Adaptive Responses to Climate Change: The Effects of Temperature Levels on Residential Electricity use in China

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Abstract: Rising temperatures are likely to boost residential demand for electricity in warm locations due to increased use of air-conditioners, fans, and refrigeration. Yet the precise effect of temperatures on residential electricity use may vary by geographical area and with socio-economic conditions. Knowledge on this effect in developing countries is limited due to data availability and reliability issues. Using a high-quality provincial-level monthly dataset for China and fixed-effect panel methods, we find a U-shaped and asymmetrical relationship between ambient temperature and monthly household electricity use. An additional day with a maximum temperature exceeding 34°C on average results in a 1.6% increase in monthly per capita household electricity use relative to if that day's maximum temperature had been in the 22–26°C range. The effect of an additional cold day is smaller. There are differences in effects for the south and the north of China and in urban versus rural areas. We estimate that temperature increases associated with climate change will lead to about a 3–5% increase in annual household electricity consumption by the end of the century under different carbon emission trajectories according to the projections in the 2021 IPCC report. The estimated effect is larger for summer months.

Key words: adaptation; China; climate change; electricity consumption; residential

1 Introduction

Adaptive capacity to climate change and to extreme temperatures is known to vary as a result of differences in incomes and other underlying variables (Yohe and Tol, 2002; Ghimire et al. 2010; IPCC, 2014). However, specific adaptive responses among developing countries are less well understood than those among developed countries (Dell et al. 2014; Revesz et al., 2014; Burke et al. 2016). China, the largest developing country and world's most populous country, has suffered a faster temperature rise than the global average level, at an average rate of 0.26°C per decade over 1951–2020 (CMA, 2021). This paper focuses on the response of residential electricity use to temperatures in China.

A key likely adaptation strategy to higher temperatures is increased used of electricity for air-conditioning, fans, and refrigeration (Barreca et al. 2016; Park et al. 2020). In addition, people are often more likely to stay at home on days of extreme heat. Household electricity consumption is likely to be affected by temperature increases along both an intensive margin (residents tend to consume more electricity from existing appliances) and an extensive margin (residents tend to purchase additional household appliances such as air conditioners and fans). Many residents in developing countries such as China are yet to install air-conditioning but are likely to do so over coming years (Wolfram et al. 2012).

The response of household electricity consumption to temperature may well vary across China given the country's large latitudinal span and its urban-rural dualism. Differences in climate and in residential energy use across China are large. Residents in both the north and south are inclined to rely on electricity

for cooling in summer, using either electric fans or air conditioners. However winter fuels vary. Since the 1950s, coal has been widely used for centralized heating in urban areas north of the Qinling-Huaihe Line (Ebenstein et al. 2017). In recent times, some cities such as Beijing have used an increasing amount of natural gas for heating. In the south, heating is primarily powered by electricity and there is little centralized heating. Rural residents throughout the country are typically not connected to centralized heating, instead relying on the combustion of biomass and scattered coal plus some use of electric heaters.

Electricity consumption in China's household sector has increased thirtyfold since 1990. As of 2017, the residential sector accounted for 14% of China's total final electricity consumption (NBS 2019a). The number of residential air conditioners in urban areas of China far exceeds that in rural areas, with more than 200 air-conditioning units per 100 households in some urban areas often less than 100 units in rural areas (NBS 2019b).

There is a body of research focusing on factors that influence electricity consumption such as electricity prices, incomes, population, gender, urbanization level, and air pollution levels (Zhou and Teng 2013; Al-Bajjalía and Shamayleh 2018; Tjørring et al. 2018; Eom et al. 2020). Many papers have examined how electricity use responds to the number of cooling degree days (CDD) and heating degree days (HDD) (Warren and Leduc 1981; Lam 1998). Prior studies vary between using time-series, cross-sectional, or panel data (Franco and Sanstad 2008; Auffhammer and Aroonruengsawat 2011).

Most prior research has focused on developed countries, and especially the United States (Vine 2012;

Burke and Abayasekara 2018; Fonseca et al 2019; Garrido-Perez et al. 2021). Baxter and Calandri (1992) estimated the effect of temperatures on demand for electricity for the heating and cooling of buildings and for water pumping in California. They found that a scenario in which the average temperature increases by 1.9°C would lead to an increase in electricity use of about 2.6%. McCulloch and Ignatieva (2020) used high-frequency electricity consumption data from Australia, finding a strong and time-dependent relationship between electricity use and temperature. Mansur et al. (2008) estimated the relationship between temperatures and fuel choices in the household and business sectors of the US, finding higher demand for electricity and less demand for other fuels in warmer areas.

Among studies of developing countries, Zhang et al. (2019) used annual electricity consumption data at the county level in rural areas in China, finding a difference in the responsiveness of rural electricity consumption to high and to low temperatures. Berkouwer (2020) used micro data from South Africa to explore the relationship between temperatures and household electricity consumption, concluding that residential electricity consumption is likely to decrease by 6.2% per household relative to the counterfactual if there is a 3.25°C increase in temperature by mid-century. This is largely due to reduced heating needs in winter.

Most studies for China have examined the response of electricity to temperature at a fairly aggregated level. Fan et al. (2015) and Asadoorian et al. (2008) used data by sector and region. There is a notable gap in terms of research on rural areas. Evidence using household data is also rare due to data constraints. One exception is the study of Li et al. (2019), who used daily household electricity consumption data

for Shanghai over 2014–2016. They observed a U-shaped temperature-electricity response curve.

In this paper we explore the relationship between monthly residential electricity consumption and temperature at the provincial level in China, conducting various heterogeneity analyses. The use of relatively high frequency and geographically-disaggregated data is more suitable for identifying temperature response functions than more aggregated approaches such as using national and/or annual data.¹ We also use the results to understand the likely effects of different climate scenarios on residential electricity use in China by 2100. Residential electricity consumption is particularly relevant for human welfare and may be more sensitive to temperature than the electricity use of other sectors such as heavy industry given the importance of temperature control at the residential level.

2 Data and method

2.1 Data

Accurate provincial temperature data are needed for the study. Station-averaged or area-weighted temperature data would not be ideal, as it is the temperatures where people live that should matter for residential electricity use. Some provinces are geographically large and have clustered populations. We thus use population-weighted temperature data.

Daily temperature variables were constructed as follows. First, we obtained daily maximum and daily average temperature from the National Meteorological Information Center (NMIC) for around 700 weather stations. The data are believed to be highly accurate, with quality tests having been undertaken

¹ Monthly data are the most time-granular data on residential electricity consumption available for our sample.

by the NMIC. County-level daily maximum and daily average temperatures were then calculated using an inverse distance weighting procedure (Chen et al. 2017). This was done using average data from weather stations located within 200 km of each county's centroid. We then constructed provincial variables by weighting the county data by each county's population in China's 2010 census. Provincial-level measures of relative humidity were calculated in the same way.

The empirical estimations will use "temperature bin" variables so as to focus on the effects of daily weather fluctuations in a monthly specification. The approach also allows for potential non-linearity in the effect of daily temperatures on monthly electricity use (Bessec and Fouquau 2008). First, all months were normalized to 30 days. The daily maximum temperature data were then divided into ten bins, ranging from below 2°C to above 34°C. We then calculated the number of days in each temperature bin in each province in each month. The dataset covers 2008–2017 and 30 provinces. The weather data were processed using ArcGIS and Python.

Figure 1 plots the distribution of the daily-maximum temperature bins, with each column showing the average number of daily maximum temperatures in a bin for the dataset in 2017. While extreme hot and cold weather is somewhat rare, some regions face relatively high exposures. We use 22–26°C as the baseline temperature bin in the estimations.

Insert Fig. 1

Figures 2 shows the average daily maximum temperatures in January and July of 2017 by province. There is a huge gap in January maximum temperatures between the north and the south: the average

daily maximum temperature is below 0°C in the northeast and northwest and above 20°C in some provinces in the south. Southern provinces thus have much smaller heating requirements. In contrast, there are relatively minor differences in the July average daily maximum temperature across China. This temperature is below 30°C in most northern provinces and above 32°C in some southern provinces.

Insert Fig. 2

For residential electricity use, we use aggregate monthly data at the provincial level from the China Electricity Council (CEC) and also provincial Bureaus of Statistics. Data were collected for 2008–2017. Data are also available in a disaggregated form for both the urban and rural areas of each province for the sub-period 2012–2017. Prior to 2006, China faced quite serious electricity shortages (NEA 2007). Our sample period focuses on the more recent period of China’s development history.

Figure 3 shows monthly per capita household electricity consumption in both summer and winter of 2017, as well as the number of air conditioners per 100 households in the residential sector. In most provinces, per capita household electricity consumption is slightly higher in summer than winter, likely due to use of air conditioners and electric fans. Electricity consumption in advanced provinces such as Beijing exceeds that in the northwest, consistent with variation in the number of air conditioners. The number of air conditioners in some southeast coastal provinces is above 130 per 100 households. This number is below 10 in some northeast and northwest provinces.

Insert Fig. 3

We obtained data on average annual per capita household incomes and the annual urbanization rate from the *China Statistical Yearbooks*. The available statistics switch from per capita rural net income to per capita rural disposable income as of 2013. We used a fixed rate of change method to unify the two series into a single annual per capita disposable income measure.²

2.2 Method

The basic regression model is shown in equation (1):

$$\ln EC_{i,y,m} = \sum_j \alpha_j TEMP_{i,y,m,j} + \beta \ln Y_{i,y} + \lambda \vec{X}_{i,y}' + \gamma_i + \omega_y + \varphi_m + \epsilon_{i,y,m} \quad (1)$$

$EC_{i,y,m}$ is monthly per capita household electricity consumption divided by the number of days per month (in consideration of month-to-month differences in the number of days). $TEMP_{i,y,m,j}$ represents the number of days for which the daily maximum temperature was in each temperature bin j (with each month normalized to 30 days). We set 22–26°C as the base range. To focus on extremes, we initially consider the daily maximum temperature. We then present estimates using the daily average temperature. $Y_{i,y}$ is provincial per capita disposable income, and $\epsilon_{i,y,m}$ is an error term. i , y , and m represent province, year, and month. α_j is a vector of coefficients showing how monthly household electricity consumption varies as a result of an additional day in each temperature bin. An additional day in each bin will result in an increase in household electricity consumption of $100(\exp(\alpha_j) - 1)\%$.

The specification controls for province fixed effects, γ_i , to capture time-invariant unobserved factors

² We assumed that the growth rate of per capita disposable income prior to 2013 equaled the growth rate of per capita rural net income.

681 at the province level such as the degree of isolation of a province and other aspects of its geography.

682 Geographical differences in electricity prices are partly captured by these province fixed effects³. Year

683 fixed effects, ω_y , are included to control for common time-varying factors such as fluctuations in the

684 national economy. Month-of-year fixed effects, φ_m , are also controlled for to capture seasonal factors,

685 such as holidays, cultures, and customs. For example, Chinese weddings are usually held in May,

686 October, and December. Rural work schedules are also a function of the season.

687 The vector of control variables, $\vec{X}_{t,y}'$, includes monthly average relative humidity, as relative humidity

688 is likely to be a key factor influencing the use of air conditioners (Garrido-Perez et al 2021). The annual

689 provincial urbanization rate is also included, as urbanization is closely linked to the penetration of air

690 conditioners (IEA 2018). Cities can also generally provide more effective adaptation options to extreme

691 temperatures, for example the ability to visit an air-conditioned mall (Bretschger and Pittel 2020). The

692 vector also includes a Spring Festival binary variable. Spring Festival is the most important festival on

693 the Chinese calendar, with large movements of people from urban to rural areas and from developed to

694 less developed ones. Spring Festival is in either January or February or can overlap the two (depending

695 on the year), so its effects are not fully picked up by the month-of-year fixed effects.⁴

³ China implemented a step tariff for electricity since 2012, with three pricing steps established. The first step, covering around 80% of residents, has modest differences between provinces and has varied only slightly over time.

⁴ We set the variable as 1 if Spring Festival is in a given month and 0 otherwise. If the festival overlaps months, we set the variable as 1 for the month covering the majority of the vacation. For jobholders, the duration of the vacation is generally around a week.

Lagged temperatures may affect current electricity usage, for example if temperatures are relevant for decisions in an earlier month regarding the purchase of an air conditioner (Auffhammer 2014). We thus also consider a model with one-month lagged temperature bin terms as in specification (2). The total effect of an extra day in a temperature bin over the current plus lagged month is $\alpha_j + \alpha_{1j}$:

$$\ln EC_{i,y,m} = \sum_j \alpha_j TEMP_{i,y,m,j} + \sum_j \alpha_{1j} TEMP_{i,y,m-1,j} + \beta \ln Y_{i,y} + \lambda \vec{X}_{i,y}' + \gamma_i + \omega_y + \varphi_m + \epsilon_{i,y,m} \quad (2)$$

To examine potential heterogeneity as a result of climatic and other differences, we explore the importance of the north-south regional divide according to the Qinling-Huaihe Line.⁵ Specifically, we interact north/south regional dummy variables with the temperature bin variables to obtain separate estimates for the north and south:

$$\ln EC_{i,y,m} = \sum_j \alpha_j TEMP_{i,y,m,j} + D_i \sum_j \alpha_j TEMP_{i,y,m,j} + \beta \ln Y_{i,y} + \lambda \vec{X}_{i,y}' + \gamma_i + \omega_y + \varphi_m + \epsilon_{i,y,m} \quad (3)$$

where $D_i = \begin{cases} 0, & \text{provinces located in the south} \\ 1, & \text{provinces located in the north} \end{cases}$

We also estimate separate responses for urban and rural areas. To do so we use separate urban and rural residential electricity consumption measures by province, while controlling for urban and rural measures of per capita disposable income. We use the same temperature measures as in the main analysis.

⁵ The north includes Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong, Henan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The south includes Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hubei, Hunan, Guangdong, Chongqing, Sichuan, Guizhou, and Yunnan.

In robustness checks we control for interactions between the province and month-of-year fixed effects so as to account for unobserved geographically-varying seasonal factors. We also control for month fixed effects (i.e. year by month-of-year) to take common time-varying factors into account and explore potential non-linear effects of per capita income by including a quadratic term. In addition we pursue estimations using temperature bins based on the daily average rather than the daily maximum temperature, with 14–18°C as the base group when doing so. Ten temperature bins are again used, varying from above 30°C to below –2°C.

Temperatures are likely to be highly exogenous to any province’s residential electricity use (Wang et al. 2008; Zivin and Neidell 2014; Levinson 2016). While greenhouse gas emissions from local electricity generation will contribute to climate change (Hsiang and Kopp 2018), this is a global and gradually-building effect rather than an immediate within-province feedback loop. China’s emissions from electricity and heat production for the residential sector also only accounted for 2.3% of the world’s carbon dioxide emissions from fuel combustion in 2017 (IEA 2019a). The link between household electricity use and the urban heat island effect is also not expected to be strong, as urban heat effects mainly relate to city size, urban surface geometry, and the radiative and thermal properties of physical surfaces (Oke et al. 2017). Electricity is also typically generated outside cities. As a result, our regressions should carry causal interpretations. The province fixed effects and various sets of time fixed effects also help to control for key dimensions of unobserved variation that may be correlated with both residential electricity use and temperatures.

3 Results

3.1 Baseline results

Table 1 shows the baseline results. Column (1) is an initial specification. Province fixed effects are controlled for in column (2), year and month-of-year fixed effects in column (3), and the additional variables in (4). The results are similar across the columns.

Insert Table 1

A key finding in Table 1 is that the response of household electricity to hot temperatures is larger than the response to low temperatures. The likely reason is that cooling is currently more electricity-intensive than heating in China. An additional day in the $>34^{\circ}\text{C}$ maximum temperature range on average results in around a 1.2–1.6% increase in monthly per capita household electricity consumption compared to if that day had a maximum temperature in the range $22\text{--}26^{\circ}\text{C}$. The effect for an additional day in the $30\text{--}34^{\circ}\text{C}$ maximum temperature range is 1.1% (column (4)). For cold days, each additional day with a maximum temperature of only $2\text{--}6^{\circ}\text{C}$ on average leads to monthly per capita electricity consumption increasing by only about 0.6% relative to if that day's maximum temperature had been in the base category (column (4)). The hot and $2\text{--}6^{\circ}\text{C}$ effects on residential electricity use are statistically different from one another at the 1% significance level.

The estimates in Table 1 also indicate that residential electricity consumption is influenced by average income levels. A 1% increase in average per capita disposable income on average leads to around a 0.6–1.5% increase in per capita household electricity consumption, depending on which control variables

are included. As expected, the urbanization rate is found to have a positive effect. A percentage point increase in the provincial urbanization rate on average leads to an increase in residential electricity consumption of about 2.4%.

Figure 4 displays the basic and distributed lag results in visual form. A U-shaped relationship between household electricity consumption and the temperature bins is observable. For hot temperatures the two-month response is larger than the one-month response, with each additional day with a maximum temperature $>34^{\circ}\text{C}$ leading to a 3.4% increase in the month's electricity consumption once the lagged effect is included.

Insert Fig. 4

3.2 Heterogeneity tests

Figure 5 shows separate marginal effects for the south and north, obtained from a single estimation with interaction terms. The lagged effects are not included. The results indicate that the proportional response of residential electricity use to hot weather is larger in the north than the south (a difference that is significant at the 1% level). This may be for two key reasons. First, households in the south are likely to be more familiar with higher temperatures and tend to live in dwellings that are better equipped with fittings such as external window shadings.⁶ Second, households in the south on average consume more

⁶ The average number of days for which the maximum temperature exceeds 34°C in southern provinces is around 22 per annum, five times the average for northern provinces.

electricity relative to the north.⁷ As a result, a smaller proportional response to an additional hot day should be expected.

Insert Fig.5

The coefficient for the number of <2°C days in the south is not significantly different from zero (Figure 5). It is also imprecisely estimated given that it is rare to have extremely cold weather in the south. For the north, the effect for the <2°C temperature bin is significant at the 5% level and is slightly smaller than that for the 2–6°C temperature bin. This is perhaps because some residents switch to using solid fuels on extremely cold days.

Figure 6 shows separate response curves for urban and rural residents. For urban residents, the curve rises steeply for days with a maximum temperature over 26°C as well as days below 10°C. An additional day >34°C in a month tends to result in a 1.6% increase in monthly per capita electricity consumption in urban areas, but in rural areas this figure is only 1.0%. A probable contributor to this difference is that there are fewer air conditioners in rural China. Each additional day per month with a maximum temperature in the range 2–6°C tends to make urban monthly per capita electricity consumption increase by about 0.9%. The effect of days in this temperature bin is just 0.5% for rural residents.

Insert Fig. 6

For rural areas, the estimated effect for the 6–10°C temperature bin is larger than for the <2°C

⁷ Per capita annual electricity consumption in the south was around 27% higher than the north in 2017.

temperature bin, though the latter effect is not statistically significant. This is perhaps due to some dependence on electricity instead of coal for heating in the rural south, where maximum temperatures do not drop too low. Heating in the rural north remains dominated by solid fuels rather than electricity. Solid fuels exhibit low combustion efficiency and lead to serious air pollution problems (Chafe et al. 2014).

As shown in Table 2, electricity consumption appears to be quite insensitive to per capita income in urban areas, while in rural areas the income elasticity is above 3. It makes sense that residential electricity use is more closely tied to incomes. Rural residents remain at an earlier stage in the process of energy transition, with residents typically transitioning to cleaner energy sources such as electricity as their incomes rise (Barnes et al. 1997).

Insert Table 2

3.3 Robustness checks

Table 3 presents results for alternative specifications. Columns (7)–(8) control for the alternative sets of fixed effects: province by month-of-year fixed effects and month fixed effects, respectively. We take non-linear effects of income into consideration in column (9), observing an inverted U-shaped effect of per capita disposable income on per capita residential electricity consumption. The turning point is at around 83,000 yuan per capita (in year-2008 terms), which will be reached after 2050 according to the Economist Intelligence Unit (EIU).⁸

⁸ See <https://www.eiu.com>.

Insert Table 3

Column (10) of Table 3 uses temperature bins based on the daily average instead of the daily maximum temperature. An additional day per month with an average temperature $>30^{\circ}\text{C}$ on average results in a 2% increase in per capita electricity consumption in the month relative to the reference average temperature of $14\text{--}18^{\circ}\text{C}$. The trough-to-peak magnitude is slightly higher than when using the daily maximum, perhaps because the daily average is more closely related to day-long electricity use needs. Each additional day with a low average temperature on average leads to an increase of around 0.4–0.6% in monthly electricity use.

4 Scenario: increase in residential electricity use induced by climate change

The IPCC 6th Assessment Report (WG I Chapter 4; Lee et al 2021) provided scenarios for global average surface air temperature in the long-term (2081–2100) under different greenhouse gas emission trajectories. We consider three scenarios: SSP2-4.5, SSP3-7.0, and SSP5-8.5. These will see average temperature increases of around 1.8°C , 2.8°C , and 3.5°C by 2100 relative to 1995–2014, respectively. We make the assumption that the temperature increase in China accords with the global-average temperature increase and that the temperature shifts up by the same amount throughout the day and year. Based on our main estimates we then estimate the change in electricity consumption by 2100 attributed solely to the rise in temperature under the three climate scenarios, using provincial population weights in the aggregation process. The calculation is shown in equation (4), where $y1$, $y2$, and m represent the base year (2010), the final year, and each month, respectively. We use year-2010 population weights.

$$effect\%_m = \sum_j \alpha_j (TEMP_{j,m}^{y2} - TEMP_{j,m}^{y1}) \quad (4)$$

The results are shown in Figure 7. Under all three scenarios, annual per capita household electricity consumption in 2081–2100 is expected to be about 3–5% higher in 2100 due to the expected temperature rise alone. This is a small overall effect when considered against the large increase in residential electricity use that is likely to result from future income growth and ongoing electrification of residential energy services. The effect is highly seasonal. Under the SSP2-4.5 scenario, per capita household electricity consumption in summer will increase by around 8% due to the warming effect. In winter, electricity consumption will decrease by about 1% as heating needs decline. Under SSP5-8.5, residential electricity use in China is expected to increase by 14% from June to August relative to 2010 levels. Demand for residential electricity in spring and autumn would also increase.

Insert Fig. 7

5 Comparisons to previous studies

In order to compare our results with other research we refer to results using the daily average temperature. Compared to 14–18°C, an additional day per month in the 26–30°C or >30°C average temperature bins on average leads to monthly per capita electricity consumption increasing by 1.1% or 2.0%, respectively. This figure is approximately 0.6% and 0.4% for an extra day <−2°C or in the range −2 to 2°C. We compare our results with the studies for the US of Deschenes and Greenstone (2011), Davis and Gertler (2015), and Li et al. (2019). The temperature-electricity response function estimates in these studies are also generally non-linear, with a larger increase in electricity consumption for hot days than

839 for cold days. However the response relationship estimates vary by country.

840 Deschenes and Greenstone (2011) estimated the response function between the daily average
841 temperature and household energy consumption at the state level in the United States. They found a U-
842 shaped effect, consistent with our results for China. They found that each additional day with an average
843 temperature in the range 80–90°F (around 27–32°C) and above 90°F (around 32°C) will lead to a 0.2%
844 and 0.4% increase in annual household energy consumption, respectively, compared to if that day's
845 average temperature had been in the range 50–60°F (around 10–16°C).

846 Davis and Gertler (2015) used micro data from Mexico to estimate the relationship between temperature
847 and residential electricity consumption. They found that an additional day with an average temperature
848 in the range 85–90 °F (around 29–32°C) or 90°F (around 32°C) and above will increase monthly
849 electricity consumption by 2.2% and 3.2%, respectively, relative to if that day's average temperature
850 was in the range 65–70°F (around 18–21°C). The response curve estimated in their study is J-shaped,
851 which differs from our U-shaped response profile. However Mexico and China differ substantially in
852 their climates. The response curve is not well measured for low temperature ranges in Mexico given its
853 warm climate. Our results are otherwise quite similar to those for Mexico.

854 Li et al. (2019) used micro data on household electricity consumption in Shanghai to construct a
855 temperature-electricity response relationship. They found that an additional day with an average
856 temperature >32°C per month would result in a 5.7% increase in the monthly household electricity
857 consumption, a larger effect than our results for urban areas. This is perhaps explained by the fact that

Shanghai is one of the wealthiest cities in China, with a high penetration of air conditioners.

6 Conclusions

Understanding key responses to temperature extremes is important for modeling of the effects of climate change (Tol and Yohe 2006), for electricity system planning, and for other purposes. In this study we assembled a dataset of daily temperatures using an inverse distance weighting method and explored the effect of daily temperatures on monthly household electricity consumption data in China. The paper contributes to understanding the responses to climate change in a key country in the developing world. We draw conclusions and implications as follows:

6.1 The response function is U shaped, with heterogeneity by region

We found that the temperature response function for residential electricity use is U-shaped. Responses to high temperatures are larger than responses to low temperatures, for the likely reason that residential demand for air conditioning, electric fans, and refrigeration increases on hot days. Electricity is typically less vital as an energy source on cold days, with biomass, coal, and natural gas all quite commonly being used for space heating in China.

The electricity consumption of residents is less sensitive to high temperatures in southern provinces than in the north (in proportional terms), likely because people and residences are more accustomed and adapted to heat and because the underlying residential electricity usage level is higher in the south. Urban residents are more likely to increase their electricity use in hot or cold weather than rural residents, likely at least in part due to greater availability of air conditioners. There is still huge growth potential

in both air-conditioner adoption and use in China, especially in rural areas.

6.2 Effects of future warming

Our estimates are useful for understanding the effects of future climate change on residential electricity consumption in China. We estimate the effects by 2100 relative to 2010 under different carbon emission scenarios based on the IPCC projections. As the climate warms, residents will face greater cooling needs in summer and reduced heating needs in winter. Our estimates suggest that total residential electricity consumption will likely increase by about 3–5%, with an increase that could be as high as 14% in summer months. Residential electricity demand in China tends to peak in summer, so additional pressure on summer demand will add to China’s investment needs in electricity generation, transmission, and distribution.

One way to alleviate the emission pressures from rising summertime residential electricity demand is increased use of rooftop solar photovoltaic (PV) and battery storage technologies. These distributed technologies would also reduce the need for grid-level infrastructure investments. China accounted for 30% of solar PV electricity generation globally in 2017 (IEA 2019b), and there is substantial potential for expansion in the country’s rooftop solar PV market. As the cost of solar PV decreases, electricity storage technologies improve, and household wealth accumulates, residents are more likely to install solar panels (Best et al. 2019). Rural residents in China are advantaged in terms of greater physical potential to install rooftop solar PV due to higher prevalence of private roofing. Urban residents are more likely to live in apartment buildings.

Future research may be able to explore the effect of temperature on adoption of air-conditioners in China, a key topic from a climate change adaptation point of view. It would also be of interest to explore the effects of extreme temperature days – both hot and cold – on the use of other types of energy at the residential level, such as coal and natural gas.

Declarations

Conflict of interest The authors declare no conflict of interest.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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Tables

Table 1 Main results

Model	(1)	(2)	(3)	(4)
Ln mean daily-average per capita household electricity consumption				
Number of days in month:				
>34°C	0.012*** (0.001)	0.012*** (0.001)	0.016*** (0.002)	0.016*** (0.002)
30–34°C	0.008*** (0.002)	0.008*** (0.002)	0.011*** (0.002)	0.011*** (0.002)
26–30°C	0.000 (0.001)	0.000 (0.001)	0.003*** (0.001)	0.003*** (0.001)
18–22°C	0.002* (0.001)	0.002* (0.001)	0.001 (0.001)	0.002** (0.001)
14–18°C	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
10–14°C	0.002* (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
6–10°C	0.007*** (0.001)	0.008*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
2–6°C	0.007*** (0.002)	0.007*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
< 2°C	0.004*** (0.001)	0.005*** (0.001)	0.003 (0.002)	0.003 (0.002)
Ln income per capita	0.861*** (0.046)	0.866*** (0.048)	1.461*** (0.411)	0.594 (0.429)
Average humidity				-0.000 (0.001)
Urbanization rate (%)				0.024*** (0.007)
Spring festival (Binary)				-0.071*** (0.009)
Province fixed effects	No	Yes	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Month-of-year fixed effects	No	No	Yes	Yes
Provinces	30	30	30	30
Observations	3,600	3,600	3,600	3,600

Note: The base temperature bin is 22–26°C. Temperature refers to the daily maximum. Robust standard errors are in parentheses. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

Table 2 Responses to temperature in urban and rural areas

Model	(5)	(6)
	Ln urban electricity consumption	Ln rural electricity consumption
Number of days in month:		
>34°C	0.016*** (0.003)	0.010*** (0.003)
30–34°C	0.013*** (0.002)	0.009*** (0.002)
26–30°C	0.002 (0.002)	0.002 (0.001)
18–22°C	0.002 (0.002)	0.001 (0.001)
14–18°C	-0.001 (0.001)	0.001 (0.001)
10–14°C	0.001 (0.002)	-0.001 (0.002)
6–10°C	0.007*** (0.002)	0.007* (0.003)
2–6°C	0.009*** (0.003)	0.005* (0.003)
<2°C	0.004 (0.003)	0.001 (0.002)
Ln urban income per capita	0.030 (0.235)	
Ln rural income per capita		3.498*** (0.766)
Control variables	Yes	Yes
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Month-of-year fixed effects	Yes	Yes
Provinces	30	30
Observations	2158	2159

1039 Note: We show regression results for both urban and rural areas, comparing to 22–26°C, with robust standard errors in
1040 parentheses. Data are for 2012 – 2017. The dependent variables use mean daily-average per capita data. *** Statistical
1041 significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

Table 3 Robustness checks

	(4)	(7)	(8)	(9)	(10)
Ln mean daily-average per capita household electricity consumption					
Number of days in month:					
>34°C	0.016*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.014*** (0.002)	
30–34°C	0.011*** (0.002)	0.007*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	
>30°C					0.020*** (0.003)
26–30°C	0.003*** (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.011*** (0.002)
22–26°C					0.004** (0.001)
18–22°C	0.002** (0.001)	0.002* (0.001)	0.002* (0.001)	0.002 (0.001)	0.000 (0.001)
14–18°C	-0.000 (0.001)	0.001 (0.001)	0.002 (0.002)	0.002 (0.002)	
10–14°C	0.002 (0.001)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002* (0.001)
6–10°C	0.005*** (0.001)	0.003** (0.002)	0.004** (0.002)	0.004** (0.002)	0.002* (0.001)
2–6°C	0.006*** (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.004** (0.002)
<2°C	0.003 (0.002)	0.003* (0.002)	0.005** (0.003)	0.005* (0.003)	
–2–2°C					0.004** (0.002)
<–2°C					0.006** (0.003)
Ln income per capita	0.594 (0.429)	0.620*** (0.107)	0.622*** (0.108)	2.038*** (0.284)	0.629*** (0.108)
(Ln income per capita) ²				-0.090*** (0.017)	
Province by month-of-year fixed effects	No	Yes	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes	Yes

Note: Columns (4) and (7)–(9) use the daily maximum temperature, with 22–26°C set as the baseline group. Column (10)

uses the daily average temperature, with 14–18°C as the baseline group. Province, year, and month-of-year fixed effects and

the control variables are controlled for in all columns. Robust standard errors are in parentheses. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%. Each column covers 30 provinces and 3,600 observations.

Figures

Fig. 1 Daily maximum temperature in 2017 (average for provinces)

Note: All months are normalized to 30 days.

(a) January

(b) July

Fig. 2 Average daily maximum temperature in January and July 2017

Note: Figure 2 shows the average daily maximum temperature at the province level in January (a) and July (b) of 2017.

Four provincial regions of China (Tibet, Hong Kong, Macau, and Taiwan) are not included in the econometric analysis

due to data unavailability.

Fig. 3 Per capita residential electricity consumption and the residential air conditioner stock by province, 2017

Note: Shows provincial per capita residential electricity consumption in summer (June–August) and winter months (January, February, December) of 2017. The bubble size represents the number of residential air conditioners per 100 households in 2017, derived from the *China Statistical Yearbook*. For selected provinces, the number is shown in parentheses.

Fig. 4 Same-month and two-month response functions

Note: Shows the overall marginal effects from the basic model and the total effects from a model with one-month lagged temperature bin variables. Province, year, and month-of-year fixed effects and the control variables are controlled for. 95% confidence intervals are shown.

Fig. 5 The response function in the south and the north

Note: Regression results by region, with province, year, and month-of-year fixed effects and control variables considered.

The solid line is the regression coefficient. The dashed lines show the 95% confidence interval.

Fig. 6 The response function in urban and rural areas

Note: Shows separate regression results for urban and rural areas for 2012–2017. Province, year, and month-of-year fixed effects and the control variables are controlled for. The solid line is the regression coefficient. The dashed lines show the 95% confidence interval. The regression results are shown in Table 2.

Fig. 7 Monthly electricity consumption change under different climate scenarios

Note: We estimate the change in household electricity consumption attributed to expected temperature increases over 2010 – 2100 under three climate change scenarios. The estimation applies the estimates in our basic model for the temperature bins only and does not incorporate expected changes in other variables.