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The inequality in household electricity consumption due to temperature change: Data driven analysis with a function-on-function linear model

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ABSTRACT

This paper constructs a function-on-function linear model that identifies the unknown comprehensive response of household electricity consumption toward temperature changes from a data-driven perspective. We also analyze the contribution of dynamic temperature changes to electricity consumption inequality based on large-scale smart meter data. Specifically, we use the Gini index, which characterizes electricity consumption inequality, to explore the heterogeneity of household behaviors. The results show that extreme temperatures will significantly affect household electricity consumption, and the response inertia is approximately 48 days. The response inertia is mainly affected by the household electricity consumption scale. The inertia of large electricity users is four times that of small users. This response inertia difference leads to the occurrence of household electricity consumption inequity inequality in a relatively narrow time window of approximately 18 days. The results also reveal that extreme temperature fluctuations play a key role in enlarging this inequality.

1. Introduction

Climatological factors have a strong impact on electricity demand, which explains most of the intra-annual variability [1]; Moral-Carcedo and Pérez-García, 2019) and influence the sustainability of human life [2,3]. Temperature stands out among climate factors that affect electricity demand [4,5], although humidity, cloudiness, rainfall, and solar radiation are also related to the demand for electricity [6]. Understanding climate response patterns is critical to improving integrated assessment models (IAMs) [3,7]. It is also crucial to better understand how demand response policies can contribute to mitigating energy poverty and inequality issues.

The electricity demand of the residential sector is more responsive than other sectors to temperature changes [8,9]. The response function of the residential sector can therefore provide a better understanding of temperature-driven energy demand [1,10]. The literature has conducted an in-depth analysis of electricity–temperature response patterns. Previous studies confirmed the nonlinear relationship between electricity demand and temperature (Alberini et al., 2018; [11]. People are more inclined to turn on heating or cooling appliances on extreme temperature days than on warm or cool days [3,12]. Based on this, heating degree days (HDDs) and cooling degree days (CDDs) are derived. The degree days method, however, has some limitations, such as the determination of the threshold temperature and the lag time interval [13]. To reduce the potential biases of exogenous thresholds, semiparametric [14], nonparametric [15], and smooth transition regression (STR) models [16] were employed in previous studies. These semiparametric and nonparametric methods captured the nonlinear relationship and computed the temperature threshold more scientifically. Existing literature also pays more attention to the electricity consumption inequality issues. There has been a relatively in-depth discussion on the measurement of electricity inequality and the analysis of influencing factors. For example, based on daily data [17], used econometric methods to study the relationship between temperature and electricity consumption inequality. Cabello (2022) assessed the electricity consumption inequality in Colombia by using the Gini coefficient.

These existing studies focus on the concurrent impact of temperature on electricity consumption and inequality. The specific historical electricity–temperature response, which is called response inertia, however, has still not been identified. Through the actual observation of household electricity consumption data from smart meters, we find that temperature and electricity consumption may exhibit strictly real-time

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correspondence, and there may be a time delay. This phenomenon is consistent with [18] findings that the past temperature has a significant impact on present electricity consumption. However, fewer empirical studies identify how long the past temperature had an impact on current electricity consumption and what the specific response relationship is. Instead, empirical lag values are commonly adopted. At the same time, there is also a research gap in the dynamic response relationship between temperature and electricity consumption inequality.

To move this literature forward and gain a comprehensive understanding of the climate–electricity relationship, the historical functional linear model (HFLM) is applied in this paper. We first specify the response inertia intervals that will impact current electricity consumption. The functional response function is also estimated to give a more complete picture of the climate–electricity relationship. We also specify the response heterogeneity in different electricity consumption levels, which suggests that there are three response inertia interval modes, and the past temperature plays an important role in reshaping electricity consumption patterns. Therefore, the electricity Gini–temperature response is further estimated to determine whether this reshaping process occurs concurrently or historically.

A major contribution of this paper is that we quantitatively identify the unknown temperature–electricity response inertia interval and the dynamic response function based on a novel historical functional method. To the best of our knowledge, this is the first time that the HFLM has been applied to temperature-related energy consumption research. We find that the HFLM can accurately identify the response inertia effect on electricity consumption. The response inertia interval and functional electricity–temperature response enable us to perform further analysis, such as the historical impact of climate change on residents, and then assess economic damages. This approach is novel because it allows different time scales between independent variables and response variables. For instance, the response variable can be monthly data, and the independent variable can be day-based data. Another contribution is that we reveal the important roles of historical temperature in reshaping household electricity redistribution based on massive smart meter data, which can reveal the heterogeneity of residents' real response behaviors in response to climate change. This provides the possibility for us to research inequality evolution in response to temperature change.

The remainder of the paper is organized as follows. Section 2 shows the methods and data sources we used in the paper. Section 3 presents the results and main findings. Section 4 reports the main conclusions.

2. Methods and data sources

2.1. Historical functional linear model

Since electricity consumption and temperature are both functional variables, we use a function-on-function linear model to characterize the relationship between the history of a functional covariate and the current state of a functional response. First, we consider the full-time interval function-on-function linear model:

$$y_i(t) = \alpha(t) + \int_0^T \beta(s,t) TEMP_i(s) ds + \mathbf{X}^{\mathbf{T}}\boldsymbol{\gamma} + \varepsilon_i(t) \tag{1}$$

where y_i(t) is the response curve, x_i(t) is the regression variable and $\alpha(t)$ is the intercept function. $\beta(s,t)$ is the response coefficient function, which represents the effect of the functional covariate at time *s* on the functional response at time *t*. $\varepsilon_i(t)$ is the error term. Considering that the current filter electricity consumption is likely dependent on temperature changes over the past few days but the more distant past, we adopt the historical functional linear model developed by Ref. [19] to identify this lag effect. Given the lag δ = T, the domain of $\beta(s,t)$ is the triangular region defined by vertices (0,0), (0,T), (T,T), which is the classical function-on-function model. Given $\delta < T$, the model becomes a nonglobal historical functional linear model [20]:

$$y_i(t) = \alpha(t) + \int_{\max(0,t-\delta)}^{t} \beta(s,t) x_i(s) ds + \varepsilon_i(t), t \in [0,T] \tag{2}$$

where x_i(t) and y_i(t) are the functional covariate and response for the *i*-th subject, respectively, i = 1 …,n. $\alpha(t)$ is the intercept function, and $\varepsilon_i(t)$ is the error term. $\beta(s,t)$ is the response coefficient function, which represents the effect of the functional covariate at time *s* on the functional response at time *t*. δ is the time lag, which means that the response y_i(t) at current time *t* is affected by the covariate x(s) during the time interval [max (0,t-δ), t], as shown in Fig. 1.

We define δ as the temperature–electricity response inertia. The greater the delta value is, the stronger the response inertia and the lower the influence weight of temperature change on residents at a single time point, which reflects the greater adaptability of residents to temperature.

Since the domain of the coefficient function *β(s,t)* is nonrectangular, using the bivariate spline generated via tensor product would result in a jagged shape along the boundary t = s. To address this problem, we approximate the coefficient function *β(s,t)* with triangular basis functions [21] from finite element method theory. Referring to the method developed by Ref. [19], we divide the interval [0,T] into M subintervals, and the step length is d = T/M. Then, the number of triangle basis functions $\varphi_k(s,t)$ is K = (M +1) (M + 2)/2. Each basis function $\varphi_k(s,t)$ has a compact support. For example, for the 9th node in Fig. 2 (a), the support of the basis function $\varphi_9(s,t)$ is the triangular region defined by the nodes {5, 6, 8, 9, 10, 13, 14}. As shown in Fig. 2 (b), these functions are tent-shaped, piecewise linear, positive over at most M+1 adjacent triangles and continuous with value 1 at node *k* and value 0 at the boundary of the hexagon. Due to this compact support property, if we approximate *β(s,t)* by a linear combination of triangular basis functions, then such approximation is locally sparse if the coefficients are sparse in groups.

Our focus is on the estimation of lags δ and *β(s,t)*. The historically sparse and smooth estimators for *β(s,t)* are defined as follows:

$$\widehat{\beta}_n(s,t) = \sum_{k=1}^{K} \varphi_k(s,t) \widehat{b}_{nk} \tag{3}$$

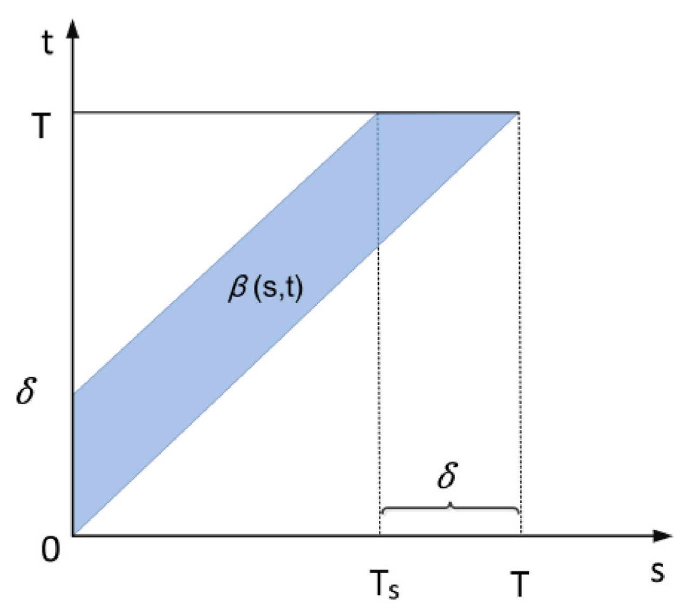


Fig. 1. The mechanism of the historical functional linear model
Notes: The domain of the coefficient function β(s,t) is displayed in the blue area. δ is the unknown forward time lag. The x-axis s is the time axis for temperature. The y-axis t is the time axis for the response variable.

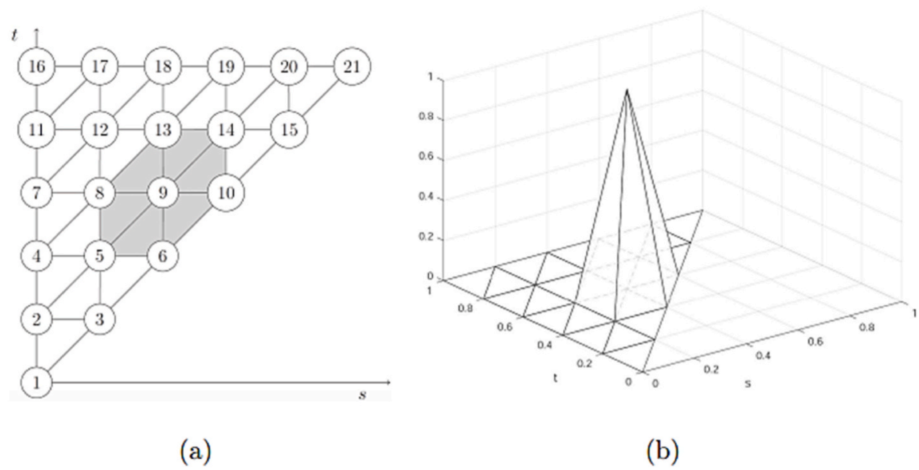


Fig. 2. The mechanism of the triangular nested group bridge approach [19]
Notes: (a) is triangulation and indexation of the nodes. The grey hexagon indicates the support of the 9th basis function $\varphi_9(s,t)$. (b) Is the basis function $\varphi_9(s,t)$ corresponding to the 9th node, which is of a tent shape peaked at the 9th node.

where $\varphi_k(s,t)$ is the triangular basis function. In econometrics, β usually refers to regression coefficients, which can reflect the degree of influence of each independent variable on the dependent variable and the statistical significance. In functional data analysis, *β(s,t)* value is used to measure the degree of influence of the independent variable on the dependent variable, which can reflect the magnitude and direction of the influence of the independent variable on the dependent variable in the time dimension. The lag δ can be obtained as follows [19]:

$$\widehat{\delta}_n = \frac{T}{M}\min_j\{1 \le j \le M : \widehat{\beta}_n(s,t) = 0 \ on\ D_j\} - \frac{T}{M} \tag{4}$$

D_j denotes the triangle with vertices (0,T), (0, (j-1)d), ((M+1-j)d, T), for j = 1, …,M. $\widehat{\mathbf{b}}_n = (\widehat{b}_{n1}, \ldots, \widehat{b}_{nK})$ minimizes the penalized least squares:

$$\frac{1}{N}\int_0^T \sum_{i=1}^{N}\left(y_i(t) - \sum_{k=1}^{K} b_k \int_0^t x_i(s)\varphi_k(s,t)ds\right)^2 dt + \lambda\sum_{j=1}^{M+1} c_j \|b_{Aj}\|_1^{\gamma} + \mathbf{b}^T\mathbf{R}\mathbf{b} \tag{5}$$

where $\gamma \in (0,1)$. Referring to Ref. [19], we set $\gamma = 0.5$, where λ is a nonnegative tuning parameter. c_j is the weight parameter, where $c_j \propto |A_j|^{1-\gamma}$, and $|A_j|$ denotes the cardinality of A_j [22]. $\|\mathbf{b}\|_1$ denotes the L_1 norm of a q-dimensional vector **b**. A_j is set of the index of nodes contained in triangle D_j. Therefore, $\mathbf{b}_{A_j} = \{b_k : k \in A_j\}$. **R** is a discrete smoothness penalty matrix. The nested group bridge penalty and discrete roughness penalty are introduced to shrink the estimated coefficient function toward zero over the upper left triangular region [22] and enforce the smoothness of the estimate $\hat{\beta}_n(s,t)$ [21,23], respectively. In particular, the discrete smoothness penalty contains the horizontal, vertical, and diagonal directions with nonnegative weights.

In meteorological data and home smart meter data, the data format is recorded in the form of discrete data points, and the number of data observation points is limited. Therefore, it is necessary to perform discrete numerical continuity processing on the observation data of each city. The actual observation value is the sum of the fitting value and estimation error:

$$y_{ij} = x_i(t_j) + \xi_i(t_j) \tag{6}$$

Where y_{ij} represents the observed value of city i at time t_j, and $x_i(t)$ represents the estimated fitted smooth curve of the original data. $\xi(t_j)$ represents a random variable with fitting error, which follows an independent covariance distribution with zero mean. After completing the functional fitting process of the original data, select a suitable basis function for linear fitting approximation $x_i(t)$ based on the data variation pattern, and the formula is as follows:

$$x_i(t) = \sum_{l=1}^{L} c_{il}\varphi_l(t) \tag{7}$$

Where $\varphi_l(t)$ is the basis function, c is the coefficient vector of the basis function, and L is the number of bases. Both residential electricity data and meteorological data have certain periodic patterns. Therefore, this article uses Fourier basis functions for basis expansion and curve fitting, and the expression is as follows:

$$\varphi_l(t) = \begin{cases} 1, & l = 0 \\ \sin lwt, & l = 2r-1 \\ \cos lwt, & l = 2r \end{cases} \tag{8}$$

Where r is a non-zero natural number.

2.2. Temperature-related electricity consumption filter method

As the literature points out, household electricity consumption is affected by several factors. To investigate the temperature–electricity response, it is necessary to remove the non-climatic effects. Following the method proposed by Ref. [24], we first remove the demographic trend by using the average electricity consumption data. Second, some control variables, such as income, daily precipitation and relative humidity, are taken into consideration to explain the impact of the economy and other meteorological factors on electricity consumption [25]. We also control for the holiday effect since people may have different electricity usage behaviors during holidays. Therefore, the filtered electricity demand is obtained as the residuals of the ordinary linear square regression method [4,24]:

$$E_i(t) = \alpha + \mathbf{X}_i^T\boldsymbol{\beta} + \mathbf{H}_i^T\boldsymbol{\gamma} + w_i + FD_i(t) \tag{9}$$

where $E_i(t)$ is the electricity consumption of the *i*-th city in the *t*-th month. X is the control variable. H and W are the count days of holidays and weekends, respectively. *w* controls the city fixed effect. $FD_i(t)$ is the filtered electricity demand. The nonsignificant terms are removed from the model. Then, we consider the HFLM to analyze the relationship between the daily average temperature and the filtered electricity demand $FD_i(t)$:

$$FD_i(t) = \alpha(t) + \int_{t-\delta}^{t} x_i(s)\beta(s,t)\,ds + \varepsilon_i(t) \tag{10}$$

where $\alpha(t)$ is the intercept function and $\varepsilon_i(t)$ is the error term. β(s,t) represents the effect of the temperature at time s on the electricity demand at time t. The constant δ represents the time lag. We also use this method to analyze the historical effect of temperature on electricity redistribution, namely the of electricity consumption inequality.

To investigate the historical lag effects of temperature on electricity redistribution, the Gini index is introduced. The electricity Gini index has already been used for the measurement of social inequality [26–28]:

$$Gini_i = 1 - \sum_{j=1}^{n} \left(H_{i,j+1} - H_{i,j}\right)\left(E_{i,j+1} + E_{i,j}\right) \tag{11}$$

where H_i is the proportion of the cumulative household in city i. E_i is the cumulative electricity proportion therein. The *j* is the household ID.

2.3. Data sources

Meteorological data. The historical daily temperature data from January 1 to December 12, 2018, were collected from the China Meteorological Data Service Center. The dataset contains daily temperature, precipitation, wind velocity, and relative humidity from 78 weather stations matching 78 cities. The weather station selection and temperature variable construct rule are as described by Ref. [29]. We then merge the electricity consumption data with temperature for further analysis. The average daily temperature curves are shown in Fig. 4 (A).

Large-scale smart meter data. We use household electricity consumption data to fit and validate the historical functional regression models. The data cover 78 subtropical cities in southern China. For each city, the dataset consists of a time series of monthly consumption load during the period from January to December 2018. The data cover a total of approximately 189,380 households. Fig. 3 shows the density distribution map of these residential electricity consumptions.

We aggregate household-level electricity consumption data into city-level data and then perform functional data analysis. The monthly consumption varies significantly across cities and by season, as shown in Fig. 4 (B). Furthermore, a large amount of household-level data allow us to calculate the inequality of electricity consumption in various cities based on the Gini algorithm.

Fig. 4 (A) shows that the temperature curves reach their maximum value in July. However, the household electricity reaches its maximum value in August, as shown in Fig. 4 (B). Therefore, it seems that there is indeed a time lag effect of temperature on electricity demand. The descriptive statistics of the variables are shown in Table 1.

3. Results and discussion

3.1. Historical lag effect identification

To establish the dynamic historical response model of temperature and electricity consumption and retain the temperature fluctuation characteristics as much as possible, we first fit the temperature data into functional curves. A total of 365 Fourier basis functions are selected for fitting to ensure that each point can be captured. We refer to the method proposed by Harezlak (2007) to set the penalty function parameters. Fig. 5 shows that the fitted curve is generally smooth and retains some fluctuation information. In this way, we can better identify the functional fluctuation of data without losing too much data information.

The filter data are used to investigate the response functions, and the regression result is shown in Table 2. Model 5 controls time fixed effects and city fixed effects. The results show that the influence of different variables on residential electricity consumption has strong robustness, and the R^2 of Model 5 is the largest, which means that the overall explanation of Model 5 is better. Therefore, this paper uses the residual value estimated by Model 5 as the filtered variable of temperature electricity consumption.

Previously accumulated temperature will affect the apparent temperature perceived by humans. Therefore, the temperature-related electricity consumption is probably dependent on the historical temperature. We divide the time range [0,365] into 40 subintervals with equidistant nodes. The number of nodes divided have impact on the results but not very significant because we added a roughness penalty in the objective equation (5), the choice of interval number is no longer

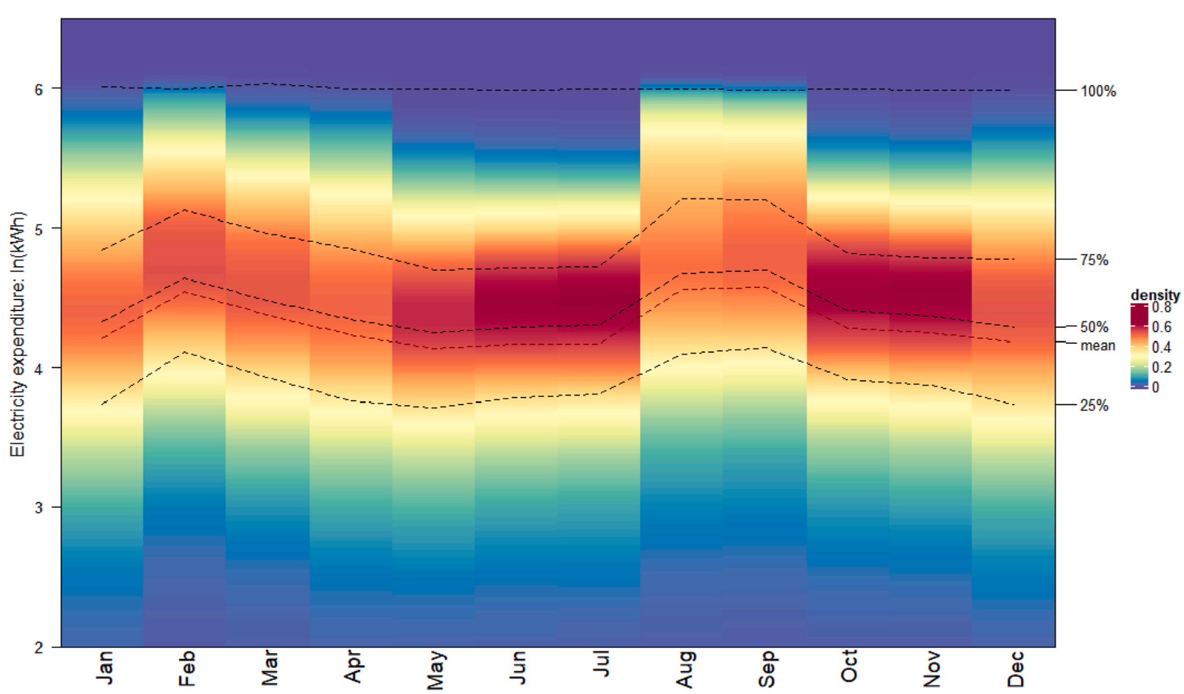


Fig. 3. Density distribution map of household electricity expenditure
Note: This heat density map is constructed based on 189,380 households' smart meter data. The darker the red color, the more concentrated the distribution of electricity consumption. The y-axis represents the ln form of electricity consumption. The black dash lines are the electricity consumption quantile lines.

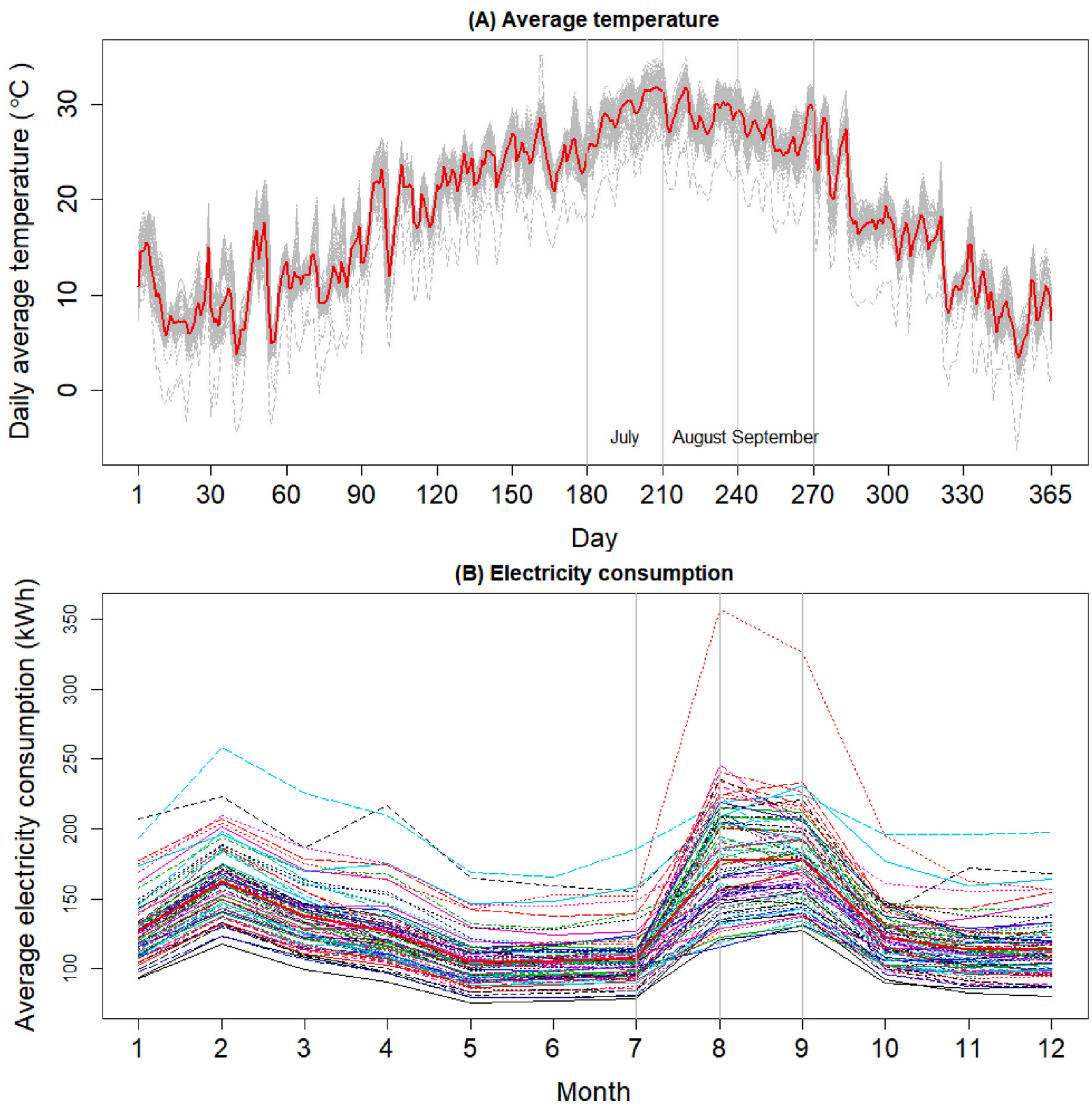


Fig. 4. Daily temperature curves (A) and household electricity consumption curves (B)
Notes: In Fig. 4 (A), the grey curves are the original temperature curves of 78 cities. The red curve is the mean temperature curve of 78 cities. In Fig. 4 (B), different coloured lines represent the average household electricity consumption of different cities.

Table 1
Descriptive statistics of the variables.

Variables	Definition	Observations	Mean	Std. Dev.	Min	Max
TEMP	Daily average temperature (°C)	936	18.89	8.129	−6.20	35.20
RH	Daily relative humidity in percent (%)	936	78.59	5.64	64.06	95.81
PREC	Daily precipitation (0.1 mm)	936	42.68	24.88	1.86	145.16
WIND	Daily mean wind velocity (0.1 m/s)	936	18.06	5.88	7.10	46.39
Income	Log form of monthly per capita income (Chinese Yuan)	936	7.26	0.26	6.68	7.61
POV	Percentage form of poverty alleviation rate (%)	936	1.89	1.46	0.17	6.24
ALTI	Log form of the altitude of the city	936	6.96	0.71	5.35	9.36

important. In addition, the larger the M value, the slower the calculation speed. To find a balance between accuracy and computational efficiency, we finally chose M = 40. The estimation result is shown in Fig. 6. Fig. 6 (a) shows the thermodynamic diagram of the dynamic influence coefficient function of temperature on household electricity consumption.

The estimated electricity–temperature response inertia is approximately 48 days, indicating that the current electricity consumption is the result of the complex effects of historical temperature. Specifically, the temperature-related electricity in a certain month can be regarded as a weighted average result of the past 48 days' temperature. We select a typical inertia effect pattern on the 240th day (Fig. 6 (b)) as an example. The β value of the 240th day is 0, which means that the current temperature has little effect on electricity consumption. The

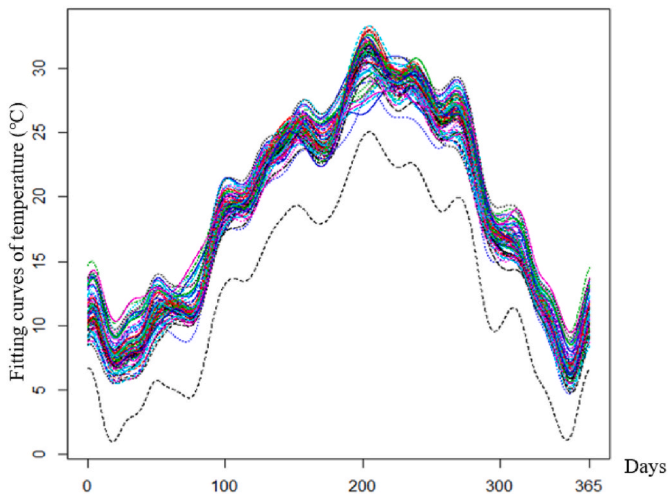


Fig. 5. Fitting curves of daily average temperature change in cities in southern China.
Note: We use Fourier basis functions to fit the temperature curves. At the same time, in order to solve the over fitting problem and keep the curves smooth, the penalty parameter is introduced. For the setting strategy of penalty function, we refer to Harezlak (2007).

most influential points appear on the 210th day and 220th day. During the 210th-220th days, the response coefficient changes from positive to negative. This transition occurs mainly because the cooling weather reduces the cooling-degree days. We also found that there are significant differences in electricity consumption behavior among electricity consumers in different quantiles at these points, which directly leads to inequality in electricity consumption. The 95 % confidence interval for δ is [43.46, 52.90], which is constructed via the bootstrap method by resampling the residuals and then re-estimating the model.

Another finding is that the historical electricity–temperature response is more sensitive on cold or hot days than on comfortable days. For instance, the β(s,t) values of May and June, in which the temperature is approximately 20° Celsius, are approximately equal to 0. This means that temperature has little impact on future electricity consumption. The temperature in July and August has the greatest impact on electricity. The reason is that the hot or cold temperature plays a key role in increasing the HDDs or CDDs, which will reduce residents' tolerance for current temperature changes and therefore improve the electricity consumption level.

3.2. Sensitivity and robustness check for different quantiles

Household-level adaptation to climate change greatly depends on the economic level [30]. We therefore would expect that the households in different electricity consumption groups respond differently to the same temperature change since electricity is an indicator of the income level to a certain extent [27]. Identifying the response differences between poor and rich families is the basis for understanding the family's adaptation behaviors to temperature changes and improving their adaptability. Table 3 presents the estimated results based on the 25 %, 50 %, and 75 % quantile samples.

The response inertia value of the low electricity consumption level is smaller than that of the high level, as shown in Table 3. This means that poor households are more susceptible to recent temperature changes. In particular, the response inertia effect on 25th percentile households is 36.50 days, and the average response inertia is 35.69 days through bootstrap analysis. The inertia value of the 50th and 75th percentile

Table 2
Effect of non-temperature factors on household electricity consumption.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Income	0.6149*** (0.050)	0.5798*** (0.049)	0.5898*** (0.048)	0.5876*** (0.050)	0.5864*** (0.072)
ALTI	0.0656*** (0.008)	0.0769*** (0.007)	0.0766*** (0.007)	0.0767*** (0.007)	0.0817*** (0.011)
RH		−0.0120*** (0.001)	−0.0107*** (0.001)	−0.0107*** (0.001)	−0.0116*** (0.001)
PREC			−0.0365*** (0.010)	−0.0364*** (0.010)	−0.1254*** (0.011)
WIND				0.0027 (0.017)	0.0245 (0.023)
Constant	−2.3881*** (0.553)	−1.0178* (0.558)	−1.0924** (0.555)	−1.0775* (0.562)	−0.7243 (0.785)
Observations	936	936	936	936	936
R^2	0.194	0.251	0.262	0.262	0.311

Note : ① * Significant at 10 % level. ** Significant at 5 % level. *** Significant at 1 % level.
②The standard error is in brackets.

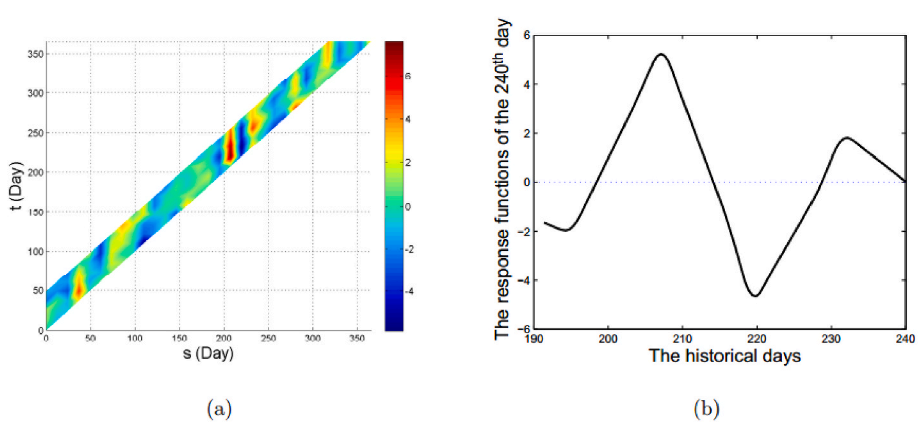


Fig. 6. The dynamic effect of temperature on household electricity consumption.
Notes: Figure (a) is the estimated regression coefficient function β(s,t) with a historical lag of 48 days. The x-axis s (Day) is the time axis for temperature. The y-axis t (Day) is the time axis for electricity consumption. Figure (b) shows the historical electricity-temperature response function of the 240th day. The β(s,t) coefficients are significant at a 5 % significance level.

Table 3
The response inertia effects of different percentiles.

Percentile	Lag days	Mean	Min	Max	Standard error
25	36.50	35.69	29.64	41.74	3.08
50	48.66***	48.64	37.60	55.68	4.61
75	48.67	48.67	48.67	48.67	0.00

Note: The standard errors are obtained by bootstrap. * Significant at 10 % level. ** Significant at 5 % level. *** Significant at 1 % level.

households is 48.67 days. These findings show that the response inertia interval of the poor is narrow, and the impact weight of temperature at a single point is larger than that of the rich. Thus, the poor are vulnerable to extreme temperatures. For wealthy families, the inertia interval is wider, and the temperature impact factor at a single time point is small, which reveals that the rich have a better ability to adapt to extreme temperatures.

Another finding is that there is a significant difference in temperature response inertia for the households in the 50 % quantile group. This means that residents at this electricity consumption level have a greater difference in adaptation behaviors when responding to temperature changes.

Fig. 7 reports the historical electricity–temperature response function β(s,t) of different electricity consumption percentiles. Different electricity consumption groups have similar response patterns to temperature changes. The temperature in summer has the largest historical impact on electricity consumption, while the impact in spring is the smallest. The extraordinarily large β(s,t) appears on the 210th day, $(s,t) \in (210,210) \times (210,240)$. To analyze the results more specifically, we extract the response functions on the 50th, 240th, and 300th days, as shown in Fig. 8 (a)-(c).

Notes: The figures show the functional relationship between the electricity consumption and the historical temperature on the 50th day (left), 240th day (middle), and 300th day (right), respectively. The x-axis s (Day) is the time axis for temperature. The y-axis is the electricity-temperature consumption response coefficients. The *β(s,t)* coefficients are significant at a 5 % significance level.

We find that households at low quantiles have weaker adaptation behaviors than households at high quantiles in winter. Fig. 8(a) shows the response functions in January and February when the temperature is relatively low. The *β(s,t)* of households at the 25th quantile is almost 0 from the 35th to 50th day. This indicates that households lack resilience when facing a cold temperature shock. The response function coefficients at the higher quantiles have large values, which indicates that they have good adaptability to cold temperatures.

When faced with extreme temperatures, poor and rich families have similar response patterns (see Fig. 8 (b)). The response curve profiles of different quantiles are the same. Thus, the extreme temperature response patterns are similar for families with different quantiles. The slight difference is that the response coefficient of low-quantile residents is higher than that of high-power residents in the previous 20 days. In the time before this 20-day period, however, the coefficient of the high quantile is higher than that of households in the low quantile. This finding shows that when faced with extreme heat, the poor are more susceptible to the current temperature than the rich since they have a shorter response inertia range. When the temperature is in the comfort zone, as shown in Fig. 8 (c), the temperature response of poor families is lower than that of rich families. This shows that rich families are more sensitive to temperature than poor families. This response behavior difference between small and large electricity users is the main reason for the electricity consumption inequality, and extreme temperatures exacerbate the unfairness of this electricity consumption behavior. To test the robustness of the results, we used the bootstrap method to perform 500 resampling inspections. The results are shown in Table 4.

The results show that the lower the electricity consumption of households is, the smaller the historical impact of temperature. Residents in the 5 % quantile are only affected by the first 12.48 days. This means that the temperature at a single time point has a greater impact factor on poor temperatures, especially extreme temperatures. With the increase in the quantile of electricity consumption, the response inertia range of temperature has also expanded, and the longest lag is 48.67 days. For residents in the higher quantiles, the temperature has the same length of time lag, as shown in Fig. 9. This similarity may be because the temperature adjustment equipment for rich families is basically in a saturated state, and when encountering temperature changes, they have the same temperature change adaptation behaviors.

Another interesting finding is that there are three types of response inertia among residents. Type 1 is the household group below the 20 % quantile. For these households, the inertia range gradually widens with the increase in electricity consumption. Type 2 is the 20–60 % quantile family group. The response lag of these families is approximately 36.5 days. The response inertia time is longer than the low quantile, and the temperature lag days are relatively stable. An interesting phenomenon is that the 95 % confidence interval narrowed on 40 quantile. That is because residents who consume electricity in the 40 % percentile have a high degree of consistency in their electricity consumption behavior. The third type is households with electricity consumption above the 60 % quantile, and the response inertia of these families is stable at approximately 48.67 days. The possible reason is that these families pay more attention to comfort than low-quantile families. When the temperature shows a slight increase or decrease, they begin to respond to the temperature; therefore, they have a longer temperature decision range.

This historical response inertia can be used to more accurately set up the step tariff. For example, for households with electricity consumption

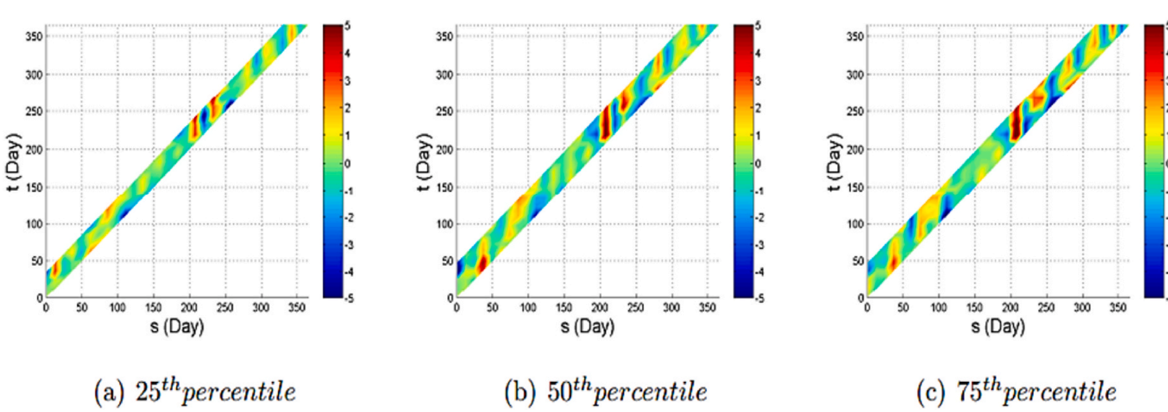


Fig. 7. The quantile dynamic electricity-temperature response function maps.
Notes: The x-axis s (Day) is the time axis for temperature. The y-axis t (Day) is the time axis for electricity consumption. (a)–(c) are the estimated results of the 25th, 50th, and 75th percentile, respectively. The response function *β(s,t)* is significant at a 5 % level by using a pointwise *t*-test.

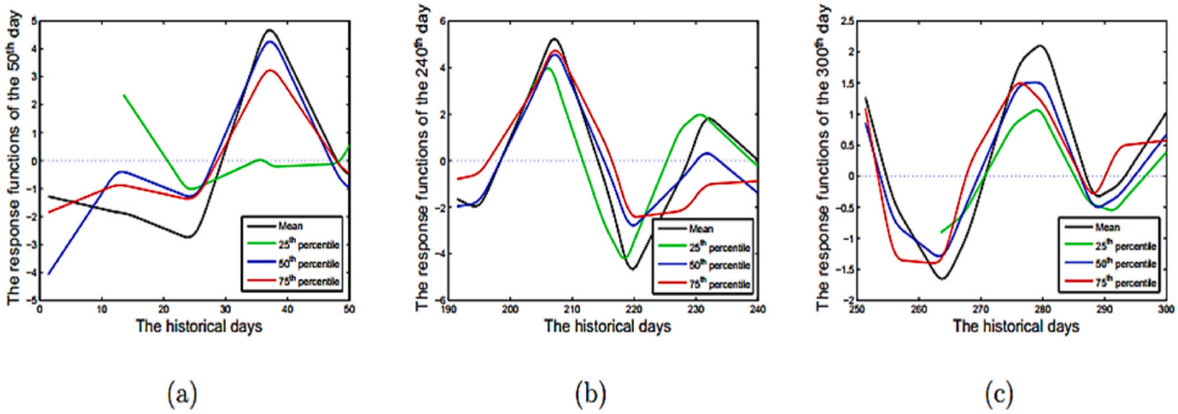


Fig. 8. The dynamic electricity-temperature consumption response function lines.

Table 4
The response inertia of temperature on household electricity consumption.

Percentile	Lag days	Mean	Min	Max	Std.Err
5	12.17	12.47	8.70	16.24	1.92
10	24.33***	21.17	10.60	31.73	5.40
20	36.50	36.26	32.88	39.63	0.99
30	36.50*	35.89	30.56	41.22	2.72
40	36.50	36.50	36.50	36.50	0.00
50	48.67**	46.64	37.60	55.68	4.61
60	48.67**	48.67	38.80	55.82	3.65
70	48.67	48.67	48.67	48.67	0.00
80	48.67	48.67	48.67	48.67	0.00
90	48.67	48.67	48.67	48.67	0.00
95	48.67	48.67	48.67	48.67	0.00

Note: ① The standard error was obtained by bootstrap method.
② Significance: * represents P < 0.1, ** represents P < 0.05, *** represents P < 0.01.

less than 20 % of the quantile, their response inertia interval is short, indicating that their adaptability to temperature is weak. Therefore, lower electricity prices should be set to improve their climate adaptability. However, for households with electricity consumption between 20 % and 60 % quantile, the confidence interval of their response inertia is wider, which indicates that the electricity consumption behavior of these households has great heterogeneity. Therefore, the step tariff should be more finely divided to reduce the subsidy cost of the step tariff without damaging the households' climate adaptability.

For households whose electricity consumption is higher than the 60 % quantile, their response inertia intervals are longer than others, indicating that they have better temperature adaptability. For these households, a "luxury tax" could be set up in addition to the step tariff to guide their energy-saving behavior. Fig. 9 reveals that the response inertia intervals for electricity consumption by household above the 60th percentile remain unchanged. This is due to a saturation effect on temperature-related electricity consumption. In other words, once electricity consumption surpasses the 60th percentile, the majority of households' electricity consumption behavior and temperature adaptation ability converge.

Therefore, the time lag length of the response stabilizes and no longer varies. Hence, the electricity consumption inequality can be attributed to two factors. Firstly, there is heterogeneity in electricity consumption behavior among residents below the 60th percentile. This means that there are differences in the amount of electricity consumed by individuals, which can lead to unequal distribution of electricity consumption. Secondly, there are differences in total electricity consumption between residents on both sides of the 60th percentile. This means that even if individuals below the 60th percentile have similar electricity consumption behavior, the total amount of electricity

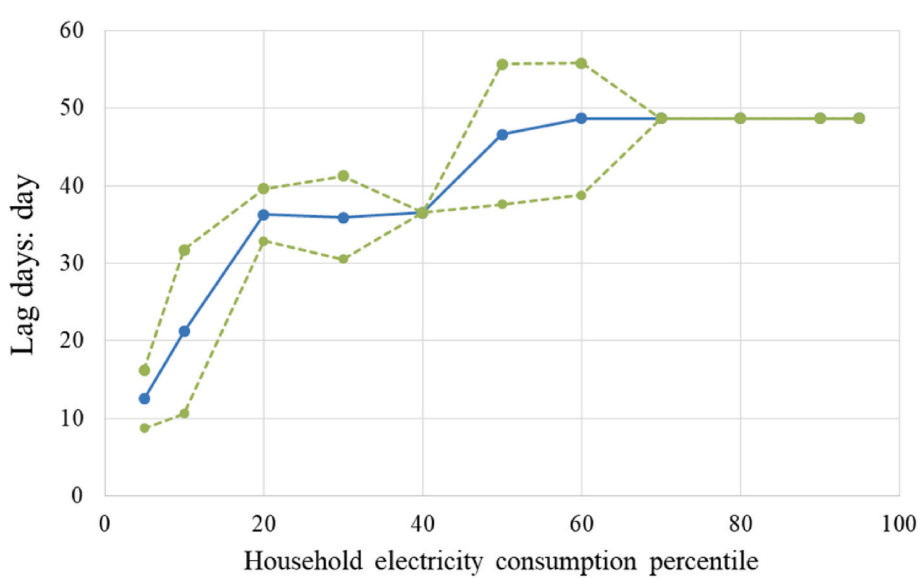


Fig. 9. Response inertia effects of temperature on different electricity consumption percentiles
Notes: The solid line shows the lag days using HFLM. The dashed lines indicate the 95 % confidence intervals.

consumed by them may still vary due to differences in overall consumption levels.

3.3. *Historical temperature impact on the electricity consumption inequality*

The quantile results reveal that households in different electricity consumption levels have different response behaviors to temperature changes, which suggests that temperature plays an important role in reshaping electricity consumption patterns, as shown in Fig. 10. We wondered whether this reshaping process occurs concurrently. Therefore, the electricity consumption Gini coefficient is adopted as a distribution index to investigate the functional relationship with temperature. The electricity Gini index represents a major social inequality issue since it is closely related to lifestyle choices and living standards [31] and has been defined as a new indicator of inequality [28]. Hence, identifying the functional Gini–temperature response provides a basis for promoting social equity.

The filter Gini data are used, and the regression result is shown in Table 5. According to the estimated HFLM, the historical response inertia is 18.25 days, which is much shorter than the electricity–temperature response inertia time. This indicates that the temperature-related electricity distribution reshaping process takes place in a relatively narrow time window. The 95 % confidence interval for δ is [16.73, 20.82] via the bootstrap method.

Fig. 11 shows the corresponding estimate of the bivariate coefficient function $\beta(s,t)$. $\beta(s,t)$ reveals that the response coefficient is relatively large when facing extreme temperatures, which means that extreme weather has a greater impact on reshaping the electricity consumption distribution. There are different functional response modes in different seasons. The extraordinarily severe impact of high temperature on the Gini coefficient occurred in August and September, while the strongest effect of low temperature occurred in February. By comparing with Fig. 8, it is not difficult to find that the inequality in electricity consumption is more severe on the 35th and 250th days. This is mainly because residents have significant heterogeneity in electricity response at these time points as is shown in Fig. 8. Behind this is the difference in residents' adaptability to temperature changes, which is their ability to pay for electricity consumption in response to temperature changes. To provide a clearer description of the changing curve of electricity inequality, we extract the response functions of the 50th and 210th days for further analysis, as reported in Fig. 12.

Fig. 12 (a) shows the response functions in January and February when the temperature is relatively low. The Gini–temperature response during this period is mostly negatively correlated, which means that the lower the temperature is, the greater the disparity in electricity consumption among residents. In hot summers, Gini and temperature are positively correlated; that is, the higher the temperature is, the greater the difference among household electricity consumption. We also find that both the severe temperature fluctuations, such as on the 35th and the 45th day, and the extreme temperatures, such as on the 210th day in Fig. 12 (b), have a greater impact on reshaping electricity distribution. The possible reason is that when faced with extreme temperature or severe temperature fluctuations, different families have different adaptive behaviors. This creates a large gap in electricity consumption levels.

4. Conclusions and policy implications

This research provides a fresh look at the electricity–temperature dynamic relationship based on large-scale household smart meter data. The historical functional linear model is employed to identify how historical temperature dynamically affects current electricity consumption, which provides a new perspective for studying the electricity consumption inequality evolution. We come to the following conclusions.

There is response inertia between temperature change and household electricity consumption. The finding reveals that current electricity consumption is the result of the complex effects of historical temperature, and the estimated response inertia is approximately 48 days. The historical electricity–temperature response is more sensitive on cold or hot days than on comfortable days. This finding complements theoretical research and shows that, in addition to the concurrent effect of temperature, historical temperature, especially extreme temperature and severe temperature fluctuations, also has an important effect on household electricity demand. Compared to econometric research methods, this data-driven approach offers us a dynamic perspective to examine the relationship between electricity consumption and temperature in the time dimension, thus clarifying the reasons behind the emergence of electricity consumption inequality.

Another finding is that the electricity–temperature response inertia varies greatly across the different household groups. Poor households tend to pay more attention to short-term temperature changes because their adaptive behaviors are constrained by income level. The response inertia of the poor is only 12.48 days. This means that the temperature at a single time point has a greater impact factor on the poor. That is, they are more vulnerable to extreme temperatures. For wealthy families, the electricity–temperature response inertia is more than 48 days. The long

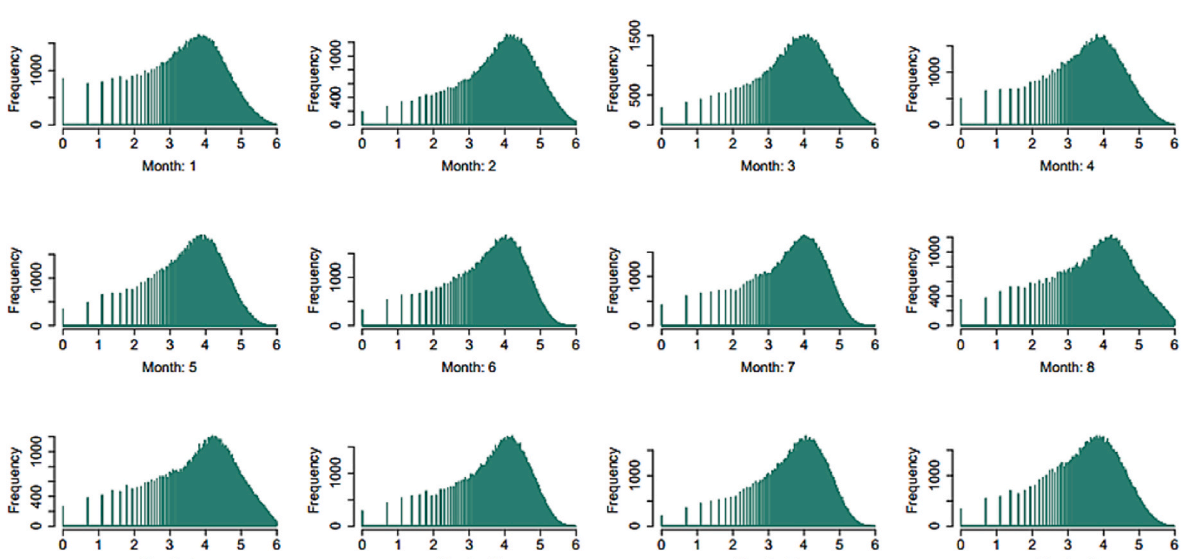


Fig. 10. The distribution of household electricity consumption.

Table 5
Effect of non-temperature factors on households' adaptive electricity consumption Gini.

	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
Income	0.0376	0.0278	0.0269	0.0590**	0.0516*
	(0.025)	(0.024)	(0.025)	(0.025)	(0.030)
ALTI	0.0099***	0.0131***	0.0131***	0.0116***	0.0110**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
RE		−0.0034***	−0.0035***	−0.0034***	−0.0013**
		(0.001)	(0.001)	(0.001)	(0.001)
PREC			0.0031	0.0027	−0.0180***
			(0.005)	(0.005)	(0.005)
WIND				−0.0409***	−0.0191**
				(0.008)	(0.010)
Constants	−1.3529***	−0.9681***	−0.9617***	−1.1841***	−1.2646***
	(0.272)	(0.281)	(0.282)	(0.282)	(0.325)
Observations	936	936	936	936	936
R^2	0.021	0.043	0.044	0.068	0.050

Note : ① * Significant at 10 % level. ** Significant at 5 % level. *** Significant at 1 % level.
② The standard error is in brackets.

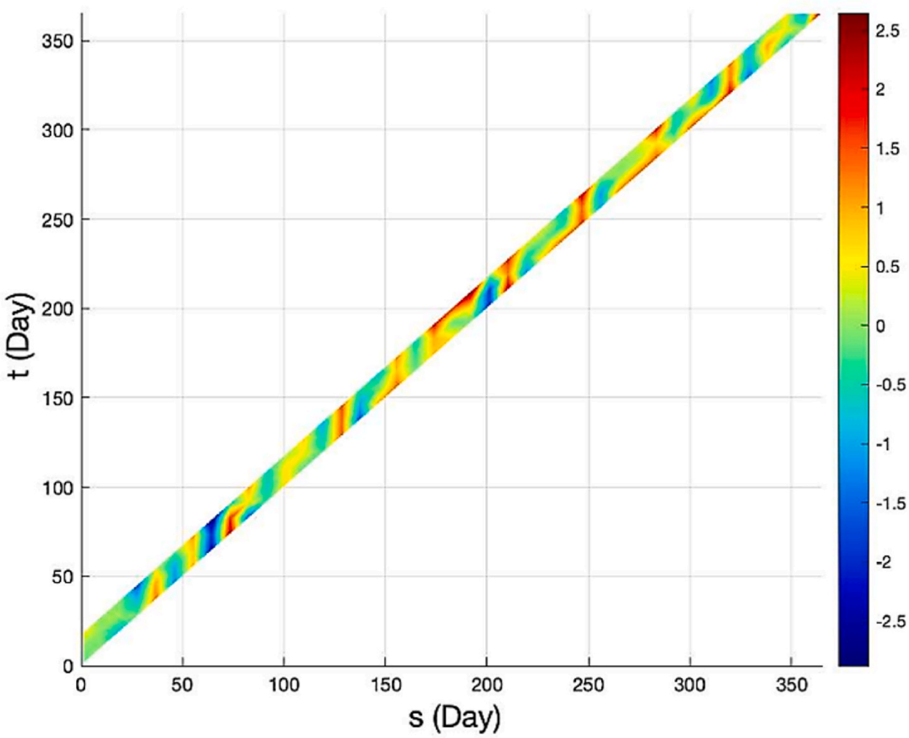
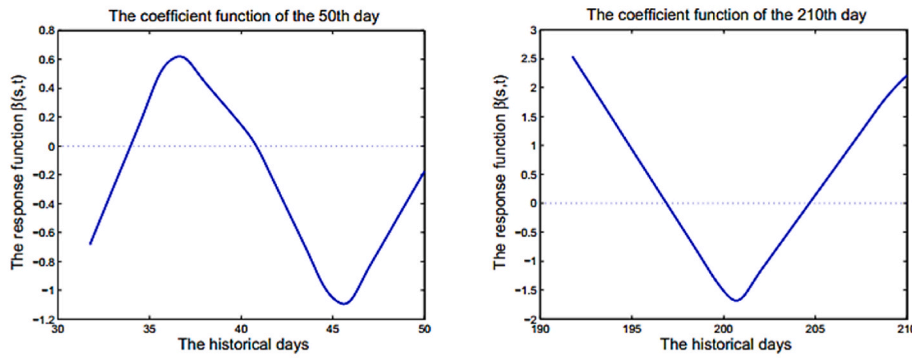


Fig. 11. The inertia effect of temperature on electricity Gini index.
Notes: The x-axis s (Day) is the time axis for temperature. The y-axis t (Day) is the time axis for the electricity Gini index. The β(s,t) coefficients are significant at a 5 % significance level.

response inertia interval means that the temperature influence weight at a single time point is diluted; that is, families have stronger adaptability to temperature. Through the data-driven method, we also find three temperature response patterns. The 20 % and 40 % electricity consumption quantiles are the critical threshold points. There is great heterogeneity in electricity consumption behavior for households whose electricity consumption is lower than the 20 % quantile and between the 40 % and 60 % quantiles. The division of these three types of resident response modes is an important reference for more in-depth research on residents' responses to climate change.

We further investigates the dynamic impact of temperature on electricity consumption inequality. Based on existing theories, we defines electricity consumption Gini index as electricity inequality The result shows that historical extreme temperatures, as well as temperature fluctuations, play a key role in reshaping electricity consumption distributions with a short time interval. This reveals that when facing extreme weather, the adaptability of families is different, which creates a sharp gap in electricity consumption levels. There is only a slight response inertia in reshaping the process of electricity consumption distribution. These results shed light on the residential adaptation behavior to temperature changes and can aid in the formulation of adaptation policies that enhance the ability of the poor to adapt to climate change.

Our findings have several implications for improving climate adaptability and electricity consumption fairness. First, according to the historical response inertia, the step tariff should be more finely divided to improve the adaptability of the poor and guide the rich to save energy. For example, reduce the electricity price whose electricity consumption



(a) (b)

Fig. 12. The dynamic temperature and electricity Gini index response functions.
Notes: The figures show the functional relationship between the electricity Gini index and the historical temperature on the 50th day (left) and 210 days (right), respectively. The x-axis s (Day) is the time axis for temperature. The y-axis is the electricity-temperature Gini index response coefficients. The β(s,t) coefficients are significant at a 5 % significance level.

is lower than 20 % quantile to ensure the basic electricity demand and improve their climate adaptability. Second, promote the appliances penetration of the poor household by subsiding for air conditioners and electric fans to narrow the gap of electricity inequality. Third, climate change mitigation and adaptation policies should be made to reduce the incidence of extreme weather, which will benefit both the rich and poor.

Authors' contributions

Dr. Haitao Chen conceived and designed the study. Prof. Zhang Bin designed the methodology and wrote the manuscript. Dr. Hua Liu collected the related data. Prof. Jiguo Cao reviewed and edited the manuscript. All authors read and approved the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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