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Climate change, electricity consumption, and households in impoverished areas in China

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A B S T R A C T

Using electricity for cooling and heating is critical for households to adapt to climate change, yet such consumption can simultaneously exacerbate it. While a large literature has documented household temperature-electricity response functions, most studies focus on developed regions. Far less is known about developing areas, particularly low-income households, who are more vulnerable to climate change and have significant potential in electricity demand. Using high-frequency household-level meter data from Xin County, an impoverished area in China, this paper investigates how household electricity consumption responds to temperature variation. We find that the response curve follows a U-shaped pattern similar to that observed in developed areas but is notably flatter, indicating a weaker sensitivity to climate change among households in developing regions. Considering that key differences likely stem from income constraints and urbanization levels, we conduct a mechanism analysis and compare our results with data from Zhejiang Province, one of China's most developed regions. Our analysis reveals that in Xin County, income mainly affects temperature responsiveness by limiting the use of air conditioners and heating appliances. Although better urban infrastructure accounts for part of the urban-rural gap in temperature response, demand-side constraints appear to play a more dominant role. These findings underscore the importance of incorporating regional and socioeconomic heterogeneity into the design of climate and energy policies.

1. Introduction

Electricity consumption is an important way to adapt to climate change (Allen et al., 2016; Auffhammer and Aroonruengsawat, 2011; Fan et al., 2019). Meanwhile, electricity consumption produces greenhouse gas emissions, thereby exacerbates climate change (Ou et al., 2011; Solomon et al., 2010). To break this vicious cycle, it is important to understand the impact of temperature changes on electricity consumption. Therefore, there has been a large literature on this topic (e.g., Aufhammer, 2022; Biddle, 2008; Chen et al., 2017; Sailor and Muñoz, 1997; Sailor and Pavlova, 2003). However, due to data availability, most of them focused on developed areas. Utilizing a unique high-frequency household-level meter data, we study the temperature response curve of households in impoverished areas of China, one of the largest emerging economies and the main electricity consumer in the world.

Developing areas, especially the lower-income households there, deserve more attention, because climate change could exacerbate the incidence and intensity of household energy poverty, which is a prominent issue in developing areas (Wu et al., 2025). Low-income households often cannot afford clean and efficient energy and mainly rely on cheap but polluting biomass fuels. They also generally have very limited ownership and use of cooling and heating appliances. These constraints increase discomfort and pose health risks to the low-income households during extreme temperatures (Dell et al., 2014).

Low-income households in developing areas are disproportionately vulnerable to climate change and have limited adaptive capacity (Hallegatte and Rozenberg, 2017; Hsiang et al., 2017; Zhang et al., 2020), which intensifies environmental inequality (Diffenbaugh and Burke, 2019; Paglialunga et al., 2022). Studying their temperature response curves provides insights into the disparities in adaptation behavior and climate change consequences, and thereby supports the designing of inclusive and effective climate adaptation strategy.

We should care about electricity response in developing areas also because along with the economic growth, their electricity consumption will be the major contributor to the increase in enengy consumption worldwide (Gertler et al., 2016). These areas may have unique energy consumption patterns that need to be considered when designing renewable energy projects and energy efficiency programs (Herrerias

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et al., 2017). Focusing on developing areas not only provides support for power grid planning in the context of future climate change and economic growth, but also plays a crucial role in ensuring a just and sustainable energy transition (Bazilian et al., 2011).

Similar to the international literature, existing research on China primarily focuses on relatively developed regions such as Shanghai and Zhejiang (e.g., Cui et al., 2023; Li et al., 2019; Zhang et al., 2020). This paper addresses this gap by investigating the temperature-electricity response of households in an impoverished inland county of China and contrasting it to one of the most developed provinces. Using high-frequency household-level electricity consumption data and econometric models, we find that although households in the impoverished county display a U-shaped temperature-electricity response curve, it is notably flatter than that observed in developed regions. We further find that while income significantly shapes temperature responsiveness in both developing and developed areas, the underlying mechanisms differ. In the impoverished county, income operates mainly through the use of heating appliances and dwelling size, reflecting binding budget constraints and limited capacity to utilize electrical appliances. In contrast, in the developed province, income predominantly influences the intensive use of air conditioners, against a backdrop of already high AC penetration. In addition, urban-rural disparities substantially affect temperature responsiveness. Although infrastructural differences account for part of the regional gap, demand-side constraints appear to play a more decisive role, given the generally high level of electricity supply in China.

This paper makes three contributions to the literature. First, it provides novel empirical evidence on temperature-electricity response curves in developing regions, with a focus on middle- and low-income households, a group largely overlooked in prior studies. Second, through a systematic comparison between an impoverished county and a developed province within China, we demonstrate how income constraint affects climate adaptation via distinct mechanisms across different development stages. In particular, we disentangle the roles of appliance ownership, usage intensity, and housing characteristics in shaping income-driven disparities in temperature response. We further examine the influence of the urban-rural divide and assess the role of infrastructure. Third, by simulating future electricity consumption under climate change scenarios, we quantify the potential growth in electricity demand from less developed regions. This offers valuable insights for electricity grid investment planning, which is a crucial adaptive infrastructure to climate change.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the conceptual framework for the analysis. Section 4 describes the data and presents graphical evidence on household electricity consumption response to extreme temperatures. Section 5 introduces the empirical specification of the temperature response function and conducts empirical analysis of temperature response in Xin County. Section 6 conducts the comparative analysis to Zhejiang, a developed province in China. Section 7 simulates household electricity consumption under climate change scenarios. Section 8 concludes with policy implications.

2. Literature review

There is a large literature on temperature response in developed countries. Many studies have estimated the temperature response curves and found that the response is higher at extreme weathers (e.g., Auffhammer and Aroonruengsawat, 2011; Considine, 2000; Deschenes and Greenstone, 2011; Franco and Sanstad, 2008; Sailor and Muñoz, 1997). In the long term, climate change leads to increased AC adoption and higher electricity consumption (e.g., Biddle, 2008; Sailor and Pavlova, 2003). In the short term, extreme temperatures lead to fluctuations in electricity consumption (e.g., Auffhammer et al., 2017; Li et al., 2019; Wenz et al., 2017).

Temperature response in developing countries have received increasing attention in recent years (e.g., Auffhammer, 2014; Auffhammer and Wolfram, 2014; Cui et al., 2023; Davis and Gertler, 2015; Du et al., 2020; Gupta, 2016; Li et al., 2018; Li et al., 2019). Davis and Gertler (2015) found that the temperature response curve for Mexico corresponded to the right half of a U-shape, reflecting increased electricity consumption primarily on hot days. Sun and Hanemann (2024) also found a U-shaped temperature response curve in southern China, using monthly electricity consumption data.

The temperature responses of low-income households, however, remain under explored. Previous research emphasized the significant role of income in electricity consumption. On the extensive margin, income influences the adoption of electricity appliances such as ACs (e.g., Auffhammer, 2014; Auffhammer and Wolfram, 2014; Davis and Gertler, 2015). McNeil and Letschert (2008) and Gertler et al. (2016) found a S-shaped relationship between income and AC adoption. On the intensive margin, income affects the quantity of electricity consumption (e.g., Cayla et al., 2011; Karanfil and Li, 2015; Sanquist et al., 2012). Belaid and Garcia (2016) showed that household income was one of the main determinants of energy-saving behavior. He and Reiner (2016) found that electricity consumption only responded to income changes after reaching a certain income threshold.

The S-shaped relationship between AC adoption and income suggests that low-income groups will play a significant role in driving future electricity consumption, a trend supported by the rapid growth of energy demand in China and other developing countries (Sari and Soytas, 2007; Wolde-Rufael, 2006). However, due to the lack of fine-scale data, existing studies on China have covered relatively developed regions, such as Shanghai (Li et al., 2019), Zhejiang and Jiangsu (Bai et al., 2026; Cui et al., 2023; Zhang et al., 2020). Attention to broader regions and middle- and low-income populations is insufficient.

Recent studies document substantial income gap in temperature responses across and within regions. At the cross-country level, households in wealthier countries exhibit stronger responses to extreme weathers (Petrick et al., 2010). At state and city levels, a hotter climate has greater marginal effects in states and cities with higher residential income (Du et al., 2020; Gupta, 2016; Jones et al., 2023). At household level, higher-income groups have more pronounced temperature responses (Harish et al., 2020; Li et al., 2019). The income gap is also reflected in the responses between urban and rural groups: urban households respond more strongly to temperature extremes than rural households, which is perceived to be due to income constraints (Bai et al., 2026; Sun and Hanemann, 2024).

The income gap in temperature responses is not static and may evolve over time as households adjust along different margins. In the short term, households respond to temperature changes along intensive margin, which means adjusting the usage of existing appliances (Auffhammer and Mansur, 2014; Davis and Gertler, 2015). When it comes to long term, households respond to climate change along the extensive margin, which refers to appliance adoption decisions (Auffhammer and Mansur, 2014; Auffhammer, 2014; Asadoorian et al., 2008; Davis and Gertler, 2015), and will in turn change the intensive margin (Drivas et al., 2019). Given the impact of income on AC adoption, Davis and Gertler (2015) predicted near-universal saturation of AC in all warm areas within just a few decades, implying a convergence in adaptive capacity across income groups. Consistent with this view, Sun and Hanemann (2024) found that, with the increase of the proportion of high temperature days, the temperature-response coefficients rise more rapidly in rural areas. Similarly, Bai et al. (2026) document little evidence of persistent urban-rural disparities in long-term climate adaptation. The convergence between urban and rural areas to some extent implies the narrowing of the income effect in shaping climate adaptation.

Despite the horizontal and vertical comparative studies of income gap, few studies have analyzed the mechanisms behind the differences. In particular, little is known about how income constraints influences temperature response, especially in less developed areas. This paper diverges from previous studies by estimating the income effect in the temperature response, and more importantly, exploring the mechanisms behind it.

Recent studies have highlighted the importance of investigating impacts of climate change within countries and among vulnerable populations (Hallegatte and Rozenberg, 2017; Jones et al., 2023; Rao et al., 2017). However, existing studies solely focus on low-income groups or a single type of region (Jones et al., 2023), limiting their ability to disentangle income effects from broader differences in regional development. This paper fills this gap by conducting a unified comparison of developing and developed areas within the same country. By exploring the income effect and urban-rural effect, this paper contributes to a more mechanistic understanding of electricity consumption behavior in developing regions and among low-income groups, which is crucial for designing inclusive climate policies.

3. Conceptual framework

In this section, we incorporate the theoretical basis to understand the differences in temperature-response functions between high-income groups and middle- and low-income groups. We focus on short-term effects, assuming adaptive appliance ownership is fixed.

Consider a household with disposable income denoted as I. The household derives utility u from the use of adaptive appliances X_a that the household already owns and other consumption C. We assume that the utility brought by the consumption of adaptive appliances will change with temperature T. The more the temperature deviates from the reference temperature T_0, the higher the utility brought by the consumption of adaptive appliances, which is captured by a constant coefficient α. Thus, the utility function can be expressed as:

$$u = lnC + \alpha(T - T_0)^2 lnX_a \, . \tag{1}$$

The budget constraint is given by:

$$C + P_E X_a = I \tag{2}$$

where P_E is the exogenous price of electricity, which powers the adaptive appliance.

Use (1) and (2) to solve the utility maximization problem. The optimal solution for X_a is as follows:

$$X_a = \frac{\alpha I (T - T_0)^2}{P_E\left[1 + \alpha(T - T_0)^2\right]} \tag{3}$$

The partial derivative of X_a with respect to T is given by:

$$\frac{\partial X_a}{\partial T} = \frac{2aI(T - T_0)}{P_E\left[1 + a(T - T_0)^2\right]^2} \tag{4}$$

Eq. (4) shows that as the temperature deviates from reference temperature, the utility-maximizing electricity consumption increases. It indicates the “U” shape of the temperature response curve.

Differentiate eq. (4) with respect to I. The derivative is given by:

$$\frac{\partial(\partial X_a/\partial T)}{\partial I} = \frac{2a(T - T_0)}{P_E\left[1 + a(T - T_0)^2\right]^2} \tag{5}$$

It shows that households with higher income will exhibit steeper response function at both high and low temperatures.

4. Data

In this section, we describe the datasets used for Xin County in Henan Province, China. The corresponding datasets used for Zhejiang Province can be referred to Cui et al. (2023). We study Xin County because of its availability of high-frequency fine-level electricity consumption data, its representativeness of impoverished areas in China, and the typical weather condition (See Appendix 1 for more details of Xin County's representativeness). We choose Zhejiang as the comparison region because of its data availability and its identical data structure to Xin County. Also, Zhejiang has the representativeness of China's developed regions, characterized by substantially higher household expenditures than national statistics (Cui et al., 2023).

For the empirical analysis and simulation, we merge five datasets: (1) daily household-meter-level electricity consumption data from the State Grid Corporation of China (SGCC); (2) station-level daily weather data from the National Meteorological Information Center of China; (3) daily air quality data from the China Air Quality Online Monitoring and Analysis Platform; (4) climate change scenarios from the NASA Earth Exchange Global Daily Downscaled Projections; and (5) household demographic data from Chinese Residential Energy Consumption Survey (CRECS), conducted by the School of Applied Economics at Renmin University of China.

4.1. Electricity consumption

The daily household-level electricity consumption data include the electricity meter readings for all residents in Xin County from May 10, 2018, to June 30, 2019. The electricity consumption is recorded at the interval of 4–5 days, and we calculate the average daily electricity consumption between every two records. Observations are excluded if daily electricity consumption is missing for more than half of the sample period (28.4% of the full sample), as these observations are unlikely to represent regular residents. Additionally, observations with an average daily electricity consumption exceeding 100 kWh (0.03% of the full sample) are also excluded, as these likely represent commercial activity but not households' consumption behavior. The final sample size is 5,946,264 readings from 79,127 meters.

The dots in Fig. 1 are the weekly electricity consumption of households in the sample. We can see clear cyclical fluctuations. Therefore we use the Hodrick-Prescott filter analysis method to decompose the electricity consumption time series into trend (red line in Fig. 1) and cyclical components (blue line). Hodrick Prescott filter, introduced by Hodrick and Prescott (1997), is a tool to remove the cyclical component of a time series from raw data and obtain a smoothed curve. The results show seasonal fluctuations, with peaks observed during summer (July and August) and winter (January and February). This pattern aligns with the expected seasonal variation in household electricity consumption, driven by increased cooling and heating demand during extreme weather.

4.2. Weather and air quality data

The daily weather data include daily average, maximum, and minimum temperatures, daily accumulative precipitation, wind speed and sunshine duration. We use daily average temperature to capture the temperature change. The daily air quality data include concentration levels of six pollutants ($PM_{2.5}$, PM_{10}, SO_2, CO, NO_2 and O_3) and one comprehensive index AQI (Air Quality Index). We use $PM_{2.5}$ concentration level as a measure of air quality, as in China $PM_{2.5}$ is the most severe air-borne pollutant. We also use AQI as an alternative measure, and the results remain stable (See Table A1).

Since the meter reading dates of different households are not exactly the same, the electricity consumption of each observation used is the average daily electricity consumption between the two date readings. Therefore, the meteorological data of each observation is also the average of the weather data and air quality data between the two adjacent reading dates, and the corresponding weather data and air quality data also vary at both the household and temporal levels.

Fig. 2 illustrates the correlation between temperature and electricity consumption. In addition to average electricity consumption (represented by the solid line), we also plot the correlations for different quartile of electricity consumption (represented by dashed lines). The

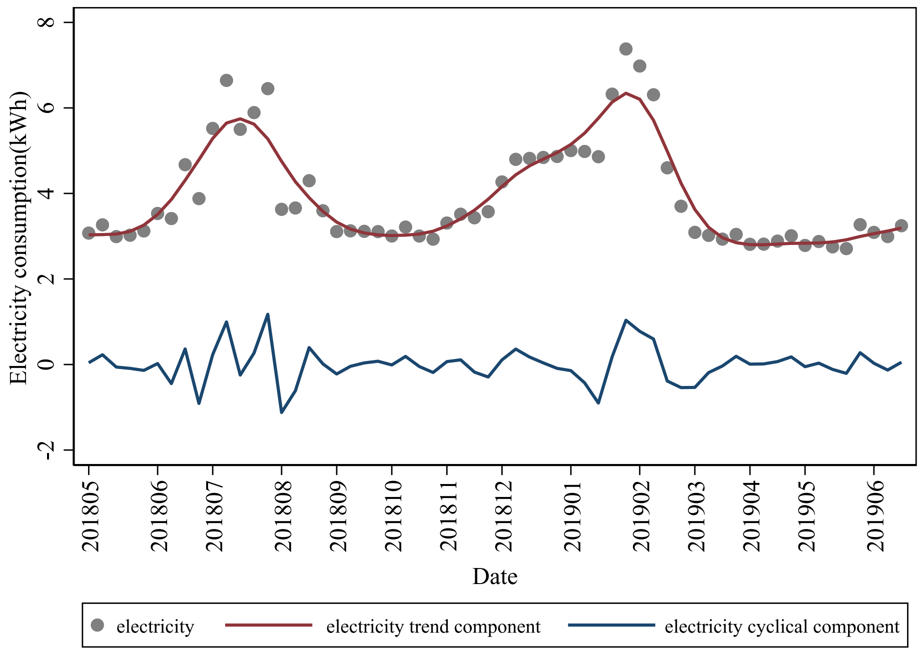

Fig. 1. HP filter analysis of electricity consumption. Notes: The scatter points in the figure represent weekly electricity consumption data. The red line represents the trend component from Hodrick-Prescott filter, and the blue line represents the cyclical component. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

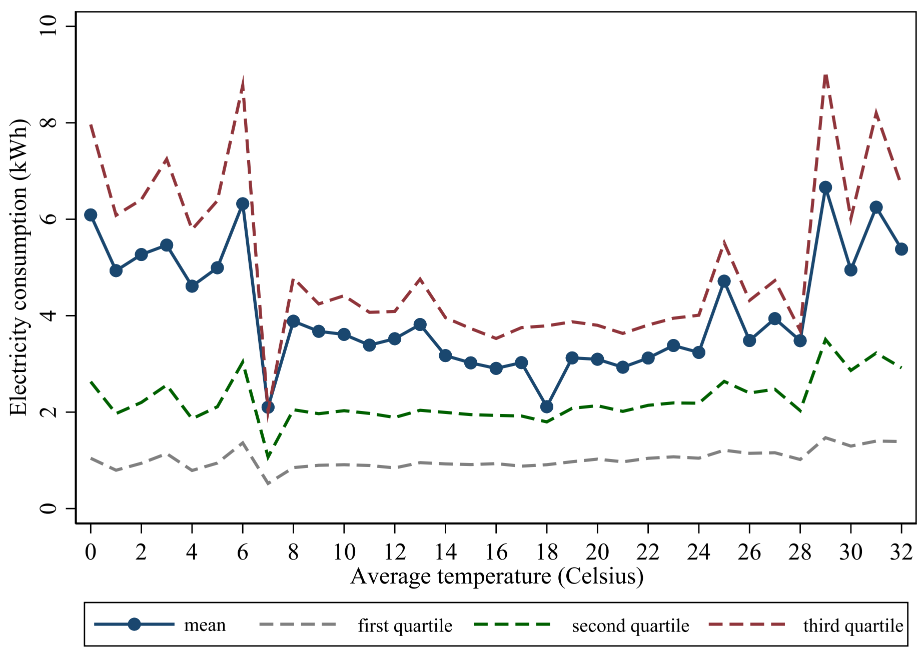

Fig. 2. Correlation between temperature and electricity consumption. Notes: The average daily temperature is divided into temperature intervals according to an interval of 1 °C, and the horizontal scale indicates the left endpoint of the corresponding temperature interval. The average household electricity consumption is calculated in each interval.

results indicate that electricity consumption is negatively correlated with average temperature at low temperatures and positively correlated at high temperatures. This relationship is particularly pronounced for the third quartile and average electricity consumption. These findings suggest the presence of a U-shaped temperature response function, and the heterogeneity in the response.

4.3. Climate change scenarios

The climate change scenarios used in this paper are sourced from the NASA Earth Exchange Global Daily Downscaled Projections. Under scenarios SSP2–4.5 and SSP5–8.5, we simulate the daily average electricity consumption of Xin County for the period from 2090 to 2099. To be specific, we use the model with estimated coefficients and replaced the temperatures with the future forecast temperatures to calculate future electricity consumption.

Fig. A1 in Appendix 2 compares the temperature distributions during the sample period with those projected under the two future scenarios. It shows that the temperature distributions for both scenarios shift rightward relative to the sample period, indicating a general increase in average temperatures by 2090–2099. Furthermore, the frequency of extreme high temperatures is projected to dramatically increase.

4.4. Household demographics and housing characteristics

To collect household characteristics for heterogeneity analysis, we use a stratified sampling method to select 1043 households from five towns out of 16 towns in Xin County, and conduct questionnaire surveys in person. The survey collected detailed information on household demographics, housing characteristics, household energy consumption, appliance ownership and usage. The survey data were then merged with electricity consumption data using electricity meter codes, resulting in a matched sample of 983 households.

We divide home appliances into three categories: heating, cooling, and other appliances. Heating appliances include air conditioners (AC) and electric radiators, and cooling appliances include ACs and electric fans. Other appliances include rice cookers, refrigerators, light bulbs, etc. Fig. A2 and A3 in Appendix 2 presents the penetration rates and electricity consumption ratios for the main appliances. Notably, 84% of households in the sample have electric fans, 39% have electric radiators, and only 11% have ACs. On average, electric fans consume 6 kWh electricity annually, radiators consume 63 kWh, and ACs consume 70 kWh. These statistics provide a preliminary picture of the limited ownership and usage of appliances in impoverished areas, highlighting deficiencies in their capacity to adapt to climate change.

While other appliances account for the majority of household electricity consumption, their usage remains relatively constant regardless of temperature changes because they are unrelated to adaptive behaviors to climate change. Therefore, by controlling for household fixed effects, we can focus on heating and cooling, which are major household-level adaptation methods to climate change.

Tables 1 and 2 summarize all variables used in the study. Table 1 includes data from all households in Xin County, and Table 2 includes data from households surveyed by CRECS. Compared to Zhejiang Province, as reported in Cui et al. (2023), our sample has substantially lower electricity consumption, lower AC adoption rate, and also much lower household income. It characterizes the households in impoverished areas.

Fig. A4 compares the distributions of annual household income in Xin County and Zhejiang. The two regions exhibit pronounced differences in both income levels and dispersion. Household income in Xin County is markedly lower and more compressed. In contrast, the income distribution in Zhejiang is right-shifted, with a thicker upper tail reflecting the presence of high-income households. As a result, households classified as high-income in Xin County may correspond to middle- or even low-income households in Zhejiang. These differences in income distributions imply that an identical change in income can have substantially different implications across the two regions.

5. Empirical analysis

In this section, we employ formal econometric models to quantify the temperature response function, which is illustrated qualitatively in the previous section. We first introduce the empirical model. Then we estimate the overall baseline temperature response. Finally we explore the roles of income and urban-rural variations in shaping the temperature response as well as the underlying mechanisms.

5.1. Empirical strategy

Following Aufhammer (2022) and Davis and Gertler (2015), we set the basic temperature response function as follows:

Table 1
Summary Statistics of all households in Xin County.

Variable	Definition	Mean	SD	Min.	Max.
1. Electricity consumption (5,946,264 observations, about 76 readings for 79,127 households)					
Electricity	Electricity consumption (kWh/day)	3.903	5.779	0	100
2. Meteorological variables (174 periods)					
Temp	Average temperature (Celsius)	21.101	8.517	0.071	32.5
Precipitation	Average precipitation from 20 to 20 (0.1 mm)	25.958	46.417	0	252.5
Sunshine	Sunshine duration (0.1 h)	47.284	34.903	0	121
Wind	Daily average wind speed (0.1 m/s)	19.893	4.761	8	34.8
Direction	The wind direction of the maximum daily wind speed	6.471	2.988	1	15
Humidity	Relative humidity (%)	76.989	11.756	40.721	95.391
3. Air quality data (174 periods)					
$PM_{2.5}$	Average $PM_{2.5}$ concentration (μg/m³)	38.190	22.793	0	132.714
AQI	Average Air Quality Index	79.549	25.750	0	170.714
4. Climate change scenario variables (3650 days)					
SSP2–4.5_2099	Daily average temperature in 2090–2099 under SSP2–4.5 (Celsius)	18.734	9.270	−8.845	35.222
SSP5–8.5_2099	Daily maximum temperature in 2090–2099 under SSP5–8.5 (Celsius)	20.444	9.246	1.053	36.840

$$EC_{it} = \sum_{n=1}^{N} \alpha_{0n} D_n(Temp_{it}) + \beta_1 \boldsymbol{Meteorological}_{it} + \beta_2 PM2.5_{it} + \beta_3 holiday_t + \beta_4 weekend_t + h_i + m_t + \varepsilon_{it} \tag{6}$$

where EC_{it} indicates the average daily electricity consumption of household i at day t; $Temp_{it}$ denotes the average of daily average temperature of household i at day t, and $D_n(Temp_{it})$ is the dummy variable indicating whether $temp_{it}$ is in the interval [n, n + 1):

$$D_n(Temp_{it}) = \begin{cases} 1 \; if \; n \le Temp_{it} < n+1 \\ 0 \quad\quad\quad\quad otherwise \end{cases} for \; n = 0, 1 \ldots 31, 32 \tag{7}$$

We set the temperature interval of as the baseline. Therefore, the dummy variable of temperature interval 16–17 °C is omitted in the regressions.

We add meteorological variables as control because meteorological conditions such as precipitation, sunshine, humidity, wind direction and speed also affect electricity consumption (Aufhammer, 2022; Cui et al., 2023; Ito and Zhang, 2020; Li et al., 2019). We control all these meteorological variables, as well as the interaction of wind speed and direction. Furthermore, we control $PM_{2.5}$ concentration as air quality also affects electricity consumption (He et al., 2020; Salvo, 2018).

Furthermore, we control for month fixed effects m_t and household fixed effects h_i. Month fixed effects absorb the effects of monthly characteristics which are the same for all households. Household fixed effects absorb the effects of time-invariant variables for each household, such as household appliance ownership, household demographics and housing characteristics variables, as well as grid variables. For example, we do not include electricity price because the price scheme is time-invariant and absorbed by household fixed effects.

Table 2
Summary Statistics of households surveyed by CRECS.

Variable	Definition	Mean	SD	Min.	Max.
1. **Electricity consumption (76,826 observations, about 79 readings for 983 households)**					
Electricity	Electricity consumption (kWh/day)	2.769	3.617	0	73.816
2. **Meteorological variables (139 periods)**					
Temp	Average temperature (Celsius)	20.734	8.692	0.071	32.5
Precipitation	Average precipitation from 20 to 20 (0.1 mm)	24.578	44.947	0	252.6
Sunshine	Sunshine duration (0.1 h)	46.558	34.432	0	121
Wind	Daily average wind speed (0.1 m/s)	19.791	4.719	8	34.8
Direction	The wind direction of the maximum daily wind speed	6.535	3.040	1	15
Humidity	Relative humidity (%)	76.665	11.843	40.721	95.391
3. **Air quality data (139 periods)**					
PM2.5	Average PM2.5 concentration (μg/m^3)	39.892	26.106	0	132.714
4. **Household demographics and housing characteristics variables (983 households)**					
Income	Annual household income in 2017 (Chinese Yuan)	27,883	32,560.72	1700	800,000
Cooling	Proportion of households with cooling appliance	87.49%			
Heating	Proportion of households with heating appliance	46.29%			

To address the fact that electricity consumption on weekends and holidays is likely to be different from workdays, we further include $weekend_t$ and $holiday_t$ to indicate whether day t is a weekend and a holiday, respectively.

5.2. Baseline results

To estimate the overall temperature response curve, we use the full sample, with 5,946,264 meter readings included. We plot the temperature response curve in Fig. 3 (A), and summarize the detailed regression results in Table A1 in Appendix 3. We find that overall the U shape of the response curve is consistent with findings from previous literature; however, the response intensity is different from the findings in developed countries and areas.

When the temperature increases beyond 26 °C, the electricity consumption starts to respond. The higher temperature, the larger is the response. On average, for one degree Celsius increase at high temperatures, the daily electricity consumption increases by 0.39 kWh, which is 12.23% increase from 3.19 kWh electricity consumption on mild days (i.e. when the average temperature is between 14 and 26 °C). Compared to the results from Zhejiang, which is 0.62–0.82 kWh increase for rural households and 1.39–1.70 kWh for urban households (Cui et al., 2023), the temperature response in Xin County is about half that of rural areas in Zhejiang.

When the temperature decreases below 14 °C, the electricity consumption starts to respond. The lower temperature, the larger is the response. On average, for on degree Celsius decrease at low temperature, the daily electricity consumption increases by 0.23 kWh, which is 7.21% increase from 3.19 kWh electricity consumption on mild days. Compared to the results from Zhejiang, which is 0.11–0.21 kWh increase for rural households and 0.14–0.62 kWh for urban households (Cui et al., 2023), the temperature response in Xin County is slightly higher than that in rural areas of Zhejiang.

For robustness check, we reconstruct the temperature variables using intervals of two Celsius degrees. As shown in Fig. 3 (B), the curve of the two Celsius intervals is similar to that of one Celsius interval, confirming the robustness of the findings.

5.3. Effect of income

In this section, we investigate income effect on temperature response and the mechanisms underlying the effect. Low-income households often face tighter financial constraints, which can restrict both the purchase and use of energy-intensive appliances. Consequently, their electricity consumption may respond less strongly to temperature fluctuations than that of higher-income households. Therefore, we focus on the following three potential mechanisms. First, ownership of cooling and heating appliances. Low-income households may have fewer appliances, and thus have less electricity consumption and lower temperature response. Second, use of cooling and heating appliances. Among households with appliances, low-income households may be reluctant to use them due to electricity cost, which leads to limited response. Third, dwelling sizes. Low-income households may live in smaller houses, and thus have less demand for space cooling or heating.

5.3.1. Estimation of income effect

We use the sample with household survey data and divide the households into low-, middle-, and high-income groups based on their annual income, with thresholds set at 13.1 and 32.5 thousand Chinese Yuan. Income group dummies are included as interaction terms in the regression, as specified in Eq. (8). This approach allows us to capture variations in electricity consumption responses between the three groups.

$$\begin{aligned} EC_{it} = & \sum\nolimits_{n=1}^{N} \alpha_{1n} Low_i D_n(Temp_{it}) + \sum\nolimits_{n=1}^{N} \alpha_{2n} Middle_i D_n(Temp_{it}) \\ & + \sum\nolimits_{n=1}^{N} \alpha_{3n} High_i D_n(Temp_{it}) + \boldsymbol{\beta_1 Meteorological_{it}} + \beta_2 PM2.5_{it} \\ & + \beta_3 holiday_t + \beta_4 weekend_t + h_i + m_t + \varepsilon_{it} \end{aligned} \tag{8}$$

The regression results, presented in Fig. 4 and Table A2 in Appendix 3, reveal statistically significant differences in the temperature response curves between low-income group and other two groups at both low and high temperatures, underscoring the importance of income as determinant of climate change adaptability. No significant differences are observed between middle- and high-income groups. This is likely because, although they have higher income levels within the context of the impoverished county, their absolute income remains modest. The average annual household income of high-income group is 52.02 thousand Chinese Yuan (approximately 7.07 thousand dollars); and the average income for the other two groups are 7.58 thousand Chinese Yuan (approximately 1.10 thousand dollars) and 23.51 thousand Chinese Yuan (approximately 3.41 thousand dollars).

To analyze the effects of income more precisely, we include the interaction terms of the logarithm of income and temperature in the regression and estimate the coefficients. To provide a clearer visualization of the interaction effects, we plot the coefficients of the interaction terms in Fig. 5. The results indicate that income has a significant positive effect on the temperature response at both low and high temperatures. On average, if income increases by 100%, the electricity consumption will increase by 0.23 kWh at each temperature interval, which is equivalent to the sample average AC running for 9.15 min.

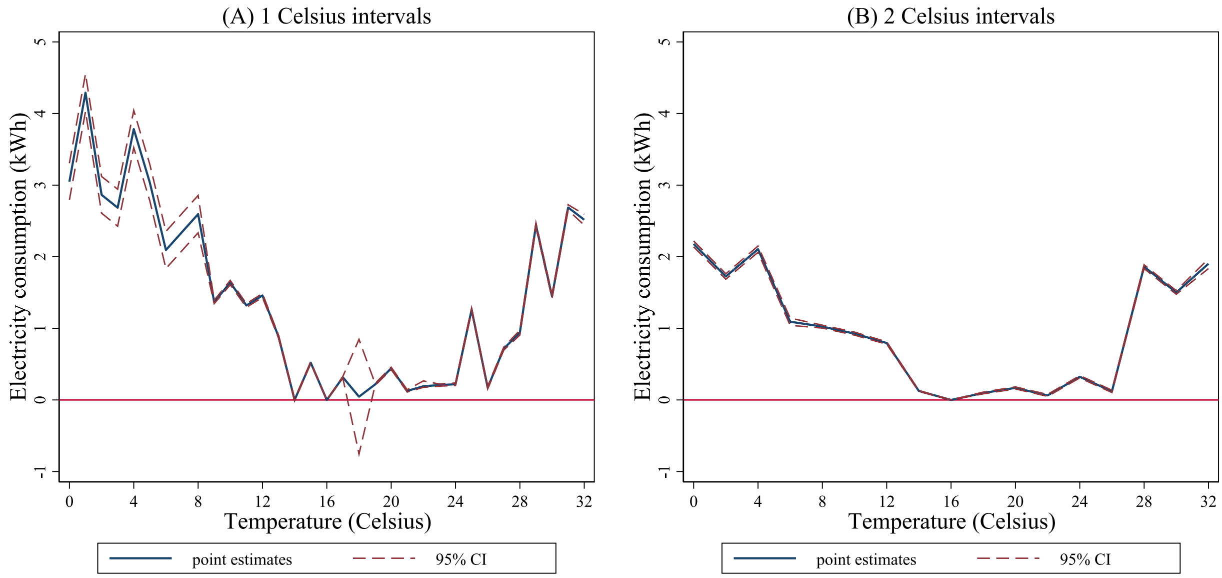

Fig. 3. Temperature response curves in Xin County. Notes: Panel (A) presents the estimates of the marginal effect of every one Celsius degree deviation from 16 to 17 °C. The estimation is based on the household fixed effects model presented in eq. (6). Panel (B) presents the estimates of the marginal effect of every two Celsius degree deviation from 16 to 18 °C.

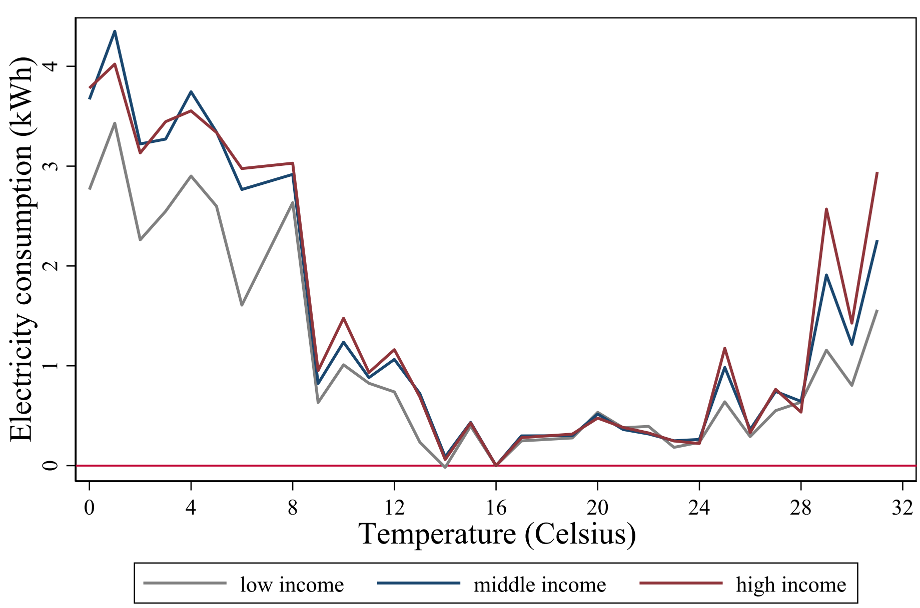

Fig. 4. Temperature response curves of households in different income groups in Xin County. Notes: The temperature interval of 16–17 °C is set as the baseline. The estimates of every temperature interval are presented in the figure. The standard errors are clustered at the household level. The results of the regression are summarized in Table A2 in Appendix 3.

5.3.2. *Mechanism 1: ownership of cooling and heating appliances*

We first focus on the ownership of cooling appliance. Here we refer cooling appliance as AC and electric fan.[1] Table 3 reports estimates of the impact of income on the probability of owning cooling appliances. In all the specifications of logit, probit and OLS, income is positively associated with appliance ownership.

To investigate whether the ownership influences temperature response, we use household survey data and include the interaction terms of cooling appliance dummy. The differences in coefficients between households with and without cooling appliance are compared in Fig. 6 (A) and detailed further in Table A4 in Appendix 3. Test results show that these differences are insignificant at nearly all temperature intervals, indicating that the temperature responses of households with and without cooling appliance are largely similar.

One explanation could be the limited use of ACs for low-income households. While these households may install ACs, they are often reluctant to use them due to the cost of electricity consumed (Pavanello et al., 2021). Among households with ACs, 17.43% report not using them. The other possible explanation is the low-energy-consuming attribute of electric fans compared to ACs.[2] In Xin County, the AC

[1] We also discuss the heterogeneity across AC only, as AC could be used for both cooling and heating. The results are presented in Appendix 4.

[2] For the household sample in this paper, the average energy consumption of electric fans is 0.035 kW per hour, and that of ACs is 0.23 kW per hour.

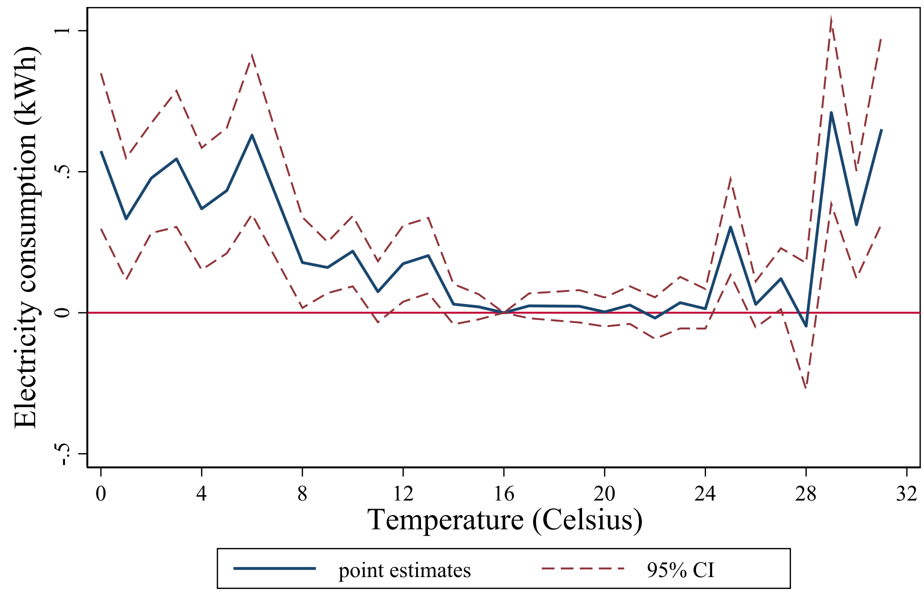

Fig. 5. Coefficients of the interaction terms of income and temperature intervals in Xin County. Notes: The temperature interval of 16–17 °C is set as the baseline. The estimates of every temperature interval are presented in the figure. The standard errors are clustered at the household level. The results of the regression are listed in Table A3 in Appendix 3.

Table 3
Income effects on the probability of owning cooling appliances in Xin County.

	(1)	(2)	(3)
	Logit	Probit	OLS
VARIABLES	Cooling appliance		
Ln(Income)	0.142***	0.141***	0.136***
	(0.0183)	(0.0182)	(0.0173)
Constant			0.942***
			(0.263)
Observations	983	983	983
R-squared			0.098

Notes: Marginal effects are reported in this table. The dependent variable is a dummy indicating whether the household has cooling appliances. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and a urban dummy. Robust standard errors are in parentheses.

penetration rate is only 11.09%. As a cheap alternative to AC, electric fans are more favored by low-income households. Electric fans have a much higher penetration rate of 81.59% and are used for nearly twice the duration of AC. It should be noted that although electric fans provide a cost-effective alternative for cooling, their cooling capacity is far lower than that of ACs, leaving low-income households inadequately equipped to cope with high temperatures.

We then focus on the ownership of heating appliance. Here we refer heating appliance as ACs and electric radiators. In Xin County, 44.45% of households rely on solid-fuel stoves, while 46.59% use electric heating appliances. We therefore estimate a multinomial logit model to analyze the heating energy choice. Table 4 reports the odds ratios of income effects on the heating choice of using stove or appliances. It shows that increase in income significantly increases the likelihood of adopting either heating stoves or electric appliances relative to no heating. Predicted probabilities in Fig. A5 reveal a clear energy ladder: the probability of no heating declines monotonically with income, heating stoves first rises and then falls, and electric heating increases steadily. This pattern indicates that Xin County remains in a transitional stage of the energy ladder.

To explore whether the ownership would result in changes in climate adaptation, we compare temperature responses of households with and without heating appliance. We use household survey data and include interaction terms of heating appliance dummy. The results are summarized in Fig.6 (B) and Table A5 in Appendix 3.

We can see a clear response at low temperatures for both groups, with no statistically significant difference. The possible explanation is that although the penetration rate of heating appliance has reached 46.59%, the usage remains insufficient. Among households with ACs, 25.45% report not using them for heating. As why households without heating appliance also exhibit a noticeable response at low temperatures, the reason could be that some households did not report their ownership of heating appliance. The small number of the observations without heating appliances leads to wide confidence intervals, contributing to the insignificance in the difference.

5.3.3. Mechanism 2: usage of cooling and heating appliances

In this subsection, we examine the intensive margin of income, which is the impact of income on usage duration conditional on ownership, measured by usage months per year and usage hours per day. The results are summarized in Table 5.

It shows that income has a significant positive effect on the use of electric fans, but no statistically significant effect on the use of ACs. On average, ACs are used for only 0.99 months per year and 2.65 hours per day, which may be too small to generate a detectable impact on temperature response, particularly given the low penetration of ACs. Electric fans are used for 1.35 months per year and 2.74 hours per day on average, and due to their low power consumption, they are also unlikely to notably affect aggregate temperature response.

Similar to cooling, the use of heating appliances is also positively associated with income, and the usage remains limited, at 1.12 months per year and 3.16 hours per day. It leads to overall electricity load too small to significantly affect the temperature response.

Taken together, in impoverished areas, appliance ownership does not necessarily translate into improved thermal comfort. Rather, the ability to afford operating costs is crucial for temperature responsiveness.

5.3.4. Mechanism 3: dwelling size

Income may also affect temperature responses through housing characteristics. Table 6 shows that higher-income households reside in substantially larger and newer homes with better insulation.

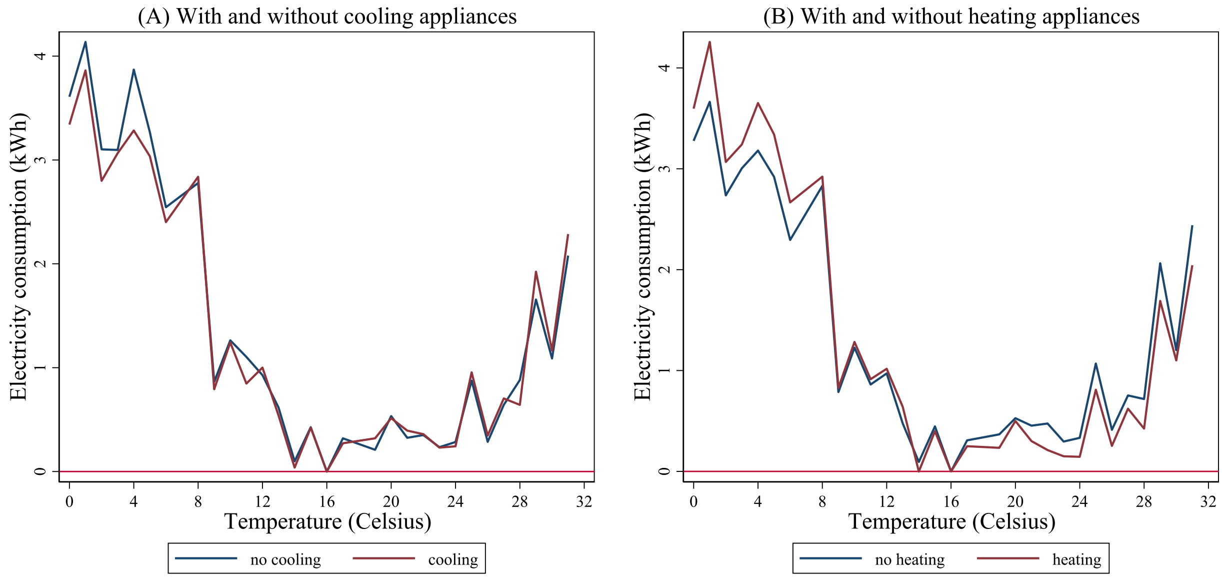

Fig. 6. Temperature response curves of households with and without cooling or heating appliances in Xin County. Notes: The temperature interval of 16–17 °C is set as the baseline. The estimates of every temperature interval are presented in the figure. The standard errors are clustered at the household level. The results of the regression are listed in Table A4 and A5 in Appendix 3.

Table 4
Odds of income effects on heating types in Xin County.

	(1)	(2)
VARIABLES	Heating stove	Heating appliance
Ln(Income)	1.326***	1.056***
	(0.188)	(0.164)
Constant	5.575**	−3.884
	(2.687)	(2.444)
Observations	983	983

Notes: The dependent variable is a category variable indicating heating choice. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

Fig. A6 in Appendix 2 shows that households in larger dwellings exhibit slightly stronger responses at extreme temperatures. Splitting the sample by median dwelling size, we find that income effects are significant for those in smaller dwellings at high temperatures, while little heterogeneity emerges at low temperatures (Table A7 in Appendix 3). These findings indicate that dwelling size is an important channel through which income shapes heat-related electricity demand, but not a channel in cold-related demand.

This asymmetry is consistent with the physics of appliances. AC needs to regulate the temperature of the entire indoor space, thus cooling loads scale with dwelling size. High-income households in bigger houses must consume significantly more electricity to maintain thermal comfort. In contrast, heating in the study region relies mainly on localized electric radiators, whose energy requirements are only weakly dependent on dwelling size. As a result, dwelling size amplifies responses in heat adaptation but plays a limited role in cold adaptation.

Housing quality may further amplify inequality in effective adaption. As shown in Table 6 Column (2) and (3), household with higher income are more likely to live in a newer house with better insulation performance. Poor insulation implies that identical energy consumption yields weaker thermal regulation, suggesting that observed disparities in electricity use may understate true inequality in thermal comfort (Doremus et al., 2022).

5.4. *Effect of urban-rural gap*

5.4.1. *Estimation of the effect of urban-rural gap*

In this subsection, we investigate the heterogeneity in temperature response between urban and rural areas. We use the dataset comprising all households with electricity meter readings and include the interaction terms of urban-rural dummy and temperature bins. Since direct information on residential areas is unavailable, we classify households as urban or rural based on the power supply station serving them. Specifically, households receiving electricity from urban power supply

Table 5
Income effects on duration of cooling and heating appliances in Xin County.

	(1)	(2)	(3)	(4)	(5)	(6)
	Electric fan		AC for cooling		Heating appliance	
VARIABLES	Month per year	Hour per day	Month per year	Hour per day	Month per year	Hour per day
Ln(Income)	0.138***	0.196***	−0.00207	−0.0823	0.0520	0.306**
	(0.0393)	(0.0653)	(0.121)	(0.355)	(0.0411)	(0.136)
Constant	3.275***	6.046***	−0.103	7.115**	0.853	0.961
	(0.654)	(1.096)	(1.495)	(2.986)	(0.575)	(2.090)
Observations	802	802	90	89	458	458
R-squared	0.098	0.056	0.139	0.105	0.035	0.055

Notes: The dependent variables are usage months and the daily usage hours of appliances, taking the maximum value among all the cooling or heating appliances in the household. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

Table 6
Income effects on housing characteristics in Xin County.

	(1)	(2)	(3)
VARIABLES	Dwelling size	Building year	Insulation
Ln(Income)	14.04***	−2.234***	0.188*
	(1.545)	(0.527)	(0.107)
Constant	118.2***	−3.643	
	(25.63)	(7.099)	
Observations	983	983	983
R-squared	0.186	0.117	

Notes: The dependent variable in Column (1) is dwelling size (square meter). The dependent variable in Column (2) is the years of house since its construction. The dependent variable in Column (3) is the households' evaluation of the insulation performance of the house, with values ranging from 1 to 5. Column (3) is estimated using ordered logit model. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

stations are categorized as urban, while those served by other stations are classified as rural.

The temperature responses for urban and rural households are plotted in Fig. 7 (A) and the regression results are summarized in Table A8 in the Appendix 3. The two response curves are roughly similar in shapes but differ in responsiveness. Urban households exhibit greater sensitivity to temperature changes compared to rural households. Statistical tests confirm that the differences in temperature responsiveness between urban and rural households are significant across nearly all temperature intervals.

For 1 °C increase at high temperatures above 26 °C, the daily electricity consumption of an urban household increases by 1.22 kWh, which is 24.06% increase from 5.07 kWh electricity consumption on mild days; for a rural household the increase is 0.37 kWh, which is 12.5% increase from 2.96 kWh consumption on mild days. For 1 °C decrease at low temperatures below 14 °C, the electricity consumption of an urban household increases by 0.66 kWh, a 13.02% increase; for a rural household the increases is 0.22 kWh, a 7.43% increase.

5.4.2. Mechanisms

Existing studies have explored the mechanisms behind the urban-rural difference in temperature response. Sun and Hanemann (2024) emphasized the type of residential construction, showing that commercial housing exhibits significantly higher electricity consumption than self-built housing due to structural and material differences.

Opinions on the urban heat island effect are mixed. Sun and Hanemann (2024) documented stronger temperature impacts in the city center of provincial capital, whereas Bai et al. (2026) found little role for heat islands in explaining urban-rural adaptation disparities.

Households in urban areas may benefit from more advanced energy infrastructure (Creutzig et al., 2015; Xie et al., 2020b) and stricter energy regulation (Keirstead and Schulz, 2010; Morlet and Keirstead, 2013). Rural households often rely on less advanced energy systems and have more access to traditional biomass energy such as wood and straw (Kishore et al., 2004; Wu et al., 2017; Xie et al., 2020a).

The availability of energy, such as power outage could also contribute to shaping the response curve, as climate change could affect both power demand (Auffhammer et al., 2017; Mideksa and Kallbekken, 2010) and power supply (Bartos and Chester, 2015; Van Vliet et al., 2012). When the supply could not meet the demand, power outage is likely to occur (Do et al., 2023), potentially leading to a relatively flat temperature response curve. China has achieved a relatively high level of energy infrastructure development, providing abundant power supply (Bai et al., 2026). Residential electricity is also given high priority during outages (Hao et al., 2025).[3] Therefore, we do not view power shortages as the primary driver of urban-rural gap in temperature responses. We treat variation in power supply reliability across regions as a proxy for differences in regional infrastructure quality. This proxy allows us to explore whether infrastructure conditions systematically shape temperature responses.

We estimate the coefficients of the interaction terms of the logarithm of reliability and temperature. Reliability indicators at prefecture-area level[4] are obtained from Power Reliability Management and Project Quality Supervision Center, National Energy Administration. In Xinyang City, the reliability rate in urban area is 99.935%, while in rural area it is 99.693%. Given the generally high reliability levels, we standardize reliability rate using z-scores to facilitate interpretation. The estimated coefficients are plotted in Fig. 7 (B), which are significantly positive. Because the reliability indicator is dependent on area within the county, we cautiously interpret the positive effect of infrastructure on the temperature response curve as one of the possible mechanisms for the urban-rural gap.

6. How does temperature response in developing areas differ from that in developed areas

In the previous section, we have examined the effects of income and urban-rural gap on temperature response and explored the underlying mechanisms in the impoverished county. In this section, we assess whether the mechanisms operate similarly in a developed province. Specifically, we apply the same analyses to Zhejiang, one of the most developed provinces in China. This comparison allows us to highlight systematic differences between developing and developed areas and to demonstrate that findings from developed regions cannot be mechanically extrapolated to impoverished contexts.

6.1. Comparison of income effect

6.1.1. Estimation of income effect

Fig. 8 illustrates the estimated temperature response curves for the three income groups (low-, middle-, and high-income groups based on annual income thresholds of 90 and 150 thousand Chinese Yuan). Corresponding regression results are reported in Table A10 in Appendix 3.

Compared to Fig. 4, we can see that Zhejiang's responses at low temperatures are similar to that of Xin County, whereas the responses at high temperatures are substantially steeper. Even the low-income group in Zhejiang has the larger responses at the high temperature than that of the high-income group in Xin County. It suggests large inequality in climate response related to income.

6.1.2. Mechanism 1: ownership of cooling and heating appliances

In Zhejiang, cooling appliance penetration reaches 94.88%, with AC and electric fan penetration rates of 74.00% and 77.32%. Given the near-universal presence of cooling appliances, we focus on AC ownership alone.[5] Table A11 in Appendix 3 shows that income significantly increases the probability of owning AC for cooling.

After estimating income effects on temperature response separately for households with and without ACs (Table A12 in Appendix 3), we find that in Zhejiang income effects are statistically significant among households with ACs but insignificant among those without ACs. These results indicate that income effects in Zhejiang operate through AC

[3] For more details on power outage related facts in China, please refer to Appendix 5 and Bai et al. (2026).

[4] Here, "area" refers to urban or rural areas.

[5] Correspondingly, the results of ownership of AC in Xin County are presented in Appendix 4, which still do not indicate that the ownership of AC is the influencing mechanism.

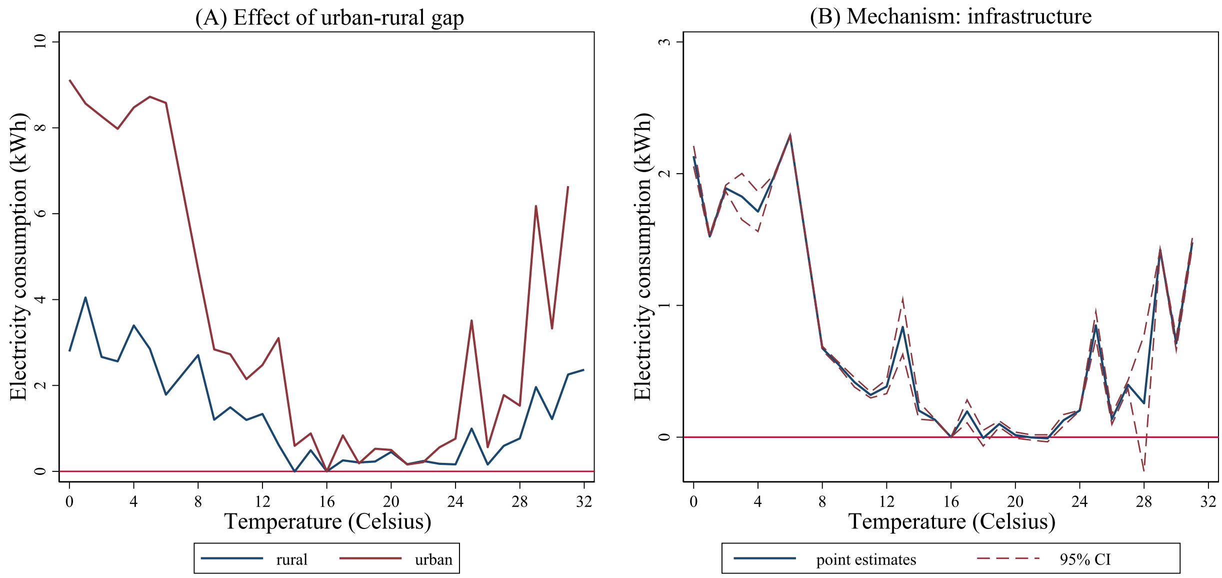

Fig. 7. Temperature response curves of urban and rural households and the mechanism of infrastructure. Notes: The temperature interval of 16–17 °C is set as the baseline. The estimates of every temperature interval are presented in the figure. The standard errors are clustered at the household level. The results of Panel (A) are listed in Table A8 in Appendix 3. The results of Panel (B) are listed in Table A9 in Appendix 3.

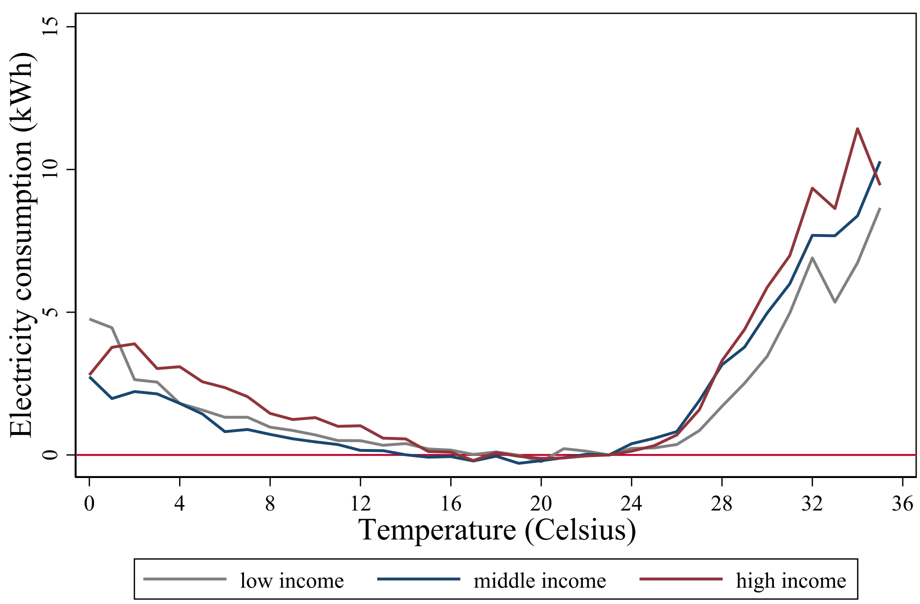

Fig. 8. Temperature response curves of households in different income groups in Zhejiang. Notes: The temperature interval of 23–24 °C is set as the baseline. The estimates of every temperature interval are presented in the figure. The standard errors are clustered at the household level. The results of the regression are listed in Table A10 in Appendix 3.

adoption, with no evidence of "buy-but-not-use" pattern observed in Xin County.

For heating, 68.33% of sampled households in Zhejiang report no heating use, 4.56% rely on heating stoves, and 27.11% use electricity or natural gas. Income has no significant effect on electric heating adoption (Table A13 in Appendix 3). Compared to Xin County, heating demand in Zhejiang is relatively limited, and the region has largely reached the later stage of the energy ladder. These patterns highlight the joint role of climate and income in shaping energy use decisions.

6.1.3. Mechanism 2: usage duration of cooling and heating appliances

Table A14 in Appendix 3 shows that income significantly increases usage duration, with the exception of cooling months of ACs. It indicates that, in a developed region where AC ownership is widespread, income continues to shape adaptive behavior through usage duration at high temperatures. In contrast to Xin County, high usage levels (3.10 months per year and 5.03 hours per day on average) in Zhejiang imply that income-induced increases in usage duration are more likely to translate into observable differences in temperature responses.

For heating, although income is positively associated with usage duration, heating usage in Zhejiang is concentrated among a relatively small subset of households due to the mild winter climate, and income has little impact on the ownership of heating appliance. As a results, the positive income effect on heating duration does not translate into strong temperature responses, and heating-related usage duration plays a limited role in aggregate temperature responsiveness in Zhejiang.

6.1.4. Mechanism 3: dwelling size

We test the impact of income on dwelling size (square meter) in Table A15 in Appendix 3, and find a significant impact. We then examine whether dwelling size amplifies temperature responses by splitting households into small- and big-house groups using a threshold of 135 square meters. As shown in Table A16 in Appendix 3, no statistically significant differences in temperature responses are observed between the two groups.

The absence of dwelling size heterogeneity is probably because the ownership and usage of AC are already widespread and close to saturation, and further increase in dwelling size is likely to generate little additional cooling demand. In this context, dwelling size no longer serves as a channel of temperature sensitivity. This contrasts sharply with Xin County, where low AC penetration and low use of ACs make dwelling size an important channel of climate adaptation.

6.2. Comparison of urban-rural effect

In Xin County, urban households exhibit greater sensitivity to temperature changes compared to rural households. Similar patterns are observed in Zhejiang (Cui et al., 2023). Substantial urban-rural differences in temperature responses persist in both developing and developed regions. It should be noted that the urbanization rate of Xin County is 50.29%, while that of Zhejiang is 68.73%. The gap in urbanization rates can also explain the differences in temperature responses between the two regions.

To access the role of infrastructure in shaping Zhejiang's temperature response, we include the interaction terms of the logarithm of electricity reliability and temperature in the regression. We find that infrastructure has significant positive effects on temperature response at all temperature intervals (Table A17 in Appendix 3). Considering that the infrastructure in urban areas is generally better than that in rural areas, the disparity in infrastructure might be one of the mechanisms responsible for the urban-rural gap. Compared to Xin County, electricity reliability in Zhejiang exhibits a substantially stronger effect in explaining the urban-rural disparities in households' temperature responses.

These findings may point to complementarity between supply-side infrastructure and demand-side conditions. In high-demand environments such as Zhejiang, when electricity supply becomes more reliable, households are better able to translate this latent demand into actual electricity use in response to extreme temperatures. In low-demand regions, similar improvements yield much smaller increases due to binding demand-side constraints. These findings underscore the importance of complementing infrastructure investments with policies addressing demand-side constraints, including appliance ownership, affordability, dwelling insulation and other income-related barriers.

7. Simulation

In this section, with estimated results from previous analysis, we simulate the future residential electricity consumption in Xin County for 2090–2099 based on the estimated coefficients from previous models and climate change scenarios SSP2–4.5 and SSP5–8.5. We consider the scenarios under climate change only and the scenarios under climate change along with urbanization and income growth.

7.1. Climate change

We first consider climate change only, assuming a constant urbanization rate and income distribution. The results are presented in Table 7. Under scenario SSP2–4.5 and SSP5–8.5, residential electricity consumption is projected to decrease slightly by 14.37 kWh (which is a 0.82% change) and 2.13 kWh (0.12%). Recall that climate change brings two opposite effects on electricity consumption: decrease in cold days decreases heating demand, and increase in hot days increases cooling demand. The results indicate that the effect of decreasing heating demand dominates under both scenarios.

Table 7
Simulated household electricity consumption under climate change scenarios.

		All households	Urban households	Rural households
sample	Annual electricity consumption (kWh)	1745.37	2145.70	1340.36
	Annual difference between urban and rural households		60.08%	
SSP2–4.5	Future annual electricity consumption (kWh)	1731.00	2134.52	1322.76
	Growth rate compared to sample	−0.82%	−0.52%	−1.31%
	Future annual difference between urban and rural households		61.37%	
SSP5–8.5	Future annual electricity consumption (kWh)	1743.24	2148.30	1333.46
	Growth rate compared to sample	−0.12%	0.12%	−0.51%
	Future annual difference between urban and rural households		61.11%	

Notes: Future electricity consumption is simulated under the two scenarios of SSP2–4.5 and SSP5–8.5 respectively, and the values of the other variables are the mean of the corresponding variables in the sample.

The comparison results for urban and rural households are also summarized in Table 7. It shows that urban households will slightly decrease their electricity consumption by 0.52% under SSP2–4.5 and increase their electricity consumption by 0.12% under SSP5–8.5, while rural households will decrease their electricity consumption by 1.31% under SSP2–4.5 and by 0.51% under SSP5–8.5. Although the percent changes for rural households are larger in both scenarios, their absolute changes are similar. It suggests that the disparity in adaptation to climate change between urban and rural households will persist.

We then look into the differences in future electricity consumption across different income groups. We conduct separate simulations for low-, middle-, and high-income households and summarize the results in Table 8. It shows that most income groups will experience slight decreases in electricity consumption, except for the high-income group under scenario SSP5–8.5. Notably, the low-income group exhibits the largest percent decrease in electricity consumption. This finding highlights the vulnerability of disadvantaged groups to climate change and

Table 8
Simulated electricity consumption of income groups under climate change scenarios.

		Low-income	Middle-income	High-income
sample	Annual electricity consumption (kWh)	914.30	1040.22	1063.54
	Annual difference between high- and low-income households		16.32%	
SSP2–4.5	Future annual electricity consumption (kWh)	880.26	1008.87	1052.58
	Growth rate compared to sample	−3.72%	−3.01%	−1.03%
	Future annual difference between high- and low-income households		19.58%	
SSP5–8.5	Future annual electricity consumption (kWh)	874.17	1003.60	1065.61
	Growth rate compared to sample	−4.39%	−3.52%	0.19%
	Future annual difference between high- and low-income households		21.90%	

Notes: Future electricity consumption is simulated under the two scenarios of SSP2–4.5 and SSP5–8.5 respectively, and the values of the other variables are the mean of the corresponding variables in the sample.

their lower contribution to climate change compared to higher-income groups. Furthermore, the gap in electricity consumption between high- and low-income groups is further widened, reflecting an increasing disparity in the capacity to cope with climate change.

7.2. Climate change with urbanization and income growth

We now consider scenarios that incorporate increases in urbanization rate and income levels. First, we consider an increase in urbanization rate. In the baseline scenarios for sample period, the urbanization rate is set as 50.28%, according to data from the Henan Statistical Book. In the growth scenario, we increase the urbanization rate to 80%, which approximates the urbanization level of the United States in 2018 (82.26%). By comparing simulated electricity consumption in the baseline and growth scenarios, we derive the combined effects of urbanization and climate change on electricity consumption. The results are plotted in Fig. 9. It can be seen that an increase in urbanization will substantially increase future electricity consumption. Specifically, climate change with urbanization will increase annual electricity consumption by 12.99% under SSP2–4.5 and 13.75% under SSP5–8.5.

Next, we consider a change in income distribution. In the growth scenarios, we assume an income growth rate of approximately 2% per year for all households. The combined effect of income growth and climate change on electricity consumption are summarized in Fig. 9. It shows that income growth significantly increases future electricity consumption. Climate change with income growth will increase annual electricity consumption by 2.75% in SSP2–4.5 and by 3.44% in SSP5–8.5.

These findings demonstrate that both urbanization and income growth will intensify the impact of climate change on electricity consumption. As urbanization and income levels continue to rise, the resulting increases in electricity consumption will further intensify, underscoring the compounded challenges in addressing climate change. In addition, these results may still underestimate the impact of climate change, since we have not considered, yet, the increase in appliance adoption along with urbanization and income growth.

8. Conclusion and policy implications

8.1. Conclusion

In the face of climate change, households usually adopt cooling and heating appliances, leading to more electricity consumption. However, low-income households are particularly vulnerable to these changes due to tight budget constraints. Meanwhile, these households have great potential in electricity consumption, yet they are neglected in previous studies due to data limitations. Using high-frequency electricity consumption data and household survey data, this paper estimates the electricity consumption response to temperature changes of households in an impoverished county in China, and more importantly, explores the income effect and the urban effect as well as the underlying mechanisms. Furthermore, we compare it with that observed in a developed province in China, thereby providing a unified analysis of developing and developed regions.

This paper provides a conceptual framework on how household income shapes temperature response, which helps reconcile why temperature response curve is U-shaped and why electricity demand responses vary substantially across income groups.

The empirical analysis extend the literature on income inequality in energy consumption by examining income gap in temperature response and identifying the channels through which income shapes temperature adaptation. In the less developed Xin County, income mainly operates through use duration of heating appliances and dwelling size. AC penetration is low and seen as a luxury. In contrast, in the more developed Zhejiang Province, where AC is widespread, income primarily influences the adoption and use of AC, thereby amplifying electricity responses at high temperatures. Beyond household income, we have a discussion on the effect of urban-rural gap. While differences in infrastructure explain part of the regional gap, demand-side constraints appear to play a more dominant role since electricity supply in China has reached a high level.

The results carry direct implications for real-world energy policy and climate governance. First, this paper provides measurable evidence of how income disparities translate into unequal electricity consumption under extreme temperatures. The same income shock may translate into fundamentally different adaptation behaviors. Second, the comparative

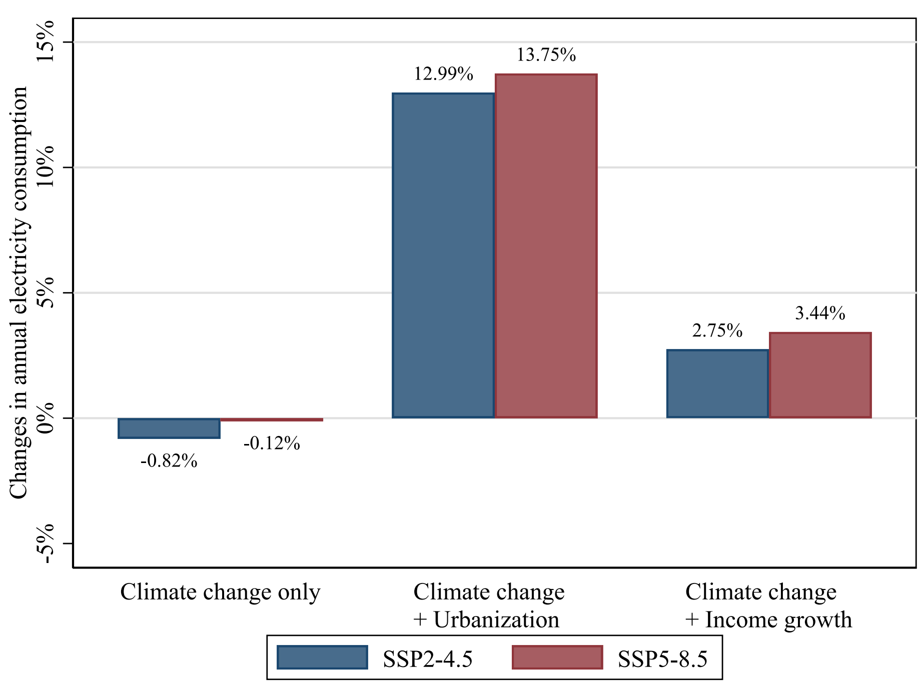

Fig. 9. Simulated household electricity consumption under climate change with urbanization and income growth scenarios.

evidence shows that adaptive behaviors observed in developed regions may not generalize to less developed areas, even within the same country. Applying estimates from developed regions to impoverished regions may lead to systematic overestimation of adaptive capacity and underestimation of climate vulnerability. Third, in the Chinese context, demand-side constraints appear to play a more binding role than supply-side limitations in shaping households' electricity responses to temperature shocks, particularly in less developed areas. While electricity infrastructure differences explain part of the regional heterogeneity, the generally high baseline level of electricity supply in China implies that infrastructure is not the dominant constraint on adaptive electricity use at present.

Due to data limitations, this paper captures only the short-term temperature response with constant appliance adoption and income. Moreover, our analysis is limited to one county and one province, restricting the ability to generate sufficient variations across counties so as to identify long-term responses. Future research should explore long-term responses in less developed areas as data on dynamic changes become available. Such studies will provide deeper insights into the evolving adaptive capacity of households in less developed areas under climate change.

8.2. Policy implications

Based on the economic implications, we propose several specific policy recommendations. First, integrate inequality concerns into energy and climate policy design. Policymakers should consider to differ responsibilities and capabilities of various groups. For instance, carbon market designs should reflect fairness across areas and groups while incorporating emission reduction contributions.

Second, promote targeted subsidies for clean and efficient appliances for low-income households. Given the income effects on expensive appliance such as ACs ownership and the fact of low penetration in underdeveloped regions, targeted subsidies, low-interest financing, or voucher programs can help low-income households acquire ACs and clean heaters. Importantly, subsidy schemes should prioritize clean and high-efficiency appliances to improve the affordability of operating cost, thereby strengthening climate adaptation while remaining consistent with long-run decarbonization goals.

Third, improve housing thermal performance as a complementary climate adaptation strategy. Policies that support housing insulation improvements can substantially reduce the electricity required to achieve thermal comfort, such as insulation retrofitting, window sealing, and building envelope upgrades. Integrating building efficiency programs into housing renovation would offer a durable means of enhancing adaptive capacity, while simultaneously lowering energy expenditure and emissions.

Fourth, prioritize demand-side interventions in the short term, and adopt a forward-looking approach to energy infrastructure investment in less developed regions. In the short term, policies that relax household budget constraints may yield larger gains in adaptive capacity, such as appliances subsidies. At the same time, the simulation results indicate that electricity demand in these areas is likely to grow disproportionately as incomes rise, placing increasing pressure on local grids. Strengthening transmission capacity, improving distribution networks, and upgrading rural substations are therefore essential to ensure reliable supply in the long term.

CRediT authorship contribution statement

Chen Zhao: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis. **Lunyu Xie:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Xinye Zheng:** Investigation, Conceptualization, Funding acquisition.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 4 in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication. The work was original research that has not been published previously, or not under consideration for publication elsewhere. All the authors listed have approved the manuscript that is enclosed.

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Appendix A. Appendix

A.1. Appendix 1: Representativeness of the studied area

Xin County is in a central inland county, with the annual average temperature of 15.20 °C, the annual average sunshine duration of 2007.70 h, the annual average precipitation of 1277.50 mm, and the frost-free period of approximately 222 days.

The disposable annual income per capita of Xin County was 18,960 Chinese Yuan in 2018, the year studied in this paper. Specifically, the income was 27,263 Yuan for urban residents and 12,826 yuan for rural residents.[6] Compared to the national disposable income per capita of 28,228 yuan, households in Xin County are among the middle- and low- income group.[7]

As shown by Zhang et al. (2023), Xin County is comparable to the median of all counties in China in many key socioeconomic variables, such as GDP per capita, population density, deposit per capita and etc.. The representativeness of Xin County alleviates the concern on the external validity of this study.

[6] Source: Henan Statistical Yearbook 2019

[7] Source: The 2018 Statistical Bulletin on National Economic and Social Development

A.2. Appendix 2: Figures

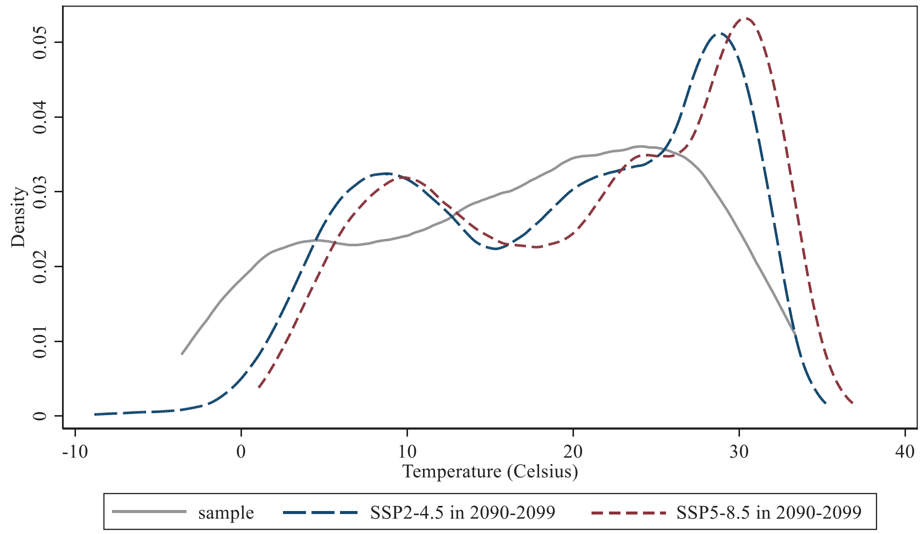

Fig. A1. The temperature distributions of sample period and two future scenarios in 2090–2099.

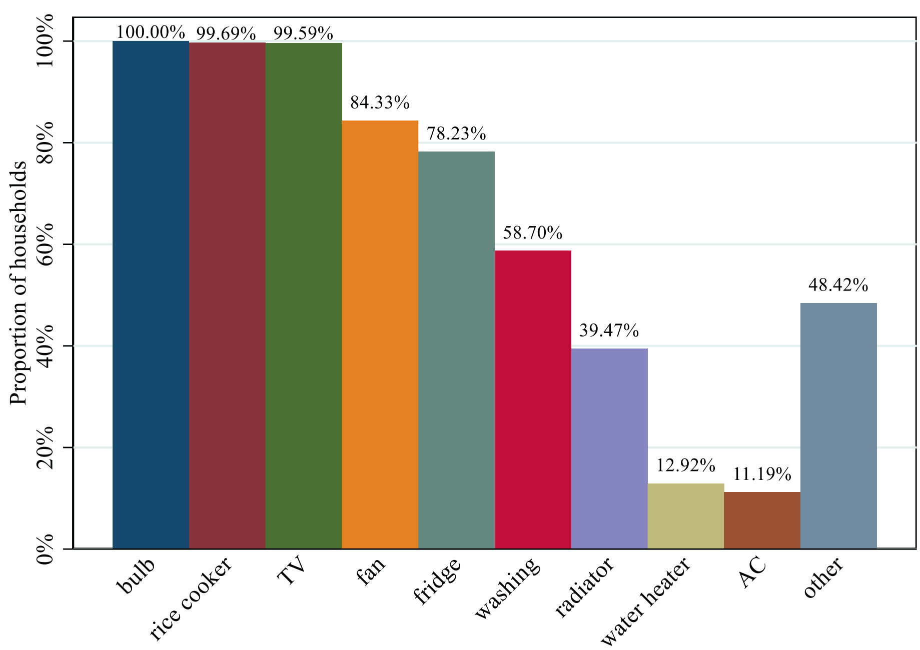

Fig. A2. Proportion of households that own the appliance in Xin County. Notes: These values are calculated based on the sample of 1043 households.

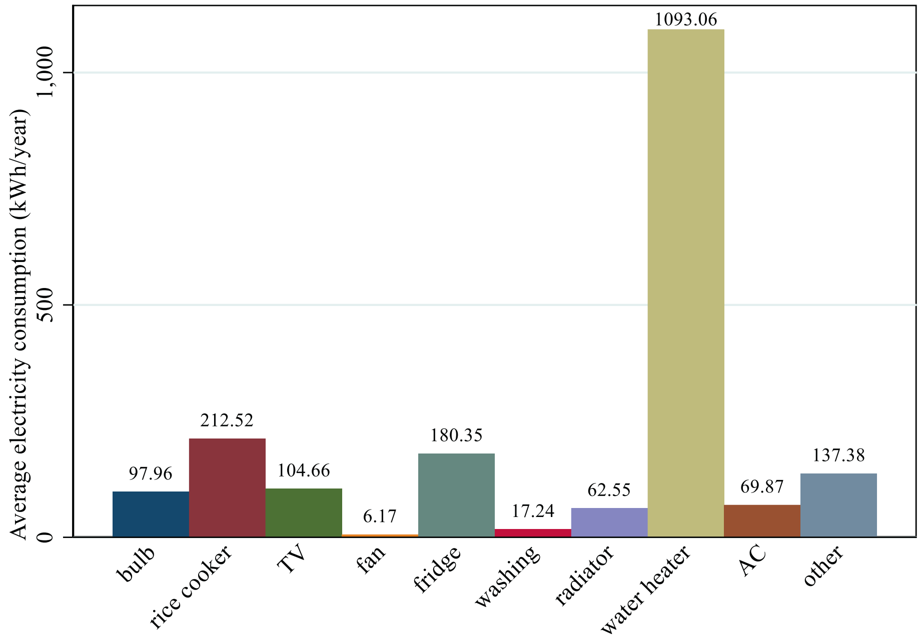

Fig. A3. Average electricity consumption of appliances in Xin County. Notes: These values are calculated based on the sample of 1043 households.

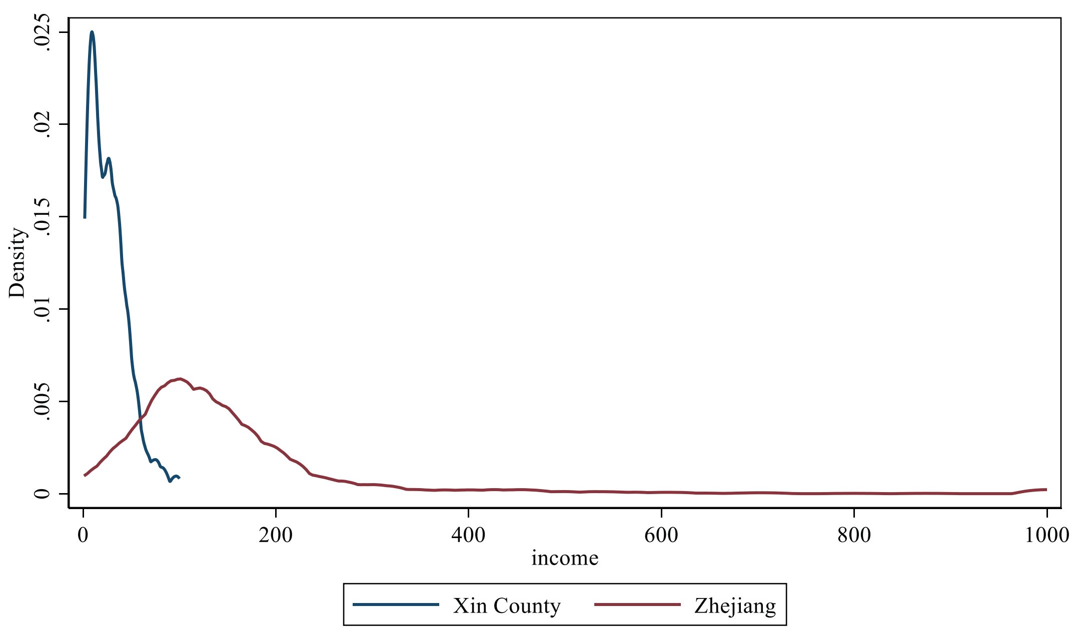

Fig. A4. The income distributions of households in Xin County and Zhejiang. *Notes:* For the aesthetic appeal of the graph, we have respectively winsorized the income of Xin County and Zhejiang by 99% and 95%.

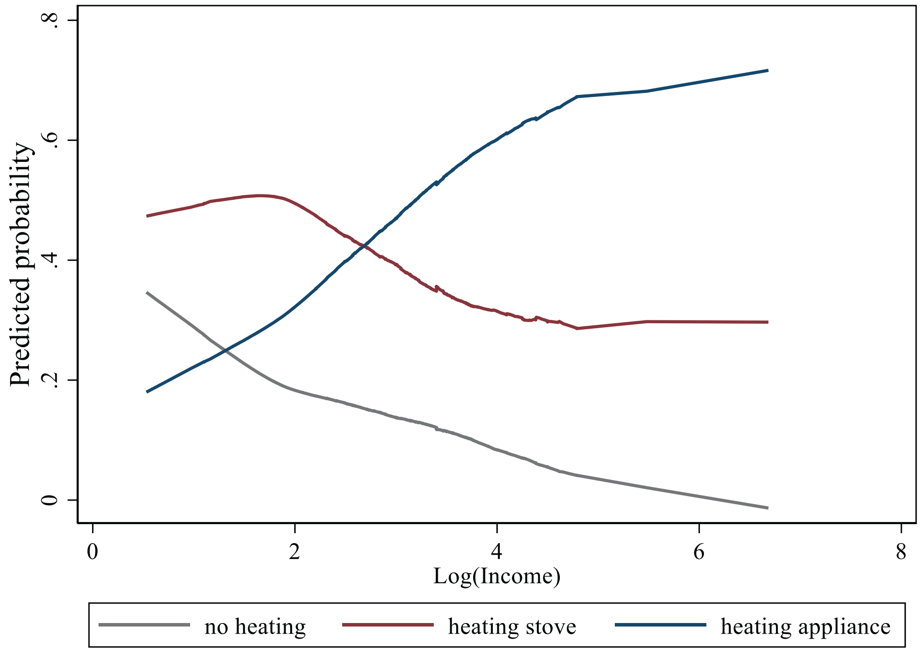

Fig. A5. Predicted probabilities of heating types by incomes in Xin County. *Notes:* Probabilities of different heating types is predicted for every household. We utilize a locally weighted regression of predicted probabilities on income (log), and display the smoothed curve.

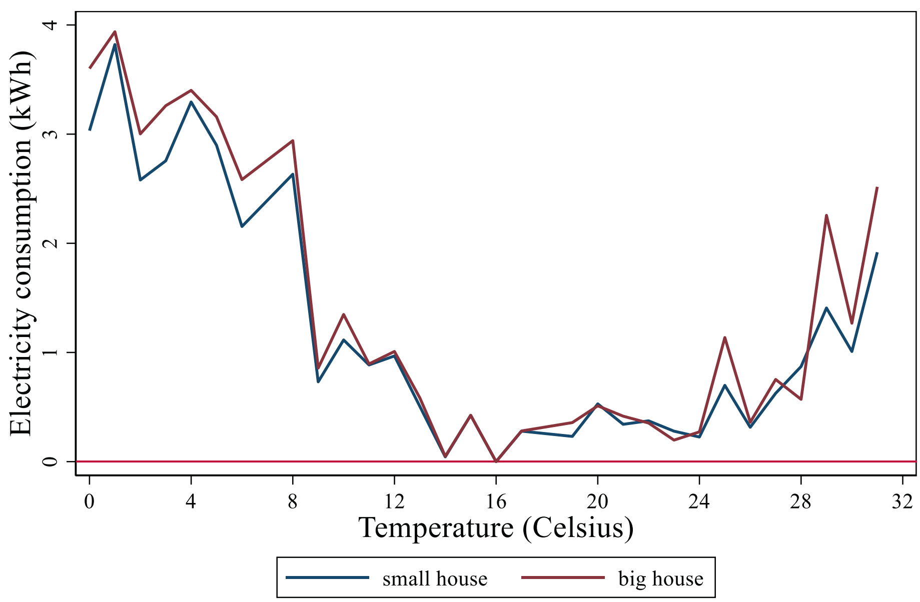

Fig. A6. Temperature response curves of households by dwelling size in Xin County. *Notes:* The temperature interval of 16–17 °C is set as the baseline. The estimates of every temperature interval are presented in the figure. The standard errors are clustered at the household level. The results of the regression are listed in Table A6 in Appendix 3.

A.3. Appendix 3: Tables

Table A1
Results of baseline analysis and robustness checks.

	(1)		(2)		(3)
	1 °C intervals $PM_{2.5}$		2°C intervals $PM_{2.5}$		1 °C intervals AQI
VARIABLES	electricity	VARIABLES	electricity	VARIABLES	electricity
0–1 °C	3.0484***	0–2°C	2.1798***	0–1 °C	3.3034***
	(0.131)		(0.021)		(0.134)
1–2°C	4.2913***			1–2°C	4.4566***

(*continued on next page*)

Table A1 (*continued*)

	(1)		(2)		(3)
	1 °C intervals $PM_{2.5}$		2°C intervals $PM_{2.5}$		1 °C intervals AQI
VARIABLES	electricity	VARIABLES	electricity	VARIABLES	electricity
	(0.134)				(0.137)
2–3 °C	2.8649***	2–4 °C	1.7240***	2–3 °C	3.1487***
	(0.131)		(0.019)		(0.134)
3–4°C	2.6850***			3–4 °C	2.9097***
	(0.132)				(0.134)
4–5°C	3.7826***	4–6 °C	2.1054***	4–5 °C	3.9072***
	(0.133)		(0.022)		(0.135)
5–6°C	3.0343***			5–6 °C	3.2819***
	(0.130)				(0.133)
6–7 °C	2.0939***	6–8°C	1.0929***	6–7 °C	2.3693***
	(0.132)		(0.026)		(0.135)
8–9 °C	2.5952***	8–10 °C	1.0242***	8–9 °C	2.8147***
	(0.133)		(0.010)		(0.136)
9–10 °C	1.3689***			9–10 °C	1.3410***
	(0.012)				(0.012)
10–11 °C	1.6395***	10–12 °C	0.9266***	10–11 °C	1.5160***
	(0.015)		(0.011)		(0.014)
11–12 °C	1.3194***			11–12 °C	1.2378***
	(0.013)				(0.012)
12–13 °C	1.4596***	12–14 °C	0.7953***	12–13 °C	1.3623***
	(0.014)		(0.009)		(0.014)
13–14 °C	0.8846***			13–14 °C	0.8416***
	(0.011)				(0.011)
14–15 °C	0.0010	14–16 °C	0.1256***	14–15 °C	−0.0050
	(0.007)		(0.003)		(0.007)
15–16 °C	0.5206***			15–16 °C	0.4591***
	(0.006)				(0.005)
17–18 °C	0.3165***			17–18 °C	0.2664***
	(0.007)				(0.006)
18–19 °C	0.0458	18–20 °C	0.0974***	18–19 °C	0.0523
	(0.409)		(0.006)		(0.407)
19–20 °C	0.2167***			19–20 °C	0.2256***
	(0.007)				(0.007)
20–21 °C	0.4412***	20–22 °C	0.1685***	20–21 °C	0.4716***
	(0.008)		(0.007)		(0.008)
21–22 °C	0.1266***			21–22 °C	0.1634***
	(0.008)				(0.008)
22–23 °C	0.1913***	22–24 °C	0.0635***	22–23 °C	0.2166***
	(0.008)		(0.007)		(0.008)
23–24 °C	0.2075***			23–24 °C	0.2346***
	(0.007)				(0.007)
24–25 °C	0.2193***	24–26 °C	0.3238***	24–25 °C	0.2249***
	(0.009)		(0.008)		(0.009)
25–26 °C	1.2598***			25–26 °C	1.2646***
	(0.012)				(0.012)
26–27 °C	0.1721***	26–28 °C	0.1200***	26–27 °C	0.1882***
	(0.009)		(0.008)		(0.009)
27–28 °C	0.7174***			27–28 °C	0.7391***
	(0.011)				(0.011)
28–29 °C	0.9398***	28–30 °C	1.8618***	28–29 °C	0.9847***
	(0.017)		(0.013)		(0.017)
29–30 °C	2.4409***			29–30 °C	2.4618***
	(0.016)				(0.016)
30–31 °C	1.4464***	30–32 °C	1.5008***	30–31 °C	1.4314***
	(0.013)		(0.013)		(0.013)
31–32 °C	2.6885***			31–32 °C	2.6972***
	(0.019)				(0.019)
32–33 °C	2.5173***	32–34 °C	1.9026***	32–33 °C	2.4964***
	(0.038)		(0.035)		(0.038)
Controls	YES	Controls	YES	Controls	YES
Month FE	YES	Month FE	YES	Month FE	YES
Household FE	YES	Household FE	YES	Household FE	YES
Observations	5,946,264	Observations	5,946,264	Observations	5,946,264
Number of id	79,127	Number of id	79,127	Number of id	79,127
R-squared	0.686	R-squared	0.684	R-squared	0.686

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households involved is 79,127.

Table A2
Results of heterogeneity in income.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low income	Middle income	High income	Low-High F-test	Low-Middle F-test	Middle-High F-test
VARIABLES	electricity	electricity	electricity	*P* value	P value	P value
0–1 °C	2.7654***	3.6691***	3.7817***	0.0064	0.0109	0.7722
	(0.966)	(0.968)	(0.975)			
1–2°C	3.4302***	4.3511***	4.0222***	0.0079	0.0001	0.2318
	(0.971)	(0.988)	(0.963)			
2–3 °C	2.2617**	3.2227***	3.1325***	0.0003	0.0001	0.7576
	(0.943)	(0.955)	(0.948)			
3–4°C	2.5484***	3.2709***	3.4455***	0.0067	0.0170	0.5935
	(0.962)	(0.960)	(0.971)			
4–5°C	2.9011***	3.7452***	3.5538***	0.0125	0.0021	0.5116
	(0.970)	(0.969)	(0.960)			
5–6°C	2.5994***	3.3420***	3.3369***	0.0180	0.0154	0.9860
	(0.962)	(0.953)	(0.946)			
6–7 °C	1.6079*	2.7662***	2.9759***	0.0000	0.0002	0.5877
	(0.938)	(0.959)	(0.969)			
8–9 °C	2.6346***	2.9175***	3.0294***	0.0416	0.0582	0.5947
	(0.950)	(0.948)	(0.935)			
9–10 °C	0.6320***	0.8221***	0.9512***	0.0086	0.0236	0.3095
	(0.078)	(0.086)	(0.117)			
10–11 °C	1.0103***	1.2373***	1.4772***	0.0043	0.0411	0.1676
	(0.106)	(0.118)	(0.166)			
11–12 °C	0.8253***	0.8817***	0.9332***	0.4119	0.5686	0.6943
	(0.098)	(0.093)	(0.119)			
12–13 °C	0.7387***	1.0642***	1.1618***	0.0301	0.0071	0.6443
	(0.085)	(0.115)	(0.194)			
13–14 °C	0.2356***	0.7232***	0.6894***	0.0057	0.0004	0.8606
	(0.077)	(0.119)	(0.135)			
14–15 °C	−0.0179	0.0892	0.0608	0.4331	0.1121	0.7911
	(0.049)	(0.057)	(0.077)			
15–16 °C	0.3961***	0.4338***	0.4283***	0.5718	0.4102	0.9296
	(0.038)	(0.044)	(0.055)			
17–18 °C	0.2479***	0.2981***	0.2801***	0.5481	0.3102	0.7616
	(0.043)	(0.048)	(0.050)			
19–20 °C	0.2773***	0.3003***	0.3160***	0.6033	0.6964	0.8430
	(0.048)	(0.053)	(0.071)			
20–21 °C	0.5342***	0.5164***	0.4764***	0.3708	0.7514	0.5641
	(0.060)	(0.060)	(0.054)			
21–22 °C	0.3796***	0.3621***	0.3826***	0.9680	0.7625	0.7977
	(0.057)	(0.062)	(0.075)			
22–23 °C	0.3935***	0.3172***	0.3277***	0.4288	0.2614	0.9126
	(0.057)	(0.067)	(0.071)			
23–24 °C	0.1832***	0.2492***	0.2471***	0.5560	0.4495	0.9863
	(0.061)	(0.076)	(0.089)			
24–25 °C	0.2335***	0.2628***	0.2219***	0.8902	0.6773	0.6648
	(0.060)	(0.072)	(0.077)			
25–26 °C	0.6394***	0.9848***	1.1761***	0.0054	0.0500	0.3641
	(0.111)	(0.129)	(0.148)			
26–27 °C	0.2907***	0.3618***	0.3303***	0.7028	0.3191	0.7752
	(0.069)	(0.069)	(0.093)			
27–28 °C	0.5511***	0.7432***	0.7646***	0.0941	0.0818	0.8826
	(0.081)	(0.098)	(0.108)			
28–29 °C	0.6357***	0.6438***	0.5362***	0.6803	0.9697	0.6880
	(0.136)	(0.176)	(0.204)			
29–30 °C	1.1571***	1.9103***	2.5705***	0.0001	0.0165	0.0901
	(0.180)	(0.230)	(0.269)			
30–31 °C	0.8039***	1.2144***	1.4269***	0.0022	0.0215	0.3694
	(0.107)	(0.148)	(0.170)			
31–32 °C	1.5613***	2.2594***	2.9418***	0.0002	0.0264	0.0913
	(0.199)	(0.241)	(0.313)			
Controls	YES					
Month FE	YES					
Household FE	YES					
Observations	76,826					
R-squared	0.600					
Number of id	983					

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households is 330 for low-income group, 326 for middle-income group and 327 for high-income group.

Table A3
Marginal effects of income.

	(1)		(1)
	Income effects		(continued)
VARIABLES	electricity	VARIABLES	electricity
0–1 °C	0.5733***	19–20 °C	0.0229
	(0.140)		(0.029)
1–2°C	0.3328***	20–21 °C	0.0028
	(0.110)		(0.026)
2–3 °C	0.4772***	21–22 °C	0.0273
	(0.099)		(0.034)
3–4°C	0.5455***	22–23 °C	−0.0190
	(0.123)		(0.038)
4–5°C	0.3685***	23–24 °C	0.0358
	(0.110)		(0.047)
5–6°C	0.4333***	24–25 °C	0.0141
	(0.113)		(0.036)
6–7 °C	0.6296***	25–26 °C	0.3036***
	(0.143)		(0.086)
8–9 °C	0.1779**	26–27 °C	0.0296
	(0.082)		(0.042)
9–10 °C	0.1604***	27–28 °C	0.1208**
	(0.046)		(0.055)
10–11 °C	0.2183***	28–29 °C	−0.0475
	(0.064)		(0.114)
11–12 °C	0.0745	29–30 °C	0.7099***
	(0.055)		(0.165)
12–13 °C	0.1740**	30–31 °C	0.3120***
	(0.069)		(0.097)
13–14 °C	0.2025***	31–32 °C	0.6509***
	(0.068)		(0.171)
14–15 °C	0.0303	Controls	YES
	(0.036)	Month FE	YES
15–16 °C	0.0209	Household FE	YES
	(0.023)	Observations	76,826
17–18 °C	0.0245	R-squared	0.600
	(0.022)	Number of id	983

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households involved is 983.

Table A4
Results of heterogeneity in cooling appliance.

	(1)	(2)	(3)
	No cooling appliance	With cooling appliance	F-test
VARIABLES	electricity	electricity	P value
0–1 °C	3.6092***	3.3412***	0.4914
	(0.993)	(0.951)	
1–2°C	4.1365***	3.8631***	0.3927
	(1.049)	(0.957)	
2–3 °C	3.1024***	2.7997***	0.2852
	(0.974)	(0.938)	
3–4°C	3.0966***	3.0655***	0.9183
	(0.976)	(0.950)	
4–5°C	3.8701***	3.2841***	0.0873
	(1.019)	(0.952)	
5–6°C	3.2672***	3.0360***	0.4197
	(0.974)	(0.939)	
6–7 °C	2.5449***	2.4022**	0.7064
	(0.982)	(0.940)	
8–9 °C	2.7789***	2.8383***	0.7255
	(0.969)	(0.936)	
9–10 °C	0.8638***	0.7926***	0.4695
	(0.104)	(0.073)	
10–11 °C	1.2635***	1.2428***	0.8809
	(0.146)	(0.104)	
11–12 °C	1.1040***	0.8472***	0.0378
	(0.130)	(0.079)	
12–13 °C	0.9283***	1.0015***	0.6342
	(0.142)	(0.102)	
13–14 °C	0.6165***	0.5392***	0.6567
	(0.157)	(0.066)	
14–15 °C	0.0989	0.0380	0.4092

(*continued on next page*)

Table A4 (*continued*)

VARIABLES	(1) No cooling appliance electricity	(2) With cooling appliance electricity	(3) F-test P value
	(0.065)	(0.035)	
15–16 °C	0.4270***	0.4225***	0.9234
	(0.050)	(0.035)	
17–18 °C	0.3203***	0.2724***	0.3423
	(0.054)	(0.037)	
19–20 °C	0.2099***	0.3202***	0.0889
	(0.063)	(0.045)	
20–21 °C	0.5342***	0.5139***	0.7097
	(0.067)	(0.045)	
21–22 °C	0.3252***	0.3942***	0.2372
	(0.065)	(0.053)	
22–23 °C	0.3519***	0.3602***	0.9018
	(0.072)	(0.046)	
23–24 °C	0.2350***	0.2307***	0.9584
	(0.077)	(0.048)	
24–25 °C	0.2848***	0.2433***	0.5859
	(0.079)	(0.054)	
25–26 °C	0.8753***	0.9556***	0.6633
	(0.166)	(0.075)	
26–27 °C	0.2865***	0.3469***	0.4544
	(0.085)	(0.057)	
27–28 °C	0.6424***	0.7044***	0.6042
	(0.117)	(0.065)	
28–29 °C	0.8819***	0.6421***	0.3609
	(0.252)	(0.101)	
29–30 °C	1.6568***	1.9250***	0.4589
	(0.320)	(0.124)	
30–31 °C	1.0887***	1.1650***	0.7189
	(0.198)	(0.087)	
31–32 °C	2.0790***	2.2870***	0.5750
	(0.332)	(0.162)	
Controls	YES		
Month FE	YES		
Household FE	YES		
Observations	76,826		
R-squared	0.597		
Number of id	983		

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The households involved include 123 households without any cooling appliance and 860 households with cooling appliance (AC or electric fans).

Table A5
Results of heterogeneity in heating appliance.

VARIABLES	(1) No electric heating appliance electricity	(2) With electric heating appliance electricity	(3) F-test P value
0–1 °C	3.2773***	3.5966***	0.2939
	(0.972)	(0.941)	
1–2°C	3.6636***	4.2575***	0.0036
	(0.984)	(0.955)	
2–3 °C	2.7366***	3.0676***	0.1241
	(0.951)	(0.935)	
3–4 °C	3.0055***	3.2413***	0.3691
	(0.969)	(0.940)	
4–5°C	3.1810***	3.6515***	0.0379
	(0.967)	(0.953)	
5–6°C	2.9200***	3.3404***	0.0883
	(0.957)	(0.933)	
6–7 °C	2.2950**	2.6672***	0.1878
	(0.954)	(0.936)	
8–9 °C	2.8307***	2.9222***	0.5577
	(0.946)	(0.938)	
9–10 °C	0.7871***	0.8281***	0.6632
	(0.083)	(0.086)	
10–11 °C	1.2265***	1.2835***	0.6449
	(0.119)	(0.116)	
11–12 °C	0.8618***	0.9144***	0.6061
	(0.086)	(0.099)	

(*continued on next page*)

Table A5 (*continued*)

	(1)	(2)	(3)
	No electric heating appliance	With electric heating appliance	F-test
VARIABLES	electricity	electricity	P value
12–13 °C	0.9718***	1.0178***	0.7490
	(0.126)	(0.108)	
13–14 °C	0.4747***	0.6394***	0.2298
	(0.091)	(0.091)	
14–15 °C	0.0939*	−0.0015	0.2154
	(0.051)	(0.047)	
15–16 °C	0.4466***	0.3986***	0.2972
	(0.041)	(0.040)	
17–18 °C	0.3079***	0.2497***	0.1969
	(0.042)	(0.042)	
19–20 °C	0.3674***	0.2340***	0.0230
	(0.052)	(0.049)	
20–21 °C	0.5276***	0.5000***	0.6028
	(0.054)	(0.050)	
21–22 °C	0.4536***	0.3009***	0.0099
	(0.062)	(0.054)	
22–23 °C	0.4749***	0.2118***	0.0001
	(0.058)	(0.054)	
23–24 °C	0.2960***	0.1502**	0.1016
	(0.062)	(0.064)	
24–25 °C	0.3329***	0.1449**	0.0070
	(0.061)	(0.063)	
25–26 °C	1.0693***	0.8099***	0.1041
	(0.107)	(0.101)	
26–27 °C	0.4126***	0.2529***	0.0485
	(0.067)	(0.068)	
27–28 °C	0.7533***	0.6223***	0.2223
	(0.078)	(0.086)	
28–29 °C	0.7175***	0.4242**	0.2161
	(0.113)	(0.213)	
29–30 °C	2.0637***	1.6905***	0.1977
	(0.181)	(0.179)	
30–31 °C	1.2021***	1.1001***	0.5528
	(0.110)	(0.126)	
31–32 °C	2.4409***	2.0441***	0.1852
	(0.215)	(0.202)	
Controls	YES		
Month FE	YES		
Household FE	YES		
Observations	76,826		
R-squared	0.598		
Number of id	983		

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The households involved include 525 households without any heating appliance and 458 households with heating appliance.

Table A6
Results of heterogeneity in dwelling area.

	(1)	(2)	(3)
	Small house	Big house	F-test
VARIABLES	electricity	electricity	P value
0–1 °C	3.032***	3.601***	0.0514
	(0.942)	(0.965)	
1–2°C	3.821***	3.938***	0.5515
	(0.973)	(0.964)	
2–3 °C	2.580***	3.002***	0.0385
	(0.938)	(0.944)	
3–4°C	2.755***	3.261***	0.0467
	(0.942)	(0.962)	
4–5°C	3.295***	3.401***	0.6293
	(0.954)	(0.962)	
5–6°C	2.898***	3.159***	0.2702
	(0.934)	(0.952)	
6–7 °C	2.154**	2.583***	0.1186
	(0.941)	(0.946)	
8–9 °C	2.633***	2.940***	0.0363
	(0.952)	(0.932)	
9–10 °C	0.731***	0.857***	0.1479

(*continued on next page*)

Table A6 (*continued*)

	(1)	(2)	(3)
	Small house	Big house	F-test
VARIABLES	electricity	electricity	P value
	(0.0791)	(0.0842)	
10–11 °C	1.115***	1.348***	0.0427
	(0.108)	(0.119)	
11–12 °C	0.885***	0.895***	0.9216
	(0.0997)	(0.0840)	
12–13 °C	0.968***	1.009***	0.7663
	(0.106)	(0.122)	
13–14 °C	0.505***	0.584***	0.5526
	(0.0853)	(0.0906)	
14–15 °C	0.0435	0.0488	0.9401
	(0.0439)	(0.0483)	
15–16 °C	0.424***	0.425***	0.9854
	(0.0385)	(0.0401)	
17–18 °C	0.279***	0.281***	0.9696
	(0.0418)	(0.0409)	
19–20 °C	0.231***	0.358***	0.0274
	(0.0473)	(0.0524)	
20–21 °C	0.529***	0.511***	0.7154
	(0.0566)	(0.0465)	
21–22 °C	0.342***	0.417***	0.1814
	(0.0574)	(0.0571)	
22–23 °C	0.374***	0.354***	0.7511
	(0.0560)	(0.0534)	
23–24 °C	0.279***	0.197***	0.3258
	(0.0640)	(0.0578)	
24–25 °C	0.226***	0.273***	0.4766
	(0.0630)	(0.0589)	
25–26 °C	0.699***	1.137***	0.0042
	(0.103)	(0.0998)	
26–27 °C	0.315***	0.360***	0.5526
	(0.0724)	(0.0620)	
27–28 °C	0.626***	0.753***	0.2193
	(0.0869)	(0.0749)	
28–29 °C	0.871***	0.571***	0.1449
	(0.180)	(0.112)	
29–30 °C	1.408***	2.256***	0.0026
	(0.176)	(0.175)	
30–31 °C	1.009***	1.268***	0.1189
	(0.126)	(0.106)	
31–32 °C	1.918***	2.518***	0.0407
	(0.200)	(0.209)	
Controls	YES		
Month FE	YES		
Household FE	YES		
Observations	76,826		
R-squared	0.598		
Number of id	983		

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The households involved include 412 households living in small house and 571 households living in big house.

Table A7
The impact of income on temperature in households living in a small or big house.

	(1)	(2)		(1)	(2)
	Small house	Big house		(continued)	
VARIABLES	electricity	electricity	VARIABLES	electricity	electricity
0–1 °C	0.528***	0.517**	19–20 °C	−0.0476	0.0459
	(0.178)	(0.253)		(0.0462)	(0.0434)
1–2°C	0.251	0.457***	20–21 °C	0.00883	0.00553
	(0.162)	(0.141)		(0.0342)	(0.0470)
2–3 °C	0.434***	0.462***	21–22 °C	0.00538	0.0246
	(0.137)	(0.160)		(0.0414)	(0.0583)
3–4°C	0.615***	0.382*	22–23 °C	−0.0471	0.0139
	(0.180)	(0.214)		(0.0412)	(0.0646)
4–5°C	0.363**	0.426**	23–24 °C	0.0557	0.0634
	(0.153)	(0.175)		(0.0522)	(0.0800)
5–6°C	0.594***	0.252	24–25 °C	−0.0485	0.0637
	(0.174)	(0.219)		(0.0490)	(0.0576)

(*continued on next page*)

Table A7 (*continued*)

	(1)	(2)		(1)	(2)
	Small house	Big house		(continued)	
VARIABLES	electricity	electricity	VARIABLES	electricity	electricity
6–7 °C	0.623***	0.611***	25–26 °C	0.128	0.379***
	(0.206)	(0.212)		(0.117)	(0.141)
8–9 °C	−0.0311	0.307**	26–27 °C	−0.0216	0.0720
	(0.113)	(0.122)		(0.0573)	(0.0647)
9–10 °C	0.190***	0.115	27–28 °C	0.0514	0.166*
	(0.0640)	(0.0753)		(0.0776)	(0.0858)
10–11 °C	0.181**	0.215**	28–29 °C	0.238	−0.0995
	(0.0872)	(0.0993)		(0.241)	(0.129)
11–12 °C	0.118	0.0461	29–30 °C	0.397*	0.864***
	(0.0922)	(0.0863)		(0.228)	(0.268)
12–13 °C	0.174*	0.204**	30–31 °C	0.152	0.448***
	(0.105)	(0.100)		(0.134)	(0.151)
13–14 °C	0.204**	0.216**	31–32 °C	0.377	0.848***
	(0.0989)	(0.109)		(0.239)	(0.268)
14–15 °C	0.0619	0.00121	Controls	YES	YES
	(0.0394)	(0.0579)	Month FE	YES	YES
15–16 °C	0.0463	−0.00141	Household FE	YES	YES
	(0.0324)	(0.0359)	Observations	32,428	44,398
17–18 °C	0.0420	0.0114	R-squared	0.633	0.577
	(0.0312)	(0.0385)	Number of id	412	571

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households involved is 412 and 571 for households living in small or big house.

Table A8
Results of heterogeneity in urban and rural areas.

	(1)	(2)	(3)
	Urban	Rural	F-test
VARIABLES	electricity	electricity	*P*-value
0–1 °C	9.1176***	2.7928***	0.0000
	(0.160)	(0.131)	
1–2°C	8.5661***	4.0501***	0.0000
	(0.159)	(0.133)	
2–3 °C	8.2675***	2.6657***	0.0000
	(0.152)	(0.131)	
3–4°C	7.9768***	2.5620***	0.0000
	(0.157)	(0.132)	
4–5°C	8.4746***	3.3984***	0.0000
	(0.159)	(0.132)	
5–6°C	8.7241***	2.8539***	0.0000
	(0.158)	(0.130)	
6–7 °C	8.5802***	1.7872***	0.0000
	(0.165)	(0.132)	
8–9 °C	4.7086***	2.7076***	0.0000
	(0.144)	(0.133)	
9–10 °C	2.8402***	1.2028***	0.0000
	(0.030)	(0.012)	
10–11 °C	2.7282***	1.4920***	0.0000
	(0.036)	(0.015)	
11–12 °C	2.1485***	1.1981***	0.0000
	(0.031)	(0.013)	
12–13 °C	2.4776***	1.3376***	0.0000
	(0.038)	(0.014)	
13–14 °C	3.1040***	0.6219***	0.0000
	(0.048)	(0.011)	
14–15 °C	0.5951***	−0.0043	0.0000
	(0.017)	(0.007)	
15–16 °C	0.8841***	0.4922***	0.0000
	(0.014)	(0.006)	
17–18 °C	0.8383***	0.2573***	0.0000
	(0.015)	(0.007)	
18–19 °C	0.1881	0.2089	0.9726
	(0.449)	(0.407)	
19–20 °C	0.5271***	0.2301***	0.0000
	(0.015)	(0.007)	
20–21 °C	0.4995***	0.4527***	0.0009
	(0.015)	(0.008)	
21–22 °C	0.1605***	0.1671***	0.5938
	(0.013)	(0.008)	

(*continued on next page*)

Table A8 (*continued*)

VARIABLES	(1) Urban electricity	(2) Rural electricity	(3) F-test *P*-value
22–23 °C	0.2165***	0.2422***	0.1433
	(0.017)	(0.008)	
23–24 °C	0.5597***	0.1765***	0.0000
	(0.023)	(0.008)	
24–25 °C	0.7630***	0.1628***	0.0000
	(0.022)	(0.009)	
25–26 °C	3.5143***	0.9969***	0.0000
	(0.051)	(0.012)	
26–27 °C	0.5636***	0.1589***	0.0000
	(0.022)	(0.009)	
27–28 °C	1.7774***	0.5951***	0.0000
	(0.031)	(0.011)	
28–29 °C	1.5298***	0.7681***	0.0002
	(0.207)	(0.017)	
29–30 °C	6.1799***	1.9641***	0.0000
	(0.078)	(0.017)	
30–31 °C	3.3277***	1.2180***	0.0000
	(0.049)	(0.014)	
31–32 °C	6.6421***	2.2568***	0.0000
	(0.083)	(0.020)	
32–33 °C		2.3668***	
		(0.038)	
Controls	YES		
Month FE	YES		
Household FE	YES		
Observations	5,946,264		
R-squared	0.697		
Number of id	79,127		

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The households involved include 8930 urban households and 70,197 rural households.

Table A9
Marginal effects of infrastructure.

VARIABLES	(1) Infrastructure effects electricity	VARIABLES	(1) (continued) electricity
0–1 °C	2.1331***	19–20 °C	0.1002**
	(0.006)		(0.002)
1–2°C	1.5231***	20–21 °C	0.0158*
	(0.001)		(0.002)
2–3 °C	1.8893***	21–22 °C	−0.0022
	(0.002)		(0.002)
3–4°C	1.8262***	22–23 °C	−0.0087
	(0.014)		(0.002)
4–5°C	1.7120***	23–24 °C	0.1293**
	(0.012)		(0.003)
5–6°C	1.9798***	24–25 °C	0.2024***
	(0.001)		(0.000)
6–7 °C	2.2911***	25–26 °C	0.8490***
	(0.000)		(0.008)
8–9 °C	0.6749***	26–27 °C	0.1365**
	(0.001)		(0.003)
9–10 °C	0.5522***	27–28 °C	0.3987***
	(0.001)		(0.003)
10–11 °C	0.4169***	28–29 °C	0.2569
	(0.003)		(0.041)
11–12 °C	0.3205***	29–30 °C	1.4219***
	(0.002)		(0.000)
12–13 °C	0.3845***	30–31 °C	0.7115***
	(0.004)		(0.004)
13–14 °C	0.8371**	31–32 °C	1.4790***
	(0.016)		(0.003)
14–15 °C	0.2021**		
	(0.005)		
15–16 °C	0.1322***	Controls	YES
	(0.000)	Month FE	YES
17–18 °C	0.1960**	Household FE	YES

(*continued on next page*)

Table A9 (*continued*)

VARIABLES	(1) Infrastructure effects electricity	VARIABLES	(1) (continued) electricity
	(0.007)	Observations	5,946,264
18–19 °C	−0.0070	R-squared	0.697
	(0.005)	Number of id	79,127

Notes: Robust standard errors in parentheses are clustered at the area level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households involved is 79,127.

Table A10
Results of heterogeneity in income in Zhejiang.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low income	Middle income	High income	Low-High F-test	Low-Middle F-test	Middle-High F-test
VARIABLES	electricity	electricity	electricity	P value	P value	P value
0–1 °C	4.7626***	2.7390***	2.8017***	0.2413	0.2433	0.9596
	(1.469)	(0.939)	(0.816)			
1–2°C	4.4565***	1.9762***	3.7703***	0.6234	0.0719	0.0660
	(1.201)	(0.668)	(0.699)			
2–3 °C	2.6383***	2.2208***	3.8935***	0.1396	0.5454	0.0401
	(0.537)	(0.454)	(0.638)			
3–4°C	2.5530***	2.1396***	3.0267***	0.4247	0.4935	0.1646
	(0.409)	(0.451)	(0.416)			
4–5°C	1.8047***	1.8056***	3.0907***	0.0553	0.9986	0.0351
	(0.427)	(0.316)	(0.477)			
5–6°C	1.5735***	1.4378***	2.5655***	0.0799	0.7721	0.0308
	(0.365)	(0.290)	(0.396)			
6–7 °C	1.3209***	0.8165***	2.3597***	0.0473	0.1771	0.0024
	(0.286)	(0.261)	(0.400)			
7–8°C	1.3210***	0.8928***	2.0426***	0.1402	0.2473	0.0092
	(0.315)	(0.228)	(0.348)			
8–9 °C	0.9738***	0.7213***	1.4549***	0.2623	0.4965	0.0523
	(0.300)	(0.225)	(0.284)			
9–10 °C	0.8579***	0.5671***	1.2423***	0.3429	0.3878	0.0499
	(0.292)	(0.188)	(0.262)			
10–11 °C	0.7026***	0.4585***	1.3087***	0.0903	0.4198	0.0056
	(0.259)	(0.176)	(0.229)			
11–12 °C	0.5048	0.3658**	1.0040***	0.2077	0.6863	0.0245
	(0.316)	(0.151)	(0.216)			
12–13 °C	0.4996***	0.1601	1.0224***	0.0807	0.1123	0.0036
	(0.181)	(0.151)	(0.230)			
13–14 °C	0.3387*	0.1503	0.5888***	0.2863	0.3478	0.0450
	(0.174)	(0.133)	(0.162)			
14–15 °C	0.3990**	0.0064	0.5631***	0.5005	0.0510	0.0163
	(0.175)	(0.141)	(0.174)			
15–16 °C	0.2110	−0.0777	0.1218	0.6536	0.0853	0.3196
	(0.135)	(0.127)	(0.148)			
16–17 °C	0.1712	−0.0566	0.0985	0.6535	0.1745	0.3559
	(0.131)	(0.130)	(0.121)			
17–18 °C	0.0179	−0.2110*	−0.1947	0.2626	0.1937	0.9275
	(0.137)	(0.117)	(0.136)			
18–19 °C	0.1046	−0.0418	0.0862	0.9165	0.3465	0.3976
	(0.142)	(0.094)	(0.115)			
19–20 °C	−0.0070	−0.2924***	−0.0465	0.8319	0.1123	0.1104
	(0.151)	(0.104)	(0.112)			
20–21 °C	−0.2355	−0.2002***	−0.1211	0.6206	0.8667	0.5369
	(0.207)	(0.065)	(0.105)			
21–22 °C	0.2205***	−0.0952	−0.1030	0.0210	0.0007	0.9536
	(0.069)	(0.061)	(0.115)			
22–23 °C	0.1323**	0.0228	−0.0323	0.0543	0.1614	0.5037
	(0.056)	(0.052)	(0.063)			
24–25 °C	0.2309*	0.3933***	0.1336	0.5643	0.2532	0.0419
	(0.127)	(0.064)	(0.106)			
25–26 °C	0.2477**	0.5841***	0.3241*	0.7455	0.0494	0.2648
	(0.123)	(0.114)	(0.193)			
26–27 °C	0.3656***	0.8177***	0.7014***	0.1930	0.0251	0.6459
	(0.141)	(0.125)	(0.206)			
27–28 °C	0.8545***	1.9057***	1.5857***	0.0825	0.0061	0.4731
	(0.224)	(0.249)	(0.312)			
28–29 °C	1.7046***	3.1581***	3.3015***	0.0066	0.0057	0.8211
	(0.299)	(0.350)	(0.446)			

(*continued on next page*)

Table A10 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
	Low income	Middle income	High income	Low-High F-test	Low-Middle F-test	Middle-High F-test
VARIABLES	electricity	electricity	electricity	P value	P value	P value
29–30 °C	2.5123***	3.7776***	4.3969***	0.0090	0.0333	0.3736
	(0.405)	(0.347)	(0.530)			
30–31 °C	3.4541***	4.9718***	5.8702***	0.0067	0.0507	0.2809
	(0.557)	(0.461)	(0.644)			
31–32 °C	4.9684***	5.9933***	6.9817***	0.0785	0.2817	0.3422
	(0.714)	(0.535)	(0.843)			
32–33 °C	6.9020***	7.6922***	9.3455***	0.0621	0.4826	0.1945
	(0.785)	(0.725)	(1.009)			
33–34 °C	5.3529***	7.6782***	8.6324***	0.0053	0.0262	0.4656
	(0.598)	(0.810)	(0.998)			
34–35 °C	6.7323***	8.3761***	11.4283***	0.0106	0.2792	0.1176
	(0.981)	(1.165)	(1.572)			
35–36 °C	8.6557***	10.2857***	9.4482***	0.7114	0.4293	0.6896
	(1.505)	(1.427)	(1.567)			
Controls	YES					
Month FE	YES					
Household FE	YES					
Observations	263,895					
R-squared	0.664					
Number of id	723					

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households is 240 for low-income group, 227 for middle-income group and 256 for high-income group.

Table A11
The impact of income on the probability of having cooling appliances and AC for cooling in Zhejiang.

	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	Probit	OLS	Logit	Probit	OLS
VARIABLES	Cooling appliance			AC		
Ln(Income)	0.0218*	0.0196	0.0247	0.0841***	0.0789***	0.0889***
	(0.0124)	(0.0136)	(0.0164)	(0.0236)	(0.0224)	(0.0238)
Constant			0.649**			0.0403
			(0.309)			(0.449)
Observations	723	723	723	723	723	723
R-squared			0.013			0.100

Notes: The dependent variable in Column (1) to (3) is a dummy indicating whether the household has cooling appliances and the dependent variable in Column (4) to (6) is a dummy indicating whether the household has AC. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

Table A12
The impact of income on temperature in households with and without air conditioners in Zhejiang.

	(1)	(2)		(1)	(2)
	No air conditioners	With air conditioners		(continued)	
VARIABLES	electricity	electricity	VARIABLES	electricity	electricity
0–1 °C	−2.0449	1.7047	19–20 °C	0.2508	2.5197**
	(2.589)	(1.418)		(1.809)	(1.154)
1–2°C	−1.9719	2.1631	20–21 °C	0.4441	2.6138**
	(2.289)	(1.539)		(1.789)	(1.176)
2–3 °C	0.2715	2.9313**	21–22 °C	0.2958	2.4824**
	(2.107)	(1.360)		(1.827)	(1.152)
3–4°C	0.0884	2.6642**	22–23 °C	0.4415	2.4439**
	(1.935)	(1.249)		(1.789)	(1.154)
4–5°C	0.4673	3.1435**	24–25 °C	0.4118	2.6222**
	(2.139)	(1.256)		(1.728)	(1.196)
5–6°C	0.4072	2.9747**	25–26 °C	0.2929	2.6457**
	(2.013)	(1.264)		(1.683)	(1.192)
6–7 °C	0.4409	3.1869***	26–27 °C	0.3546	2.6881**
	(1.982)	(1.221)		(1.703)	(1.212)
7–8°C	0.3756	2.7184**	27–28 °C	0.2499	2.9345**
	(1.947)	(1.230)		(1.695)	(1.253)
8–9 °C	0.2322	2.7464**	28–29 °C	0.6026	3.4809***
	(1.872)	(1.209)		(1.717)	(1.319)
9–10 °C	0.4589	2.4882**	29–30 °C	0.4789	3.6225***
	(1.918)	(1.196)		(1.709)	(1.383)

(*continued on next page*)

Table A12 (*continued*)

	(1)	(2)		(1)	(2)
	No air conditioners	With air conditioners		(continued)	
VARIABLES	electricity	electricity	VARIABLES	electricity	electricity
10–11 °C	0.4123	2.8961**	30–31 °C	0.6574	3.5313**
	(1.855)	(1.238)		(1.873)	(1.509)
11–12 °C	0.4038	2.7951**	31–32 °C	0.5452	3.7186**
	(1.936)	(1.184)		(1.891)	(1.549)
12–13 °C	0.3562	2.6805**	32–33 °C	−0.6927	4.5410***
	(1.877)	(1.163)		(1.923)	(1.631)
13–14 °C	0.3180	2.5425**	33–34 °C	1.1332	5.1235***
	(1.863)	(1.170)		(1.803)	(1.436)
14–15 °C	0.3746	2.5979**	34–35 °C	−1.3958	6.7262***
	(1.875)	(1.157)		(1.892)	(1.956)
15–16 °C	0.3290	2.3902**	35–36 °C	−1.8483	5.0585***
	(1.811)	(1.126)		(1.815)	(1.805)
16–17 °C	0.4404	2.3682**	Controls	YES	YES
	(1.812)	(1.154)	Month FE	YES	YES
17–18 °C	0.2972	2.5323**	Household FE	YES	YES
	(1.761)	(1.150)	Observations	74,460	209,510
18–19 °C	0.3656	2.5475**	R-squared	0.508	0.491
	(1.837)	(1.147)	Number of id	204	574

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households involved is 574 and 204 for households with and without air conditioners.

Table A13
The impact of income on the probability of having heating appliances in Zhejiang.

	(1)	(2)	(3)
	Logit	Probit	OLS
VARIABLES	Heating appliance		
Ln(Income)	−0.0127	−0.00912	−0.0140
	(0.0198)	(0.0198)	(0.0185)
Constant			0.257
			(0.400)
Observations	723	723	723
R-squared			0.103

Notes: The dependent variable is a dummy indicating whether the household has heating appliances. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

Table A14
The impact of income on duration of cooling appliance, AC for cooling and heating appliance in Zhejiang.

	(1)	(2)	(3)	(4)	(5)	(6)
	Electric fan		AC for cooling		Heating appliance	
VARIABLES	Month per year	Hour per day	Month per year	Hour per day	Month per year	Hour per day
Ln(Income)	0.157**	0.177*	0.0539	0.195*	0.173*	0.858***
	(0.0665)	(0.0906)	(0.0742)	(0.109)	(0.104)	(0.247)
Constant	1.492	0.455	1.741	7.007***	0.329	−6.433
	(1.170)	(1.810)	(1.245)	(2.122)	(1.845)	(4.515)
Observations	559	559	536	536	191	191
R-squared	0.035	0.025	0.036	0.056	0.119	0.175

Notes: The dependent variables are usage months and the daily usage hours of appliances, taking the maximum value among all the cooling or heating appliances in the household. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

Table A15
The impact of income on dwelling size in Zhejiang.

	(1)
VARIABLES	Dwelling size
Ln(Income)	5.087*
	(2.676)

(*continued on next page*)

Table A15 (*continued*)

	(1)
VARIABLES	Dwelling size
Constant	27.78
	(49.01)
Observations	723
R-squared	0.118

Notes: The dependent variable is dwelling size (square meter). The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

Table A16
Results of heterogeneity in dwelling size in Zhejiang.

	(1)	(2)	(4)
	Small house	Big house	F-test
VARIABLES	electricity	electricity	P value
0–1 °C	3.0464***	4.7778***	0.3378
	(0.690)	(1.668)	
1–2°C	3.4487***	2.2810***	0.1492
	(0.594)	(0.550)	
2–3 °C	3.1488***	1.9916***	0.0425
	(0.398)	(0.391)	
3–4°C	2.7279***	1.9873***	0.1240
	(0.323)	(0.349)	
4–5°C	2.4342***	1.5815***	0.0529
	(0.275)	(0.323)	
5–6°C	1.9497***	1.4054***	0.1625
	(0.229)	(0.302)	
6–7 °C	1.5933***	1.0489***	0.1198
	(0.223)	(0.256)	
7–8°C	1.4775***	1.0811***	0.2388
	(0.187)	(0.284)	
8–9 °C	1.1265***	0.7658***	0.2084
	(0.190)	(0.213)	
9–10 °C	0.8493***	0.8153***	0.9042
	(0.155)	(0.241)	
10–11 °C	0.8599***	0.5815***	0.2551
	(0.146)	(0.203)	
11–12 °C	0.6403***	0.4640**	0.4712
	(0.164)	(0.185)	
12–13 °C	0.5681***	0.3894**	0.3785
	(0.119)	(0.177)	
13–14 °C	0.3806***	0.2291	0.3830
	(0.106)	(0.153)	
14–15 °C	0.2860***	0.2975*	0.9487
	(0.106)	(0.165)	
15–16 °C	0.0314	0.1721	0.2997
	(0.097)	(0.113)	
16–17 °C	0.0502	0.0701	0.8853
	(0.096)	(0.127)	
17–18 °C	−0.2179**	−0.0004	0.1026
	(0.101)	(0.099)	
18–19 °C	0.0280	0.0744	0.7070
	(0.087)	(0.104)	
19–20 °C	−0.1365	−0.0978	0.7696
	(0.098)	(0.092)	
20–21 °C	−0.2468**	−0.0878	0.1872
	(0.109)	(0.064)	
21–22 °C	−0.0226	0.1024	0.1758
	(0.055)	(0.072)	
22–23 °C	0.0539	0.0366	0.8039
	(0.041)	(0.055)	
24–25 °C	0.2020***	0.3892***	0.1426
	(0.066)	(0.106)	
25–26 °C	0.4135***	0.3609***	0.7346
	(0.111)	(0.096)	
26–27 °C	0.7790***	0.4174***	0.0521
	(0.107)	(0.133)	

(*continued on next page*)

Table A16 (*continued*)

	(1)	(2)	(4)
	Small house	Big house	F-test
VARIABLES	electricity	electricity	P value
27–28 °C	1.6270***	1.1432***	0.1633
	(0.173)	(0.233)	
28–29 °C	2.9901***	2.2261***	0.1064
	(0.247)	(0.309)	
29–30 °C	3.8115***	2.9912***	0.1446
	(0.266)	(0.411)	
30–31 °C	4.7191***	4.3914***	0.6679
	(0.332)	(0.628)	
31–32 °C	6.1669***	5.3308***	0.3638
	(0.430)	(0.747)	
32–33 °C	8.5660***	6.5854***	0.0552
	(0.585)	(0.787)	
33–34 °C	7.1975***	6.9266***	0.7849
	(0.553)	(0.788)	
34–35 °C	9.4673***	7.7105***	0.2625
	(0.969)	(1.243)	
35–36 °C	10.0091***	8.7300***	0.4539
	(1.160)	(1.282)	
Controls	YES		
Month FE	YES		
Household FE	YES		
Observations	263,895		
R-squared	0.663		
Number of id	723		

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households is 470 for small-house group and 253 for big-house group.

Table A17
Marginal effects of infrastructure in Zhejiang.

	(1)		(1)
	Infrastructure effects		(continued)
VARIABLES	electricity	VARIABLES	electricity
0–1 °C	9.2021***	19–20 °C	3.9219***
	(1.764)		(0.598)
1–2°C	8.0612***	20–21 °C	3.7822***
	(1.297)		(0.553)
2–3 °C	6.0295***	21–22 °C	4.1624***
	(1.122)		(0.694)
3–4°C	5.3823***	22–23 °C	4.1525***
	(0.874)		(0.707)
4–5°C	5.4666***	24–25 °C	4.1825***
	(0.812)		(0.740)
5–6°C	4.8298***	25–26 °C	4.2711***
	(0.832)		(0.714)
6–7 °C	4.8463***	26–27 °C	4.8919***
	(0.785)		(0.715)
7–8°C	5.0922***	27–28 °C	4.6136***
	(0.875)		(0.820)
8–9 °C	4.6199***	28–29 °C	5.8655***
	(0.698)		(0.960)
9–10 °C	4.4918***	29–30 °C	6.7931***
	(0.746)		(1.311)
10–11 °C	4.4432***	30–31 °C	8.5821***
	(0.714)		(1.731)
11–12 °C	4.4210***	31–32 °C	8.9756***
	(0.678)		(2.103)
12–13 °C	4.5213***	32–33 °C	9.0078***
	(0.715)		(2.277)
13–14 °C	4.2168***	33–34 °C	7.5609***
	(0.679)		(1.969)
14–15 °C	4.1239***	34–35 °C	10.0410***
	(0.669)		(3.147)
15–16 °C	3.8683***	35–36 °C	5.6428***
	(0.620)		(1.764)
16–17 °C	4.1834***	Controls	YES
	(0.708)	Month FE	YES
17–18 °C	3.8626***	Household FE	YES

(*continued on next page*)

Table A17 (*continued*)

	(1)		(1)
	Infrastructure effects		(continued)
VARIABLES	electricity	VARIABLES	electricity
	(0.656)	Observations	263,895
18–19 °C	3.9592***	R-squared	0.510
	(0.625)	Number of id	723

Notes: Robust standard errors in parentheses are clustered at the prefecture-area level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The number of households involved is 723.

A.4. Appendix 4: mechanism analysis of the ownership of ACs

In the manuscript we discussed the mechanisms across cooling (including AC and electric fan) and heating appliances (AC and electric radiators). As AC is used for both cooling and heating, we also present the results of AC. First we show the impact of income on the ownership of AC in Table A18. The impact is significantly positive in all estimating methods.

Table A18
The impact of income on the probability of having AC in Xin County.

	(1)	(2)	(3)
	Logit	Probit	OLS
VARIABLES	AC		
Ln(Income)	0.0807***	0.0791***	0.0666***
	(0.0163)	(0.0157)	(0.0140)
Constant			0.137
			(0.263)
Observations	983	983	983
R-squared			0.058

Notes: The dependent variable is a dummy indicating weather the household has cooling appliances. The key independent variable is annual household income in the form of the natural logarithm. Control variables include household size, household head's gender, age, education, and urban or rural areas. Robust standard errors are in parentheses.

Then we compare the temperature response coefficients for households with and without ACs. The results are summarized in the Fig. A7 and detailed in the Table A19.

Statistic tests show that the difference of the two curves is not statistically significant, which indicates that the temperature response curves of households with and without air conditioners are similar. This finding suggests that the ownership of air conditioners alone does not significantly influence electricity consumption, regardless of whether temperatures are high or low.

One possible explanation, as we discussed in the paper, is the usage patterns of ACs for low-income households. While these households may install ACs, they are often reluctant to use them due to the cost of electricity consumed (Pavanello et al., 2021). As a cheap alternative to ACs, electric fans are more favored by low-income households.

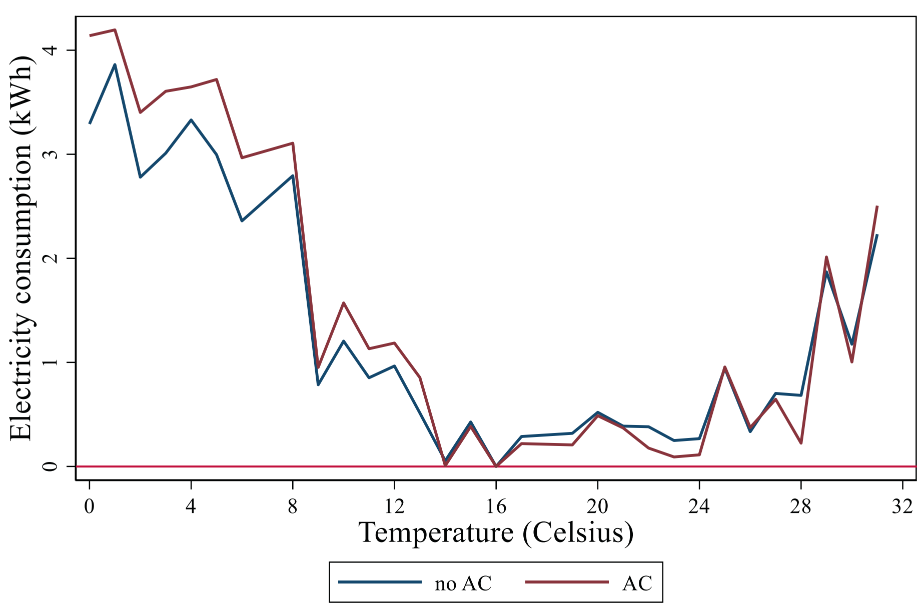

Fig. A7. Temperature response of households with and without air conditioners. *Notes:* The temperature interval of 16–17 °C is set as the baseline. The estimates of every temperature interval are presented in the figure. The standard errors are clustered at the household level.

Table A19
Results of heterogeneity in air conditioner ownership.

	(1)	(2)	(3)
	No air conditioner	With air conditioner	F-test
VARIABLES	electricity	electricity	P value
0–1 °C	3.2913***	4.1397***	0.1352
	(0.951)	(1.070)	
1–2°C	3.8623***	4.1957***	0.3661
	(0.975)	(0.969)	
2–3 °C	2.7801***	3.4022***	0.1648
	(0.942)	(1.015)	
3–4°C	3.0108***	3.6057***	0.2209
	(0.950)	(1.048)	
4–5°C	3.3304***	3.6479***	0.4052
	(0.957)	(1.019)	
5–6°C	2.9964***	3.7191***	0.1076
	(0.942)	(1.022)	
6–7 °C	2.3603**	2.9666***	0.2592
	(0.939)	(1.056)	
8–9 °C	2.7942***	3.1070***	0.3455
	(0.945)	(0.965)	
9–10 °C	0.7851***	0.9522***	0.4153
	(0.071)	(0.203)	
10–11 °C	1.2050***	1.5720***	0.1574
	(0.101)	(0.261)	
11–12 °C	0.8526***	1.1313***	0.2384
	(0.078)	(0.231)	
12–13 °C	0.9655***	1.1862***	0.4477
	(0.095)	(0.286)	
13–14 °C	0.5142***	0.8546***	0.2317
	(0.063)	(0.270)	
14–15 °C	0.0542	0.0080	0.7512
	(0.033)	(0.137)	
15–16 °C	0.4278***	0.3844***	0.6921
	(0.034)	(0.107)	
17–18 °C	0.2880***	0.2197**	0.5017
	(0.037)	(0.099)	
19–20 °C	0.3183***	0.2072*	0.2899
	(0.042)	(0.106)	
20–21 °C	0.5203***	0.4879***	0.7991
	(0.047)	(0.122)	
21–22 °C	0.3876***	0.3702**	0.9083
	(0.053)	(0.145)	
22–23 °C	0.3819***	0.1768	0.2391
	(0.048)	(0.164)	
23–24 °C	0.2493***	0.0915	0.4061
	(0.047)	(0.179)	
24–25 °C	0.2675***	0.1119	0.3095
	(0.053)	(0.149)	
25–26 °C	0.9438***	0.9562***	0.9598
	(0.074)	(0.226)	
26–27 °C	0.3346***	0.3737**	0.8015
	(0.056)	(0.154)	
27–28 °C	0.7019***	0.6460***	0.7752
	(0.064)	(0.190)	
28–29 °C	0.6831***	0.2239	0.3353
	(0.100)	(0.464)	
29–30 °C	1.8702***	2.0132***	0.7395
	(0.121)	(0.390)	
30–31 °C	1.1746***	1.0042***	0.5240
	(0.088)	(0.248)	
31–32 °C	2.2324***	2.5060***	0.6034
	(0.156)	(0.494)	
Controls	YES		
Month FE	YES		
Household FE	YES		
Observations	76,826		
R-squared	0.598		
Number of id	983		

Notes: Robust standard errors in parentheses are clustered at the household level. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. The estimation is based on baseline model using 1 °C intervals.

A.5. Appendix 5: Power outrage related facts in China

During the study period, China had largely completed rural power grid upgrades, which significantly improved the power supply infrastructure. In 2010 and 2016, China launched two rounds of rural power grid renovation and upgrading, which significantly improved the power supply infrastructure. The average power outage time in rural areas has dropped from over 50 h in 2015 to around 15 h in 2020.[8]

Between 2016 and 2018, Xin County (the study area in this paper) invested heavily in grid upgrades as well, including the expansion of a 220-kV substation, the construction of a second 110-kV substation, the expansion of three 35-kV substations, and the completion of 634 lower-voltage projects. These upgrades covered 308.78 km of power lines, 559 distribution transformer areas, and 657.89 km of 0.4-kV lines, 77,300 households and 114,300 newly-installed smart electricity meters. In rural areas, the upgrading involved the grid connection and construction of power stations in 36 central villages and 73 impoverished villages throughout the county.[9]

In 2018 (the study period of this paper), for the rural areas of the prefecture-level city to which Xin County belongs, the average power supply reliability rate was 99.693%, with an average annual outage time of 26.91 h and a frequency of 4.85 times per household.[10] No large-scale or prolonged power outages occurred in Xin County during the study period. The longest power outage lasted 37 h and affected only 7 out of 205 villages in the county.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2026.109305.

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