Supporting Information

Electricity consumption and adaptation to climate change: heterogeneity across regions and economic sectors in China

This document contains three SI Appendix sections.

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Appendix Tables

Table S1. List of 92 Chinese cities, electricity consumption, and tertiary GDP share in 2019. The listed statistics are from the China City Statistical Yearbook 2021. Cities are ranked by their total electricity consumption.

	City	**Province**	**Daily Electricity Consumption (GWhs)**	**Tertiary GDP share (%)**
1	Shanghai	Shanghai	156.86	73
2	Suzhou	Jiangsu	154.45	52
3	Beijing	Beijing	116.64	84
4	Chongqing	Chongqing	116.02	53
5	Tianjin	Tianjin	87.84	63
6	Hangzhou	Zhejiang	81.67	66
7	Ningbo	Zhejiang	80.79	49
8	Wuxi	Jiangsu	75.08	51
9	Nanjing	Jiangsu	62.15	62
10	Wuhan	Hubei	61.55	61
11	Jiaxing	Zhejiang	53.80	44
12	Fuzhou	Fujian	51.73	54
13	Quanzhou	Fujian	51.53	39
14	Changzhou	Jiangsu	50.59	50
15	Zhengzhou	Henan	48.57	59
16	Shaoxing	Zhejiang	46.24	48
17	Nantong	Jiangsu	45.16	46
18	Luoyang	Henan	44.22	49
19	Wenzhou	Zhejiang	44.11	55
20	Xi'an	Shaanxi	41.85	63
21	Jinhua	Zhejiang	39.47	57
22	Hefei	Anhui	37.55	61
23	Xuzhou	Jiangsu	37.11	50
24	Taizhou	Zhejiang	33.12	49
25	Yancheng	Jiangsu	32.77	48
26	Huzhou	Zhejiang	29.50	45
27	Xiamen	Fujian	28.30	58
28	Lanzhou	Gansu	27.55	65
29	Xinxiang	Henan	26.10	45
30	Nanchang	Jiangxi	24.72	49
31	Nanyang	Henan	24.30	52
32	Yichang	Hubei	23.41	45

33	Ningde	Fujian	21.75	36
34	Jiujiang	Jiangxi	21.37	45
35	Maanshan	Anhui	21.06	47
36	Anyang	Henan	21.05	46
37	Suqian	Jiangsu	20.92	47
38	Ganzhou	Jiangxi	20.90	50
39	Yichun	Jiangxi	20.28	47
40	Wuhu	Anhui	20.27	47
41	Pingdingshan	Henan	20.22	47
42	Chuzhou	Anhui	19.16	42
43	Huai’an	Jiangsu	19.13	48
44	Lianyungang	Jiangsu	18.37	45
45	Shangqiu	Henan	17.77	44
46	Shangrao	Jiangxi	16.98	50
47	Sanming	Fujian	16.58	34
48	Xiangyang	Hubei	16.48	42
49	Fuyang	Anhui	15.90	49
50	Weinan	Shaanxi	15.71	45
51	Zhumadian	Henan	15.11	43
52	Huangshi	Hubei	14.83	43
53	Xiaogan	Hubei	14.58	44
54	Jingzhou	Hubei	14.52	46
55	Xuchang	Henan	14.51	37
56	Huanggang	Hubei	13.98	45
57	Xianyang	Shaanxi	13.96	40
58	Longyan	Fujian	13.76	44
59	Xinyang	Henan	13.62	45
60	Xuancheng	Anhui	13.48	43
61	Zhoukou	Henan	12.54	41
62	Kaifeng	Henan	11.98	46
63	Ji’an	Jiangxi	11.92	44
64	Sanmenxia	Henan	11.67	42
65	Nanping	Fujian	11.65	42
66	Anqing	Anhui	11.62	46
67	Baiyin	Gansu	11.32	45
68	Lishui	Zhejiang	11.24	55
69	Yan’an	Shaanxi	11.07	31
70	Jingmen	Hubei	10.95	41
71	Lu’an	Anhui	10.38	50

72	Shiyan	Hubei	10.31	48
73	Tongling	Anhui	9.83	48
74	Baoji	Shaanxi	9.79	35
75	Xianning	Hubei	9.73	43
76	Suzhou	Anhui	9.60	50
77	Bengbu	Anhui	8.93	48
78	Pingxiang	Jiangxi	7.66	48
79	Zhoushan	Zhejiang	6.55	55
80	Jingdezheng	Jiangxi	6.03	49
81	Ankang	Shaanxi	5.41	42
82	Yingtan	Jiangxi	5.19	40
83	Dingxi	Gansu	5.13	65
84	Wuwei	Gansu	4.97	55
85	Zhangye	Gansu	4.63	55
86	Suizhou	Hubei	4.60	40
87	Shangluo	Shaanxi	4.53	43
88	Qingyang	Gansu	4.41	38
89	Longnan	Gansu	4.41	58
90	Huangshan	Anhui	4.10	58
91	Tianshui	Gansu	4.00	57
92	Pingliang	Gansu	3.57	53

Table S2. Summary statistics of the data in baseline regression model.

Variable	Obs.	Mean	Std. Dev.	Min	Max
city-level Daily EC (GWh)	67,086	56.05	67.73	25.93	64.93
Temperature(°C)	67,086	16.09	9.74	-20.10	34.60
Precipitation(mm)	67,086	2.90	9.01	0.00	319.10
Wind speed(m/s)	67,086	2.15	1.05	0.00	12.60
Relative humidity	67,086	71.84	16.25	9.00	100.00
Non-workday	67,086	0.31	0.46	0.00	1.00

Table S3. Summary statistics of the daily electricity consumption (GWh) by sector. In this table, F – T are the tertiary sectors. The mean is computed across cities and days, hence lower than the average city-level daily consumption (of all sectors).

Sector	Obs.	Mean	Std. Dev.	Min	Max
A: agriculture	67,086	1.18	1.47	0.02	16.62
B: mining and quarrying	65,700	1.17	1.73	0.00	12.96
C: manufacturing	65,996	34.37	40.85	0.11	350.33
D: utilities	64,901	0.80	1.04	0.04	8.03
E: construction	64,903	1.11	1.93	0.02	30.01
F: transport, storage, and postal services	61,627	2.18	2.74	0.07	21.47
G: information transfer, computer services, and software	67,083	1.07	2.17	0.04	19.10
H: wholesale and retail trades	67,084	3.60	6.62	0.05	96.52
I: accommodation and catering	67,085	1.08	1.62	0.06	17.05
J: finance	66,724	0.35	1.19	0.01	15.74
K: real estate	65,995	3.85	16.39	0.00	231.25
L: leasing and commercial services	65,621	0.69	1.87	0.00	21.06
M: scientific research, polytechnic services, and geological prospecting	65,260	0.47	2.07	0.00	30.83
N: administration of water, environment, and public facilities	65,992	0.99	2.50	0.04	29.39
O: resident and other services	67,086	0.60	1.77	0.01	26.18
P: education	67,082	1.16	2.01	0.03	22.61
Q: health care, social insurance / welfare	67,085	0.77	1.20	0.02	15.05
R: culture, sports, and entertainment	65,994	0.49	0.96	0.01	12.48
S: public administration and social organizations	67,084	1.04	2.47	0.05	32.71
T: international organizations	17,134	0.02	0.04	0.00	0.43

Table S4. Estimates of the baseline regression models. Column (1) uses daily electricity consumption data from 92 cities. Column (2) uses daily peak consumption data from 11 cities. Column (3) uses daily electricity consumption data from 11 cities. Standard errors are clustered at the city-week level.

	(1) 92 cities ln(□□$_{□□□}$)	(2) 11 cities ln(□□$_{□□□□}$)	(3) 11 cities ln(□□$_{□□□}$)
Spline: □$_{0}$(□□□□)	-0.00957***	-0.0299***	-0.0176***
	(0.000539)	(0.00470)	(0.00302)
spline: □$_{1}$(□□□□)	-0.00921***	-0.0146***	-0.0101***
	(0.000513)	(0.00402)	(0.00245)
spline: □$_{2}$(□□□□)	-0.000714**	0.00304	0.000292
	(0.000358)	(0.00218)	(0.00163)
spline: □$_{3}$(□□□□)	0.0101***	0.00113	0.00585***
	(0.000439)	(0.00241)	(0.00181)
spline: □$_{4}$(□□□□)	0.0212***	0.0199***	0.0233***
	(0.000449)	(0.00163)	(0.00127)
Wind Speed	-0.00598***	-0.0141***	-0.00778***
	(0.000530)	(0.00275)	(0.00202)
Precipitation	-8.06e-05	-0.000374	-0.000114
	(4.91e-05)	(0.000372)	(0.000194)
Humidity	-0.000164***	0.00123***	8.96e-05
	(4.29e-05)	(0.000307)	(0.000225)
Non-Workday	-0.0549***	-0.134***	-0.110***
	(0.00139)	(0.00957)	(0.00762)
Constant	10.57***	6.125***	11.30***
	(0.00591)	(0.0403)	(0.0305)
Observations	67,086	6,624	6,624
R-squared	0.992	0.964	0.978
city-year-month Fixed Effects	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table S5. Estimates of the panel regression model by tertiarisation level. Dependent variable is the natural log of daily electricity consumption of the city. Column (1) uses data from 23 cities in the "low" tertiarisation tier. Column (2) uses data from 46 cities in the "middle" tertiarisation tier. Column (3) uses data from 23 cities in the "high" tertiarisation tier. Standard errors are clustered at the city-week level.

	(1)	(2)	(3)
Spline: □$_0$(□□□□)	-0.00942***	-0.0101***	-0.00879***
	(0.00106)	(0.000808)	(0.000973)
spline: □$_1$(□□□□)	-0.00785***	-0.00867***	-0.0118***
	(0.000876)	(0.000755)	(0.00108)
spline: □$_2$(□□□□)	-0.000635	-0.00122**	0.000315
	(0.000638)	(0.000537)	(0.000709)
spline: □$_3$(□□□□)	0.00960***	0.00853***	0.0138***
	(0.000744)	(0.000633)	(0.000913)
spline: □$_4$(□□□□)	0.0193***	0.0205***	0.0255***
	(0.000917)	(0.000600)	(0.000942)
Wind Speed	-0.00593***	-0.00646***	-0.00495***
	(0.00103)	(0.000776)	(0.000978)
Precipitation	-6.40e-05	-0.000120*	1.36e-05
	(7.64e-05)	(7.10e-05)	(0.000106)
Humidity	-0.000229***	-0.000179***	-2.72e-05
	(7.86e-05)	(6.20e-05)	(8.90e-05)
Non-Workday	-0.0407***	-0.0590***	-0.0607***
	(0.00242)	(0.00213)	(0.00261)
Constant	10.02***	10.63***	11.02***
	(0.0113)	(0.00870)	(0.0110)
Observations	16,760	33,550	16,776
R-squared	0.982	0.988	0.995
city-year-month Fixed Effects	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Appendix Figures

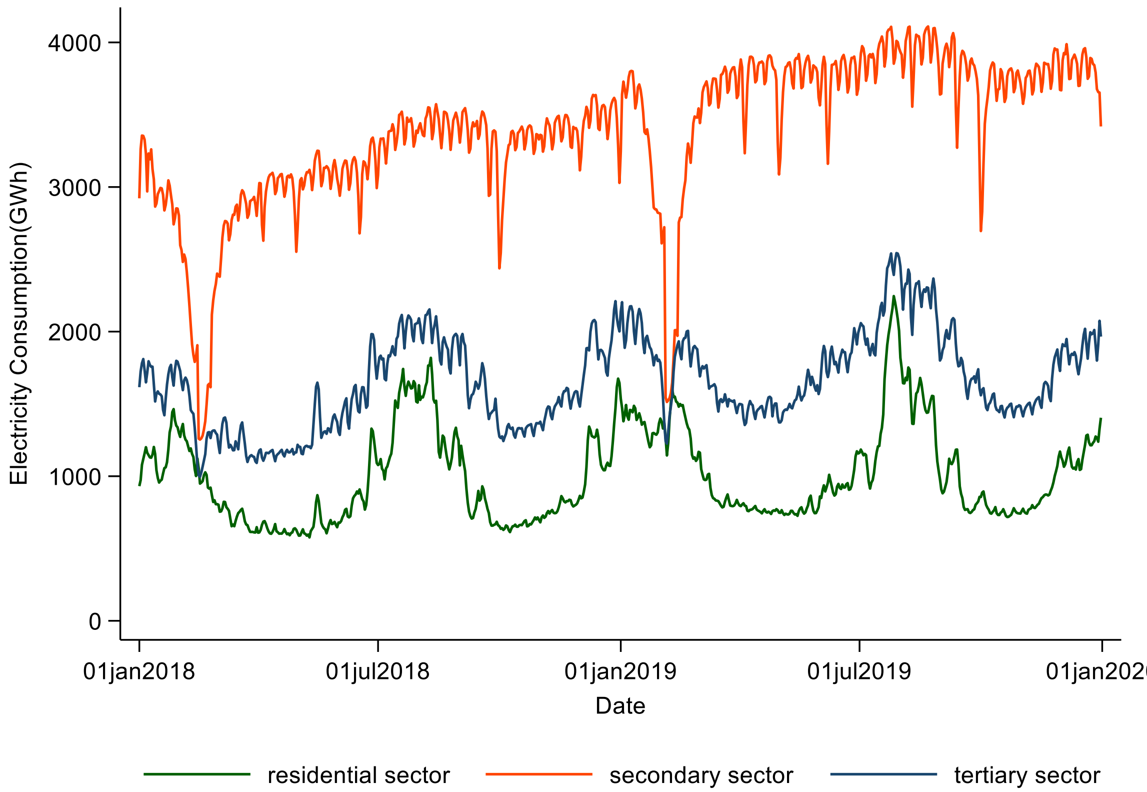

Fig. S1. This figure shows the variation of daily load by sector (secondary and tertiary) and the residential load aggregating electricity consumption of 92 cities in the two-year period.

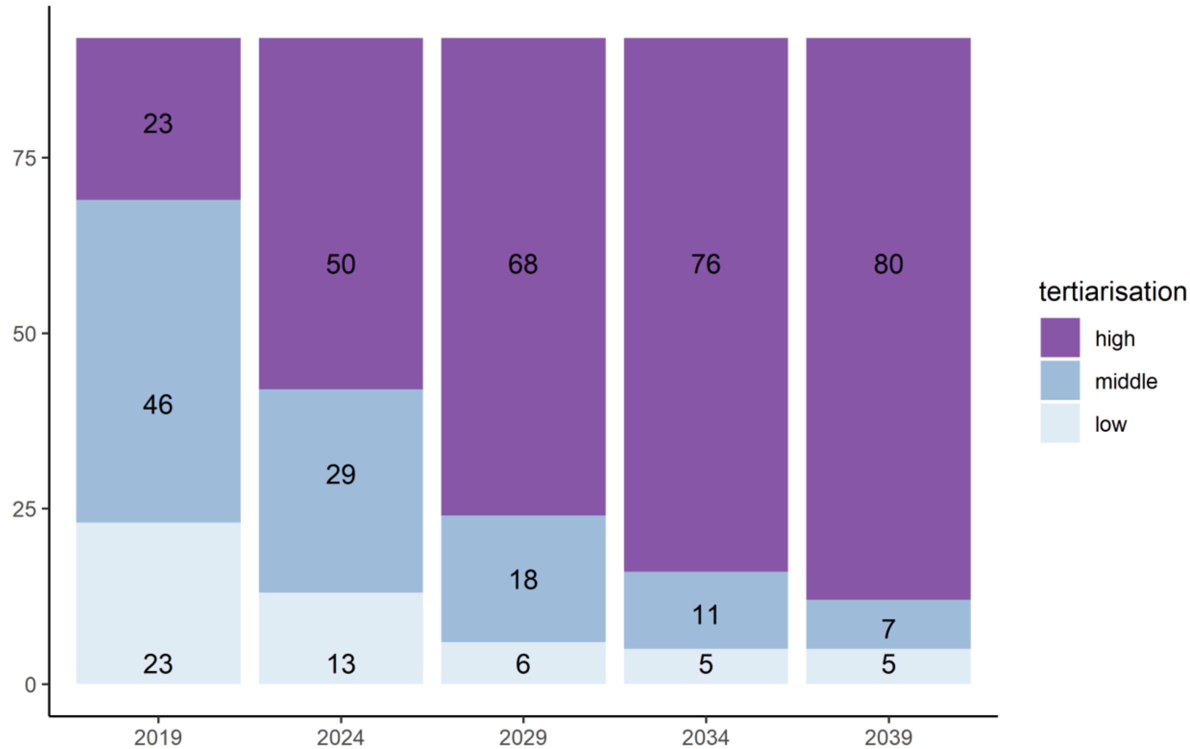

Fig. S2. This figure depicts the tertiarisation scenario. The labeled values are the number of cities classified into the low, middle, and high tiers, according to their historical tertiary GDP shares year 2019 and predicted shares in future years.

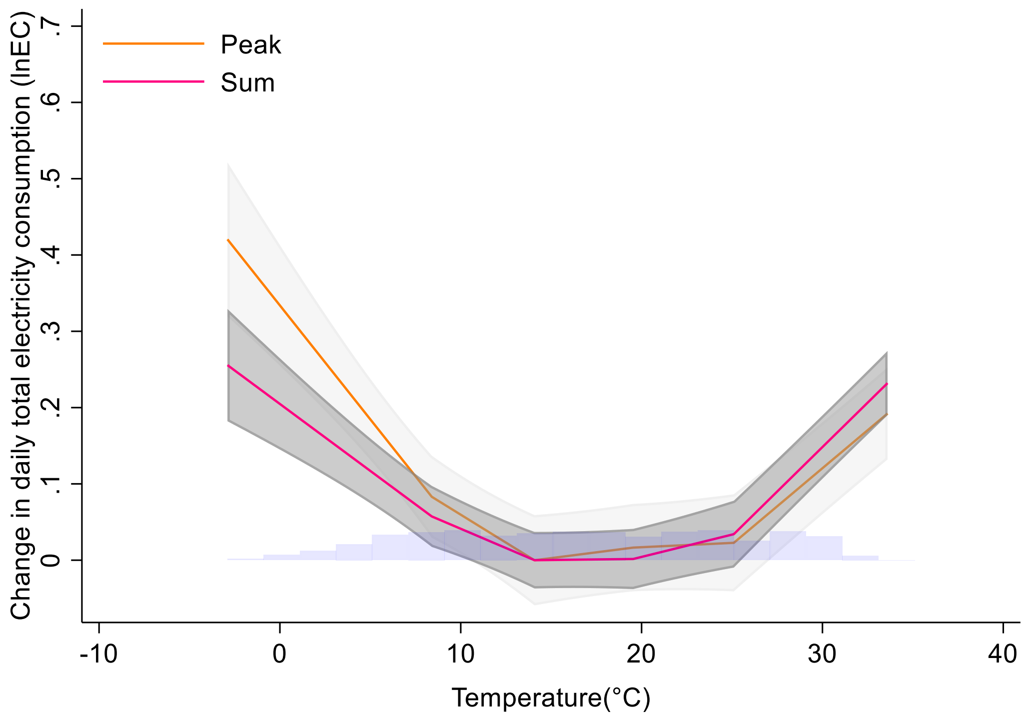

Fig. S3 Responsiveness of daily peak load to daily mean temperature. The light blue histogram illustrates the temperature distribution. This figure compares the temperature responses of daily peak load (orange line) and the daily aggregated load (pink line) using 11 cities in our data sample. The y axis plots the natural log of electricity consumption with the lowest value normalized to zero. The gray shade represents the 95% confidence interval, using standard errors clustered at the city-month level.

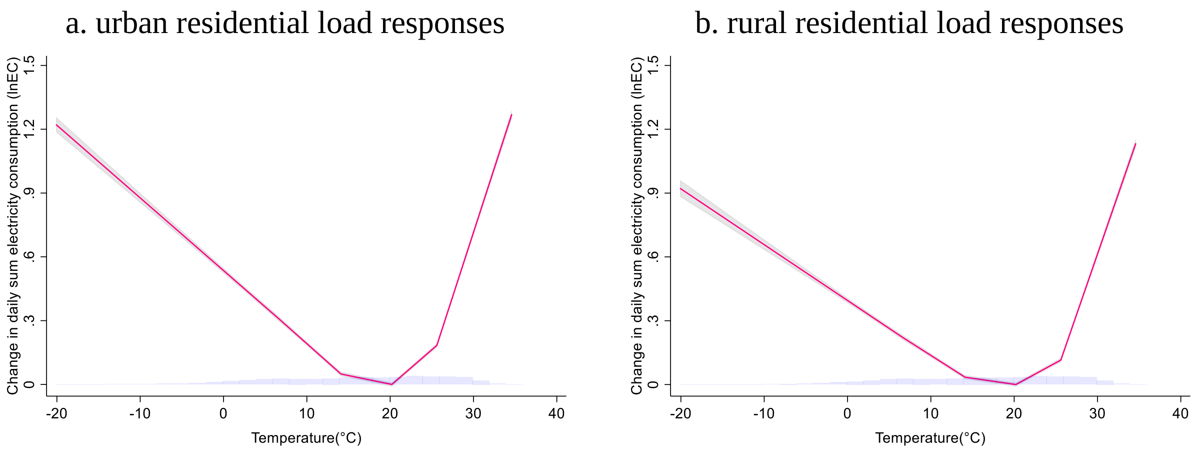

Fig. S4. Temperature-load responses for urban and rural residential electricity consumptions. Panel a. (urban) and panel b. (rural) present the response functions using the temperature spline estimates with daily electricity consumption data from 92 cities.

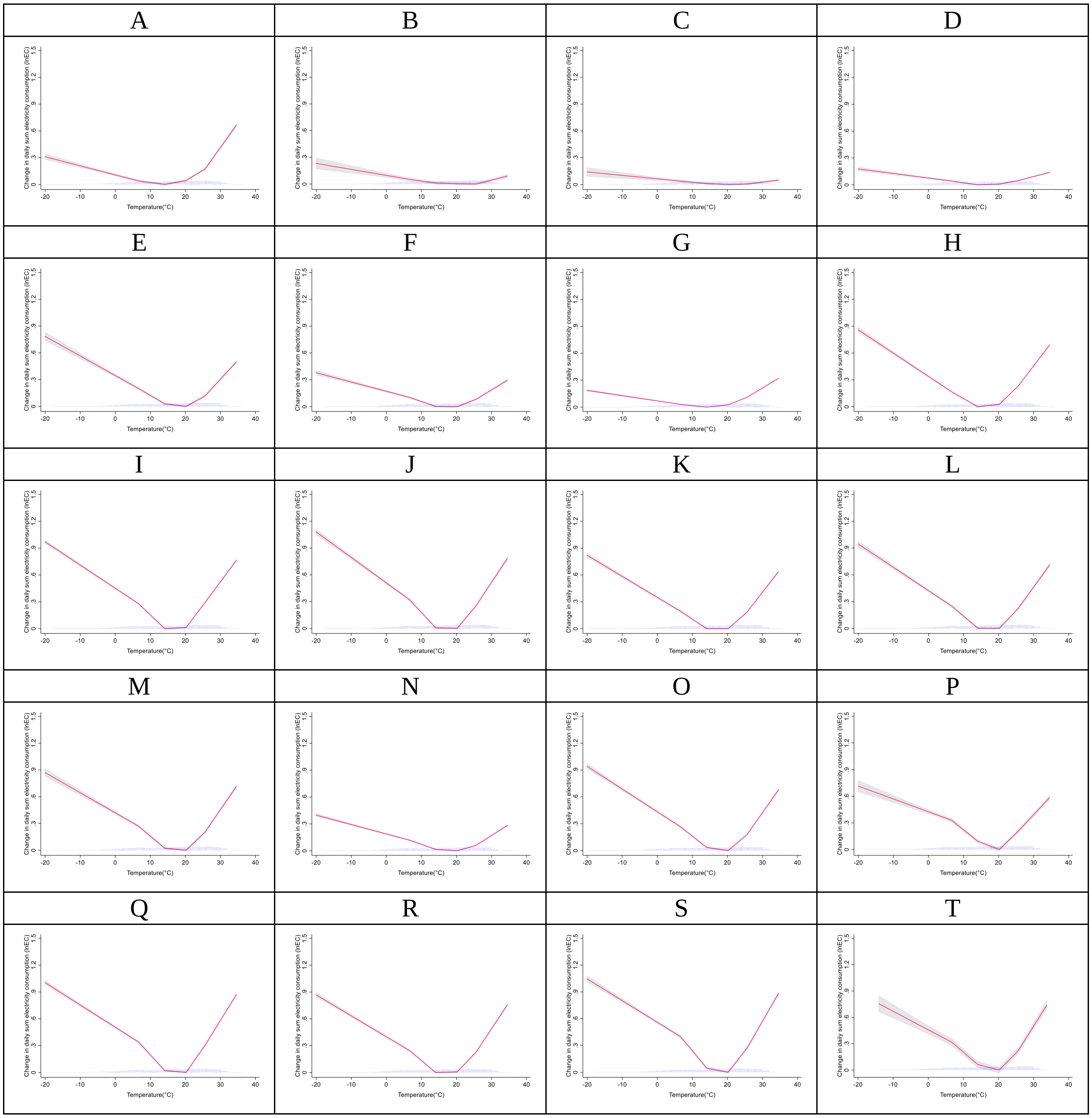

Fig. S5. Temperature-load responses for 20 non-residential economic sectors. F – T are the estimated response functions for the tertiary sectors.

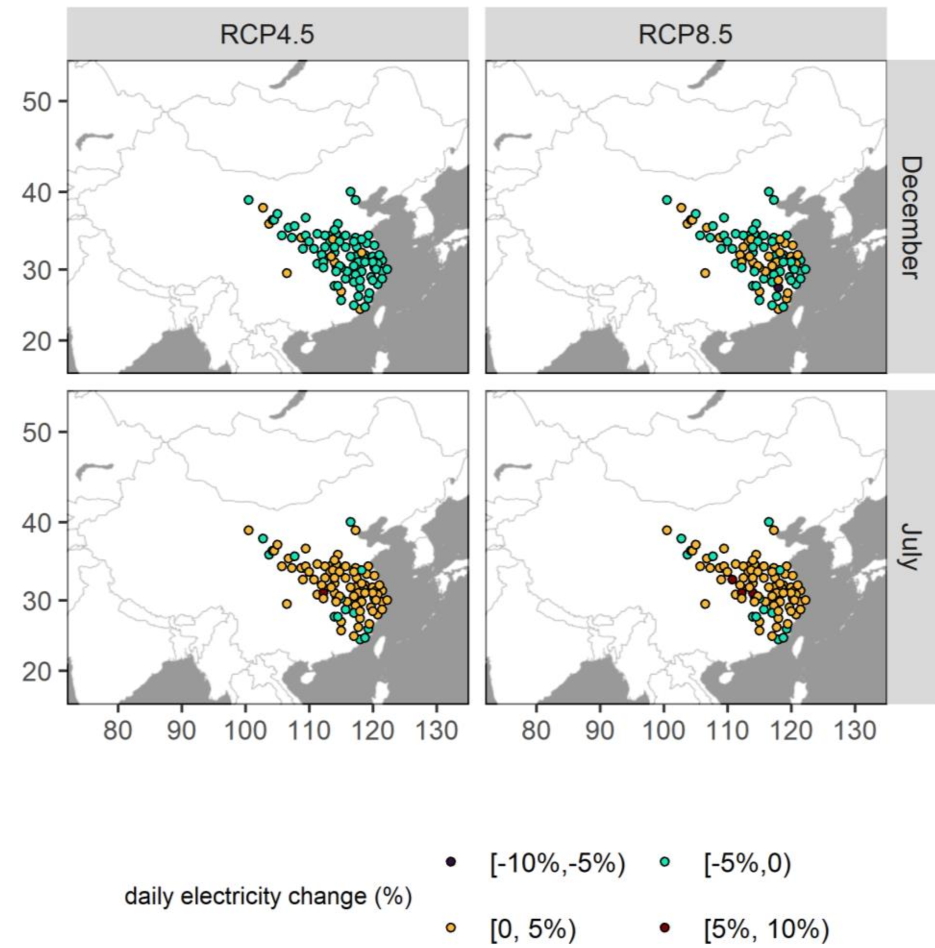

Fig. S6. This figure maps the regional variation of city's load predictions for the 2051-2055 future period in a winter month (December) and a summer month (July). The warm colors illustrate positive load changes. The cool colors illustrate negative load changes.

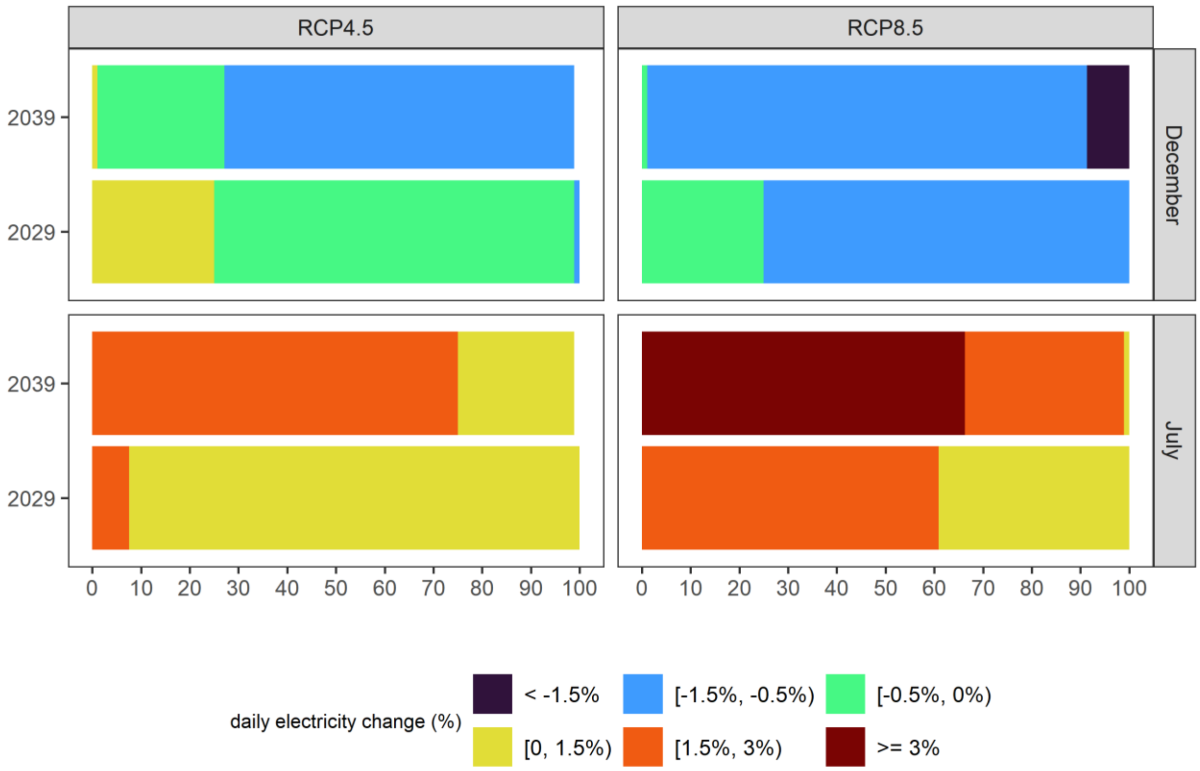

Fig. S7. Load projection with predicted tertiarisation trend under climate RCP4.5. Each bar depicts the predicted percentage of cities experiencing increase (warm colors) or decrease (cool colors) in their future daily electricity loads in year 2029 and 2039 for a winter month (December) and a summer month (July).

Appendix: Model Selection

For our sample from Jan 1, 2018 to Dec 31, 2019, the first day is a Monday. Each month has about 4.5 weeks. We used 4-fold cross-validation (CV) to select the number of knots for the spline function in our regression model[1]. Because of the fixed-effect model, we form the CV test groups making sure each group contains observations from all the city-year-month combinations:

- CV Group 1 has observations from the 1st week of every month,
- CV Group 2 has observations from the 2nd week of every month,
- CV Group 3 has observations from the 3rd week of every month,
- CV Group 4 has observations from the last week of every month (this can be the 4th or 5th week).

First day of the week is set to Monday. For example, CV Group 1 contains the first week of Jan 2018 (01-01 to 01-07) and that of Feb 2018 (02-05 to 02-11). CV Group 4 contains the last week of Jan 2018 (01-29 to 02-04) and that of Feb 2018 (02-26 to 03-04). For each test group, the rest of the sample is used as our training to estimate a spline function with k number of knots (j from 1 to 10). After estimating the city-level spline response function, we apply the estimates to the test group to compute the root-mean-square error (RMSE) across 92 cities.

As depicted by Figure S8, the average RMSE value (across 4 CV tests) stops improving after j = 5, and the difference between j = 4 and 5 is insignificant. We therefore choose j = 4 for the spline function used in our regression model. As a robustness check, we estimated the model using a 5-knot spline, and observe the shape of the response curve to be consistent with that of a 4-knot spline.

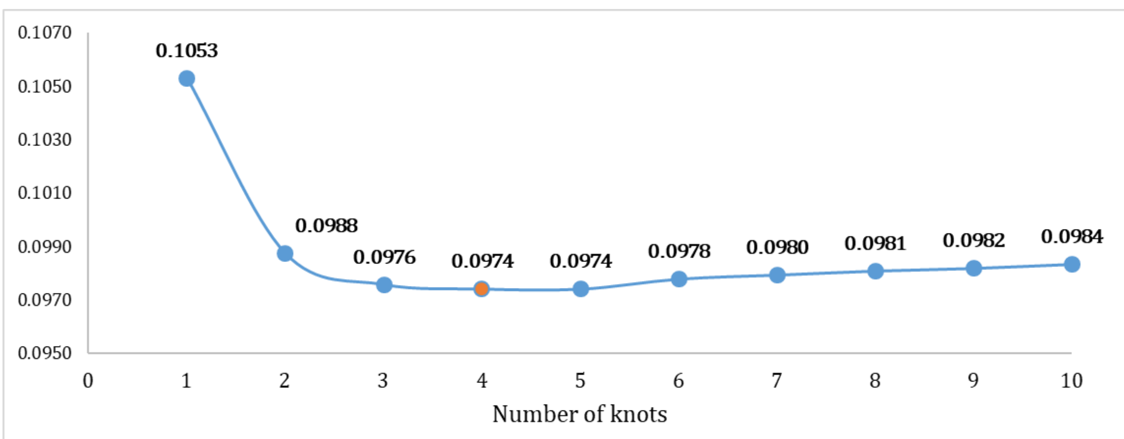

Fig. S8. Average of root-mean-square error (RMSE) across four cross-validation test groups. The orange dot highlights the choice of spline knots □ = *4*, beyond which the value of RMSE is not significantly improved.

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[1] We did not use the 10-fold cross validation because it cannot be directly applied to fixed-effect models, but split the sample based on months with all cities in each month instead of randomly select cities.