



Climate change, air conditioning, and urbanization—evidence from daily household electricity consumption data in China

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Abstract

Energy consumption is a chief contributor to climate change, which increases as households use more air conditioning (AC) in response to climate change. As such, climate change–induced energy consumption is expected to increase more drastically in fast-emerging economies, where the rapidly increasing household income and urbanization promote the large-scale adoption of ACs. Based on data on daily household electricity consumption in the Zhejiang Province of China, this study estimates the household temperature response functions. In particular, we consider urban and rural households with and without AC to chart their various cooling demand and consumption behavior, typically indicated by U-shaped temperature-response functions. Compared to rural households and those without AC, urban households and those with AC exhibit steeper response functions at both high and low temperatures. Based on these estimates, we simulate the household electricity consumption under climate change scenarios RCP4.5 and RCP8.5. The simulation results reveal that (1) under constant urbanization and AC adoption rates, the electricity consumption in the residential sector will increase by 5.04–16.37% because of climate change; (2) as the AC adoption rate increases from 82.50 to 95.00% in urban areas and from 74.40 to 85.00% in rural areas, the household electricity consumption in Zhejiang Province will further increase by 0.52–1.05%; (3) combined with the increase of urbanization from 68.73 to 80.00%, the increase rate of annual electricity consumption of the residential sector will further rise to 25.60–55.79%. These findings highlight the vicious cycle of climate change and cooling along with the challenges encountered by electricity grids.

Keywords Air conditioning · Climate change · Electricity consumption · Household temperature response function

JEL classification D10 · R20 · Q40

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1 Introduction

Climate change and energy consumption are connected in a vicious cycle—energy consumption produces greenhouse gas emissions¹ and climate change induces higher energy consumption through adaptive behaviors such as air conditioning (AC) (Auffhammer 2014; Davis and Gertler 2015). To disrupt this cycle, the interaction between the temperature and energy consumption requires a deeper understanding. Several studies empirically estimated the impact of climate change on electricity consumption (Auffhammer and Aroonruengsawat 2011; Auffhammer et al. 2017; Auffhammer 2022). Excluding Auffhammer (2014) and Li et al. (2019), most studies have primarily focused on developed countries and regions. Notably, the vicious cycle of climate change and energy consumption demands attention in developing economies owing to their rapidly increasing income, which causes drastic and large-scale adoption of AC and a steep rise in energy consumption.

As the world's largest carbon emitter, China's electricity consumption soared to 6523 TWh in 2019, accounting for 28.5% of the global electricity consumption². However, the per capita electricity consumption in China's residential sector was approximately 732 kWh in 2019³, which was only one-sixth of that of the USA⁴. This finding signifies the immense growth potential of China's residential sector in terms of electricity consumption, which can be a potential source of increasing carbon emissions. Thus, this study examines the response of China's household electricity consumption to climate change. We consider households with and without ACs because the adoption of AC, one of the major appliances for heating and cooling in China, considerably affects the residents' electricity consumption⁵.

Previous studies estimating the impact of climate change on electricity consumption primarily focused on two aspects, the first being consumer adaptation to climate change by adopting energy-consuming durable equipment such as ACs. This adaptation is typically referred to as an extensive margin. Using cross-sectional data from 39 cities on the saturation of the air-conditioner market and a simple linear regression technique, Sailor and Pavlova (2003) documented the significance of long-term adjustment of the AC market to estimate the response of residential electricity consumption to climate change. Subsequently, researchers improved the data structure and model construction. Based on cross-sectional data at the national level, McNeil and Letschert (2008, 2010) developed a logistic function to estimate the relationship between the penetration rate of ACs and income in developing countries, thereby influencing climate change-induced market saturation. They determined that adoption behavior was primarily determined by income. Focused on the residential sector in China, Auffhammer (2014) used province-level panel data to control the effects of time-invariant province characteristics and common disruptions, indicating that the adoption of ACs is affected by both income and weather. Other studies assessing the adoption rate of ACs in the USA (Biddle 2008; Rapson 2014), Europe (Aebischer et al.

¹ IEA, Global Energy Review: CO₂ Emissions in 2020, <https://www.iea.org/articles/global-energy-review-co2-emissions-in-2020>

² Source: IEA, <https://www.iea.org/reports/electricity-information-overview>

³ Source: China Statistical Yearbook 2020

⁴ Source: U.S. Energy Information Administration, <https://www.eia.gov/electricity/data/browser>

⁵ The ACs studied herein include appliances with both heating and cooling functions, which are common among the investigated samples.

2007) and developing countries (Isaac and Van Vuuren 2009; Akpinar-Ferrand and Singh 2010) inferred similar conclusions.

The second aspect is the response of consumers to weather shocks, with other constraints remaining overall constant. In particular, the studies estimate the response of household electricity consumption to temperature based on the income, population, and other fixed characteristics of the household (Davis and Gertler 2015; Auffhammer 2022). This response is typically referred to as an intensive margin. Most early studies on intensive margins employed time-series data (Sailor and Muñoz 1997; Lam 1998; Considine 2000; Franco and Sanstad 2008). Notably, these studies varied in terms of the frequency of data and control variables. A common problem is that the unobserved factors correlated to temperature can yield bias in the causal estimation. In addition, without variations among the observational units, a time-series analysis cannot explore the distributional effects of climate change, which could be critical for policy design.

Unlike time-series data, panel data provide insights into individual and temporal variations, which promote the control of individual characteristics as well as the temporal effects, thereby improving the accuracy of model estimation and supporting the assessment of heterogeneity effects. Using state-level annual panel data, Deschênes and Greenstone (2011) controlled the effects of the time-invariant state characteristics using fixed effects and determined a classic U-shaped relationship between electricity and temperature. Employing a similar identification strategy, Auffhammer and Aroonruengsawat (2011) and Li et al. (2019) employed monthly and daily residential electricity billing data, respectively, to determine similar U-shaped temperature-response functions. Li et al. (2019) explored heterogeneous income-based response functions and determined that household electricity consumption was more sensitive to cold weather as income increased.

Based on rich household-level data, we explore the heterogeneous effects of climate change on electricity consumption across income and appliance ownership. Herein, the existing studies are extended by further incorporating the effects of urbanization and AC adoption into the temperature-response functions derived from high-frequency household-level data. In particular, we emphasize the significance of the effects of urbanization and AC adoption on the energy consumption and carbon emissions based on the context of climate change. As such, both the intensive and extensive margins are analyzed to improve the prediction of long-term electricity consumption under climate-change scenarios.

Furthermore, we contribute to the literature by conducting a rigorous study on developing countries. Most studies using high-frequency data are based on developed countries owing to the data availability constraints in the developing world. However, the findings from the developed nations may not be applicable to developing regions owing to the non-linear income effects, diverse infrastructure, market, and policy environments, and consumption habits, among other factors. Thus, this study focuses on developing nations because the rising middle-income class in emerging economies constitutes the fundamental driver of energy consumption (Gertler et al. 2016). Although Li et al. (2019) acquired data from China, the source was primarily a single metropolis (Shanghai). Regardless, this study selects Zhejiang Province as the study region because it is one of the fastest-growing provinces in China. Between 2011 and 2021, the urbanization rate increased from 62.3 to 72.7%, and the average annual growth rate of GDP per capita was 5.6%⁶. Thus, the current study on Zhejiang may provide experiences and/or lessons for rapidly developing countries

⁶ Source: Zhejiang Statistical Yearbook 2022

and regions, especially those on the path of urbanization. The daily electricity consumption data of households are acquired from both urban and rural households in Zhejiang, China. Based on these data, we explore the response heterogeneity across the urban and rural households to obtain new estimations of the household behavior in less-developed regions with low-yet-increasing incomes.

This study determines a nonlinear temperature-response function describing the electricity consumption, wherein the electricity consumption increases dramatically in case of extremely hot weather. The results indicate that the adoption of AC significantly increases the slope of the response function, especially at the hot end. Furthermore, the response function of the urban households is steeper than that of the rural households, signifying that poverty alleviation and urbanization intensify the response of residential electricity consumption to climate change. Therefore, these findings highlight the significance of considering the impact of appliances and the rural differences for studying the temperature response functions and predicting the increase in electricity consumption in the context of climate change.

The remainder of this paper is organized as follows. The data and graphical evidence are presented in Section 2. Thereafter, the econometric models are detailed in Section 3. The major results of this study are discussed in Section 4. Lastly, the findings and policy implications of this study are summarized in Section 5.

2 Data description

For the current analysis, we merge five datasets: (Aebischer et al. 2007) household micro-data for 2017 sourced from the 2018 Residential Energy Consumption Survey in Zhejiang, China, (Akpınar-Ferrand and Singh 2010) daily household-level electricity consumption data from the State Grid Corporation of China (SGCC), (Auffhammer 2014) station-level daily weather data from the National Meteorological Information Center of China, (Auffhammer 2022) climate change scenarios from the NASA Earth Exchange Global Daily Downscaled Projections, (Auffhammer and Aroonruengsawat 2011) daily air quality data from the China Air Quality Online Monitoring and Analysis Platform⁷.

2.1 Household survey

In July and August 2018, the School of Applied Economics, Renmin University of China, and the Economics and Technology Research Institute at State Grid Zhejiang Electric Power Corporation combinedly conducted the 2018 Residential Energy Consumption Survey that assessed the energy consumption of Zhejiang households in 2017 and acquired demographic data of interviewees. As such, stratified sampling was used to ensure sample representation, and based on previous surveys, the SGCC selected a representative village and community in each city of Zhejiang. As the survey focused more on rural development, it was deliberately oversampled. Thereafter, we allocated the number of observations according to the weight of the number of households in the villages and communities. Accordingly, the households were randomly selected for in-person interviews. In total, 1282 household-level questionnaires were completed, among which 847 and 435 pertained

⁷ Source: <https://www.aqistudy.cn/historydata>

Table 1 Sample sizes of urban and rural households in each city of Zhejiang

	Urban households	Rural households	Total
Jinhua	7	96	103
Quzhou	8	79	87
Hangzhou	24	56	80
Jiaxing	8	72	80
Huzhou	11	66	77
Zhoushan	0	68	68
Shaoxing	16	43	59
Ningbo	22	33	55
Wenzhou	10	38	48
Lishui	6	33	39
Taizhou	14	13	27
Zhejiang Province	126	597	723

to rural and urban areas, respectively. Upon merging the electricity consumption data, we use a subset of survey data comprising 597 rural households and 126 urban households as reported in Table 1.

In 2017, the survey collected information on household characteristics, dwelling characteristics, household appliances, energy consumption behaviors, and electricity meter codes, which enabled us to obtain the daily electricity consumption data. The per capita expenditure, annual household electricity consumption, and the number of durable equipment in the survey data for urban and rural households are comparatively listed in Table 2 with the corresponding statistics of Zhejiang and China in 2017. The sample statistics are similar to those of Zhejiang, thereby confirming the representativeness of the samples used in this study. Further comparison with the national statistics indicates the higher expenditures and greater number of durable equipment in households in Zhejiang Province, especially rural households, which reflect their higher income and consumption compared to the respective national averages. However, the present survey data encompass a wider range of household income and expenditure than the national statistics, which permits us to examine the response of the households in regions with low-yet-rising incomes. This aspect improves the external validity of this study for developing regions.

2.2 Household daily electricity consumption

The daily household electricity consumption data for 2017 are merged with the survey data based on the electricity meter code information. After data cleaning, the number of observations is reduced to 597 and 126 households in rural and urban areas, respectively, for the following reasons. First, the grid company did not record the electricity consumption information from the self-installed meters. Second, the sample observations with daily electricity consumption data missing for over 180 days are excluded from the analysis, because zero electricity consumption for over half a year indicates that the residents of such households are not permanent residents of Zhejiang. Moreover, these households are not availed by permanent residents of Zhejiang, and their temperature response behaviors differ from those of permanent households, thereby indicating a correlation between the missing electricity consumption data and temperature. Thus, the inclusion of these variables in the

Table 2 Descriptive statistics for household survey data in 2017

Variable	Obs.	Mean	Std. dev.	Min	Max	Zhejiang	China
Urban households:							
Per capita expenditure (CNY)	126	33479.33	25332.56	3350.00	168333.30	31924.00	24445.00
Household annual electricity consumption (kWh)	126	2389.48	2293.34	45.68	12921.93	2506.85	2325.89
Number of durable equipment owned by each household							
AC (set)	126	1.03	0.81	0.00	5.00	2.06	1.29
Water heater (set)	126	0.71	0.52	0.00	3.00	0.98	0.91
Washing machine (set)	126	0.66	0.52	0.00	3.00	0.93	0.96
Refrigerator (set)	126	0.97	0.44	0.00	3.00	1.00	0.98
TV set (set)	126	0.83	0.40	0.00	2.00	1.79	1.24
Electric fan (set)	126	1.25	1.19	0.00	5.00	-	-
Electric heater (set)	126	0.01	0.09	0.00	1.00	-	-
Rural households							
Per capita expenditure (CNY)	597	20967.36	18043.19	900.00	226000.00	18093.00	10954.50
Household annual electricity consumption (kWh)	597	1869.83	1083.02	14.24	8520.26	1999.78	1267.95
Number of durable equipment owned by each household							
AC (set)	597	1.01	1.07	0.00	6.00	1.19	0.53
Water heater (set)	597	0.70	0.72	0.00	4.00	0.89	0.63
Washing machine (set)	597	0.69	0.47	0.00	2.00	0.82	0.86
Refrigerator (set)	597	1.00	0.53	0.00	3.00	1.03	0.92
TV set (set)	597	0.97	0.50	0.00	4.00	1.76	1.20
Electric fan (set)	597	1.43	1.27	0.00	6.00	-	-
Electric heater (set)	597	0.01	0.07	0.00	1.00	-	-

The abovementioned samples are compiled after data cleaning and matching, which are subsequently used for model estimation. The statistics for Zhejiang and China are acquired from the Zhejiang Statistical Yearbook 2018, China Statistical Yearbook, 2018, and China Electric Power Statistical Yearbook, 2018

Table 3 Descriptive statistics of meteorological variables

Variable	Obs.	Mean	Std. dev.	Min	Max
Daily mean temperature (°C)	6935	18.34	8.40	0.60	35.60
For urban areas	2555	18.47	8.49	0.90	35.20
For rural areas	4380	18.26	8.35	0.60	35.60
Daily precipitation (mm)	6935	3.79	10.36	0.00	286.70
Daily sunshine duration (h)	6935	4.94	4.23	0.00	13.00
Daily mean wind velocity (m/s)	6935	2.60	1.66	0.10	19.00
Daily maximum wind velocity (m/s)	6935	5.36	2.42	0.90	23.00

sample may create biases in estimating the variations in household electricity consumption with respect to temperature. Third, the observations with extremely high daily electricity consumption are excluded from the sample set, because the survey reports the occupation of small restaurants, shops, or other businesses in these households. In this case, electricity is consumed for commercial purposes. As this study focuses on the electricity consumption and AC adoption/usage in the residential sector, these observations are excluded from the current analysis⁸. This data-cleaning process reflects the advantages of using survey data for accurately selecting the residential electricity consumption. Given that households with small businesses and temporary residents exhibit vastly distinct electricity-consumption patterns compared to those with permanent residents, the inclusion of such samples in the regression analysis can yield an estimation bias.

The trends of average daily electricity consumption among urban and rural households as well as those with and without AC are plotted in Fig. S1. As observed, the daily electricity consumption trends are similar among urban and rural households, with peak electricity consumption occurring during summer (June–August)⁹; however, the level of daily electricity consumption is higher in urban households than in rural households. Notably, in both summer and winter (December–February), the daily electricity consumption is higher in households with AC than those without AC. This variation signifies the impact of AC on the electricity-consumption responses of households.

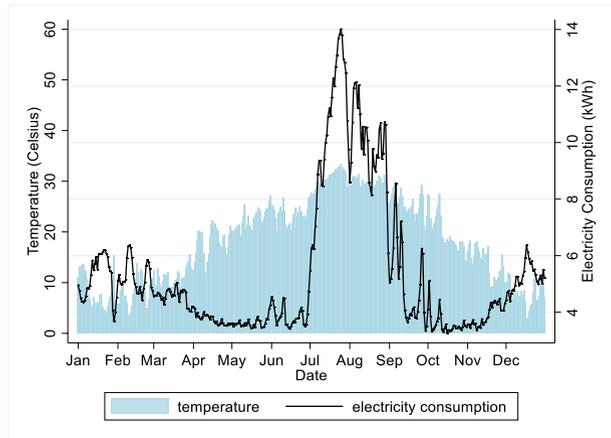
2.3 Weather

The station-level daily weather data include the location of the meteorological stations; daily average, maximum, and minimum temperatures; daily accumulative precipitation;

⁸ The observations with extreme load are excluded based on two criteria. First, the households report the operation of restaurants or accommodation/shops in their houses during the survey. Second, the average daily electricity consumption exceeds 100 kWh, which is nearly 20 times that of the sample.

⁹ Herein, the four seasons are classified according to the "Division of Climatic Seasons" issued by the China Meteorological Administration (<https://std.samr.gov.cn/gb/search/gbDetailed?id=5DDA8B9DC86C18DEE05397BE0A0A95A7>). Specifically, the onset of summer is marked by a daily average temperature of greater than 22°C for five consecutive days. Conversely, the onset of winter is confirmed by a daily average temperature of less than 10°C for five consecutive days. Thus, according to the daily average temperature in Zhejiang in 2017 and considering the comparability between the seasons, we regard every 3 months as a season, i.e., summer prevails from June to August, whereas winter spans from December to February.

Fig. 1 Daily average temperature and electricity consumption. Notes: Bars and lines represent the average temperature and average electricity consumption of the entire sample ($N = 723$) for each day in 2017



daily sunshine hours; daily average wind speed; and the direction of maximum wind speed. Based on the geographical location of the station and household, we match the data of households with the nearest weather station. Therefore, households in the same city may exhibit varying weather conditions. Accordingly, 19 weather stations were matched with the household survey data. The descriptive statistics of the meteorological variables are summarized in Table 3.

To preliminarily analyze the impact of temperature on electricity consumption, the electricity consumption is plotted against the daily average temperature in Fig. 1. As observed, the air temperature and electricity consumption are positively correlated in summer and negatively correlated in winter. This implies a U-shaped response curve between the temperature and electricity consumption, which is consistent with the shape of the curve estimated in most previous studies (Auffhammer et al. 2017; Auffhammer 2022; Li et al. 2019).

2.4 Climate change scenarios

Based on the climate change scenarios referred from NEX-GDDP, the daily average temperature of Zhejiang Province is evaluated from 2090 to 2099 under two commonly used scenarios: RCP4.5 and RCP8.5¹⁰.

The temperature distributions of 2017 and the two scenarios are illustrated in Fig. S2. Compared with 2017, the temperature under both the RCP4.5 and RCP8.5 scenarios is predominantly distributed between 25 and 30°C, indicating that climate change will shift the temperature distribution toward the right. As RCP8.5 represents a more severe scenario, the temperature distribution will be shifted further to the right. Thus, the temperatures under the RCP8.5 scenario are predominantly distributed above 30°C compared to those in the RCP4.5 scenario. The low temperature under RCP8.5 is primarily distributed at 9–11°C, whereas it was concentrated at 8–10°C in the RCP4.5 scenario.

¹⁰ The NEX-GDDP provides air-temperature forecast data from 21 General Circulation Models for both RCP4.5 and RCP8.5 scenarios. The projections detail the forecasts of daily maximum and minimum temperatures with a spatial resolution of $0.25^\circ \times 0.25^\circ$. Based on these data, we utilize the average of maximum and minimum temperatures as a proxy for daily average temperature and calculate the mean temperature of 21 models to develop the scenarios applicable herein.

2.5 Air quality

As reported in previous studies (Salvo 2018; Li et al. 2019), air quality influences household electricity consumption and is correlated with temperature. Households tend to turn on air purifiers, ventilation fans, and other appliances to manage inferior air quality, which results in increased electricity consumption. The China Air Quality Online Monitoring and Analysis Platform provides city-level daily Air Quality Index (AQI), PM2.5, PM10, and other air quality data measured by the Ministry of Environmental Protection. To measure the air quality, we consider particulate matter with a diameter < 2.5 μm (PM2.5), because the concentration of particulate matter can be easily sensed by residents who spend the majority of their time within the household and/or switch on an air purifier, both of which consumes additional electricity.

The trends of the daily average temperature and PM2.5 are comparatively illustrated in Fig. S3, which indicates a negative correlation and implies the necessity of controlling PM2.5 to study the impact of temperature on electricity consumption.

3 Model

To accurately estimate the nonlinear relationship between temperature and household electricity consumption, we initially express temperature as a set of dummy variables ($Dtemp_{n, it}$), referring to Schlenker and Roberts (2008):

$$Dtemp_{n, it} = \begin{cases} 1 & \text{if } n - 1 \leq Temp_{it} < n \\ 0 & \text{otherwise} \end{cases} \text{ for } n = \dots, 0, 1, 2 \dots 23, 25 \dots 35, 36 \dots, \quad (1)$$

where $Temp_{it}$ denotes the average temperature in household i on day t , and $Dtemp_{n, it}$ denotes the dummy variable indicating the prevalence of temperature in the interval $[n - 1, n)$. Based on Eq. (1), the average temperature is segmented into dummy variables with an interval span of 1°C to facilitate the accurate estimation of the nonlinear relationship. To avoid collinearity, one of the temperature dummy variables is omitted. As the estimated response functions remain equivalent (Suits 1984), regardless of eliminating any dummy variable, we select the interval of 23–24°C ($Dtemp_{24, it}$), corresponding to the lowest average electricity consumption in the sample, as the omitted variable. Accordingly, the temperature interval of 23–24°C is regarded as the baseline to evaluate the deviations of the estimated coefficients of the remaining temperature dummy variables from those at the baseline temperature.

To investigate the variations between the urban and rural households and quantify the impact of AC on the response function, the rural dummy variable and AC dummy variable are defined as follows.

$$rural_i = \begin{cases} 1 & \text{a rural household} \\ 0 & \text{an urban household} \end{cases} \quad (2)$$

$$AC_i = \begin{cases} 1 & \text{household with air conditioning} \\ 0 & \text{household without air conditioning} \end{cases} \quad (3)$$

The response functions for each household group are estimated based on the interaction of these three sets of dummy variables, i.e., $Dtemp_{n,it}$, $rural_i$, and AC_i . Therefore, the fundamental equation for estimation can be derived as follows:

$$\begin{aligned}
 EC_{it} = & \sum_{n=1}^N \alpha_{1,n} rural_i AC_i Dtemp_{n,it} + \sum_{n=1}^N \alpha_{2,n} rural_i (1 - AC_i) Dtemp_{n,it} \\
 & + \sum_{n=1}^N \alpha_{3,n} (1 - rural_i) AC_i Dtemp_{n,it} \\
 & + \sum_{n=1}^N \alpha_{4,n} (1 - rural_i) (1 - AC_i) Dtemp_{n,it} + \beta_1 Prec_{it} + \beta_2 Sunshine_{it} \\
 & + \beta_3 WSpeed_{it} + \sum_{d=1}^{15} (\beta_{4,d} WDdirec_{d,it} + \beta_{5,d} WDSpeed_{it} WDdirec_{d,it}) \\
 & + \beta_6 PM2.5_{it} + \beta_7 Price2tier_{it} + \beta_8 Price3tier_{it} + \sum_{m=1}^{11} \beta_{9,m} Month_{m,t} \\
 & + \beta_{10} Weekend_t + \beta_{11} Holiday_t + h_i + \varepsilon_{it}
 \end{aligned} \tag{4}$$

The dependent variable EC_{it} represents the electricity consumption of household i on day t . To estimate the influence of temperature, the temperature response curves for the four household groups are estimated via four series of interaction terms. Specifically, the coefficients $\alpha_{1,n}$, $\alpha_{2,n}$, $\alpha_{3,n}$, and $\alpha_{4,n}$ represent the response functions of rural households with AC, rural households without AC, urban households with AC, and urban households without AC, respectively. This method is equivalent to conducting a subsample regression with the same control variables and estimation strategies.

As control variables, we consider the region-specific and time-variant climate characteristics including daily precipitation ($Prec_{it}$), daily sunshine duration ($Sunshine_{it}$), daily mean wind velocity ($WDSpeed_{it}$), wind direction¹¹ ($WDdirec_{d,it}$), and the interaction terms between wind velocity and direction. Furthermore, we consider the daily concentration of PM2.5 ($PM2.5_{it}$) as a control variable of the air quality characteristics. These variables are correlated with the temperature and affect the residents' electricity consumption (Li et al. 2019; Auffhammer 2022). As such, β_1 , β_2 , β_3 , $\beta_{4,d}$, $\beta_{5,d}$, and β_6 denote the coefficients of the corresponding control variables and measure the impact of these control variables on electricity consumption.

Furthermore, we include a control to assess the impact of the electricity prices on electricity consumption. In 2017, a three-tier electricity tariff was implemented in the residential sector of Zhejiang, corresponding to 0.538, 0.588, and 0.838 CNY/kWh with thresholds of 2760 and 4800 kWh for the second and third tiers, respectively. Based on this tariff, we use dummy variables $Price2tier_{it}$ and $Price3tier_{it}$ to determine whether the cumulative electricity consumption of household i ranges within the second or third tiers on day t . The coefficients of the second and third tiers are β_7 and β_8 , respectively, which measure the impact of the electricity price tiers on electricity consumption. Although the cumulative electricity consumption influences the price, we expect no endogeneity problem in this case because the daily electricity consumption depicts a short-term trend. In particular, the electricity price is predetermined by the short-term past consumption, and current consumption cannot affect the past consumption.

Furthermore, we control the time-fixed effects, including month-fixed effects ($Month_{m,t}$) to represent the seasonal characteristics of residential electricity consumption, weekend effects ($Weekend_t$) to measure the variations in electricity consumption caused by weekend activities in the households, and holiday effects¹² ($Holiday_t$) to account for the variations in electricity consumption during holidays owing to the travel or entertainment activities of the residents during holidays. Similar to the aforementioned scenarios, $\beta_{9,m}$, β_{10} , and β_{11} denote the coefficients of these time-fixed effects, i.e., month, weekend, and holidays, respectively.

¹¹ In total, 15 dummy variables are used to represent 16 orientations.

¹² According to China's *Regulation on Public Holidays for National Annual Festivals and Memorial Days*, we include New Year, Spring Festival, Tomb-sweeping Day, Labor Day, Dragon Boat Festival, Mid-Autumn Festival, and National Day in the variable $Holiday_t$.

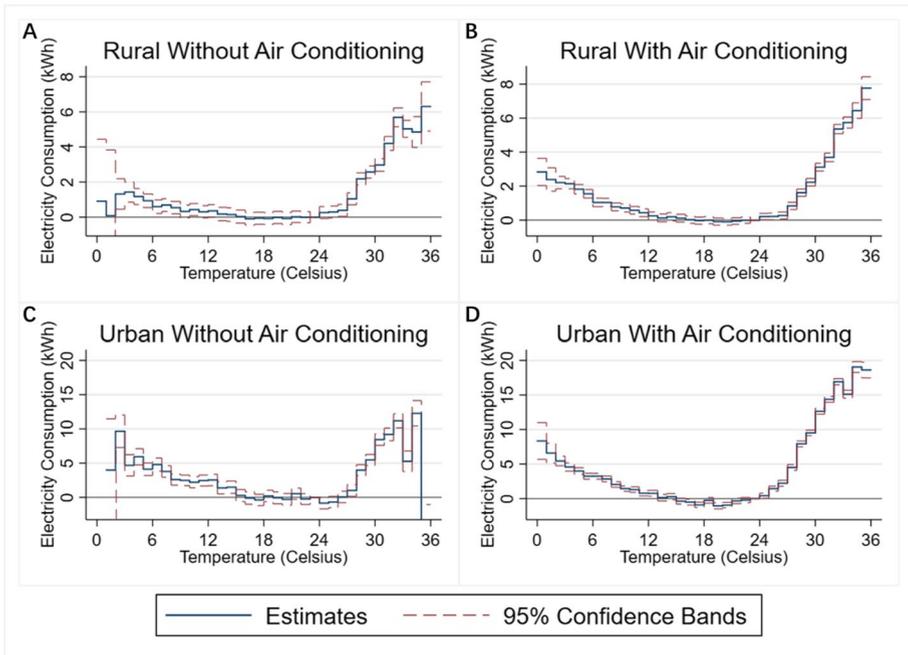


Fig. 2 Temperature response curve. Notes: Solid line represents the estimated response of electricity consumption to temperature; the dashed line represents the 95% confidence interval. Each panel represents a specific household. The numbers of observations for panels A, B, C, and D are 55,845, 162,060, 8030, and 37,960, respectively. The estimates and standard errors are listed in Table S1.

In addition, we consider the individual fixed effects h_i to capture the effects of individual-specific and time-invariant characteristics. Specifically, these include observable (income and housing structure) and unobservable (energy-saving awareness and personal comfort) household characteristics, where ε_{it} denotes the error term.

4 Empirical results

4.1 Main results

The temperature response curves for rural households without AC, rural households with AC, urban households without AC, and urban households with AC are plotted in Fig. 2. The estimate at temperature n is interpreted as the variations in the daily electricity consumption for an average temperature of n °C, compared to the consumption at 23–24°C, assuming other variables as constant. The comparative analyses of the four panels in Fig. 2 indicate the following results.

4.1.1 Response function

The four plots exhibit a typical U-shaped temperature response function, which are consistent with those reported in previous studies (Engle et al. 1986; Auffhammer and Aroonruengsawat

2011; Deschênes and Greenstone 2011; Li et al. 2019). As observed, the response curves are relatively flat in the temperature range of 12–24°C, implying the comfortable temperature zone for residents. However, the responses are steeper if the temperature range increases beyond 24°C than if it decreases below 12°C. This finding can be deemed reasonable because electricity is the primary energy source for cooling and not heating.

4.1.2 Urban–rural differences

Compared to rural households, the electricity consumption in urban households is more sensitive to temperature variations. First, the flat portion of the response curve for urban households is shorter than that of rural households, indicating the narrower comfortable temperature range of urban household residents. Second, compared with rural households, urban households exhibit a steeper response function at both high and low temperatures. If the temperature increases by 1°C in the high-temperature range (> 27°C), the daily electricity consumption of an urban household increases by 1.39–1.70 kWh¹³ on average, whereas that in a rural household is 0.62–0.82 kWh. If the temperature decreases by 1°C in the low-temperature range (< 12°C), the daily electricity consumption increases by 0.14–0.62 kWh for an urban household and 0.11–0.21 kWh for a rural household. This result implies that urbanization reinforces the climate change-induced increase in electricity consumption in the residential sector. Thus, we simulate this increased electricity consumption under various climate change scenarios.

4.1.3 Impact of AC

The electricity consumption in households with AC is more sensitive to high temperatures. In particular, two relevant phenomena are observed. First, AC apparently diminishes the comfortable temperature range of urban household residents within 24–27°C. Accordingly, the increase in electricity consumption at 24°C implies that urban households with AC may have switched it on at that instant. In contrast, urban households without AC appear to endure until the temperature reaches 27°C before switching on other cooling appliances (e.g., electric fans). However, similar evidence is not observed for rural households, which can be attributed to the energy-saving habits of residents and the ventilated house structures of rural households. Second, AC steepens the response curve in the high-temperature range. If the temperature increases by 1°C in the high-temperature range (> 27°C), the daily electricity consumption of a household with AC increases in both urban and rural areas by 1.70 and 0.82 kWh, respectively. The increase in electricity consumption for households without AC is 1.38 kWh in urban areas and 0.62 kWh in rural areas. Presumably, the variations in the daily electricity consumption result from the fluctuating energy efficiency and usage period between AC and other cooling appliances. Overall, these results suggest that electricity consumption increases with AC utilization in the residential sector in hot weather.

4.1.4 Impact of other factor

The estimates of other variables such as precipitation, wind, sunshine hours, air quality, weekend and holiday effects, and prices are reported in Table S1. Investigating the impacts

¹³ The lower limit represents the response of households without AC, whereas the upper limit indicates the response of households with AC.

of factors other than temperature can lead to a more comprehensive understanding of the potential impacts of climate change on electricity consumption.

As expected, precipitation and PM2.5 significantly increase the daily electricity consumption, because residents tend to remain indoors for longer durations on days of heavy rain or high air pollution. More specifically, the residents are more likely to turn on their air purifiers if the air is heavily polluted. Wind speed negatively impacts household electricity consumption, because high wind speeds produce a cooling effect, thereby reducing the cooling demand.

The marginal variations in electricity prices do not significantly influence the household electricity consumption. Compared with the first tier of consumption, the electricity consumption does not vary significantly even if the household consumed electricity up to second- or third-tier units. This result implies that the tiered electricity price policy does not influence in reducing the daily electricity consumption of households.

Compared with weekdays, households consume 0.22 kWh more electricity on weekends and 0.31 kWh less on holidays on average, indicating that they tend to stay at home on weekends and travel on holidays.

4.2 Alternative specifications

To validate the robustness of the developed mode, we replace the temperature response function in model (Auffhammer 2022) with piecewise linear and Chebyshev polynomials, as follows:

$$\begin{aligned}
 EC_{it} = & \sum_{j=1}^{J_1} \omega_{1,j} rural_i AC_i F_{1,j}(Temp_{it}) + \sum_{j=1}^{J_2} \omega_{2,j} rural_i (1 - AC_i) F_{2,j}(Temp_{it}) \\
 & + \sum_{j=1}^{J_3} \omega_{3,j} (1 - rural_i) AC_i F_{3,j}(Temp_{it}) \\
 & + \sum_{j=1}^{J_4} \omega_{4,j} (1 - rural_i) (1 - AC_i) F_{4,j}(Temp_{it}) + X_{it} \beta + h_i + \varepsilon_{it},
 \end{aligned}
 \tag{5}$$

where $F_j(\cdot)$ represents the piecewise-linear function and j indicates the number of segments. For each group, we employ several thresholds and threshold values. To select the optimal number of thresholds and values, we perform iterations with all possible threshold temperatures and select the result with the least sum of squared residuals for a given group. Subsequently, the Wald test is employed to determine the significance of the inflection point at the level of 0.01, i.e., 99%. If deemed significant, the first threshold value is derived. Accordingly, we include the first threshold temperature and follow the same procedure to determine the subsequent threshold until the Wald test cannot reject the null hypothesis. Herein, X_{it} denotes a vector composed of all the control variables in Model (Auffhammer 2022).

The Chebyshev polynomials equation is stated as follows:

$$\begin{aligned}
 EC_{it} = & \sum_{h=1}^{H_1} \gamma_{1,h} rural_i AC_i \Phi_h(Temp_{it}) + \sum_{h=1}^{H_2} \gamma_{2,h} rural_i (1 - AC_i) \Phi_h(Temp_{it}) \\
 & + \sum_{h=1}^{H_3} \gamma_{3,h} (1 - rural_i) AC_i \Phi_h(Temp_{it}) \\
 & + \sum_{h=1}^{H_4} \gamma_{4,h} (1 - rural_i) (1 - AC_i) \Phi_h(Temp_{it}) + X_{it} \beta + h_i + \varepsilon_{it}
 \end{aligned}
 \tag{6}$$

where $\Phi_h(\cdot)$ denotes the h th order Chebyshev polynomial, and H_c denotes the endogenous number of polynomials for group c , determined by the Wald test.

The response curves estimated using Eqs. (5) and (6) are illustrated in Figs. S4 and S5, respectively. As observed, the response curves estimated by the two model settings are consistent with the results in Fig. 2. First, the response functions maintain the U-shape, and the

response to a temperature increase at the high-temperature range is steeper than that toward temperatures decreasing at the low-temperature range, thereby validating the asymmetric response to the temperature variations. Second, the urban households exhibit narrower comfortable temperature zones, respond more rapidly to the increase in the high-temperature range, and decrease in the low-temperature range. Third, the consumption trend in households with AC is more sensitive to temperature increases in hot weather than that in households without AC.

5 Simulations

Based on the estimates of the main model and the climate change scenarios RCP4.5 and RCP8.5, we simulate the future electricity consumption in the residential sector of Zhejiang Province for 2090–2099.

5.1 Climate change scenarios

Initially, we evaluate the impact of climate change on household electricity consumption considering the same rate of urbanization and AC adoption. The trend of simulated electricity consumption of representative households under the climate change scenarios is summarized in Table 4. To show the seasonal variations, we also plot the daily electricity consumption curve of simulated households under different scenarios in Fig. S6. Herein, we consider the RCP4.5 scenario to analyze the impact of climate change on the four types of representative households. As climate change shifts the temperature distribution toward the right, the electricity consumption of urban households with AC increases by 6.24%, and that of urban households without AC increases by 2.58%. Notably, the results of rural households vary, with an increase of 2.58% in those with AC and 6.30% in those without AC. This variation can be attributed to the usage of more ACs for heating in rural area, and climate change through warming will yield savings in this aspect of electricity consumption, i.e., less increase in annual electricity consumption. Upon comparing the urban and rural households, the average increase in the electricity consumption is 5.61% in urban areas, which is higher than the 3.50% increase in rural areas. Considering the constant rate of urbanization and AC adoption, scenario RCP4.5 will increase the average electricity consumption of the residential sector by 5.04%, whereas scenario RCP8.5 will increase the average electricity consumption by 16.37%.

Subsequently, we calculate the differences between the households with and without AC to analyze the impact of AC on electricity consumption under various climate change scenarios. Reviewing the econometric model results in Section 4, AC affects electricity consumption by altering the temperature response function of households. Considering climate change, the results in Table 4 indicate that AC usage will increase the annual electricity consumption of urban households by 5.13% and 10.03% under RCP4.5 and RCP8.5, respectively, whereas that in rural households will increase by only 1.05% and 0.11% under these two scenarios, respectively. This result demonstrates that AC primarily affects the electricity consumption of urban households, which increases with the intensity of climate change. In Table 4, the differences between the rural households with and without AC demonstrate the weaker impact of AC on rural households in the RCP8.5 scenario than that in the RCP4.5 scenario. This can be attributed to the declining electricity consumption for heating in rural households under increasing temperature, thereby partially offsetting the increase in electricity consumption caused by increased AC usage.

Table 4 Simulated electricity consumption of representative households under climate change scenarios

	Rural household		Urban household	
	without AC	with AC	without AC	with AC
Annual electricity consumption of sample in 2017 (kWh)	1806.52	1891.65	2360.17	2395.68
RCP4.5				
Annual electricity consumption (kWh)	1920.25	1940.50	2420.97	2545.20
Growth rate compared to 2017	6.30%	2.58%	2.58%	6.24%
Average growth rate of urban/rural households	3.50%		5.61%	
Average growth rate of residential sector	5.04%			
Annual difference between with and without AC	1.05%		5.13%	
RCP8.5				
Annual electricity consumption (kWh)	2093.87	2096.22	2603.04	2864.12
Growth rate compared to 2017	15.91%	10.81%	10.29%	19.55%
Average growth rate of urban/rural households	12.07%		17.95%	
Average growth rate of residential sector	16.37%			
Annual difference between with and without AC	0.11%		10.03%	

AC, air conditioning; all growth rates are calculated assuming a constant rate of urbanization and AC adoption at the 2017 level; differences between with and without AC are compared within climate change scenarios

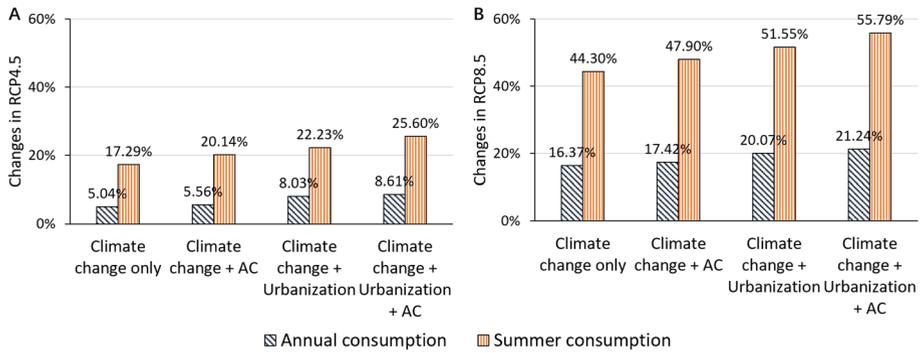


Fig. 3 Electricity consumption simulation. Notes: The rate of variation is calculated in comparison to the electricity consumption with an urbanization rate of 68.73% and an AC adoption rate of 82.5% and 74.4% in urban and rural households in 2017 under the respective climate change scenarios; urbanization corresponds to increased urbanization rate of 80%. AC adoption implies an adoption rate of 95% for urban households and 85% for rural households

5.2 Climate change with urbanization and AC adoption

Herein, we consider the scenario of increase in urbanization and AC adoption rates. In the baseline scenario, the rate of urbanization (68.73%) and AC adoption (82.5% for urban and 74.4% for rural) remained the same as those in 2017 (calculated based on the proportion of the urbanized population and the size of urban and rural households in Zhejiang Statistical Yearbook 2018, and according to the survey used in this study, respectively). In the growth scenario, we increase the urbanization rate to 80%, which is proximate to the proportion of the urban population (82.26%) in the USA in 2018, and increase the AC adoption rate to 95% for urban households and 85% for rural households based on an International Energy Agency (IEA) report¹⁴. Upon comparing the simulated electricity consumption in the baseline and growth scenarios, we derive the reinforcement effect of urbanization and climate change as well as that of AC adoption and climate change on household electricity consumption. The results are illustrated in Fig. 3.

The results reveal that under the RCP4.5 climate change scenario, on the basis of climate change, (1) an increase in the adoption rate poses a slight impact on the annual electricity consumption but further increases the electricity consumption by 2.85% in summer, considering constant urbanization rate; (2) an increase in the urbanization rate will further increase the annual electricity consumption per household in the residential sector by 2.99%, and the electricity consumption will further increase by 4.94% in summer, considering that the AC adoption rate remains unchanged; and (3) combining the increase in the rate of urbanization and AC adoption, the annual electricity consumption will further increase by 3.57% and the electricity consumption will further increase by 8.31% in summer. With higher temperatures in RCP8.5, both urbanization and AC adoption will further increase the electricity consumption of the residential sector.

These results imply that increased urbanization intensifies the impact of climate change on the electricity consumption in the residential sector, and increased AC adoption rate amplifies the impact of climate change on household electricity consumption during high-temperature weather conditions, especially in the summer.

¹⁴ IEA's The Future of Cooling in China Report predicts that by 2030 as many as 85% of households are expected to own at least one AC unit.

6 Conclusions and policy implications

Although energy consumption contributes to climate change, the energy consumption behavior of households is affected by climate change. To optimize climate change policies, the response of households to climate change through energy consumption behavior requires further clarification in the residential sector. Based on energy surveys and daily electricity consumption data, this study estimates the impact of AC on the temperature-response functions of urban and rural households, which depicts a typical U-shaped response curve for electricity versus temperature. Moreover, the response curves of the urban households are more sensitive to temperature variations than those of rural households. The present findings signify that households with AC are more sensitive to high temperatures, because AC usage narrows the comfortable temperature range and steepens the response curve in the high-temperature range. Based on the model estimation results, we further simulate the impacts of urbanization and AC adoption on electricity consumption in the residential sector under various climate change scenarios. We observe that urbanization amplifies the impact of climate change on the electricity consumption of the residential sector, which increases with AC adoption in summer, especially in urban households under climate change.

This study contributes to the existing literature by revealing the variations in electricity consumption between urban and rural households and clarifying the impact of AC adoption. The present findings can improve policymakers' understanding of the adaptation mechanism of households toward climate change. The present findings suggest that investors and policymakers in the power sector should consider the impact of urbanization and electrification on the electricity consumption behavior of the residential sector while investing and devising climate change-related policies. Urbanization increases electricity consumption in the residential sector as well as increase the sensitivity of households toward temperature variations, which may strengthen the impact of extreme weather conditions on the electricity consumption of the residential sector and restrict the safety and stability of the power system. As such, high-temperature periods strongly correspond with peak periods of electricity demand, partly because of AC usage. With greater penetration of AC in the future, power systems will encounter greater differences between the peak and valley power demands, which will create challenges to ensure stable power supplies and increase the cost of power systems.

To mitigate the impact of urbanization and the penetration of energy-consuming durable equipment, investing in only power generation capacity may prove to be ineffective. In general, power generation investment decisions are based on the maximum power demand to ensure the reliability of power consumption. This decision neglects the shape of the electricity consumption curve, which results in overcapacity and inefficient power generation. However, these potential problems can be resolved with market insights. As such, market-oriented reforms in the electricity sector ensure that electricity prices reflect the real-time supply costs. This is expected to generate price signals influencing the residents' electricity consumption behavior, especially over the medium- or long-term period, by shifting the electricity consumption from peak periods to valley periods. Furthermore, the establishment of a capacity market and demand response mechanisms can potentially improve the flexibility of the power system and its ability to fulfill peak demands, thereby improving the resilience of the power sector toward climate change.

Owing to data limitations, we can estimate only the impact of AC on the responses of the households toward climate change; however, we cannot determine the effect of

climate change on the AC adoption behavior of households. Thus, a comprehensive analysis of the long-term adaptations and short-term responses of households to climate change will deepen our understanding of the relationship between climate change and energy consumption, which forms the scope of future research if data are available.

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Author contribution Cui wrote the original draft, modeled the electricity response function, performed the climate change scenario analysis, and visualized all the figures in the article. Xie proposed the concept of this study and significantly contributed toward writing, reviewing, and editing this article. Zheng proposed the concept of this study and acquired relevant data.

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Declarations

Competing interests The authors declare no competing interests.

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