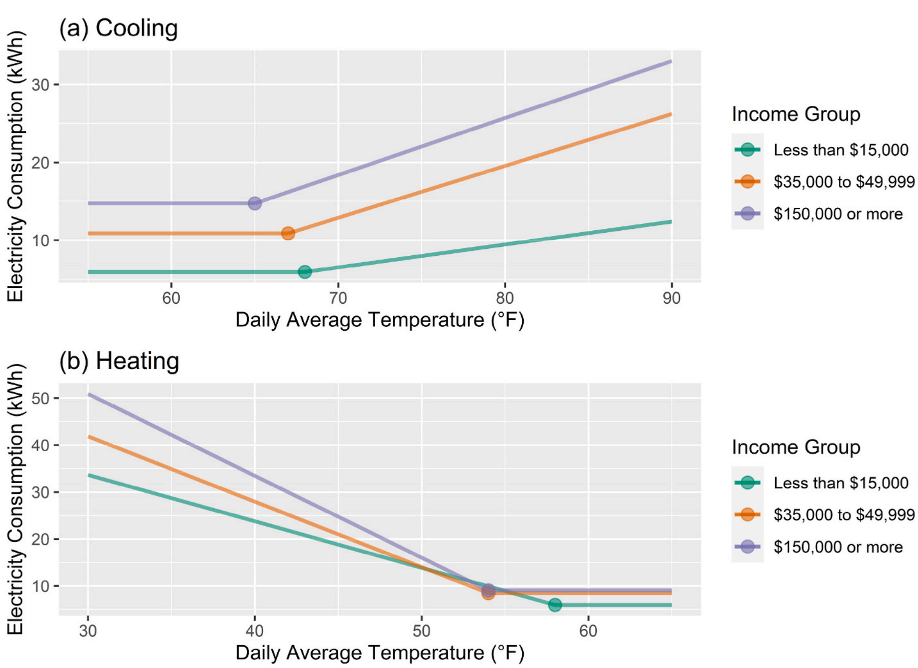

Fig. 8. Electricity use as a function of daily average temperature by three income groups in the cooling case (Panel a) and the heating Case (Panel b). *The green, orange, and purple lines represent Income Group-Less than $15,000, Income Group-$35,000 to $49,999, and Income Group-$150,000 or more, respectively. For cooling (Panel a), the electricity consumption when daily average temperature = 90 °F is the median daily average consumption of an income group in July 2020 when electricity consumption peaked in that cooling season; for heating (Panel b), electricity consumption when daily average temperature = 30 °F is the median daily average consumption of an income group in February 2021 when electricity consumption peaked in that heating season. Filled circle represents the median balance point of an income group. The horizontal segment represents the median baseload of an income group. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)*

income group turned on their heating units the earliest when heating season started (58 °F) with a flatter slope of 0.99 kW h/°F. In contrast, the highest-income group waited longer into the heating season to use heating units (54 °F) but had a much steeper slope of 1.74 kW h/°F (i.e., quickly consumed much electricity in response to lower temperatures).

3.3. Identifying energy-limiting households

In our analysis of energy burden, in both the cooling sector and the heating sector, although lower-income households consumed less electricity than higher-income households, we found that high and severe energy burden was more prevalent among lower-income households than higher-income households. However, it has been stated that multiple energy metrics can reveal the many experiences of energy poverty. The energy burden measure may fail to cover some households who display energy limiting behavior. Thus, we use the estimated balance points to identify the energy-limiting households who are identified as having low energy burden.

For cooling, we follow the tier system of energy insecurity risks based on energy limiting behavior created in a previous study (Cong et al., 2022). In this tier system, the energy-insecure line (71 °F) is calculated as the median cooling balance point of the highest-income group (65 °F) plus two times energy equity gap (6 °F); the energy-poor line (78 °F) is the recommended indoor set point in the cooling season recommended by the U.S. Department of Energy (2021a). For the four lower-income groups together, we found 18% of the households had low energy burden but can be categorized under the energy-insecure tier, and 2% of the households had low energy burden but can be categorized under the energy-poor tier. That is, without examining energy limiting behavior, 20% of the low-to-middle-income households, or 19,001 households, who had high energy insecurity risks would have been neglected by the energy burden measure.

For heating, we created a tier system that takes two aspects of energy limiting behavior into account (Fig. 9). First, the lower-income households who had an extremely low heating balance point should be considered vulnerable. Based on the four lower-income groups, we define the 25th quantile (47 °F) and the 15th quantile (43 °F) of heating balance point as the energy-insecure line and the energy-poor line at the lower-end of heating balance point, respectively. Second, because we found that lower-income households tended to turn on and off heating units at higher outdoor temperatures than high-income households, we also need thresholds at the higher-end of heating balance point. Importantly, because lower-income households also consumed less electricity overall, we categorized a household who had a high heating balance point as vulnerable *only when this household also consumed little electricity*. Therefore, at the higher-end of heating balance point, we define the 75th quantile (60 °F) and the 85th quantile (63 °F) of heating balance point as the energy-insecure line and the energy-poor line heating balance point, respectively. In addition, we define the 15th quantile of electricity consumption (2,810 kWh) as a threshold of low electricity consumption. Under this tier system, we found that for the four lower-income groups together, 9% of the households can be categorized under the energy insecure tier (dark blue points in Fig. 9), and 15% of the households can be categorized under the energy poor tier (dark orange points in Fig. 9). Again, without examining energy limiting behavior, these 1,290 households (24% in total) would have been neglected by the energy burden measure.

3.4. Energy equity gaps by racial groups

To examine how the energy equity gaps vary by race, we calculated the cooling gap and the heating gap for each racial group. For the cooling energy equity gaps by racial groups (Fig. 10), we found that households residing in black-majority block groups (Fig. 10a) had a wider cooling gap (3.5 °F) than the households residing in the rest of block groups (white: 3 °F; multi-race: 3 °F; other: 2 °F). This result was further supported in our second-stage regression analysis (see Appendix C). The households living in black-majority block groups ($H[7] = 267.85$, $p < 0.001$) and the households living in white-majority block groups ($H[7] = 5258.4$, $p < 0.001$) showed an expected negative relationship between the median cooling balance points and income. For the household living in multi-race block groups ($H[6] = 566.88$, $p < 0.001$), the lowest-income group had the lowest median cooling balance points; but if we hide this group due to a relatively small sample size only for interpretation purposes, there was also an expected negative relationship between the median cooling balance points and income. Lastly, for the households living in other (regarding categorization based on race) block groups ($H[4] = 75.59$, $p < 0.001$), the lowest-income group had the lowest median cooling balance points.

For the heating energy equity gaps by racial groups (Fig. 11), we found that the households living in white-majority census block groups ($H[7] = 172.38$, $p < 0.001$) had the widest gap (7 °F) than the households living in black-majority block groups at 5 °F ($H[4] = 26.84$, $p < 0.001$), and the households living in multi-race block groups at 3 °F ($H[5] = 26.34$, $p < 0.001$). The distributions of the median heating balance points followed a similar pattern, with the lower-income groups having higher median heating balance points. We did additional analysis by examining the electricity consumption during heating season by income for each racial group (see Fig. C3, Appendix C). Consistent with our assumption of energy limiting behavior, for every racial group, lower-income households consumed less electricity (from 58% to 95% less) during heating season than higher-income households.

To compare the cooling sector and the heating sector, the major difference is that in the former, the households living in black-majority block groups had a wider gap than the households living in the rest of the block groups, whereas in the latter, the households living in white-majority block groups had a wider gap than the households living in the rest of the block groups. In addition, only in the cooling sector, we found a racial group whose pattern deviated from the rest of the racial groups: the “Other” racial group (Fig. 10d) showed a positive relationship between the median cooling balance point and income.

In our additional analysis, we regressed balance points on several sociodemographic and energy efficiency variables and examined the interaction effect between income and race (Appendix C). In this second-stage regression analysis, for the cooling sector, we found that the cooling energy equity gaps were indeed independently contributed by income. In addition, households living in black-majority block groups were more likely to endure higher cooling balance points in general (see also Figure C7 in Appendix C), and they were susceptible to greater cooling energy equity gaps than the rest of the racial groups.

3.5. Limitations

There are several limitations in the current study. First, to measure energy equity gap as defined in our study, it would be beneficial to analyze the actual temperatures recorded on home thermostats or to place thermostat sensors in homes. It also would be beneficial to directly ask residents about the average temperature they set on thermostats in a typical cooling season or heating season and what their desired temperature set point is (albeit with this method’s own limitation like social desirability bias).

The second limitation concerns other issues related to data availability. Our focus on the electricity sector is due to lack of information on natural gas usage at the household level in the study region. In Illinois, 76.6% of households use natural gas for heating (American Community Survey, 2022). Thus, in the future it would be beneficial to explore inequities in natural gas usage in this region. Because most households have either electricity or natural gas as the main fuel source

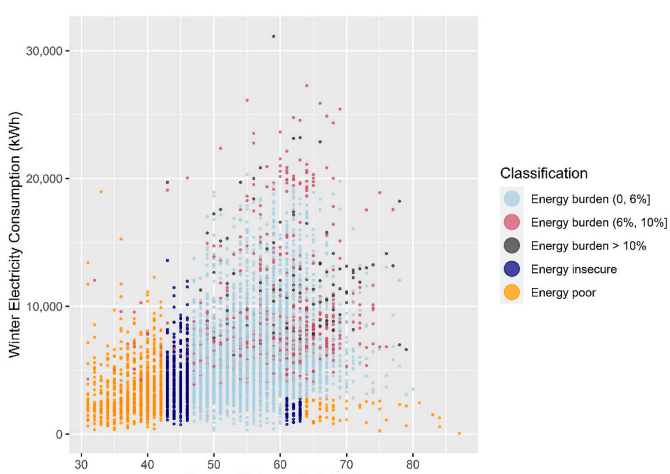

Fig. 9. Identifying hidden energy insecure and poor households by energy limiting behavior in the heating sector. *Data point represents household in the four lower-income groups. Light blue dot: household who has low energy burden; red dot: household who has high energy burden; black dot: household who has severe energy burden; dark blue dot: household who has low energy burden but is energy insecure with energy limiting behavior (either with: [1] a heating balance point between 43 [inclusive] and 47 °F; or with [2] a heating balance point between 60 and 63 [inclusive] °F and a heating season electricity consumption level lower than 2810 kWh); dark orange dot: household who has low energy burden but is energy poor with energy limiting behavior (either with: [1] a heating balance point lower than 43 °F; or with [2] a heating balance point higher than 63 °F and a heating season electricity consumption level lower than 2810 kWh). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)*

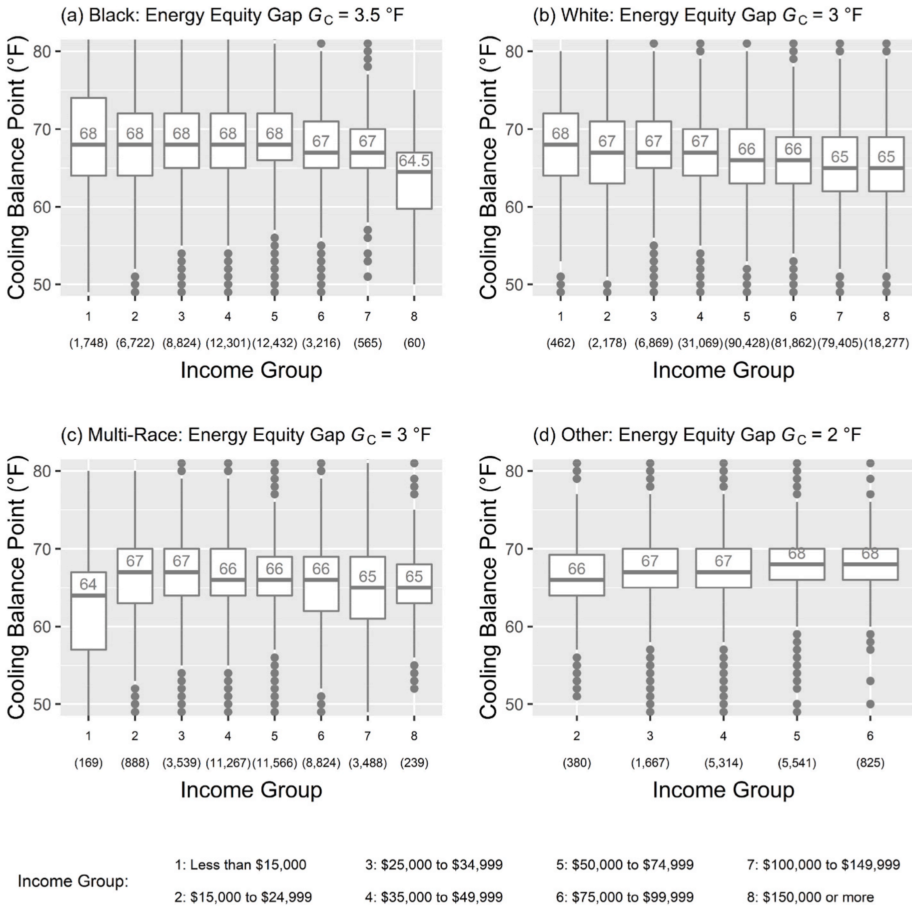

Fig. 10. Energy equity gaps in cooling balance points (G_C) by racial groups. *The energy equity gap in cooling (G_C) is calculated as the difference between the highest and lowest median cooling balance point (indicated by the middle bar and number) among all income groups. (a) Gap among black population; (b) gap among white population; (c) gap among multi-race population; (d) gap among other population. Each box and whiskers plot indicates the minima and maxima of balance point of one racial group (the lower and upper bound of the whiskers), the first and third quantiles (the lower and upper bound of the box), and the median (the middle line). The outliers are shown as dots on either side of the whiskers. The sample size for each racial group is shown under the x-axis in parentheses. Any missing income groups in a racial group was due to the lack in the data. Racial group labels were determined by the majority group (>50%) in a U.S. Census block group that a household lives in.*

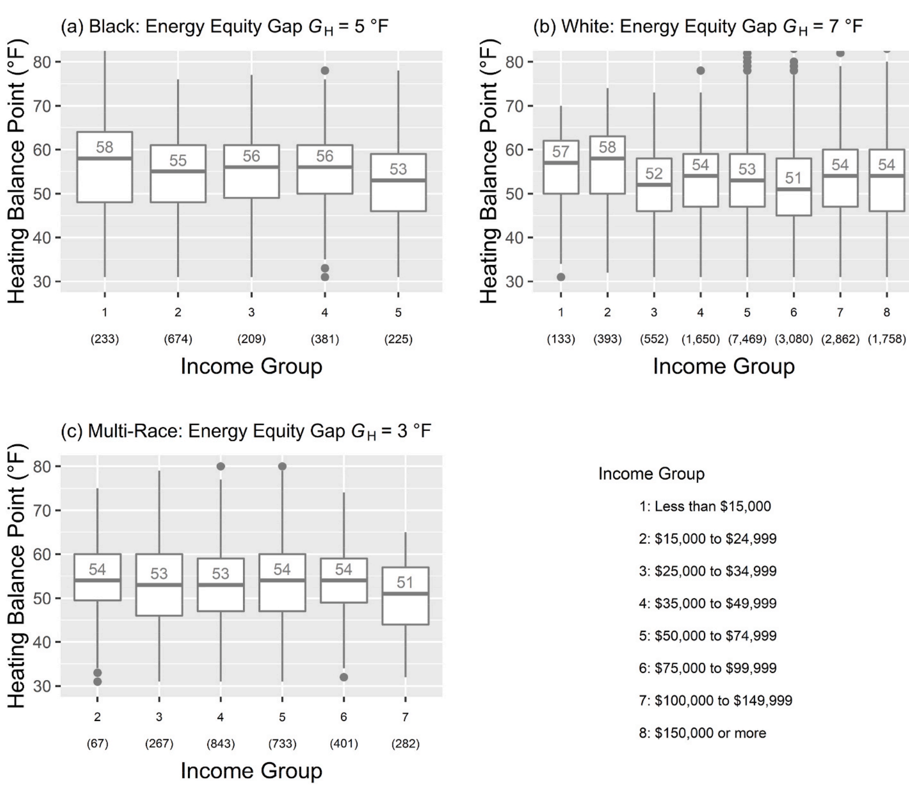

Fig. 11. Energy equity gaps in heating balance points (G_H) by racial groups. *The energy equity gap in heating (G_H) is calculated as the difference between the highest and lowest median heating balance point (indicated by the middle bar and number) among all income groups. (a) Gap among black population; (b) gap among white population; (c) gap among multi-race population. Each box and whiskers plot indicates the minima and maxima of balance point of one racial group (the lower and upper bound of the whiskers), the first and third quantiles (the lower and upper bound of the box), and the median (the middle line). The outliers are shown as dots on either side of the whiskers. The sample size for each racial group is shown under the x-axis in parentheses. Any missing income groups in a racial group was due to the lack or a too small group sample in the data. There was no 'other' racial group found among the households that had an estimated heating balance point. Racial group labels were determined by the majority group (>50%) in a U.S. Census block group that a household lives in.*

for heating, with the data of natural gas consumption at the household level available, in most cases, the analysis in a future study would have three separate parts: the electricity consumption case in the cooling season (for all households), the electricity consumption case in the heating season (for households who have electric heating), and the natural gas consumption case in the heating season (for households who use natural gas for heating). Despite this limitation our analysis highlights current inequities in electricity usage, which are vital to understand during the country's energy transition due to large pushes for electrification of the heating sector (Harris, 2020; Nadel, 2023; U.S. Department of Energy, 2022, 2021b). Another source of data that future studies can benefit from is home size at the household level, because electricity consumption for space cooling and heating depends on the size of living area. The current study controlled for home size by using electricity use intensity (electricity consumption divided by home size) at the ZIP Code level. Increasing data granularity can make the evaluation of energy limiting behavior more precise. For example, when both electricity consumption and home size at the household level are available, future studies should include these two variables as individual controls when they regress income on balance point. Other useful data at the household level include year built, number of windows, utility rate plan, and utility rates. To strengthen future iterations of the work, a household survey that identified appliances used in the home, main light bulb type, as well as age, racial group, income level, and owner or renter status of occupants would also strengthen the analysis and reveal more disparities between households.

The third limitation concerns the time span of our analysis. We have only one year of data for adequate analysis, and these data happen to be within the period of the COVID-19 pandemic. Therefore, our results only apply to the situation under the impacts of stay-at-home orders and a shift to more remote work time. If more data during non-COVID years are available, extending our analysis to more years would be helpful in two ways: (1) to further validate the existence of energy equity gap in the northern Illinois region; (2) to provide a baseline to examine the impact of COVID on energy equity gap. Regarding the first goal, we expect that we would find energy equity gap in northern Illinois given the current study and a previous study that found energy equity gap in Arizona during multiple non-COVID years (Cong et al., 2022). Regarding the second goal, we expect that the energy equity gap in the COVID period may be different from the gap in the non-COVID period. This is due to the fact that the COVID stay-at-home order increased the time spent at home, and this increased the income-based energy burden for low-income and ethnic minority groups (Lou et al., 2021). It has also been found that the pandemic brought about the disproportionately increased job loss and financial burden faced by ethnic minority groups (Chen et al., 2022; Gemelas et al., 2022; Holder et al., 2021). Future studies need to further examine the impact of COVID-19 on energy equity gaps.

3.6. Discussion

We found different patterns of energy limiting behavior between the cooling sector and the heating sector. Consistent with past work on energy limiting behavior (Cong et al., 2022), our results provided evidence of energy limiting behavior in a cold-climate region. In the current study, the cooling energy equity gap between income groups was 3 °F, while the heating gap was 6 °F. Further analysis on electricity consumption in the cooling season indicates that the lower-income households do consume less electricity than high-income households, which further supports the existence of energy limiting behavior due to unaffordability. Thus, the type of energy limiting behavior in the cooling sector can be summarized as "use little for a short period."

On the other hand, in the heating sector, the type of energy limiting behavior is "use little for a long period." We found that low-income groups started heating their houses earlier in heating season and kept using heating towards the end of heating season longer than their high-income counter parts. Meanwhile, the lower-income households also consume less electricity than high-income households in the heating season. In other words, under a cold climate where residents are more susceptible to cold-related deaths than to heat-related deaths (Friedman et al., 2020), a household who lacks financial resources is more sensitive to temperature drop and takes early precautions to heat their homes. When the heating season comes to an end, this household also delays turning off their heating units. To explain this pattern, it is important to emphasize that during the cooling season, individuals can leave their homes at the peak of the day's heat. On the contrary, during the heating season, the lowest temperatures usually occur at night. As a result, this decline in temperature may be more noticeable to those residing within the homes in the heating season. This may lead to the unexpected pattern where lower-income households keep their heating equipment on for a longer period considering two more factors: lack of insulation in older homes which low income groups are more likely to live in (U.S. Census Bureau, 2022) and higher potential healthcare burden resulted from cold-related illness for a low-income household than for a high-income household (Moore and Liang, 2020). However, during the whole heating season, due to unaffordability, this household's slope (change in energy usage per degree temperature change) is flatter in low-income households when compared with higher-income households. This leads to a low level of total electricity usage in the heating season.

We also demonstrated how to use balance point to identify those vulnerable households who may be neglected by the energy burden metric. We found that without examining energy limiting behavior, 20% of low-to-middle-income households in the cooling sector and 24% of low-to-middle-income households in the heating sector who had high energy insecurity risks would have not been identified by the energy burden measure.

Regarding energy equity gaps among racial groups, we found that households living in black-majority census block group had a slightly wider cooling gap (3.5 °F) than the households living in the rest of the block groups (2–3 °F), whereas households living in white-majority block groups had the widest heating gap (7 °F). In the cooling sector, our study provided important evidence regarding the relationship between race and energy limiting behavior: households living in black-majority block groups were more likely to endure higher cooling balance points in general (see Figure C7 in Appendix C), and they were susceptible to greater cooling energy equity gaps than the rest of the racial groups. As previous studies have found that black households in the U.S. are more vulnerable regarding energy poverty and had greater inequality in energy efficiency (Adua et al., 2022; Dogan et al., 2022; Goldstein et al., 2022; Wang et al., 2021), we contributed to the literature by further supporting the proposition that energy inequity is driven by the intersection of income and race (Adua et al., 2022). Therefore, policy design should focus on addressing the income inequality and other systematic inequalities (e.g., poor living conditions due to historical policies; Goldstein et al., 2022) that have impacted the black American households.

4. Conclusion and policy implications

In the reported study, we estimate energy limiting behavior in the cooling and heating sectors under a cold climate in the United States using a large residential electricity dataset and piecewise linear regression. Specifically, we estimate the outdoor temperatures at which households turn on and off their electricity-based cooling and heating units (i.e., cooling balance point and heating balance point) under a cold climate in northern Illinois, USA ($N = 418{,}255$ for cooling; $N = 22{,}628$ for electric heating). The estimated temperature comfort levels (balance points) are then compared across income groups to assess inequalities in the distributions of these balance points (i.e., energy equity gaps). We find that the cooling energy equity gap between low and high income groups is 3 °F (1.7 °C), while the electric-based heating energy equity gap is 6 °F (3.3 °C). In the cooling season, low-income households consume less electricity and use electricity for space cooling for a shorter period than high-income households; in the heating season, low-income households also consume less electricity but use electricity for space heating for a longer period than high-income households. Among low-to-middle-income households, our metric identifies 19,001 households (20%) in the cooling sector and 1,290 households (24%) in the heating sector who may be neglected by the traditional income-based energy poverty measure. Lastly, we find that households living in black-majority block groups have a cooling gap that is 17% wider than households living in white-majority block groups.

Consequently, policy design should address income inequality and other systematic inequalities, such as poor living conditions stemming from historical policies, to alleviate the energy burden on vulnerable communities. Our metrics contribute to the policy design of home energy bill and weatherization assistance programs to identify vulnerable households in a cold climate. Our balance-point metrics need to be combined with any existing measures of energy poverty, so that those governmental programs at multiple levels (federal, state, and local) can better identify those households who are in need. To maximize the effectiveness of assistance programs, collaboration and communication between government-based programs and utility-based programs are critical.

All existing and new programs tackling energy poverty in Illinois at the state level determine eligibility by income (Illinois Commerce Commission, 2022). However, the current study has demonstrated that, if households limit energy consumption due to financial stress in the first place, an income-based criterion is insufficient, and misses the health impacts of forgoing electricity use. Moreover, as ComEd noted in its recommendation to Illinois Commerce Commission regarding the new low-income discount rate policy (ComEd, 2022), the moving poverty line every year poses challenges to categorize which households fall into the "low-income" class, and existing data policy from utilities prohibits collection of private information like income. The metrics developed in the current study can address these concerns directly using smart meter data which can better target vulnerable households. For assistance programs from utility providers, our metrics present a unique advantage: data availability. Utility providers can directly conduct balance point analysis using first-hand consumption data from their customers to identify energy limiting behavior while protecting data privacy. A yearly evaluation of balance point and overall consumption level can help detect signs of unhealthy indoor environments. Considering the current study, the signs of energy limiting behavior are expected to be different between the cooling and the heating season: For cooling, low-income households consume less electricity for a shorter period than high-income households; for heating, low-income households consume less electricity for a longer period than high-income households. After identifying vulnerable households with regard to energy limiting behavior, utilities and governmental energy assistance programs can then reach out to affected households by sending check-in mails, emails, or text messages and refer interested households to energy assistance programs as needed. Additionally, our metrics can be used by utility regulators to analyze how investments made by utilities and energy assistance funding impact multiple forms of energy poverty (e.g., energy limiting behavior and energy burden).

The metrics developed in the current study imply that there are many households that may need energy assistance that may be overlooked due to the limitations of income-based measures. Against a backdrop of utility rate increases (Adams, 2023), we believe a sustained and increasing funding at the federal and state levels is crucial to assist households who may be suffering from unhealthy indoor environments. This can be achieved through charging a higher surcharge for large non-residential users, and through better connecting eligible households to available funds (Illinois Commerce Commission, 2022).

We also note that investments in community infrastructure (e.g., via weatherization programs), job creation, and affordable housing can help to reduce income disparities and improve living conditions for those in energy-insecure households. The Home Efficiency Rebates Program and the Home Electrification Rebates Program authorized by the 2022 Inflation Reduction Act signal a major step forward to help households (especially low-to-middle-income households) to improve energy efficiency at home. With better insulated walls and more energy-efficient heating equipment, lower-income households can have a healthier indoor environment without too much concern about energy bills. Policy design should also focus on addressing the income inequality and other systematic inequalities (e.g., poor living conditions due to historical policies; Goldstein et al., 2022) that have impacted Black American households.

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CRediT authorship contribution statement

Luling Huang: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Funding acquisition. **Destenie Nock:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Shuchen Cong:** Conceptualization, Methodology, Writing – review & editing. **Yueming (Lucy) Qiu:** Data curation, Writing – review & editing.

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 A

Linking ZIP Code and Temperature Data

We link each household to an outdoor temperature profile, using the EEweather package in Python (Open Energy Efficiency Inc, 2018) to find the nearest weather station for a specific ZIP Code (ZIP hereafter). The weather data is sourced from the National Climate Data Center's Integrated Surface Database (Open Energy Efficiency Inc, 2018). We mapped the geographical coordinate (the latitude and longitude of the centroid of a ZIP area, provided by a data conversion file made available by EASI Analytic Software Inc, 2021) linked to each ZIP to the closest weather station with available temperature data. A geographical presentation of the ComEd service area in northern Illinois is provided below (Fig. A1). The general climate characteristics of the region related to cooling and heating demands is shown in Fig. A2.

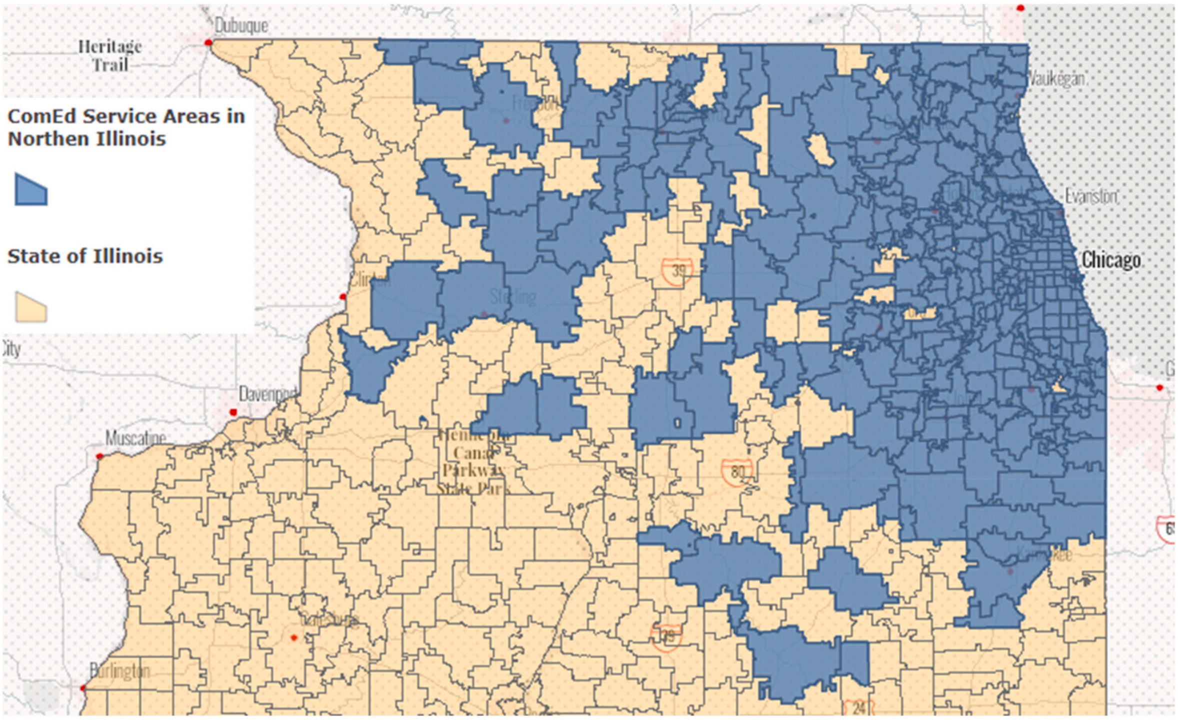

Fig. A1. ComEd service areas in northern Illinois, USA.

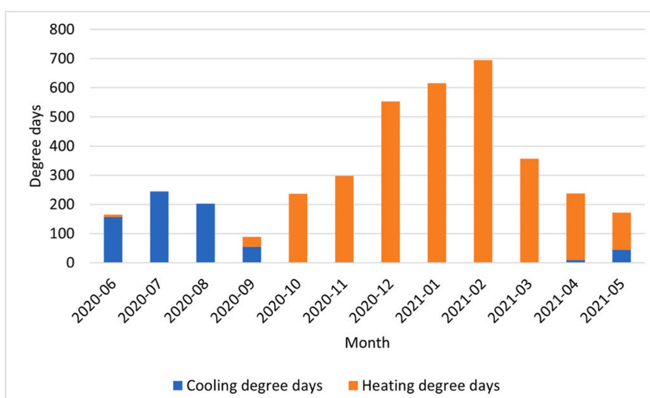

Fig. A2. Cooling and heating degree days in northern Illinois, USA (June 2020–May 2021). *Data source: Global Summary of the Month (GSOM). Weather station: USW00094846* (Lawrimore et al., 2016).

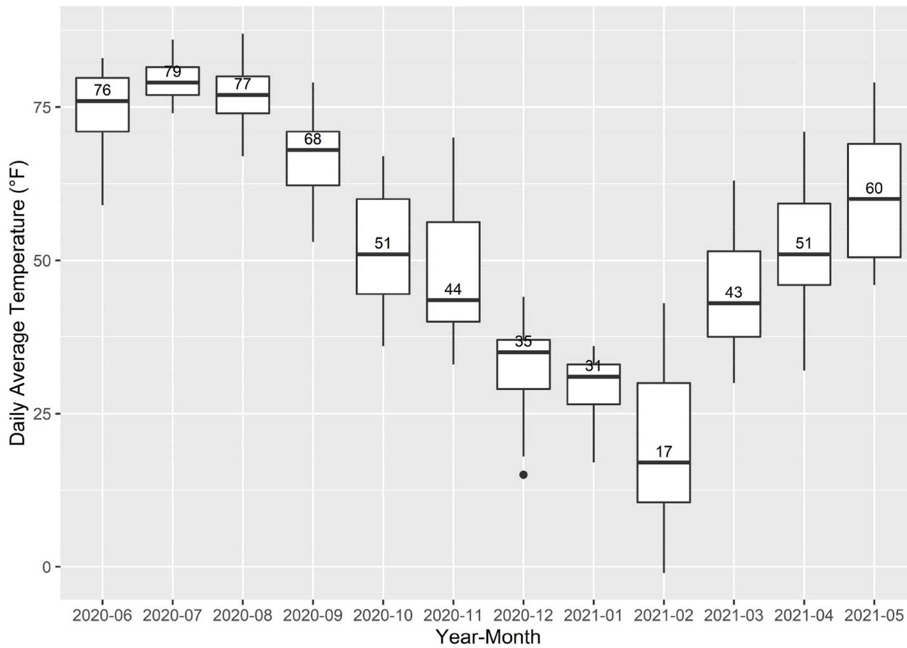

Fig. A3. Monthly fluctuation of outdoor daily average temperature in northern Illinois, USA (June 2020–May 2021). *Data source: U.S. Local Climatological Data. Weather station: USW00094846* (U.S. Department of Commerce, n.d.). *For each month, a boxplot of daily average temperature is shown with the number representing the median.*

Creating a Demographic Profile for Each Household

Because the raw data from ComEd does not include demographic data at the household level and only has nine-digit ZIP Code, we approximated the demographic characteristics of a household by using the demographic characteristics of the U.S. Census block group that this household belongs to. The block group is the smallest geographical unit for which the U.S. Census publishes sample data (U.S. Census Bureau, n.d.). First, we referred to a crosswalk file that provided a relationship between nine-digit ZIP Code and block group (EASI Analytic Software Inc, 2021). We then assigned the demographic characteristics at the block group level to each household. For example, if Household A is in Block Group A, then the median income of this block group would be assigned to Household A. The way we assigned a racial group label to each household was described in the main text (Section 2.1). The Block-Group level demographic data (the 2019 5-year estimates) were sourced from the American Community Survey (ACS; U.S. Census Bureau, 2020).

Connecting ZIP Code and Building Performance Data

To create an energy efficiency profile for a household, we sourced the residential building performance data from the Building Performance Database curated by the Lawrence Berkeley National Laboratory (n.d.), and we used the 2017 data, the latest available. We also note that only five-digit ZIP (instead nine-digit ZIP) was available in the Building Performance Database. Therefore, the median electricity use intensity at the level of five-digit ZIP was used for analysis.

Appendix B

Specification of Regression Models for the Estimation of Balance Point

We randomly drew a sample of 10,000 households within the ComEd utility region to conduct a preliminary analysis using data from three months. We first ran the models using the regression equations based on the original OpenEEmeter method (Plagge et al., 2017). The mean and the median adjusted R^2 were 0.40 and 0.42, respectively. We then fit our own temperature response functions (Equations (3)–(5)). The mean and the median adjusted R^2 improved to 0.55 and 0.59, respectively. We report the comparison of the aggregate levels of goodness of fit across different specifications of the temperature response functions and an evaluation of the stability of the estimated balance points across specifications, below.

The original OpenEEmeter method (Plagge et al., 2017) only included *CD* and *HD* in the temperature response functions:

$$E_i = \mu + \beta_C CD_i + \varepsilon_i, \tag{B1}$$

$$E_i = \mu + \beta_H HD_i + \varepsilon_i, \tag{B2}$$

$$E_i = \mu + \beta_C CD_i + \beta_H HD_i + \varepsilon_i, \tag{B3}$$

where the mean and the median adjusted R^2 were 0.40 and 0.42, respectively ($N = 10{,}000$).

Based on Cong et al. (2022), we added the following covariates to the above temperature response functions (Equation (B1) to B3): the weekend and holiday dummy variables, the day-of-the-week fixed effects, and the month-of-the-year fixed effects.

$$E_i = \mu + \beta_C CD_i + \beta_H HD_i + \beta_W W_i + \beta_{HL} HL_i + \delta_i + \theta_i + \varepsilon_i, \tag{B4}$$

$$E_i = \mu + \beta_C CD_i + \beta_W W_i + \beta_{HL} HL_i + \delta_i + \theta_i + \varepsilon_i, \tag{B5}$$

$$E_i = \mu + \beta_H HD_i + \beta_W W_i + \beta_{HL} HL_i + \delta_i + \theta_i + \varepsilon_i, \tag{B6}$$

where the symbols are defined in the same way as those in the main text. The mean and the median adjusted R^2 were improved to 0.54 and 0.58, respectively (N = 9,997).

Based on Braun et al. (2014), we added the relative humidity as another covariate to the above temperature functions (Equation (B4) to (B6)).

$$E_i = \mu + \beta_C CD_i + \beta_H HD_i + \beta_W W_i + \beta_{HL} HL_i + \beta_{RM} RM_i + \delta_i + \theta_i + \varepsilon_i, \tag{B7}$$

$$E_i = \mu + \beta_C CD_i + \beta_W W_i + \beta_{HL} HL_i + \beta_{RM} RM_i + \delta\mathrm{i} + \theta_i + \varepsilon_i, \tag{B8}$$

$$E_i = \mu + \beta_H HD_i + \beta_W W_i + \beta_{HL} HL_i + \beta_{RM} RM_i + \delta_i + \theta_i + \varepsilon_i, \tag{B9}$$

where RM_i is the daily average relative humidity for day i. The mean and the median adjusted R^2 were slightly improved to 0.55 and 0.59, respectively (N = 9,997).

Based on Lou et al. (2021), we then added several other weather-related covariates, so the temperature response functions became those reported in the main text. The mean and the median adjusted R^2 were 0.55 and 0.59, respectively (N = 9,997), the same as those returned from Equation (B7)-B9.

Based on the goodness of fit of the above temperature response functions, we concluded that the *eemeter* + *Cong* model, the *eemeter* + *Braun* model, and the *eemeter* + *Lou* model fit the data almost equally well. We settled with the eemeter + Lou model, because it was the most exhaustive one regarding the added covariates. There may be other unknown variables that should have been included, but based on the literature on residential temperature response functions (see Fazeli et al., 2016), this seems unlikely. We further examined how stable the estimated balance points were across the eemeter + Cong model, the eemeter + Braun model, and the eemeter + Lou model. We found that 8,109 (81%) households had a 2-degree or less change in the estimated cooling balance points between any of two models, and 7,812 (78%) households had a 2-degree or less change in the estimated heating balance points between any of two models. In conclusion, we considered the estimated balance points from these households as relatively stable across different specifications of the temperature response function.

Validation of Piecewise Linear Regression

Our analysis includes households that have an estimated slope (β_C or β_h) greater than zero at the 0.1 significance level, and a nonnegative intercept (i.e., a nonnegative baseload; see Plagge et al., 2017). We exclude those households whose balance points were equal to the boundary temperatures (30 °F and 90 °F; Woods and Fuller, 2014), because outside of these boundaries the house is assumed to be a secondary residence. Table B1 details the summary of model fit statistics (in adjusted R^2), how many households are included in data analysis, and the percentages of the three model types (cooling and heating [Equation (3)], cooling only [Equation (4)], and heating only [Equation (5)]) of the best fit model.

We find that the model fit was satisfactory (Table B1), with the median adjusted $R^2 = 0.76$, which exceeds the ASHRAE Guideline 14's threshold of 0.70 (Lovvorn et al., 2002; Perez et al., 2017). As expected, we also find that most best-fit models were the combination of cooling and heating models, because this period covered a whole 12-months period when significant cooling need and heating need coexisted.

Table B1
Summary statistics of model fit, description of number of households included in study, and percentage of model type.

Model fit	
Mean R^2_{adj}	0.71
Median R^2_{adj}	0.76
SD of R^2_{adj}	0.19
Number of households included in analysis	
Cooling	418,255
Heating	22,628 (electric heating only)
Percentage of model type	
Cooling & heating	71%
Cooling only	24%
Heating only	5%

Appendix C

Summary Statistics of Estimated Balance Points

For the estimated cooling balance points, the summary statistics of the distribution are: M = 65.89 °F, Mdn = 66 °F, SD = 6.52 °F, n = 418,255; for the estimated heating balance points, M = 52.75 °F, Mdn = 53 °F, SD = 8.81 °F, n = 22,628. The central tendency measures (i.e., mean and median) of the estimated balance points was in general much lower than the recommended indoor environment in the cooling case: 78 °F (U.S. Department of Energy, 2021a) or in the heating case: 65–68 °F (Davillas et al., 2022; Jevons et al., 2016; U.S. Department of Energy, 2021a). However, we note that our estimation does not aim to recover the actual indoor temperature set points at homes. Rather, our methods only estimate the daily average outdoor temperature when households start to turn on cooling or heating units within a span of one year (see Section 2 in the main text). In addition, our model is based on outdoor daily *average* temperature, which considers the upper and lower bounds of temperature variation within a day.

Additional Analysis

Electricity Consumption by Income Groups

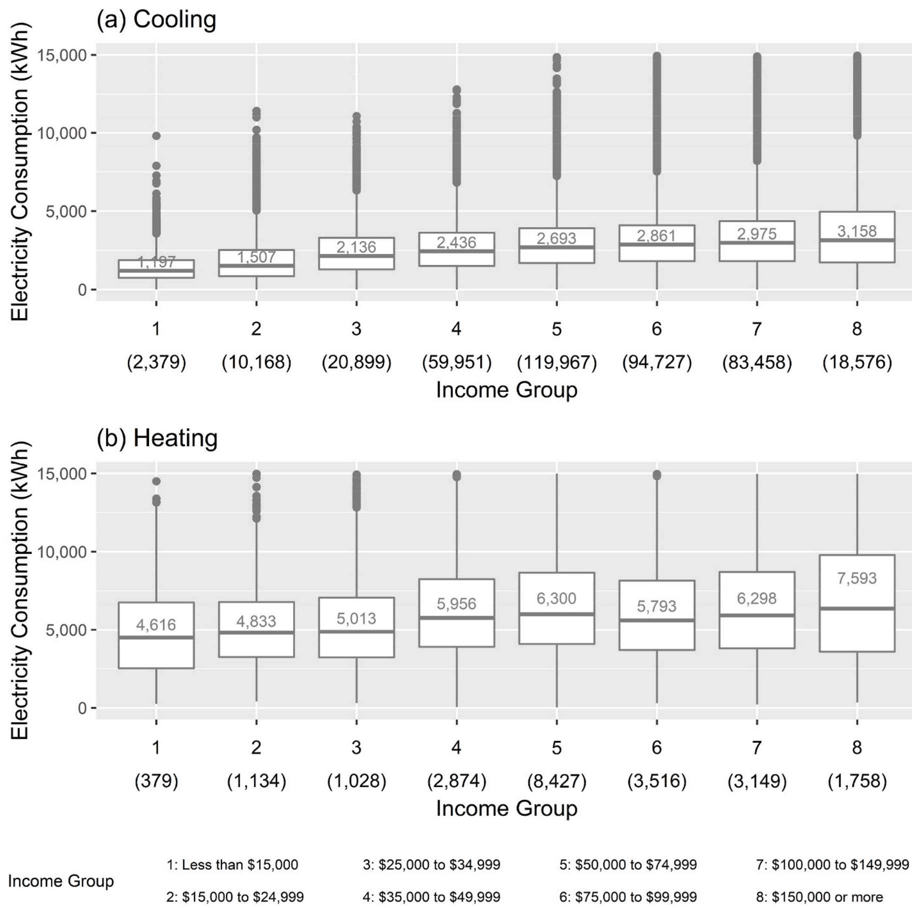

Fig. C1. Electricity consumption by income groups. *Each box and whiskers plot indicates the minima and maxima of electricity consumption (the lower and upper bound of the whiskers), the first and third quantiles (the lower and upper bound of the box), and the median (the middle line). The outliers are shown as dots on either side of the whiskers. The sample size for each racial group is shown under the x-axis in parentheses.*

Slope of Cooling Demand and Heating Demand by Income Groups

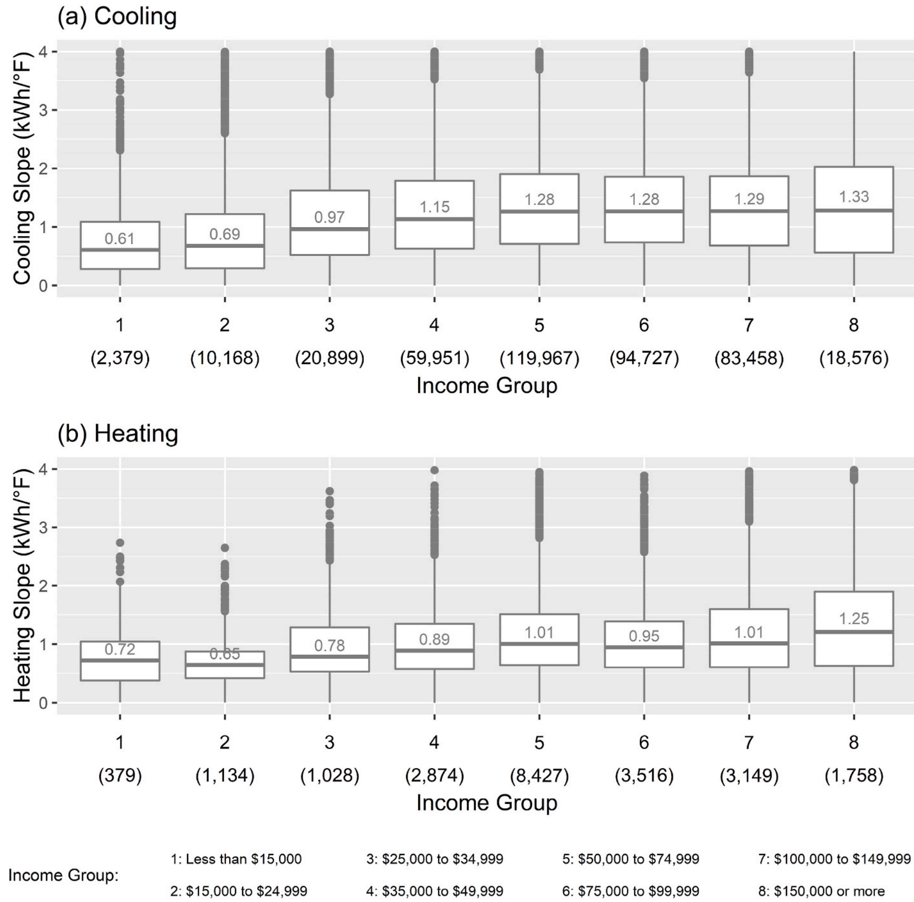

Fig. C2. Slopes by income groups. *Each box and whiskers plot indicates the minima and maxima of slopes of cooling demand (Panel a) and slopes of heating demand (Panel b; the lower and upper bound of the whiskers), the first and third quantiles (the lower and upper bound of the box), and the median (the middle line). The outliers are shown as dots on either side of the whiskers. The sample size for each racial group is shown under the x-axis in parentheses.*

Electricity Consumption by Income Groups Within Racial Groups

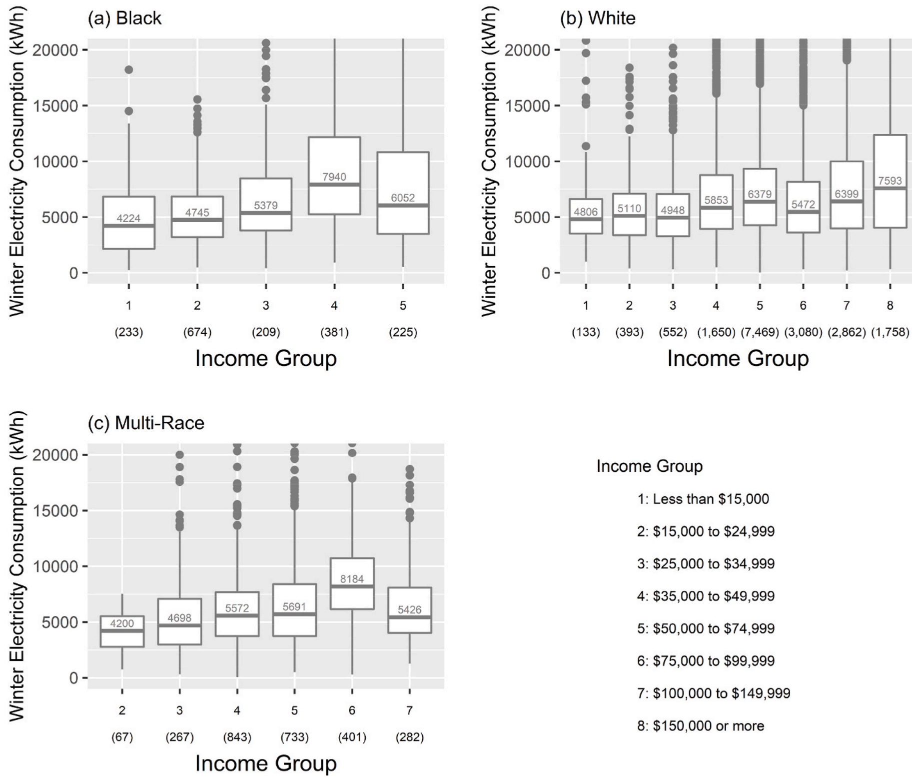

Fig. C3. Electricity consumption by income groups within racial groups. *Each box and whiskers plot indicates the minima and maxima of electricity consumption in heating season of one racial group (the lower and upper bound of the whiskers), the first and third quantiles (the lower and upper bound of the box), and the median (the middle line). The outliers are shown as dots on either side of the whiskers. The sample size for each racial group is shown under the x-axis in parentheses. Any missing income groups in a racial group was due to the missingness or a too small group sample in the data. There was no 'other' racial group found among the households that had an estimated heating balance point.*

Second-Stage Regression Analysis

Based on Equations (1) and (2), energy equity gaps are defined with regard to income. To examine whether income independently has effect on balance point, we controlled for other variables that may correlated with both income and balance point when energy equity gaps are calculated (purging possible spurious relationship from confounding variables). To achieve this goal, we specified two more regression models by adding a set of possible confounding variables based on previous studies (Best et al., 2021; Goldstein et al., 2020; Reames, 2016).

$$CBP_k = \mu + \beta_D D_k + \beta_w W_k + \beta_{OT} OT_k + \beta_M M_k + \beta_I I_k + \beta_A A_k + \beta_O O_k + \beta_{OPR} OPR_k + \beta_{HS} HS_k + \beta_{HS2} HS_k^2 + \beta_{EUI} EUI_k + \beta_{w\text{-}I} W_k \times I_k + \beta_{OT\text{-}I} OT_k \times I_k + \beta_{M\text{-}I} M_k \times I_k + \beta_{A\text{-}I} A_k \times I_k + \varepsilon_k, \tag{C1}$$

$$HBP_k = \mu + \beta_D D_k + \beta_w W_k + \beta_{OT} OT_k + \beta_M M_k + \beta_I I_k + \beta_A A_k + \beta_O O_k + \beta_{OPR} OPR_k + \beta_{HS} HS_k + \beta_{HS2} HS_k^2 + \beta_{EUI} EUI_k + \beta_{w\text{-}I} W_k \times I_k + \beta_{OT\text{-}I} OT_k \times I_k + \beta_{M\text{-}I} M_k \times I_k + \beta_{A\text{-}I} A_k \times I_k + \varepsilon_k, \tag{C2}$$

Where k is the index for household; *CBP* and *HBP* are cooling balance point and heating balance point, respectively; D_k is a dummy variable for account type (1 = Multi-Family, 0 = Single Family); W_k, OT_k, M_k are the dummy variables of racial group (W_k is for white; OT_k is for other; M_k is for mult-race) with households living in black-majority block groups being the reference group; I_k, A_k, O_k, OPR_k, and HS_k are the median income, the median age, the proportion of owner-occupied households, the proportion of households that have 0.5 or less occupants per room, and the average household size of the Census Block Group that the kth household belongs to, respectively; HS_k^2 is the squared term of the household size variable; EUI_k is the median electricity use intensity of residential buildings in the five-digit ZIP that the kth household belongs to; $W_k \times I_k$, $OT_k \times I_k$, $M_k \times I_k$, and $A_k \times I_k$ are the interaction terms either between income and race, or between income and age; ε_k is the error term. The households included in the second-stage regression analysis were the households in the Chicago region only, because the building performance data were only available in this region.

To be consistent with our definition of energy equity gap (Equations (1) and (2) in the main text), in contrast to using the ordinary least squares (OLS) estimator to estimate the conditional mean of balance point, we used the quantile regression estimator to estimate the conditional median of balance point. That is, we fit a quantile regression model with quantile set as 0.5, and we report the pseudo-R^2, a local measure of goodness of fit when quantile = 0.5 (Koenker and Machado, 1999).

In multiple linear regression, high multicollinearity indicates that interdependence among predictors is high and can lead to large standard errors of the estimated coefficients, which applies to both the least square case and the quantile regression case (Davino et al., 2022; Rockwell, 1975). In our data, there was no serious problem regarding multicollinearity among the predictors. In the cooling case, the determinant of the correlation matrix was 0.0002 (a value of zero indicating complete multicollinearity and a value of one indicating no multicollinearity); all predictors' variance inflation factors (VIF; or the squared generalized VIF raised to the power of [1/2 × df] (Fox and Monette, 1992)) were less than 10 (a value greater than 10 indicating a serious problem of multicollinearity (Hair et al., 1992)). In the heating case, the determinant of the correlation matrix was 5.56×10^{-7}, and the household size term and the squared household size both had an VIF value greater than 10. After removing the squared household size, the determinant became close to that in the cooling case (0.0002), and all predictors' VIF values were less than 10. Therefore, the inclusion of the squared household size term introduced greater multicollinearity in the heating case. However, to be consistent with the model specification in the cooling case, we decided to leave this term in the regression model in the heating case. It turned out that the effect of this term was significant.

To examine whether lower income independently associates with higher cooling and heating balance points, we regressed balance point on income and controlled for several other variables using multiple linear regression (see Section 2 in the main text). Based on previous studies (Best et al., 2021; Goldstein et al., 2020; Reames, 2016), the control variables included account type (1 = Multi-Family, 0 = Single Family), the median occupant's age, the proportion of owner-occupied households, the proportion of households that have 0.5 or less occupants per room, the average household size of the Census Block Group that a household belongs to (and the squared term of household size), and the median electricity use intensity of residential buildings in the five-digit ZIP that the a household belongs to. Based on our earlier examinations of energy equity gaps by race and by age, also included in the regression model were the interaction between income and race, and the interaction between income and age (see Equations (C1) and (C2)). Both income and age were median centered for easier interpretation. To be consistent with our definition of energy equity gaps (based on group medians; see Equations (1) and (2) in the main text), the estimator was the quantile regression estimator when the quantile was set as 0.5.

Cooling Balance Point. The regression results were presented in Table C1 for cooling balance point. After controlling for the confounding effects of the variables listed above, we found that the interaction effects between race and income were significant, with households living in black-majority block groups having the greatest negative relationship between income and cooling balance point (Fig. C4). Compared with the households living in black-majority block groups, the negative effect of income on cooling balance point was significantly smaller in magnitude among households living in white-majority block groups ($\beta_{W\text{-}I} = 4.59 \times 10^{-6}$, $SE = 2.10 \times 10^{-6}$, $p = 0.03$), other (non-black and non-white race alone) households ($\beta_{O\text{-}I} = 2.72 \times 10^{-5}$, $SE = 9.25 \times 10^{-6}$, $p = 0.003$), and multi-race households ($\beta_{M\text{-}I} = 1.24 \times 10^{-5}$, $SE = 2.78 \times 10^{-6}$, $p < 0.001$). To further corroborate the negative effect of income on cooling balance point, except for the other racial group, we show that the simple negative effect of income on cooling balance point ('simple' meaning that it is the estimated linear effect of income on balance point at each level of racial group) was significant for all racial groups: black ($\beta_{S\text{-}B} = -2.83 \times 10^{-5}$, $SE = 1.90 \times 10^{-6}$, 95% CI [-3.20×10^{-5}, -2.46×10^{-5}]), white ($\beta_{S\text{-}W} = -2.37 \times 10^{-5}$, $SE = 6.94 \times 10^{-7}$, 95% CI [-2.51×10^{-5}, -2.23×10^{-5}]), and multi-race ($\beta_{S\text{-}M} = -1.59 \times 10^{-5}$, $SE = 2.26 \times 10^{-6}$, 95% CI [-2.03×10^{-5}, -1.14×10^{-5}]). Beyond the interaction effects between income and race, we also found that on average households living in black-majority block groups had a higher cooling balance point than the rest of the racial groups by 1.27–2.50 °F when income was held constant at the median.

The interaction effect between income and age was also significant ($\beta_{A\text{-}I} = 6.68 \times 10^{-7}$, $SE = 2.10 \times 10^{-6}$, $p = 0.03$). The pattern of the interaction effect is shown in Fig. C5. As age increases, the negative effect of income on cooling balance point becomes smaller in magnitude and eventually becomes positive at the age of 80. The simple effects of income on cooling balance point (at the five selected values of age in Fig. C5) were found to be negative and significant for the three younger age groups (see Table C2); at the age of 60, the simple effect was not significant; and at the age of 80, the simple effect became positive and significant. Beyond the interaction effects between income and age, we also found that older households had a higher cooling balance point at the median income. This pattern applies to other income values as well (Fig. C5).

In sum, based on the second-stage regression analysis, we have more confidence in concluding that the cooling energy equity gaps presented in the main text were indeed independently contributed by income. More importantly, households living in black-majority block groups were more likely to endure higher cooling balance points in general, and they were susceptible to greater cooling energy equity gaps than the rest of the racial groups. On average, if we use a difference of $150,000 to approximate the income difference between the lowest-income group and the highest-income group, the corresponding differences in cooling balance point were 4.25 °F and 3.56 °F for households living in black-majority block groups and households living in white-majority block groups, respectively. Noticeably, although younger households kept a lower cooling balance point in general, the energy equity gaps among younger households were wider than their older counterparts.

Table C1
Regression results using cooling balance point as the dependent variable

Effect	Estimate	Standard Error[a]	95% Confidence Interval		p
			Lower Limit	Upper Limit	
Intercept	65.11	0.19	64.73	65.49	<0.001
Income	-2.96×10^{-5}	2.09×10^{-6}	-3.37×10^{-5}	-2.55×10^{-5}	<0.001
White (vs. Black)	−1.27	0.07	−1.41	−1.14	<0.001
Other (vs. Black)	−1.38	0.25	−1.86	−0.89	<0.001
Multi-Race (vs. Black)	−1.50	0.08	−1.67	−1.34	<0.001
Age	0.07	0.003	0.06	0.07	<0.001
Income × White	4.59×10^{-6}	2.10×10^{-6}	4.65×10^{-7}	8.72×10^{-6}	0.03
Income × Other	2.72×10^{-5}	9.25×10^{-6}	9.10×10^{-6}	4.53×10^{-5}	0.003
Income × Multi-Race	1.24×10^{-5}	2.78×10^{-6}	6.96×10^{-6}	1.79×10^{-5}	<0.001
Income × Age	6.68×10^{-7}	5.13×10^{-8}	5.67×10^{-7}	7.68×10^{-7}	<0.001
Delivery class[b]	−1.20	0.04	−1.29	−1.12	<0.001
Proportion of owner- occupied households	1.59	0.11	1.37	1.81	<0.001
Proportion of households having 0.5 or less occupants per room	1.64	0.16	1.33	1.95	<0.001
Household size	0.69	0.04	0.61	0.77	<0.001
Household size squared	−0.02	0.001	−0.02	−0.02	<0.001
Electricity use intensity	−0.04	0.002	−0.05	−0.04	<0.001

Note. Pseudo-$R^2 = 0.052$; $n = 153{,}799$. The estimator is the quantile regression estimator with quantile = 0.5. Intercept represents the predicted median of cooling balance point when the rest of the predictors equal zero (if not centered) or median (if centered).
[a] Standard error assumes the residuals are independent and identically distributed.
[b] 1 = multi-family, 0 = single family.

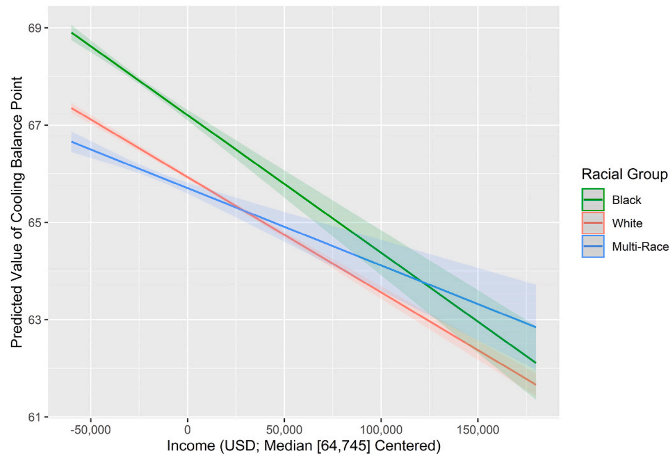

Fig. C4. Predicted Cooling Balance Points as a Function of Income by Racial Groups. *The predicted value of cooling balance point at each level of income is calculated based on the regression results (Table C1) and the averaged-over values of all other predictors (i.e., predictors excluding income and race). Income is centered at median (USD 64,745). The ribbon represents the 95% confidence intervals around the predicted value. The "other" racial group was excluded from this figure because the simple effect of income on cooling balance point for this racial group was not significant ($\beta_{S\text{-}OT} = -1.07 \times 10^{-6}$, $SE = 7.34 \times 10^{-6}$, 95% CI [-1.55×10^{-5}, 1.33×10^{-5}]).*

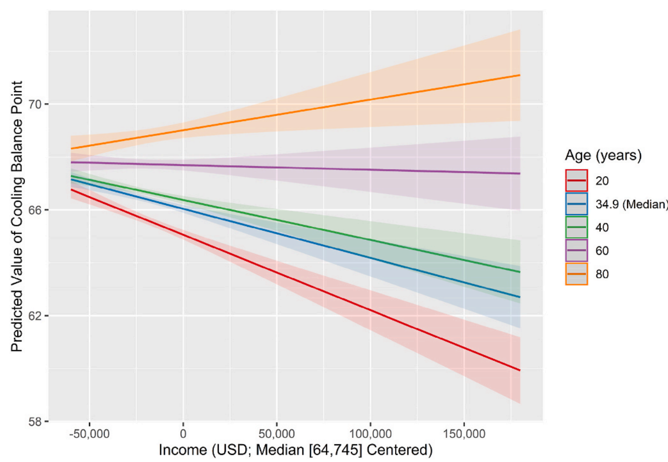

Fig. C5. Predicted Cooling Balance Points as a Function of Income by Age Groups. *The predicted value of cooling balance point at each level of income is calculated based on the regression results (Table C1) and the averaged-over values of all other predictors (i.e., predictors excluding income and age). Income is centered at median (USD 64,745). The ribbon represents the 95% confidence intervals around the predicted value. Age 34.9 is the observed median age in the data.*

Table C2
Simple Effect of Income on Cooling Balance Point by Age

Age	Estimate	Standard Error	95% Confidence Interval	
			Lower Limit	Upper Limit
20.0 Years	-2.85×10^{-5}	2.21×10^{-6}	-3.28×10^{-5}	-2.42×10^{-5}
34.9 Years (Median)	-1.86×10^{-5}	2.03×10^{-6}	-2.25×10^{-5}	-1.46×10^{-5}
40.0 Years	-1.51×10^{-5}	2.06×10^{-6}	-1.92×10^{-5}	-1.11×10^{-5}
60.0 Years	-1.79×10^{-5}	2.62×10^{-6}	-6.92×10^{-6}	3.34×10^{-6}
80.0 Years	1.16×10^{-5}	3.56×10^{-6}	4.60×10^{-6}	1.85×10^{-5}

Note. Age 34.9 is the observed median age in the data.

Heating Balance Point. For heating balance point (Table C3), the only notable significant effect that is of our major concern is the interaction between income and age ($\beta_{A\text{-}I} = 1.19 \times 10^{-6}$, $SE = 4.97 \times 10^{-7}$, $p = 0.02$). The pattern of the interaction is shown in Fig. C6. As age increases, we found the expected *positive* relationship between income and heating balance point. The simple effects of income on heating balance point (at the five selected values of age in Fig. C6) were shown in Table C4. Most importantly, the estimated linear effects are $\beta_{S\text{-}A[60]} = 5.42 \times 10^{-5}$, $SE = 2.25 \times 10^{-5}$, 95% CI [1.01×10^{-5}, 9.83×10^{-5}], $\beta_{S\text{-}A[80]} = 7.81 \times 10^{-5}$, $SE = 2.59 \times 10^{-5}$, 95% CI [2.74×10^{-5}, 1.29×10^{-4}], respectively for 60 and 80 years old. In other words, the second-stage regression analysis reveals that older households are more susceptible to heating energy equity gap, in the way that meets our assumption that lower-income households have lower heating balance points; and as age increases, the gap becomes wider.

Table C3
Regression results using heating balance point as the dependent variable

Effect	Estimate	Standard Error[a]	95% Confidence Interval		p
			Lower Limit	Upper Limit	
Intercept	44.2	6.48	31.5	56.9	<0.001
Income	-3.25×10^{-5}	4.82×10^{-5}	-1.27×10^{-4}	6.20×10^{-5}	0.50
White (vs. Black)	−0.54	3.23	−6.88	5.80	0.87
Multi-Race (vs. Black)	3.35	3.89	−4.27	10.97	0.39
Age	0.05	0.04	−0.02	0.13	0.17
Income × White	3.49×10^{-5}	4.83×10^{-5}	-5.97×10^{-5}	1.29×10^{-4}	0.47
Income × Multi-Race	1.35×10^{-4}	7.79×10^{-5}	-1.77×10^{-5}	2.87×10^{-4}	0.08
Income × Age	1.19×10^{-6}	4.97×10^{-7}	2.19×10^{-7}	2.17×10^{-6}	0.02
Delivery class[b]	−2.52	4.38	−11.1	6.10	0.57
Proportion of owner- occupied households	−6.36	1.90	−10.08	−2.65	<0.001
Proportion of households having 0.5 or less occupants per room	7.03	2.38	2.36	11.70	0.003
Household size	7.67	2.53	2.72	12.63	0.002
Household size squared	−1.12	0.46	−2.03	−0.21	0.02
Electricity use intensity	−0.11	0.05	−0.21	-7.42×10^{-4}	0.05

Note. Pseudo-$R^2 = 0.031$; $n = 5992$. The estimator is the quantile regression estimator with quantile = 0.5. Intercept represents the predicted median of heating balance point when the rest of the predictors equal zero (if not centered) or median (if centered).
[a] Standard error assumes the residuals are independent and identically distributed.
[b] 1 = multi-family, 0 = single family.

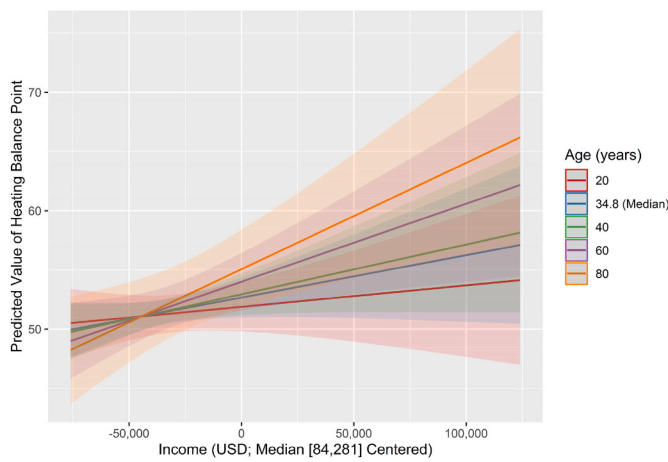

Fig. C6. Predicted Heating Balance Points as a Function of Income by Age Groups. *The predicted value of heating balance point at each level of income is calculated based on the regression results (Table C3) and the averaged-over values of all other predictors (i.e., predictors excluding income and age). Income is centered at median (USD 84,281). The ribbon represents the 95% confidence intervals around the predicted value. Age 34.8 is the observed median age in the data.*

Table C4
Simple Effect of Income on Heating Balance Point by Age

Age	Estimate	Standard Error	95% Confidence Interval	
			Lower Limit	Upper Limit
20.0 Years	6.52×10^{-6}	2.29×10^{-5}	-3.84×10^{-5}	5.15×10^{-5}
34.8 Years (Median)	2.42×10^{-5}	2.16×10^{-5}	-1.81×10^{-5}	6.64×10^{-5}
40.0 Years	3.04×10^{-5}	2.14×10^{-5}	-1.16×10^{-5}	7.23×10^{-5}
60.0 Years	5.42×10^{-5}	2.25×10^{-5}	1.01×10^{-5}	9.83×10^{-5}
80.0 Years	7.81×10^{-5}	2.59×10^{-5}	2.74×10^{-5}	1.29×10^{-4}

Note. Age 34.8 is the observed median age in the data.

Cooling Balance Points by Racial Group Alone

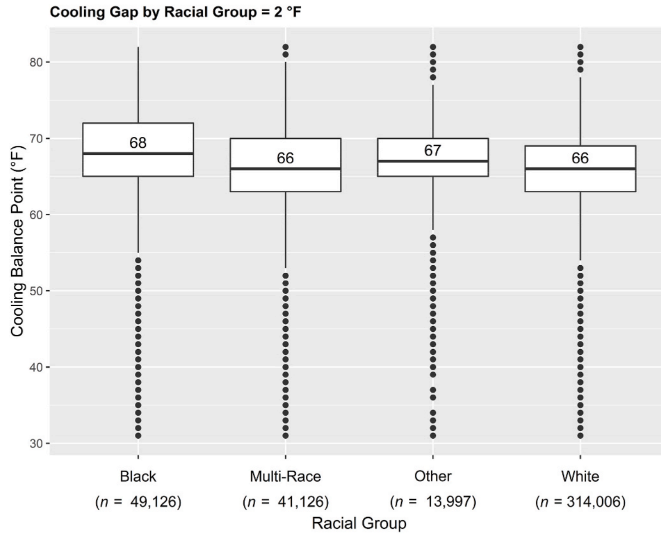

Fig. C7. Cooling balance points by racial groups. *Racial group labels were determined by the majority group (> 50%) in a U.S. Census block group that a household lives in. Each box and whiskers plot indicates the minima and maxima of balance point of one racial group (the lower and upper bound of the whiskers), the first and third quantiles (the lower and upper bound of the box), and the median (the middle line). The outliers are shown as dots on either side of the whiskers. The sample size for each racial group is shown under the x-axis in parentheses. The Kruskal-Wallis test (two-tailed) showed that the differences in group medians were significant* ($H[3] = 8874.2$, $p < 0.001$).

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