

Common Response, Unequal Vulnerability: Heat and Residential Electricity Demand Across Chinese Cities

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Abstract

Heat sensitivity of residential electricity demand is often expected to vary with development. Using a panel of 151 Chinese cities from 2000 to 2020, we find that electricity use rises by 7.9% per additional 10,000 population-weighted cooling degree-hours, with no detectable heating response. Cooling sensitivity does not systematically vary with income, urbanization, air-conditioner (AC) ownership, or urban versus rural residence. Projected climate-driven demand increases reach 81% in the hottest third of cities. Vulnerability peaks under Shared Socioeconomic Pathway (SSP) 3-7.0, where high heat hazard meets low income-based adaptive capacity, rather than the warmer SSP5-8.5. Vulnerability is highest in southern cities, whereas population-scaled risk concentrates in coastal megacities. Twenty-nine cities, home to about 160 million people and concentrated in the Pearl River Delta and middle Yangtze basin, rank high on both. Adaptation must address both the burden per resident and aggregate population risk.

Climate warming is increasing residential electricity demand as households use air conditioning more intensively and adopt it more widely (Auffhammer and Mansur, 2014; Li et al., 2018; Guo et al., 2025). This growing demand creates a challenge for electricity planning and climate adaptation, particularly when extreme heat coincides with disruptions to supply. In China, prolonged heatwaves in summer 2022 sharply increased cooling demand while severe drought in the Yangtze River basin reduced hydropower generation, prompting power rationing and temporary factory shutdowns (An and Zhang, 2023; Hao et al., 2025). Chinese panel and household studies show that cooling and heating exposure influence residential electricity use, with greater changes expected under continued warming (Fan et al., 2019; Li et al., 2019; Zhang et al., 2022; Hu et al., 2025). Understanding how these responses vary across cities is therefore essential for anticipating future demand and identifying adaptation priorities.

Socioeconomic development could either amplify or reduce the electricity response to heat. Income, population, and consumption patterns are established drivers of electricity demand (Zhao et al., 2012; Lin and Wang, 2020). Energy efficiency and supporting policies further shape this demand (Filippini and Zhang, 2016). Higher incomes and wider air-conditioner ownership strengthen cooling responses by relaxing appliance and budget constraints (Auffhammer and Mansur, 2014; Zhang et al., 2022; Caron et al., 2017). Denser urban development and stronger urban heat islands increase cooling needs (Santamouris et al., 2015; Yan et al., 2026). Conversely, income growth may support adaptation that reduces the marginal electricity response to heat, as evidence from the Yangtze River Delta suggests (Zhang et al., 2021, 2020). Urban and rural responses may also differ, although these differences could narrow as rural incomes rise and air conditioning spreads (Sun and Hanemann, 2024; Zhang et al., 2023; Wang et al., 2022a; Herrerías et al., 2017; Han and Wu, 2018). The direction and consistency of these development gradients remain uncertain.

These competing expectations have rarely been tested across China using a consistent, long-term city panel. Much of the existing evidence comes from high-income countries (Auffhammer et al., 2017; Auffhammer and Mansur, 2014; Reyna and Chester, 2017), while Chinese studies often focus on individual provinces or city clusters, aggregate or survey data, or short observation periods (Li et al., 2019; Zhang et al., 2021, 2023). Limited availability of detailed residential electricity records has constrained nationwide comparisons. Moreover, differences in marginal electricity responses alone cannot establish which cities face the greatest heat-related challenges. Cities with similar responses may experience different levels of heat exposure and have different resources for adaptation. Income thus has two distinct roles: it may modify the electricity response to heat, and it provides a proxy for the resources available for adaptation (Turner et al., 2003; IPCC, 2022). A city with a moderate electricity response can therefore remain vulnerable if high heat exposure coincides with limited resources to meet cooling needs (Lin and Wang, 2020; Li et al., 2023).

Here, we assemble a panel of 151 prefecture-level Chinese cities from 2000 to 2020, combining residential electricity and socioeconomic records with population-weighted cooling and heating degree-hours calculated from a heat index incorporating temperature and relative humidity. Using city and year fixed effects, we estimate electricity responses to cooling and heating exposure and test whether development features modify these responses within and across cities. We then project electricity demand under alternative climate and development pathways. Separately, we construct a vulnerability index combining heat hazard and income-based adaptive capacity, and a companion risk index incorporating exposed population. These indices distinguish potential vulnerability at the resident level from the scale of population exposure across cities. Together, the analyses examine whether unequal heat impacts arise from differences in electricity sensitivity, heat exposure, or adaptive capacity, and where these dimensions indicate different adaptation priorities.

Results

Heat exposure increases residential electricity use

Residential electricity consumption responds strongly to cooling exposure. In the primary two-way fixed-effects model (Table 1), an additional 10,000 pw-CDH raises log residential electricity by 0.076 points ($\hat{\beta}_1 = 0.0765$, $P < 0.001$), equivalent to about 7.9%. At the sample mean, this implies an elasticity with respect to pw-CDH of about 0.099. In contrast, the heating response is imprecisely estimated and not statistically different from zero (0.053 per 10,000 pw-HDH, $P = 0.106$).

The cooling response is robust to the addition of controls and the choice of threshold. It remains positive and significant at the 1% level across cooling thresholds from 24 to 28 °C (Table S1). The coefficient increases with the threshold as fewer degree-hours remain. The heating response remains small and insignificant across thresholds from 9 to 13 °C. This limited heating evidence may reflect the sample’s sparse coverage of the cold north (Fig. S1) and the use of district systems rather than electricity for much residential heating in China.

Descriptive patterns are consistent with the estimated cooling response, although they do not provide the same identification. Hotter and richer cities use more residential electricity per person, but these cross-sectional associations also reflect other differences between cities (Fig. S2). After removing each city’s secular electricity trend, consumption runs above trend in hot years and below it in cool years, with a pooled slope of 6% per 10,000 pw-CDH (Fig. S3a). Individual city slopes are positive in 77% of the cities included in this descriptive analysis (Fig. S3b).

Cooling sensitivity does not systematically vary with development level

We examine whether development characteristics modify cooling sensitivity at the sector and city levels. The sector analysis compares urban and rural sectors and tests AC ownership, household size, income, and population (Table 2). The city analysis tests urbanization, GDP per capita (GDPPC), population, and AC ownership (Table 3). At the sector level, AC ownership, income, and population show no statistically detectable moderation of either cooling or heating. Household size is the exception: a one-unit increase in log household size raises the cooling coefficient by 0.288 ($P = 0.008$), while the heating response shows no detectable change.

The urban interaction is negative (-0.049 , $P = 0.083$), suggesting a weaker cooling response in urban than rural sectors, although the contrast is uncertain. Rural households are larger within the same city and year (3.41 versus 3.04 persons). On the common household-reporting subsample, the urban interaction decreases in magnitude to -0.022 , and its standard error rises from 0.028 to 0.038 (Table S2). Including household size jointly reduces the urban interaction further to -0.016 , while the household-size interaction remains close to its separate estimate (0.285 versus 0.288). Sample composition and household structure therefore appear to contribute to the sector contrast, although the limited precision of the 70-city subsample does not rule out an independent sector difference.

At the city level, none of the interactions is significant at the 5% level for cooling or heating (Table 3). The smallest cooling interaction P value is 0.088, for urbanization. Given evidence that income can modify cooling sensitivity (Auffhammer and Mansur, 2014; Zhang et al., 2021), we also compare responses across GDPPC terciles (Table S3). The coefficients are 0.092, 0.066, and 0.065 from the poorest to the richest tercile. Although the poorest group has the largest point estimate, pairwise differences are not statistically distinguishable. The interaction and grouped estimates thus provide no clear evidence of a systematic income gradient.

Together, the sector and city analyses do not support assigning systematically stronger cooling responses to wealthier, more urbanized, or more air-conditioned cities. Household size is associated with cooling sensitivity, but the evidence for a separate urban and rural difference remains uncertain. We therefore apply a common cooling coefficient in the city projections. This modeling choice allows differences in projected cooling exposure to shape climate-driven demand growth without imposing a development gradient that the estimates do not clearly establish.

Warming raises demand most in hot cities, while income drives total growth

Cooling exposure increases under all four SSP scenarios in both the mid-future (2040–2059) and far-future (2080–2099) periods. Additional pw-CDH range from about 9,800 under SSP1-2.6 in the mid-future to about 49,800 under SSP5-8.5 in the far future. Applying the common cooling coefficient gives climate-driven residential electricity increases of about 8% and 49%, respectively (Fig. 1). These scenario contrasts reflect differences in projected exposure, with greater warming producing larger climate-driven demand increases under the assumed constant cooling response.

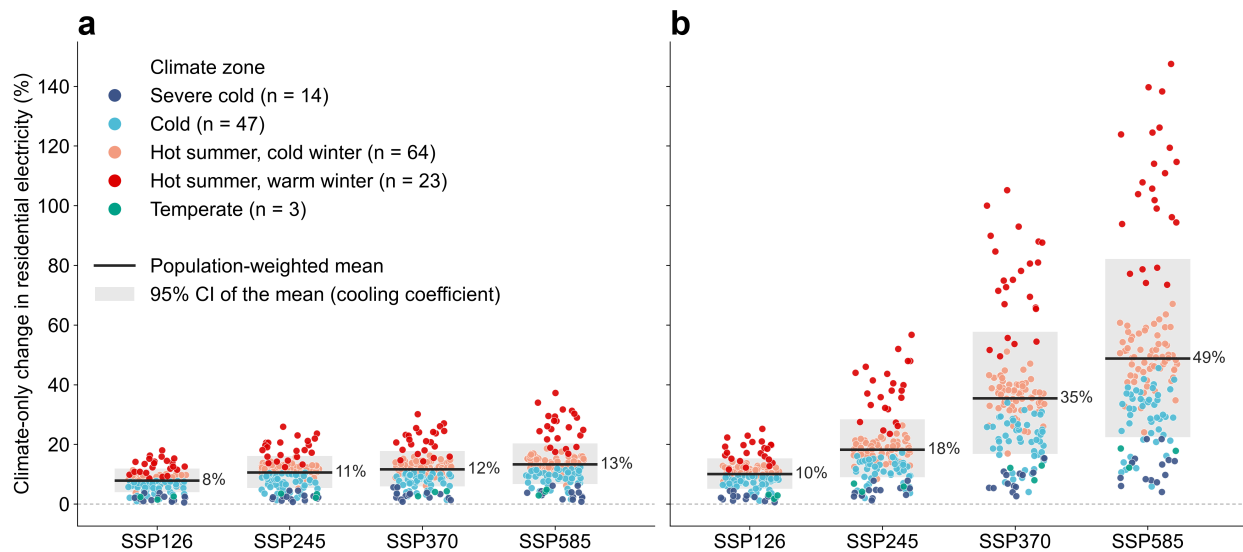


Fig. 1 | Climate-only change in residential electricity demand under each SSP scenario for the mid-future (2040–2059, **a**) and far-future (2080–2099, **b**) periods. Each dot is one of the 151 sample cities, coloured by climate zone. The black bar is the population-weighted mean, and the grey band is the 95% confidence interval implied by the cooling coefficient.

The largest increases occur in cities that are already hot. Under SSP5-8.5 in the far future, the population-weighted increase reaches about 106% in the hot summer and warm winter zone, compared with 49% in the hot summer and cold winter zone, 31% in the cold zone, and 13% in the severe cold zone. Grouping cities by historical cooling exposure gives the same pattern: increases average about 25%, 45%, and 81% in the coolest, middle, and hottest thirds (Fig. S4a). Both orderings persist across scenarios and periods, indicating that additional cooling demand concentrates in already hot cities.

Income growth nevertheless dominates the projected change in total residential electricity under the assumed socioeconomic elasticities (Fig. 2). From an observed baseline of about 435 TWh across the 151 cities, income contributes most in every scenario and period and across the specified elasticity

127 ranges. Population contributes slightly positively at mid-century and negatively thereafter, while
 128 the climate contribution remains positive and grows with warming. In absolute magnitude, late-
 129 century population decline exceeds the climate contribution under SSP1-2.6 (377 versus 92 TWh)
 130 and SSP2-4.5 (275 versus 159 TWh), whereas climate contributes more under SSP3-7.0 and SSP5-
 131 8.5.

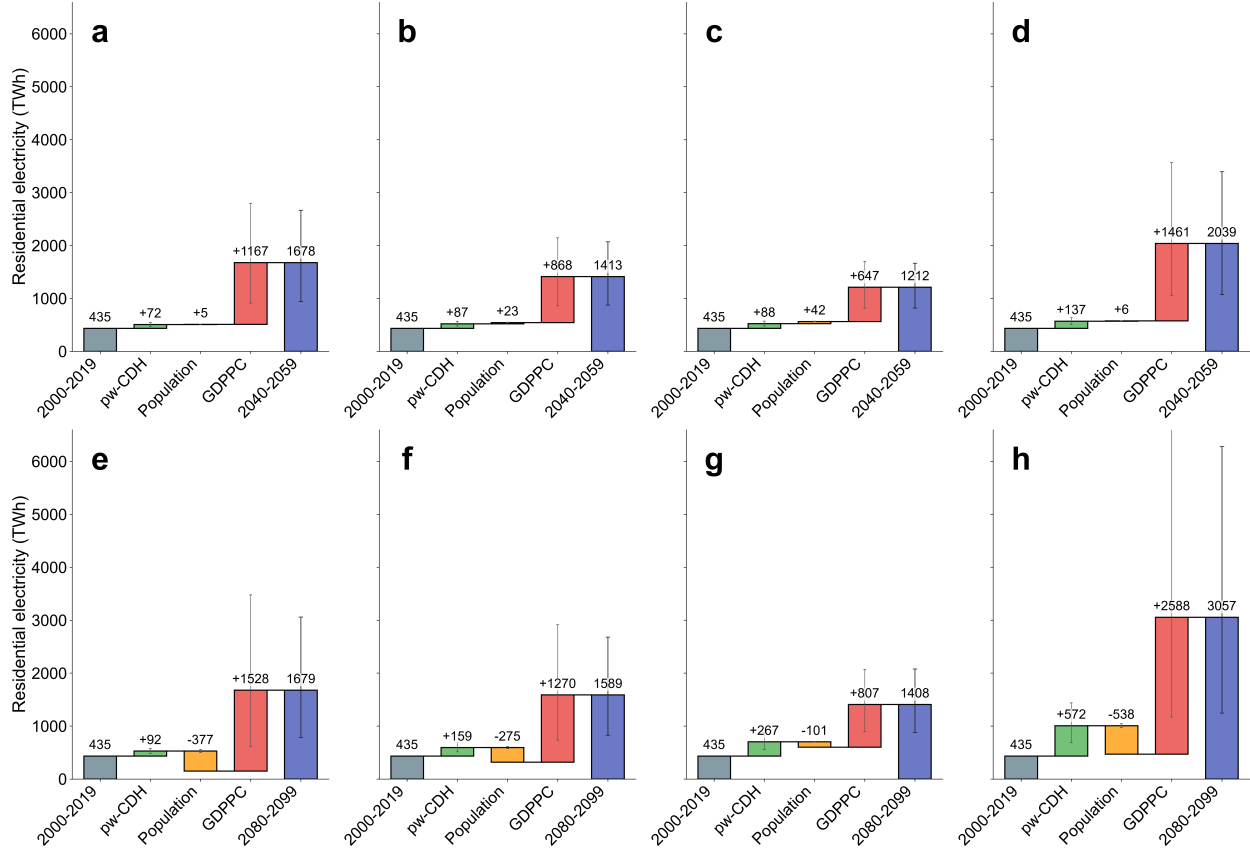


Fig. 2 | Decomposition of the projected change in total residential electricity for the 151 cities, from the observed 2000–2019 baseline to each future period. **a–d**, Mid-future (2040–2059) under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. **e–h**, Far-future (2080–2099) under the same scenarios. Each panel adds the climate (pw-CDH), population, and income (GDPPC) contributions in turn. Contributions are computed as an exact Logarithmic Mean Divisia Index (LMDI) attribution. Whiskers on the final bar give the 90% interval combining coefficient and climate-model uncertainty.

132 The dominance of income is conditional on the assigned socioeconomic responses. The cooling
 133 coefficient is estimated from annual weather variation, whereas income and population contributions
 134 depend on assumed elasticities and SSP trajectories. In particular, the income contribution assumes
 135 that a given percentage increase in income produces the same percentage response in electricity
 136 demand throughout the century, even as income rises substantially. Maps of population change,
 137 GDPPC growth, and total demand change show how these drivers combine geographically (Fig. S4b–
 138 d).

Slow income growth makes SSP3-7.0 more vulnerable than warmer SSP5-8.5

Greater total electricity demand does not necessarily imply greater vulnerability, because income both raises demand and provides resources to meet cooling needs. The vulnerability index combines the estimated electricity rise from pw-CDH with income-based adaptive capacity, while the companion risk index additionally incorporates exposed population. Under this definition, vulnerability is highest under SSP3-7.0, where strong warming coincides with slow income growth (Fig. 3). Its population-weighted mean rises from about 23 in the present to about 38 in the far future. Under SSP1-2.6, the far-future mean instead falls to about 21, below the present level.

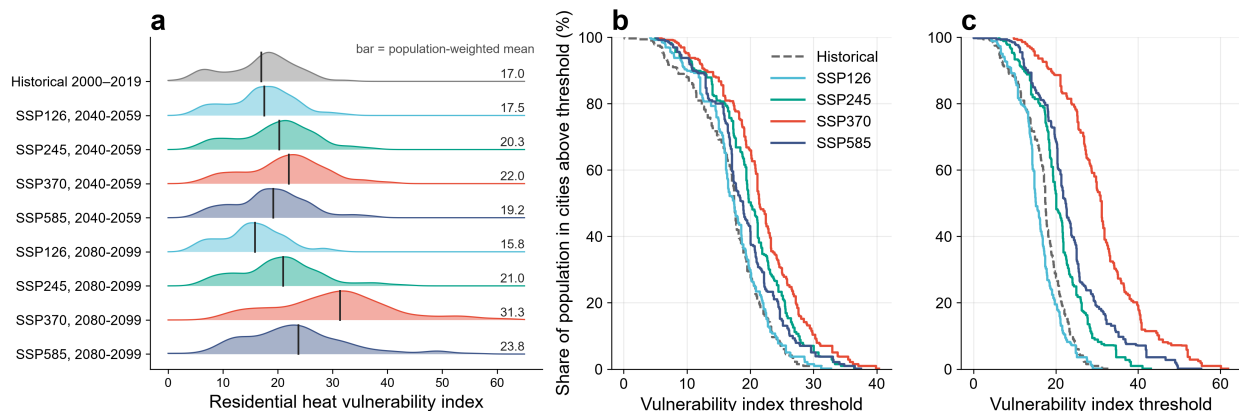


Fig. 3 | Residential heat vulnerability index across cities, scenarios, and time periods. The index is the geometric mean of normalized hazard (the estimated electricity rise from pw-CDH) and lack of adaptive capacity (one minus normalized log GDPPC). **a**, Distribution across the 151 cities for the historical baseline and each scenario-horizon combination, with the population-weighted mean marked in black. **b,c**, Share of the sample population in cities exceeding each index value, for the mid-future and far-future periods.

SSP5-8.5 produces lower vulnerability than SSP3-7.0 despite greater warming, because faster income growth provides greater adaptive capacity within the index. This contrast is also evident in individual cities (Fig. S5). In the far future, Guangzhou’s vulnerability is about 45 under SSP3-7.0 and 23 under SSP5-8.5, while Zhanjiang’s is 63 and 49, respectively. In these comparisons, higher income under SSP5-8.5 more than offsets its greater hazard. The scenario ranking therefore depends on the balance between additional cooling demand and the resources available to meet it, rather than on warming alone.

This scenario ordering is stable under the tested component weights. Doubling the weight on either hazard or adaptive capacity leaves SSP3-7.0 the most vulnerable scenario, with city rank correlations above 0.94 (Fig. S7a). An alternative vulnerability index that combines its components additively and includes rural population share retains four of the five most vulnerable cities identified by the main index. However, correlations between the two indices across cities are lower, at 0.4–0.7 (Fig. S7b). The main rankings are thus stable to the tested weight changes, while the broader change in index formulation produces greater differences.

Vulnerability and population risk identify different adaptation priorities

In the far future, the most vulnerable cities concentrate in the far south, whereas the highest population risk occurs in large cities (Fig. 4). Vulnerability is highest in the hot cities of the far south, particularly along the Guangxi and western Guangdong coast and on Hainan. Danzhou, Guigang, and Yulin rank among the most vulnerable cities across scenarios, whereas Chongqing, Shenzhen, and Shanghai are among those with the highest risk. Shantou appears most frequently in both sets of top-five lists (Fig. 4a). Under SSP3-7.0, four of the five most vulnerable cities fall in the poorest projected income quintile, and Zhanjiang falls in the second poorest. Their vulnerability reflects a large additional cooling demand burden relative to their adaptive capacity, while population risk also accounts for the number of residents exposed.

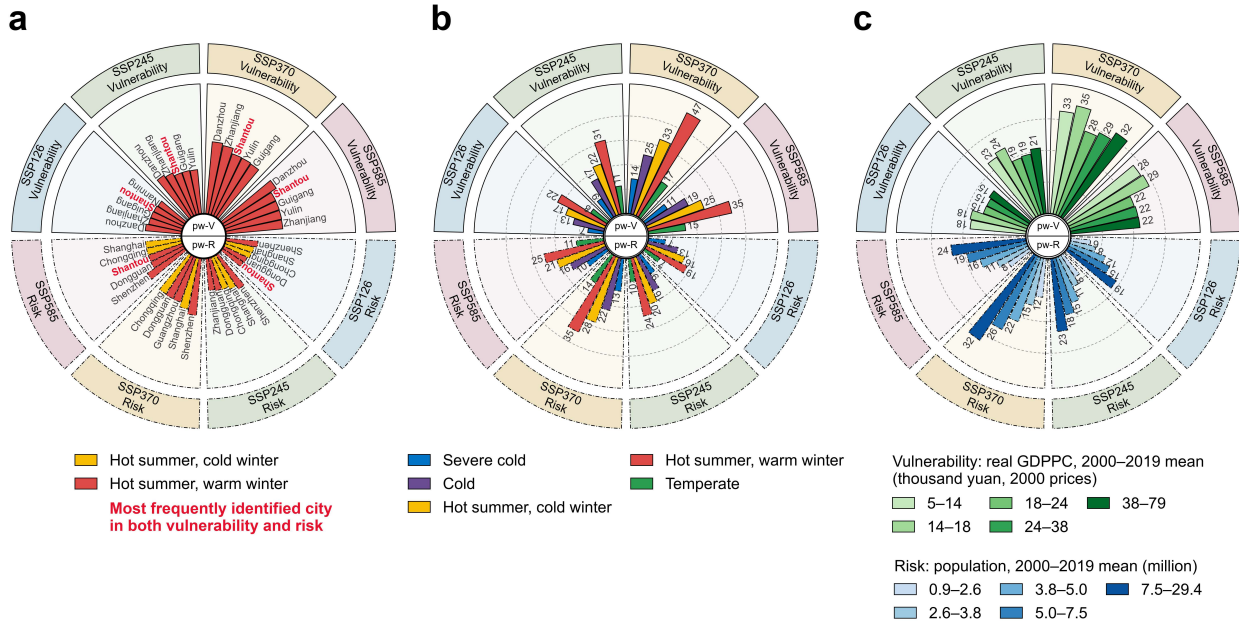


Fig. 4 | Population-weighted vulnerability and risk indices by scenario in the far future (2080–2099). Each sector shows one scenario, with vulnerability in the upper half of each circle (solid outlines) and risk in the lower half (dash-dot outlines). **a**, The five most vulnerable cities and the five cities with the highest risk, coloured by climate zone. The city identified most frequently across both indices is named in red. **b**, Five climate zones. **c**, Five income quintiles for vulnerability and five population quintiles for risk. Income and population quintiles are defined by 2000–2019 baseline means and held fixed across scenarios. Bar length is the population-weighted mean index of each group, or the city's own index in **a**. Fig. S8 shows both time periods.

Comparisons across climate, income, and population groups reinforce these contrasting priorities (Fig. 4b,c). Under SSP3-7.0 in the far future, vulnerability averages 53 in the hot summer and warm winter zone, compared with 19 in the severe cold zone. However, it varies little across baseline income quintiles, from 40 in the poorest to 38 in the richest, because projected income convergence weakens the baseline income ordering. Risk instead increases with baseline population quintile, from 14 in the smallest to 37 in the largest. Income and population quintiles are defined using 2000–2019 baseline values. Each city remains in the same quintile across scenarios and future periods.

The distinction between vulnerability and population risk also produces substantial differences in city rankings. In the far-future comparison averaged across pathways, the rankings correlate at 0.58 and share only five of their top ten cities (Fig. S6). Danzhou ranks first on vulnerability but 128th of 151 on risk, illustrating how a small exposed population can limit population risk despite high vulnerability. Shanghai ranks second on risk but 84th on vulnerability, whereas Shenzhen ranks first on risk and eighth on vulnerability. These contrasts show why screening by population risk alone can overlook smaller vulnerable cities, while screening by vulnerability alone can overlook cities with large exposed populations.

Considering both indices identifies both distinct and overlapping adaptation priorities. In the far future, 12 cities combine high vulnerability with low risk, while one combines high risk with low vulnerability (Fig. S6). Meanwhile, 29 cities rank in the top tercile of both indices and contain about 160 million residents, or 29% of the sample population. All but Nanyang lie in the south, and 28 belong to the two hot summer climate zones. They cluster particularly in the Pearl River Delta, the Guangdong and Guangxi coast, and the middle Yangtze basin. These cities warrant attention under both measures because a large cooling demand burden relative to adaptive capacity coincides with substantial population exposure.

Discussion

Residential electricity use responds strongly to cooling exposure, but we find no robust evidence that income, urbanization, or air-conditioner ownership systematically modifies this response within or across cities. The urban and rural contrast becomes small and imprecise on the common household-reporting subsample, while the household size association persists. The central finding is therefore that the data do not support a general development gradient in marginal cooling sensitivity. This does not establish identical responses across cities, but it suggests that development level alone is an insufficient basis for assigning cities different electricity responses to heat.

The estimated cooling elasticity of 0.099 is close to the provincial estimate of 0.094 reported by Fan et al. (2019). Other studies measure different responses: Li et al. (2019) estimate annual residential electricity changes in Shanghai per degree of global mean warming, while Zhang et al. (2022) estimate household consumption changes per additional hot day. These measures are not directly comparable with our response per degree-hour. Regional studies also link stronger urban sensitivity to greater AC ownership (Sun and Hanemann, 2024; Zhang et al., 2023). Differences in data and design may help explain this contrast: Sun and Hanemann (2024) use household-level, high-frequency records for southern China, whereas our analysis uses annual city records. Regional evidence that income weakens cooling sensitivity (Zhang et al., 2021) also need not generalize to this national sample, where income differences in sensitivity remain uncertain.

Similar marginal responses can nevertheless produce unequal climate impacts. Already-hot cities face the largest projected additions to cooling exposure and, consequently, the largest climate-driven increases in residential electricity use. Under the assumed socioeconomic elasticities, income growth remains the largest driver of total demand growth, while population decline partially offsets it by the end of the century. Long-term electricity planning must therefore consider climate, income, and population together, while adaptation to warming should account for the geographic concentration of additional cooling demand. The projections use the cooling response estimated from historical data, while income and population responses are assigned using regression results and modeling assumptions.

Demand growth and vulnerability identify different planning challenges. Higher income can increase electricity consumption while providing greater resources for adaptation. The vulnerability index captures this second role: SSP3-7.0 produces greater vulnerability than the warmer SSP5-8.5 because slower income growth leaves less capacity to meet additional cooling demand. Vulnerability concentrates in cities of the far south, while incorporating population into the risk index shifts attention toward large cities. The 29 cities ranking high on both indices identify locations where a large cooling demand burden relative to adaptive capacity coincides with substantial population exposure. Considering both indices also retains smaller vulnerable cities that screening by population risk alone could overlook. These rankings indicate potential adaptation priorities rather than measured cooling costs or realized damages. Together, they suggest that adaptation should address both the concentration of additional cooling demand and the resource constraints that limit residents’ ability to meet it.

Several limitations apply. The estimation sample is concentrated in warm, eastern cities, limiting generalization to colder and less represented regions, and projected totals refer to the 151 sample cities rather than China as a whole. Applying a linear degree-hour model to substantially hotter conditions involves extrapolation. The cooling coefficient reflects the historical weather response, while the projections hold technology and policy fixed and do not explicitly model future changes in appliance adoption or efficiency. Income and population elasticities are also held constant despite large socioeconomic changes. In particular, declining income elasticities as households become wealthier could make the projected income contribution an upper bound (Caron et al., 2017). GDPPC is a single proxy for adaptive capacity and does not directly measure electricity affordability (Cong et al., 2022; Li et al., 2023), grid reliability (Wang et al., 2025; Liang et al., 2025), or cooling access (Mazzone et al., 2023; Falchetta et al., 2024). Consistent projections of electricity affordability, grid reliability, and cooling access are unavailable across the sample cities and SSP scenarios. The index therefore uses income as a proxy for adaptive capacity to compare cities and identify potential adaptation priorities. Its rankings are robust to alternative component weights (Fig. S7a), although this does not establish that income fully captures adaptive capacity. These uncertainties support interpreting the projections as conditional scenario comparisons rather than precise predictions.

Methods

Electricity and socioeconomic data

Residential electricity and socioeconomic records are drawn from Chinese city statistical yearbooks for 2000–2020 (Table S4). The initial coverage comprises 293 prefecture-level cities and four municipalities spanning the five climate zones defined by GB 50176-2016 (Ministry of Housing and Urban-Rural Development of the People’s Republic of China, 2016). Electricity reporting is more complete in eastern and coastal cities (Fig. S1). GDP and disposable income are expressed in constant 2000 prices using provincial implicit gross regional product (GRP) deflators and city consumer price indices, respectively. Population refers to permanent residents rather than registered residents.

Quality control checks units, index conventions, and anomalous values against each city’s reporting history. Inconsistent values are corrected only when the intended value can be recovered from surrounding years or related fields. Otherwise, they are set to missing. Total residential electricity is also compared with the sum of its urban and rural components to identify cities whose total is compiled on a broader basis. Electricity values ≤ 0 and AC ownership outside $[0, 300]$ units per

100 households are set to missing. Listwise deletion yields 1,876 observations across 161 cities. After accounting for reporting breaks and removing singleton segments, the final estimation sample contains 1,860 observations across 151 cities and 158 segments. Table S5 compares alternative reporting-break treatments. Table S6 summarizes the regression variables.

Heat index and population-weighted degree-hours

Temperature, relative humidity, and precipitation are obtained from the China Meteorological Forcing Dataset version 2 (CMFDv2) (He et al., 2025). Temperature and humidity at 3-hourly resolution are interpolated to hourly values to calculate the extended heat index of Lu and Romps (2022). This incorporates humidity, which influences cooling demand (Maia-Silva et al., 2020; Scoccimarro et al., 2023; Li et al., 2026). Annual precipitation is averaged over each city’s area and included as a control.

Cooling degree-hours sum hourly heat index above 26 °C (Morakinyo et al., 2019; Atalla et al., 2018):

$$\text{CDH}_{g,y} = \sum_{h=1}^{N_y} \max(HI_{g,h} - HI_0, 0), \quad HI_0 = 26^\circ\text{C}, \quad (1)$$

where g is the grid cell, y the year, h the hour, and N_y the number of hours in year y . Heating degree-hours sum deviations below 11 °C (Hao et al., 2022):

$$\text{HDH}_{g,y} = \sum_{h=1}^{N_y} \max(HI_H - HI_{g,h}, 0), \quad HI_H = 11^\circ\text{C}, \quad (2)$$

Annual 1 km WorldPop population (WorldPop, 2020) weights grid-cell degree-hours within each city:

$$\text{pw-CDH}_{c,y} = \frac{\sum_{g \in c} P_{g,y} \text{CDH}_{g,y}}{\sum_{g \in c} P_{g,y}}, \quad \text{pw-HDH}_{c,y} = \frac{\sum_{g \in c} P_{g,y} \text{HDH}_{g,y}}{\sum_{g \in c} P_{g,y}}, \quad (3)$$

where $P_{g,y}$ is grid-cell population. These normalized measures retain degree-hour units and represent average resident exposure rather than population totals. For sector models, weights and climate fields are restricted to urban or rural grid cells. Annual CLCD “Impervious” cells are classified as urban and other land types as rural (Yang and Huang, 2021). Electricity outcomes come from separately reported urban and rural yearbook series, reconciled with the reported total. Robustness checks vary the cooling threshold over 24–28 °C and heating threshold over 9–13 °C (Table S1) and replace heat index with dry-bulb temperature (Table S7).

Econometric specifications

The primary model relates annual log residential electricity to cooling and heating exposure, log population, log real GDPPC, and annual precipitation:

$$\ln E_{c,y} = \beta_0 + \beta_1 \text{pw-CDH}_{c,y} + \beta_2 \text{pw-HDH}_{c,y} + \mathbf{X}_{c,y} \boldsymbol{\gamma} + \mu_{s(c,y)} + \lambda_y + \varepsilon_{c,y}, \quad (4)$$

Here c indexes cities and y years. Degree-hours are expressed in units of 10,000, and precipitation in 1,000 mm. The segment effect $\mu_{s(c,y)}$ absorbs persistent city characteristics and reporting-level shifts, while λ_y absorbs common annual shocks and trends. We split city series at annual electricity changes exceeding 50%. These persistent shifts suggest changes in reporting definition or coverage. Segment effects absorb the resulting level changes while preserving annual variation within segments. Ten breaks occur in the estimation sample, with seven cities having multiple segments. For the remaining 144 cities, segment effects reduce to city effects. Table S5 compares alternative thresholds and estimates without segmentation, which shows minimal variation in conclusions.

Standard errors are clustered by city, including across segments, and model fit is reported as within R^2 . Identification relies on annual weather variation within cities that remains after accounting for controls and fixed effects. We assume this variation is unrelated to unobserved determinants of electricity use. In contrast, income and population effects partly operate through gradual changes in appliance ownership, dwelling size, and urban form. City and year effects absorb much of the associated variation, so the remaining variation need not identify the long-term socioeconomic elasticities required for projections. We therefore assign these elasticities separately from the estimated climate response.

Urban and rural sector heterogeneity within cities is estimated on a stacked urban and rural panel. Let s denote sector, U_s the urban indicator, and $\mathbf{X}_{c,s,y}$ sector log population, log real per capita disposable income in 2000 prices, and precipitation. The urban model interacts climate terms and controls with U_s :

$$\ln E_{c,s,y} = \beta_0 + \beta_1 \text{pw-CDH}_{c,s,y} + \beta_2 \text{pw-HDH}_{c,s,y} + \delta_1 \text{pw-CDH}_{c,s,y} U_s + \delta_2 \text{pw-HDH}_{c,s,y} U_s + \mathbf{X}_{c,s,y} \boldsymbol{\gamma} + \mathbf{X}_{c,s,y} U_s \boldsymbol{\gamma}^U + \mu_{q(c,s,y)} + \lambda_{s,y} + \varepsilon_{c,s,y}, \quad (5)$$

The base climate coefficients are rural slopes and δ_1 and δ_2 are urban and rural differences. $\mu_{q(c,s,y)}$ denotes city-by-sector segment effects, using the same reporting-break rule, and $\lambda_{s,y}$ denotes sector-by-year effects.

Continuous sector moderators enter separately in centered form, $\tilde{M}_{c,s,y} = M_{c,s,y} - \bar{M}$:

$$\ln E_{c,s,y} = \beta_0 + \beta_1 \text{pw-CDH}_{c,s,y} + \beta_2 \text{pw-HDH}_{c,s,y} + \delta_1 \text{pw-CDH}_{c,s,y} \tilde{M}_{c,s,y} + \delta_2 \text{pw-HDH}_{c,s,y} \tilde{M}_{c,s,y} + \theta \tilde{M}_{c,s,y} + \mathbf{X}_{c,s,y} \boldsymbol{\gamma} + \mu_{q(c,s,y)} + \lambda_{s,y} + \varepsilon_{c,s,y}. \quad (6)$$

Moderators are AC ownership per 100 households, log household size, log per capita income, and log population. Centering makes the base climate coefficients the response at the moderator mean. Where income or population is the moderator, its centered value replaces the corresponding raw control. Urban status and household size are also estimated separately and jointly on the common household-reporting subsample to distinguish sample composition from moderation.

City-level heterogeneity returns to the aggregate panel and interacts both climate terms with a centered city characteristic $\tilde{Z}_{c,y}$:

$$\ln E_{c,y} = \beta_0 + \beta_1 \text{pw-CDH}_{c,y} + \beta_2 \text{pw-HDH}_{c,y} + \delta_1 \text{pw-CDH}_{c,y} \tilde{Z}_{c,y} + \delta_2 \text{pw-HDH}_{c,y} \tilde{Z}_{c,y} + \theta \tilde{Z}_{c,y} + \mathbf{X}_{c,y} \boldsymbol{\gamma} + \mu_{s(c,y)} + \lambda_y + \varepsilon_{c,y}, \quad (7)$$

Moderators are urbanization, log real GDPPC, log population, and city AC ownership, calculated as the urban-share-weighted mean of sector ownership. Controls and fixed effects follow Equation 4. A centered moderator replaces its raw control where applicable. All heterogeneity models cluster standard errors by city.

Scenario projections, driver decomposition, and uncertainty

Climate projections use four Coordinated Regional Climate Downscaling Experiment (CORDEX) East Asia regional climate models (RCMs) (Lee and Cha, 2020) driven by UKESM1-0-LL (Sellar et al., 2019) under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 (Table S4). The reference period is 1995–2014 and future periods are 2040–2059 and 2080–2099. Output at 3-hourly resolution is first bias-corrected against ERA5 (Hersbach et al., 2020) using quantile delta mapping (Cannon et al., 2015), which preserves projected quantile changes. The corrected output is then interpolated to hourly values. Population and GDP projections follow Wang et al. (2022b) and Wang and Sun (2022), respectively. Historical population is from WorldPop (WorldPop, 2020), and historical GDP uses the GDP projection source.

Projected log demand changes combine the estimated climate coefficient and assigned socioeconomic elasticities:

$$\Delta \ln E_c = \sum_k \hat{\beta}_k \Delta x_{k,c}, \quad (8)$$

where $\Delta x_{k,c}$ is the projected change in driver k and $\hat{\beta}_k$ its assigned response parameter. The cooling parameter is the fixed-effects estimate per 10,000 pw-CDH. Income and population parameters are elasticities. For GDPPC, the range spans the estimates with city-segment and year effects and with city-segment effects only. The former is the chosen lower endpoint, while the latter retains common temporal trends. For population, the range spans the city-segment-effects-only estimate and unit elasticity, representing proportional scaling. We do not carry the population coefficient from the model with city and year effects into the projections. These choices reflect the limited information that residual socioeconomic variation provides about long-term demand growth. The assumed central values and endpoints are listed in Table S8. These are modeling ranges, not statistical confidence intervals. All parameters remain constant to 2100, assuming the historical cooling response applies to future conditions. Table S8 documents the parameter sources.

For each RCM, cooling exposure change is future minus historical pw-CDH. These changes are averaged across the four models. The climate reference period (1995–2014) differs from the socioeconomic and electricity baseline (2000–2019) because of data availability. Using changes within each RCM removes reference-level offsets but not necessarily biases in projected changes. ERA5 comparisons indicate that differences between these baseline windows are small relative to projected cooling exposure changes (Fig. S9). Population and GDPPC changes are log ratios within each source. Baseline electricity is each city’s mean observed consumption over its reporting years in 2000–2019, summed across the 151 cities. Exact LMDI decomposition attributes the change in total electricity to climate, income, and population, with contributions summing to the total. Monte Carlo uncertainty combines cooling coefficient uncertainty, assumed socioeconomic elasticity ranges, and sampling across the four RCMs. Reported intervals cover 90%.

Vulnerability and risk indices

Two comparative indices combine heat hazard, population exposure, and income-based adaptive capacity (Turner et al., 2003; IPCC, 2022; Ahmed et al., 2023; Muñoz-Pizza et al., 2023). Hazard is the estimated electricity rise from pw-CDH ($\exp(\beta \cdot \text{pw-CDH}) - 1$), exposure is population, and adaptive capacity is log GDPPC. Income plays two distinct roles: it can increase electricity demand while also providing resources to meet cooling needs. Higher income can ease the energy burden, support more reliable grids, and widen cooling access, although GDPPC does not directly measure these dimensions. Each component is min-max normalized to $[0, 1]$ over cities, scenarios, periods, and the historical baseline, allowing comparisons across these dimensions. Vulnerability combines hazard and lack of adaptive capacity. Risk additionally incorporates population:

$$V_c = 100 \left(\tilde{H}_c^{w_H} \cdot (1 - \tilde{A}_c)^{w_A} \right)^{1/(w_H + w_A)}, \quad R_c = 100 \left(\tilde{H}_c \cdot \tilde{E}_c \cdot (1 - \tilde{A}_c) \right)^{1/3}, \quad (9)$$

Tildes denote normalized components, and vulnerability weights w_H and w_A are equal by default. Population is excluded from vulnerability to separate conditions faced by residents from the scale of population exposure. We test alternative component weights and an additive alternative incorporating rural population share (Fig. S7). More direct measures include energy burden or energy poverty (Cong et al., 2022; Liang and Asuka, 2022), outage hours (Wang et al., 2025; Liang et al., 2025; Shi et al., 2025), and cooling access (Mazzone et al., 2023; Falchetta et al., 2024). Consistent historical data and future projections of electricity affordability, grid reliability, and cooling access are unavailable for all 151 cities across the four SSP pathways. We therefore use GDPPC as a proxy for adaptive capacity to compare cities and identify potential adaptation priorities. Fig. S7 shows how the results change under alternative component weights and index formulations.

Data availability

The 3-hourly temperature and relative humidity used to construct the heat index behind the cooling and heating degree-hours, together with the precipitation control, are taken from the China Meteorological Forcing Dataset, version 2 (CMFDv2, He et al., 2025), distributed by the National Tibetan Plateau Data Center at <https://data.tpdc.ac.cn/en/data/e60dfd96-5fd8-493f-beae-e8e5d24dece4>.

The annual 1 km population used to weight the degree-hour fields and to set the historical population baseline is the WorldPop product (WorldPop, 2020), available at <https://www.worldpop.org/>. The urban and rural classification of grid cells, used for the sector split, is the China Land Cover Dataset (CLCD, Yang and Huang, 2021), available at <https://zenodo.org/records/4417810>.

For the projection, the future temperature used to build the projected cooling and heating degree-hours comes from four regional climate models downscaled over the CORDEX East Asia domain (Lee and Cha, 2020), available at <https://doi.org/10.1186/s40562-020-00162-8>. These simulations are bias-corrected against the ERA5 reanalysis (Hersbach et al., 2020), obtained from the Copernicus Climate Data Store at <https://doi.org/10.24381/cds.adbb2d47>. The historical and future gridded GDP, used to compute GDPPC in the projection, is the SSP-consistent product of Wang and Sun (2022), available at <https://doi.org/10.5281/zenodo.5880037>. The future gridded population, used for the projected population and to weight the future degree-hour fields, follows Wang et al. (2022b), available at <https://figshare.com/articles/dataset/19608594>.

The processed city-level panel used in this study contains statistical yearbook data, which provide the residential electricity consumption, GDP, population, number of households, and air-conditioner

401 ownership used as the regression outcome and the socioeconomic controls, and which are confidential
402 under government data-use requirements. It is therefore not publicly available and can be obtained
403 from the corresponding authors upon reasonable request.

404 **Code availability**

405 The Stata code used for the regression analysis and the Python code used to produce the figures
406 are available from the corresponding authors upon reasonable request.

References

- Ahmed, I., van Esch, M., and van der Hoeven, F. (2023). Heatwave vulnerability across different spatial scales: Insights from the dutch built environment. *Urban Climate*, 51:101614. <https://doi.org/10.1016/j.uclim.2023.101614>.
- An, Y. and Zhang, L. (2023). The thirst for power: The impacts of water availability on electricity generation in china. *The Energy Journal*, 44(2). <https://doi.org/10.5547/01956574.44.2.yaan>.
- Atalla, T., Gualdi, S., and Lanza, A. (2018). A global degree days database for energy-related applications. *Energy*, 143:1048–1055. <https://doi.org/10.1016/j.energy.2017.10.134>.
- Auffhammer, M., Baylis, P., and Hausman, C. H. (2017). Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the united states. *Proceedings of the National Academy of Sciences*, 114(8):1886–1891. <https://doi.org/10.1073/pnas.1613193114>.
- Auffhammer, M. and Mansur, E. T. (2014). Measuring climatic impacts on energy consumption: A review of the empirical literature. *Energy Economics*, 46:522–530. <https://doi.org/10.1016/j.eneco.2014.04.017>.
- Cannon, A. J., Sobie, S. R., and Murdock, T. Q. (2015). Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate*, 28(17):6938–6959. <https://doi.org/10.1175/JCLI-D-14-00754.1>.
- Caron, J., Karplus, V. J., and Schwarz, G. A. (2017). Modeling the income dependence of household energy consumption and its implications for climate policy in China. Report 314, MIT Joint Program on the Science and Policy of Global Change.
- Cong, S., Nock, D., Qiu, Y. L., and Xing, B. (2022). Unveiling hidden energy poverty using the energy equity gap. *Nature Communications*, 13(1):2456. <https://doi.org/10.1038/s41467-022-30146-5>.
- Falchetta, G., De Cian, E., Pavanello, F., and Sue Wing, I. (2024). Inequalities in global residential cooling energy use to 2050. *Nature Communications*, 15(1):7874. <https://doi.org/10.1038/s41467-024-52028-8>.
- Fan, J.-L., Hu, J.-W., and Zhang, X. (2019). Impacts of climate change on electricity demand in china: An empirical estimation based on panel data. *Energy*, 170:880–888. <https://doi.org/10.1016/j.energy.2018.12.044>.
- Filippini, M. and Zhang, L. (2016). Estimation of the energy efficiency in chinese provinces. *Energy Efficiency*, 9(6):1315–1328. <https://doi.org/10.1007/s12053-016-9425-z>.
- Guo, M., Choi, Y., Cheong, S.-M., and O’Neill, Z. (2025). Current and future residential electricity demand using large-scale smart meter data in a changing climate. *Sustainable Cities and Society*, 130:106623. <https://doi.org/10.1016/j.scs.2025.106623>.
- Han, H. and Wu, S. (2018). Rural residential energy transition and energy consumption intensity in china. *Energy Economics*, 74:523–534. <https://doi.org/10.1016/j.eneco.2018.04.033>.

- Hao, X., Huang, Y., and Zhang, L. (2025). High temperature, power rationing, and firm performance. *Journal of Development Economics*, 176:103541. <https://doi.org/10.1016/j.jdeveco.2025.103541>.
- Hao, Z., Zhang, X., Xie, J., Yin, K., and Liu, J. (2022). Balance point temperature and heating degree-days in different climate conditions for building energy efficiency applications. *Building and Environment*, 216:109013. <https://doi.org/10.1016/j.buildenv.2022.109013>.
- He, J., Yang, K., Li, X., Tang, W., Shao, C., Jiang, Y., and Ding, B. (2025). China meteorological forcing dataset v2.0 (1951–2024). National Tibetan Plateau Data Center. <https://doi.org/10.11888/Atmos.tpd.302088>.
- Herrerías, M. J., Aller, C., and Ordóñez, J. (2017). Residential energy consumption: A convergence analysis across chinese regions. *Energy Economics*, 62:371–381. <https://doi.org/10.1016/j.eneco.2016.06.006>.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049. <https://doi.org/10.1002/qj.3803>.
- Hu, Q., Gao, X., Zhang, T., Zhou, Y., Huang, N., Zhao, D., Varis, O., Peñuelas, J., Sardans, J., Ciais, P., Wu, J., Pan, Z., An, P., Zhang, D., Ma, W., and Lun, F. (2025). Renewal of aging residential buildings for electricity saving and carbon mitigation under climate change. *npj Urban Sustainability*, 5(1):110. <https://doi.org/10.1038/s42949-025-00298-6>.
- IPCC (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK and New York, NY, USA.
- Lee, D.-K. and Cha, D.-H. (2020). Regional climate modeling for asia. *Geoscience Letters*, 7:13. <https://doi.org/10.1186/s40562-020-00162-8>.
- Li, J., Yang, L., and Long, H. (2018). Climatic impacts on energy consumption: Intensive and extensive margins. *Energy Economics*, 71:332–343. <https://doi.org/10.1016/j.eneco.2018.03.010>.
- Li, X., Smyth, R., Xin, G., and Yao, Y. (2023). Warmer temperatures and energy poverty: Evidence from chinese households. *Energy Economics*, 120:106575. <https://doi.org/10.1016/j.eneco.2023.106575>.
- Li, X. C., Zhao, L., Luo, Z., Oleson, K., Cheng, Y., Xie, X., Varquez, A. C. G., and Sekiya, M. (2026). Divergent humidity-driven growth in urban air-conditioning energy demand under climate change. *Nature Cities*, 3(8):718–730. <https://doi.org/10.1038/s44284-026-00474-4>.
- Li, Y., Pizer, W. A., and Wu, L. (2019). Climate change and residential electricity consumption in the yangtze river delta, china. *Proceedings of the National Academy of Sciences*, 116(2):472–477. <https://doi.org/10.1073/pnas.1804667115>.
- Liang, J., Qiu, Y. L., Wang, B., Shen, X., and Liu, S. (2025). Impacts of heatwaves on electricity reliability: Evidence from power outage data in china. *iScience*, 28(2):111855. <https://doi.org/10.1016/j.isci.2025.111855>.

- Liang, Q. and Asuka, J. (2022). A multidimensional energy poverty measurement in china: Based on the entropy method. *Energy for Sustainable Development*, 71:554–567. <https://doi.org/10.1016/j.esd.2022.11.005>.
- Lin, B. and Wang, Y. (2020). Does energy poverty really exist in china? from the perspective of residential electricity consumption. *Energy Policy*, 143:111557. <https://doi.org/10.1016/j.enpol.2020.111557>.
- Lu, Y.-C. and Romps, D. M. (2022). Extending the heat index. *Journal of Applied Meteorology and Climatology*, 61(10):1367–1383. <https://doi.org/10.1175/JAMC-D-22-0021.1>.
- Maia-Silva, D., Kumar, R., and Nateghi, R. (2020). The critical role of humidity in modeling summer electricity demand across the United States. *Nature Communications*, 11(1):1686. <https://doi.org/10.1038/s41467-020-15393-8>.
- Mazzone, A., De Cian, E., Falchetta, G., Jani, A., Mistry, M., and Khosla, R. (2023). Understanding systemic cooling poverty. *Nature Sustainability*, 6(12):1533–1541. <https://doi.org/10.1038/s41893-023-01221-6>.
- Ministry of Housing and Urban-Rural Development of the People’s Republic of China (2016). *Thermal Design Code for Civil Building (GB 50176-2016)*. China Architecture and Building Press, Beijing. Issued jointly with the General Administration of Quality Supervision, Inspection and Quarantine. In force from 1 April 2017. Appendix A defines the thermal design zones and their outdoor meteorological parameters.
- Morakinyo, T. E., Ren, C., Shi, Y., Lau, K. K.-L., Tong, H.-W., Choy, C.-W., and Ng, E. (2019). Estimates of the impact of extreme heat events on cooling energy demand in hong kong. *Renewable Energy*, 142:73–84. <https://doi.org/10.1016/j.renene.2019.04.077>.
- Muñoz-Pizza, D. M., Sánchez-Rodríguez, R. A., and González-Manzano, E. (2023). Linking climate change to urban planning through vulnerability assessment: The case of two cities at the mexico-us border. *Urban Climate*, 51:101674. <https://doi.org/10.1016/j.uclim.2023.101674>.
- Reyna, J. L. and Chester, M. V. (2017). Energy efficiency to reduce residential electricity and natural gas use under climate change. *Nature Communications*, 8:14916. <https://doi.org/10.1038/ncomms14916>.
- Santamouris, M., Cartalis, C., Synnefa, A., and Kolokotsa, D. (2015). On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings: A review. *Energy and Buildings*, 98:119–124. <https://doi.org/10.1016/j.enbuild.2014.09.052>.
- Scoccimarro, E., Cattaneo, O., Gualdi, S., Mattion, F., Bizeul, A., Risquez, A. M., and Quadrelli, R. (2023). Country-level energy demand for cooling has increased over the past two decades. *Communications Earth & Environment*, 4(1):208. <https://doi.org/10.1038/s43247-023-00878-3>.
- Sellar, A. A., Jones, C. G., Mulcahy, J. P., Tang, Y., Yool, A., Wiltshire, A., O’Connor, F. M., Stringer, M., Hill, R., Palmieri, J., Woodward, S., de Mora, L., Kuhlbrodt, T., Rumbold, S. T., Kelley, D. I., Ellis, R., Johnson, C. E., Walton, J., Abraham, N. L., Andrews, M. B., Andrews, T., Archibald, A. T., Berthou, S., Burke, E., Blockley, E., Carslaw, K., Dalvi, M., Edwards, J., Folberth, G. A., Gedney, N., Griffiths, P. T., Harper, A. B., Hendry, M. A., Hewitt, A. J., Johnson, B., Jones, A., Jones, C. D., Keeble, J., Liddicoat, S., Morgenstern, O., Parker, R. J., Predoi, V., Robertson, E., Siahayan, A., Smith, R. S., Swaminathan, R., Woodhouse, M. T.,

- Zeng, G., and Zerroukat, M. (2019). UKESM1: Description and evaluation of the UK Earth System Model. *Journal of Advances in Modeling Earth Systems*, 11(12):4513–4558. <https://doi.org/10.1029/2019MS001739>.
- Shi, T., Chen, H., and Liu, Y. (2025). Extreme temperatures and residential electricity reliability in china. *Utilities Policy*, 96:102004. <https://doi.org/10.1016/j.jup.2025.102004>.
- Sun, Y. and Hanemann, M. (2024). Climate change adaptation in china: Differences in electricity consumption between rural and urban residents. *Energy Economics*, 140:107958. <https://doi.org/10.1016/j.eneco.2024.107958>.
- Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., and Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences*, 100(14):8074–8079. <https://doi.org/10.1073/pnas.1231335100>.
- Wang, B., Shi, H., Qiu, Y. L., Deng, N., Nock, D., Shen, X., Wang, Z., and Wang, Y. D. (2025). Unequal power outages induced by natural disasters. *Nature Communications*, 16(1):8947. <https://doi.org/10.1038/s41467-025-64012-x>.
- Wang, N., Fu, X., Wang, S., Yang, H., and Li, Z. (2022a). Convergence characteristics and distribution patterns of residential electricity consumption in china: An urban-rural gap perspective. *Energy*, 254:124292. <https://doi.org/10.1016/j.energy.2022.124292>.
- Wang, T. and Sun, F. (2022). Global gridded gdp data set consistent with the shared socioeconomic pathways. *Scientific Data*, 9:221. <https://doi.org/10.1038/s41597-022-01300-x>.
- Wang, X., Meng, X., and Long, Y. (2022b). Projecting 1 km-grid population distributions from 2020 to 2100 globally under shared socioeconomic pathways. *Scientific Data*, 9:563. <https://doi.org/10.1038/s41597-022-01675-x>.
- WorldPop (2020). Global high resolution population denominators project. Funded by The Bill and Melinda Gates Foundation (OPP1134076); <https://doi.org/10.5258/SOTON/WP00671>.
- Yan, X., Huang, Z., Ren, S., Yin, G., Qi, J., Zheng, J., and Bao, Y. (2026). Urban environment intensifies energy consumption sensitivity through the urban heat island effect. *Sustainable Cities and Society*, 145:107466. <https://doi.org/10.1016/j.scs.2026.107466>.
- Yang, J. and Huang, X. (2021). The 30 m annual land cover dataset and its dynamics in china from 1990 to 2019. *Earth System Science Data*, 13:3907–3925. <https://doi.org/10.5194/essd-13-3907-2021>.
- Zhang, G., Shen, L., and Su, B. (2023). Temperature change and daily urban-rural residential electricity consumption in northwestern china: Responsiveness and inequality. *Energy Economics*, 126:106973. <https://doi.org/10.1016/j.eneco.2023.106973>.
- Zhang, M., Chen, Y., Hu, W., Deng, N., and He, W. (2021). Exploring the impact of temperature change on residential electricity consumption in china: The crowding-out effect of income growth. *Energy and Buildings*, 245:111040. <https://doi.org/10.1016/j.enbuild.2021.111040>.
- Zhang, M., Zhang, K., Hu, W., Zhu, B., Wang, P., and Wei, Y.-M. (2020). Exploring the climatic impacts on residential electricity consumption in jiangsu, china. *Energy Policy*, 140:111398. <https://doi.org/10.1016/j.enpol.2020.111398>.

- 565 Zhang, S., Guo, Q., Smyth, R., and Yao, Y. (2022). Extreme temperatures and residential electricity
566 consumption: Evidence from chinese households. *Energy Economics*, 107:105890. [https://doi.](https://doi.org/10.1016/j.eneco.2022.105890)
567 [org/10.1016/j.eneco.2022.105890](https://doi.org/10.1016/j.eneco.2022.105890).
- 568 Zhao, X., Li, N., and Ma, C. (2012). Residential energy consumption in urban china: A decompo-
569 sition analysis. *Energy Policy*, 41:644–653. <https://doi.org/10.1016/j.enpol.2011.11.027>.

Table 1 | Main estimation results

	(1) No controls	(2) Social only	(3) Climate only	(4) All
pw-CDH	0.0735 (0.0226) [0.001]	0.0797 (0.0190) [<0.001]	0.0712 (0.0223) [0.002]	0.0765 (0.0187) [<0.001]
pw-HDH	0.0613 (0.0333) [0.068]	0.0526 (0.0323) [0.105]	0.0613 (0.0334) [0.068]	0.0526 (0.0323) [0.106]
Population		0.1897 (0.1390) [0.174]		0.1908 (0.1389) [0.172]
GDPPC		0.3495 (0.0816) [<0.001]		0.3503 (0.0814) [<0.001]
Precipitation			-0.0079 (0.0119) [0.508]	-0.0113 (0.0110) [0.305]
Constant	12.0921 (0.0662) [<0.001]	7.3477 (1.5197) [<0.001]	12.1049 (0.0669) [<0.001]	7.3519 (1.5177) [<0.001]
Observations	1860	1860	1860	1860
Cities	151	151	151	151
Within R^2	0.026	0.104	0.026	0.105
City-segment fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

The dependent variable is log(residential electricity). The estimation sample is held fixed across columns. Columns add: (1) no controls, (2) social controls only (population, GDPPC), (3) climate control only (precipitation), (4) all controls. Standard errors clustered at the city level are reported in parentheses. Two-sided P values are reported in square brackets.

Table 2 | Urban and rural sector heterogeneity in the cooling and heating response within cities

	(1) Urban	(2) AC ownership	(3) HH size	(4) Income	(5) Population
pw-CDH	0.1201 (0.0272) [<0.001]	0.1264 (0.0282) [<0.001]	0.1051 (0.0222) [<0.001]	0.1010 (0.0148) [<0.001]	0.0924 (0.0177) [<0.001]
pw-CDH $\times$ Urban	-0.0493 (0.0282) [0.083]				
pw-CDH $\times$ AC ownership		-0.0311 (0.0233) [0.185]			
pw-CDH $\times$ HH size			0.2884 (0.1052) [0.008]		
pw-CDH $\times$ Income				-0.0203 (0.0362) [0.576]	
pw-CDH $\times$ Population					0.0132 (0.0208) [0.526]
pw-HDH	0.0488 (0.0378) [0.199]	0.0349 (0.0388) [0.370]	0.0096 (0.0452) [0.832]	0.0271 (0.0240) [0.260]	0.0175 (0.0259) [0.501]
pw-HDH $\times$ Urban	-0.0667 (0.0388) [0.088]				
pw-HDH $\times$ AC ownership		0.0139 (0.0315) [0.659]			
pw-HDH $\times$ HH size			0.0786 (0.0672) [0.246]		
pw-HDH $\times$ Income				0.0147 (0.0271) [0.589]	
pw-HDH $\times$ Population					0.0083 (0.0190) [0.663]
Constant	8.9774 (1.4937) [<0.001]	8.7840 (1.6189) [<0.001]	9.1451 (1.7637) [<0.001]	10.9645 (0.4341) [<0.001]	9.2613 (1.3652) [<0.001]
Observations	2173	1224	1071	2173	2173
Cities	140	102	70	140	140
Within R^2	0.071	0.090	0.107	0.059	0.055
City $\times$ Sector segment fixed effects	Yes	Yes	Yes	Yes	Yes
Sector $\times$ Year fixed effects	Yes	Yes	Yes	Yes	Yes

Column 1: the base coefficient is the rural slope and the $\times$ Urban coefficient is the urban-rural difference, with all controls interacted with Urban (not shown). Columns 2 to 5 interact the cooling and heating terms with one mean-centered moderator at a time (AC ownership, household size, income, and sector population), with income, population, and precipitation as controls (not shown). Where a moderator duplicates a control, the centered form replaces the raw variable. Standard errors clustered at the city level are reported in parentheses. Two-sided P values are reported in square brackets.

Table 3 | City-level heterogeneity in cooling sensitivity

	(1) Urbanization	(2) GDPPC	(3) Population	(4) AC ownership
pw-CDH	0.1044 (0.0153) [<0.001]	0.0782 (0.0208) [<0.001]	0.0784 (0.0192) [<0.001]	0.1334 (0.0300) [<0.001]
pw-CDH $\times$ Urbanization	-0.0016 (0.0009) [0.088]			
pw-CDH $\times$ GDPPC		-0.0308 (0.0309) [0.321]		
pw-CDH $\times$ Population			-0.0012 (0.0282) [0.965]	
pw-CDH $\times$ AC ownership				0.0074 (0.0281) [0.794]
pw-HDH	0.0152 (0.0344) [0.660]	0.0467 (0.0327) [0.155]	0.0549 (0.0318) [0.086]	0.0488 (0.0331) [0.144]
pw-HDH $\times$ Urbanization	-0.0016 (0.0012) [0.200]			
pw-HDH $\times$ GDPPC		-0.0284 (0.0206) [0.170]		
pw-HDH $\times$ Population			0.0304 (0.0260) [0.245]	
pw-HDH $\times$ AC ownership				0.0055 (0.0282) [0.845]
Constant	8.9787 (1.7051) [<0.001]	11.0672 (0.8183) [<0.001]	8.4977 (0.8410) [<0.001]	3.7809 (2.1526) [0.082]
Observations	1461	1860	1860	632
Cities	141	151	151	90
Within R^2	0.126	0.114	0.107	0.308
City-segment fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Each column interacts the cooling and heating terms with one mean-centered moderator (urbanization rate, log real GDPPC, log population, or AC ownership), so the uninteracted pw CDH and pw HDH coefficients give the response at the sample mean. GDPPC, population, and precipitation are held as controls (not shown). In columns 2 and 3 the centered moderator replaces the corresponding raw control. Standard errors clustered at the city level are reported in parentheses. Two-sided P values are reported in square brackets.

Supplementary Files

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