Climate change and residential electricity consumption in the Yangtze River Delta, China

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Estimating the impact of climate change on energy use across the globe is essential for analysis of both mitigation and adaptation policies. Yet existing empirical estimates are concentrated in Western countries, especially the United States. We use daily data on household electricity consumption to estimate how electricity consumption would change in Shanghai in the context of climate change. For colder days <7 °C, a 1 °C increase in daily temperature reduces electricity consumption by 2.8%. On warm days >25 °C, a 1 °C increase in daily temperatures leads to a 14.5% increase in electricity consumption. As income increases, households' weather sensitivity remains the same for hotter days in the summer but increases during the winter. We use this estimated behavior in conjunction with a collection of downscaled global climate models (GCMs) to construct a relationship between future annual global mean surface temperature (GMST) changes and annual residential electricity consumption. We find that annual electricity consumption increases by 9.2% per +1 °C in annual GMST. In comparison, annual peak electricity use increases by as much as 36.1% per +1 °C in annual GMST. Although most accurate for Shanghai, our findings could be most credibly extended to the urban areas in the Yangtze River Delta, covering roughly one-fifth of China's urban population and one-fourth of the gross domestic product.

electricity consumption | climate change | economic impacts | China

Climate change is a major environmental policy challenge (1). Understanding the shape of damage functions is critical to improve integrated assessment models (IAMs) used to estimate the social cost of carbon. Such estimates underpin policies to reduce greenhouse gas emissions and foster adaptive behaviors. Among the categories of damages, incremental cooling consumption in the power sector is often recognized as a top component (2). (We follow the literature in using the term "damages" to refer to the valuation of impacts associated with climate changes, recognizing that some so-called damages are really adaptation costs.) Several existing studies have provided empirical evidence on the electricity–temperature response functions in the developed countries, mainly the United States (3–5) and the European countries (6–8). In contrast, we know little about the response functions in China, where an average household's electricity consumption is projected to double by 2040 even without climate change (9).

With the rapid adoption of air conditioners (that are reversible as heat pumps) in urban China over the past decade, cooling and heating have become one of the main drivers of residential electricity consumption growth. China, India, and Indonesia are projected to account for half of the total stock of air conditioners by 2050 (10), which has important implications for electricity consumption going forward. For utility companies, understanding the drivers of electricity consumption, especially peak consumption, and constructing models to obtain reliable forecasts are key components of demand-side management (11). Among other factors, residential electricity demand is very responsive to temperature fluctuations. Fig. 1 highlights this phenomenon in Shanghai, showing the contributions of residential, commercial, and industrial demand to overall use. Although residential electricity accounts for only one-quarter of the total, it increases much more dramatically during extreme heat days (around August 1) and extreme cold days (around February 1), driving peak consumption during these periods.

In this work, we use data on daily household-level electricity use from the State Grid Corporation of China to estimate the temperature–electricity response function and then predict the effect of climate change on residential electricity consumption. More specifically, we analyze >800,000 metered residential customers in Pudong, Shanghai, over the period from 2014 to 2016 (see *SI Appendix* for a data description). With this large panel dataset, we directly estimate the varying daily electricity consumption responses as the daily temperature changes. For example, for temperatures >26 °C, a 1 °C increase in daily temperature leads to a 14.5% increase in daily household electricity consumption. In contrast, previous studies using monthly or annual data could only estimate the increase in aggregate electricity bills due to counts of hot days per month or year (3, 4, 12, 13).

Another aspect missing from the previous work is consideration of household income. Use of air conditioners or other heating and cooling equipment constitutes the main channel to respond to temperature changes (14). Previous studies in Mexico (13) and China (15) have emphasized the importance of air conditioner adoption as income increases. Studies using

Significance

Estimating the impacts of climate change is essential for analysis of both mitigation and adaptation policies. Our principal finding, that annual electricity consumption increases by 9.2% per +1 °C in annual global mean surface temperature (GMST) in the Yangtze River Delta, represents one of the few estimates of impacts outside Western countries. This estimate can contribute to analyses of global mitigation efforts, helping to determine what level of emissions best balances costs and benefits. We note that energy consumption is often one of the larger categories of monetized climate change impacts. We also estimate that annual peak electricity use increases by 36.1% per +1 °C in annual GMST, assisting planning efforts for additional grid capacity that will be needed in the future.

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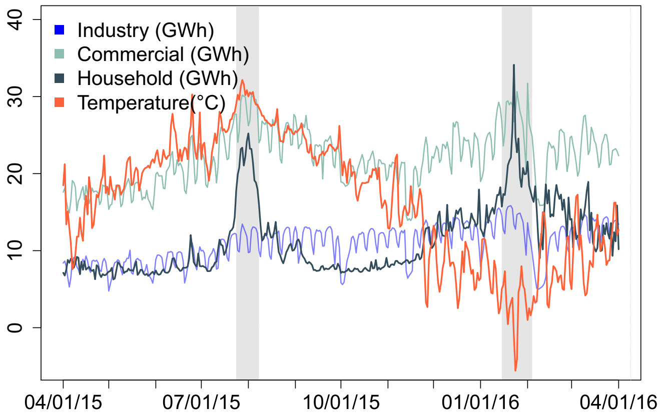

Fig. 1. Daily total electricity consumption by sector with daily temperature. The gray areas highlight the periods for extreme weather, where we see the highest response in residential electricity.

aggregate data in India suggest income growth leads to an increase in the sensitivity of electricity demand to a hotter climate (16). However, few studies have analyzed how electricity–temperature response functions change as income grows at the household level. Combined with an in-house survey on socioeconomic status covering 1,394 households, we show that the electricity response during the winter is higher for high-income groups. However, the responses to hot summer days are similar for all income groups in Shanghai.

We use our estimated temperature–electricity model to construct an aggregate damage function using 21 downscaled global climate models (GCMs). The regional and temporal detail of these GCMs allows us to construct a set of 42 data points (21 models × 2 scenarios) relating future global mean surface temperature (GMST) to future impacts on residential electricity consumption in China. Fitting a line across these data points, we find that the annual residential electricity use increases by 9.2% per 1 °C increase in GMST.

We also examine annual peak electricity consumption because it drives future investment in grid expansion (5). Our estimates show that the annual peak electricity use increases by 36.1% per 1 °C increase in GMST. Under Representative Concentration Pathway (RCP) 8.5, the annual peak electricity use is estimated to increase by as much as 120% on average across 21 models (and as much as 207%, according to the highest estimate).

Our data come from one area of Shanghai. Thus, our results are most credibly extended to the remainder of Shanghai and other urban areas in the Yangtze River Delta due to relatively similar climate and economic conditions. This triangle-shaped metropolitan region comprises the Jiangsu, Zhejiang, and Anhui provinces, covering roughly one-fifth of China's urban population and one-fourth of the gross domestic product. It is less credible to extend these estimates to other regions of China. Even if income levels converge by the end of the century, cultural and climate differences remain. Nonetheless, these results are useful benchmarks in these and other emerging-country regions for which estimates are unavailable.

Modeling the Temperature Response Function

Our theoretical framework follows Auffhammer and Mansur (17). To maximize utility, households choose the amount of electricity to consume and the number of appliances to buy subject to an income constraint. In the short run, the number of appliances remains fixed, so only the level of electricity consumption responds to exogenous weather shocks. We can therefore estimate a simple partial derivative.

Econometric Model. Based on the theoretical framework and previous studies (3, 5, 13), we model the temperature-response function using the simple log-linear equation below:

$$\begin{aligned} lnEC_{it} = {} & \beta_0 + \sum \beta_{1_j} f_j(TEMP_t) + \beta_2 HUMIDITY_t \\ & + \beta_3 V_t + \beta_4 EAST_t + \beta_5 WEST_t + \beta_6 SOUTH_t \\ & + \beta_7 EAST_t \cdot V_t + \beta_8 WEST_t \cdot V_t + \beta_9 SOUTH_t \cdot V_t \\ & + \beta_{10} PM_{2.5} + \beta_{11} WEEKEND_t + \delta_i + \delta_{m,y} + \epsilon_{it}. \quad \textbf{[1]} \end{aligned}$$

The dependent variable $lnEC_{it}$ is the natural logarithm of daily electricity consumption, and $TEMP_t$ is the daily temperature. The total number of household-day observations after cleaning is 545,768,122. The functions f_j are spline functions.* Because the nonlinearity of the response function has been well established in the literature, we assume that temperature response varies flexibly. Existing studies typically use predetermined bins. Here, we use splines because they allow for slopes within bins, smoothing the response function. The smoother response also makes it easier to implement our selection criterion to determine the number of knots and produce estimates that avoid spurious detail.

The knots are located at equally spaced quantiles once the number of knots is determined, ensuring comparable numbers of observations between adjacent knots to estimate the slope. While our high-frequency data can estimate a large number of knots, we worry that using too many knots picks spurious relationships over the relatively short overall sample period of 2 y. We solve this problem by using a 10-fold cross-validation technique to find the number of knots where the out-of-sample prediction ceases to improve. The result is a choice of $j = 6$, or five knots (*SI Appendix*, Fig. S2).

By controlling individual fixed effects δ_i, we use within-household random temperature shocks to identify the $\beta_{1_j}s$. Nonetheless, controlling for other climate variables helps to isolate the effect of temperature change by removing the impact of nontemperature confounders (18). Thus, we control for humidity and the interaction between wind velocity and direction. In addition, we control for the daily concentration of particulate matter with diameter <2.5 micrometers (PM 2.5, units: $\mu g \cdot m^{-3}$) collected by the Shanghai Environmental Monitoring Center. Higher particle pollution is found to lead to significantly higher electricity demand in Singapore, as households adopt air conditioning to replace natural ventilation (19). The mechanism in Shanghai is likely to be different. Electricity consumption may increase because of fewer outdoor activities during polluted days, accompanied by the rapid adoption of air purifiers (20). Starting in July 2012, Shanghai utilities adopted both time-of-use pricing and tiered pricing for residential households. Because households do not necessarily face the same price in the same month of different years, we control for year–month fixed effects $\delta_{m,y}$ instead of separately controlling for month fixed effects and year fixed effects. Finally, we control for possible weekend effects, as households tend to use more electricity over the weekend.

Baseline Estimates. Fig. 2 represents our main estimation results. The figure uses the $\beta_{1_j}s$ estimates to plot the projected percentage change in daily electricity consumption against temperature, relative to the least-electricity-consuming temperature. The effects of humidity and weekend, although statistically significant, are small in magnitude. For example, if humidity increases from the lowest to highest observed level, the daily electricity use will increase by 6%. Households consume 2% more electricity

*The function $f_1(TEMP_t) = TEMP_t$. For $j > 1$, the function $f_j(TEMP_t)$ is equal to zero when $TEMP_t$ is less than the defined knot value k_j, and equal to $TEMP_t$ when $TEMP_t$ is greater than the knot value.

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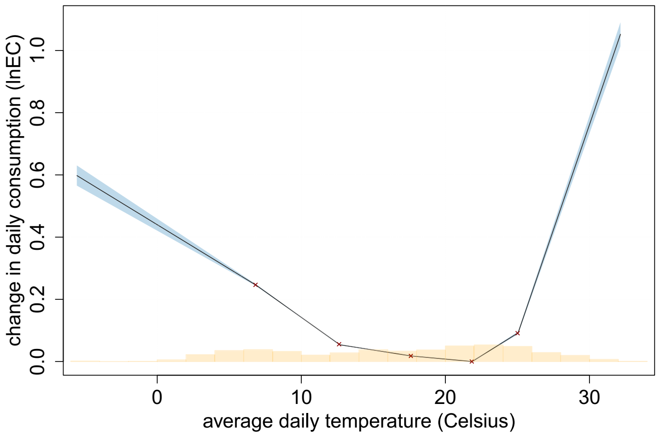

Fig. 2. The effect of temperature on daily electricity consumption. The *y* axis plots the predicted natural log of electricity consumption, *lnEC* (normalized to zero for lowest point). The light blue shading represents a 95% confidence interval, using two-way clustering at the household and week level. The orange histogram shows the temperature distribution.

during the weekend. Other variables, including air pollution, are not significantly different from zero. In contrast, the temperature splines are statistically significant, and high temperatures can double electricity consumption. Thus, we focus on the effect of temperature.

The main observation is that the temperature-response function indeed follows the U-shape established in the literature, with minimal restrictions imposed on the functional form. The curve is relatively flat over 13–25 °C, representing a comfortable temperature range. The curve rises steeply when temperature increases >25 °C while increasing moderately when temperature decreases <13 °C. Compared with a 20° day, when electricity consumption is the lowest, a 32° day would lead to a 170% increase in daily electricity consumption.

Comparison with previous studies is difficult because earlier studies rely on monthly billing data. They present similarly shaped curves, but the vertical axis is the percentage increase in monthly consumption for an additional day per month at the indicated temperature. If we focus on a "reference" month with average consumption and temperature in all days, we can compute comparable values using our model. Based on this approach, each additional day in the >32 °C (90 °F) bin would lead to an increase of 5.7% in monthly consumption, compared with the baseline of 15–21 °C (60–70 ○F). This is higher than the 3.2% increase estimated in the Mexico study (13) but falls into the range of 2–7% increases in existing estimates for the United States (3).

Coupled with average monthly consumption levels, these percent changes associated with hot days translate into monthly electricity consumption increases of 5, 11, and 20–60 kWh in Mexico, Shanghai, and the United States, respectively (based on data from the Energy Information Administration and the state-owned utility company of Mexico (Comisión Federal de Electricidad). The United States experiences the highest increase in kilowatt hours because its current consumption is among the highest worldwide. The gaps would be narrower in the future, however, as households in Shanghai and Mexico consume more electricity as income grows. On the other hand, improvement in the efficiency of air conditioners, among other energy-saving actions, could potentially curb the growth of cooling-related demand under targeted policy incentives (10).

We can calculate the slope in each segment to estimate the direct impact of 1 °C increases in daily temperature. For temperatures >25 °C, a 1 °C increase in daily temperature would lead to 14.5% increase in daily electricity consumption. This has important implications for peak-demand management as extreme temperatures rise: More investment will be necessary to meet the growth in peak demand on the hottest days. The response to lower temperatures is shallower than the response to higher temperature, but we are limited by the range of temperatures observed in Shanghai. Further research on colder areas would be valuable to see how the slope of the response function might change at low temperatures.

Sensitivity by Income Groups. Household-level adaptation to climate change requires diverting other categories of household consumption into cooling expenditure. We therefore would expect households with differing levels of income to respond differently to the same temperature change. Our reported log-linear model assumes a particular pattern of behavior—that the adjustment is the same in percent terms but can differ by income level. We can instead estimate separate response functions for income subgroups based on a subsample of ∼1,400 households for which we have collected additional demographic data. We define four groups by monthly income: less than $1,600 (15% of total households in our sample), $1,600–2,700 (30%), $2,700–4,000 (34%), and more than $4,000 (21%).

We note that Shanghai is among the richest regions in China. In 2015, the average monthly household income in Shanghai was $2,300, more than twice the national average ($900) (21). The average in our sample is slightly higher at $2,750, but we do observe heterogeneity in our sample, which we exploit in the subgroup analyses.

Fig. 3 depicts the response functions by income groups. The temperature response functions are almost the same for high temperature >25 °C. Given the near-100% penetration rate of air conditioners in Shanghai and the hot summers, this finding suggests a convergence of cooling behaviors across income levels during hot summers for relatively developed regions. The temperature response is shallower for the low-income group in the winter, however. We speculate, based on anecdotes, that poorer households may endure cooler indoor temperatures by wearing more clothes or that wealthier households may be more wasteful (e.g., opening windows more frequently to increase humidity while heating the home). Note that the absolute gap in terms of kilowatt hours will be larger than the gap in terms of percentage: Higher-income groups have higher percentage responses and baseline consumption levels (the corresponding average annual electricity consumption is 1,960; 2,260; 2,430; and 3,030 kWh, respectively, for the four income groups.

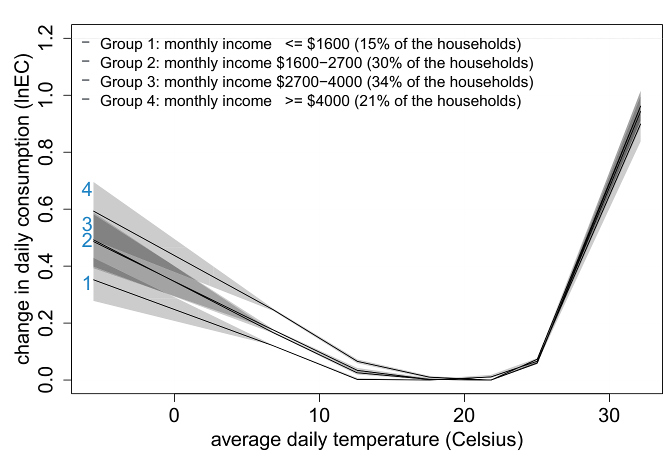

Fig. 3. Temperature response functions by income (in US dollar) groups. Each group has at least 200 households. Each spline is estimated for the subgroup separately. The shaded areas represent 95% confidence intervals.

Taken together, this result regarding cold days suggests that the increase in electricity use due to climate change could be smaller as income increases in Shanghai. Steeper slopes on cold days correspond to larger energy savings as temperatures warm. However, this result is likely sensitive to the Shanghai context, where high incomes, a high penetration rate of air conditioners, and the significant use of electric heat all combine to drive a negative correlation between income and the net sensitivity of electricity demand to climate change impacts. The situation in northern China could be very different, where incomes are lower and households use gas heating or central-station hot water. Another caveat is that our ability to identify income effects is limited because the data do not identify households in the tails of the income distribution.

End-of-Century Forecast

In this section, we calculate the changes in residential electricity consumption projected for the last two decades of the 21st century by applying the temperature-response curve expressed in Eq. **1** and presented in Fig. 2 to two climate change scenarios: RCP4.5 and RCP8.5. The RCP8.5 trajectory reflects a high climate change scenario in the face of continued high emissions growth. RCP4.5 is a more moderate scenario, in which emissions peak in ∼2040. We use 21 different implementations of these two scenarios to construct a relationship between GMST change—the typical summary measure of global climate change—and changes in annual household electricity consumption over this time period. We also examine patterns of projected daily consumption to give us some insight into how peak consumption will change.

Damage Function. We calculate the difference between the future (2080–2099) and the past (1980–1999) average calendar day temperatures for each of the 42 model × scenario combinations. We then use these changes in daily temperature to estimate the change in electricity consumption using our model results in Fig. 2. Finally, we aggregate across calendar days to estimate the change in annual electricity consumption, again for each of 42 model × scenario combinations (for details, see *SI Appendix*).

We note that this approach risks missing potential impacts on extensive margins (e.g., investment in better building design, etc.). Massetti and Mendelsohn (22) emphasize the distinction between panel estimates that capture short-term weather shocks (intensive effects) with cleaner identification and cross-sectional estimates that capture long-term climate change (intensive and extensive) but risk bias from confounding variables. More recent work by Hsiang (23) argues that panel estimates can capture unbiased long-term effects when estimated over a suitably wide range of geography and climate. However, given our limited geographic scope, we cannot appeal to Hsiang's arguments. We would hypothesize that our estimates establish an upper bound for Shanghai. That is, we imagine extensive changes would lead to lower damage estimates thanks to greater long-term flexibility to save energy. In other regions, with less existing penetration of air conditioning, such flexibility might lead to larger impacts on electricity consumption as households adopt cooling appliances in response to persistent warming.

Damage Function Calculation. Fig. 4 shows the change in temperature distribution for Shanghai under RCP8.5. Consistent with previous findings, climate change shifts the distribution of daily temperature to the right. The number of days falling within the lowest five temperature bins <12 °C decreases by >50 d, while days in the highest temperature bins occur much more frequently. Compared with the reference period of 1980–1999, Shanghai would experience almost 40 more days of temperature >33 °C on average in 2080–2099.

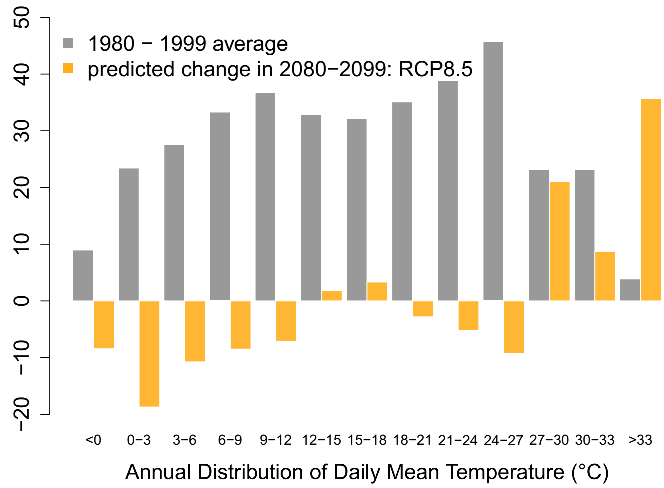

Fig. 4. Distribution of daily average temperature change. Each yellow bar represents the change in the number of days within each temperature bin under RCP8.5. The change under RCP4.5 is similar but roughly half in size (not shown in the graph).

Fig. 5*A* shows the relationship between the change in GMST and the corresponding annual change in electricity consumption. The changes in GMST are adopted from tables 2 and 4 in ref. 24. Each point represents a model run. Fitting a line using ordinary least squares (OLS), residential electricity consumption rises by 9.2% for each +1 °C at the end of the century. This is slightly higher than the estimated slope of a damage function for the United States (25) but seems reasonable because the average temperature in Shanghai is higher than the average in the United States. Alternatively, if we look at the average RCP outcomes at the end of the century, the average annual change in electricity use is 9.4% under RCP4.5, corresponding to an average 1.9 °C change in GMST. Under RCP8.5, the average annual change in electricity use is much higher at 24.6%, corresponding to an average 3.7 °C change.

Change in Annual Peak Electricity Consumption. Average annual changes in electricity consumption are the primary driver of annual climate damage estimates. However, peak consumption changes will drive future investment in grid expansion and could drive damages yet higher. Fig. 5*B* mimics the style of Fig. 5*A*. The main difference is that here we plot on the *y* axis the change in annual peak consumption, rather than the annual average. (In this paper, the peak is defined by the maximum daily electricity consumption across the year. This differs from the definition in ref. 5, where the peak refers to the highest demand hour of the day for the whole grid system.) The comparison between the two figures shows significant difference in magnitude, with annual peak consumption changing more dramatically than the annual average. Similar to Fig. 5*A*, we fit a line using OLS, finding an increase of 36.1% in peak consumption for each 1 °C at the end of the century. This is three times steeper than that of the annual damage function. Put another way, while annual electricity consumption rises 9.4% and 24.6% under RCP4.5 and RCP8.5, respectively, peak consumption rises by 57% and 120%. Thus, capacity investment will need to rise by more than the average increase suggests.

To understand this distinction, it is helpful to see the daily pattern of electricity changes due to climate change across the year. In Fig. 6, we present the average effects under the RCP4.5 and RCP8.5 (with each individual model indicated lightly in the background). Consistent with the spline estimates, the daily electricity consumption increases dramatically in the summer and decreases only slightly in the winter. But it is easy to see

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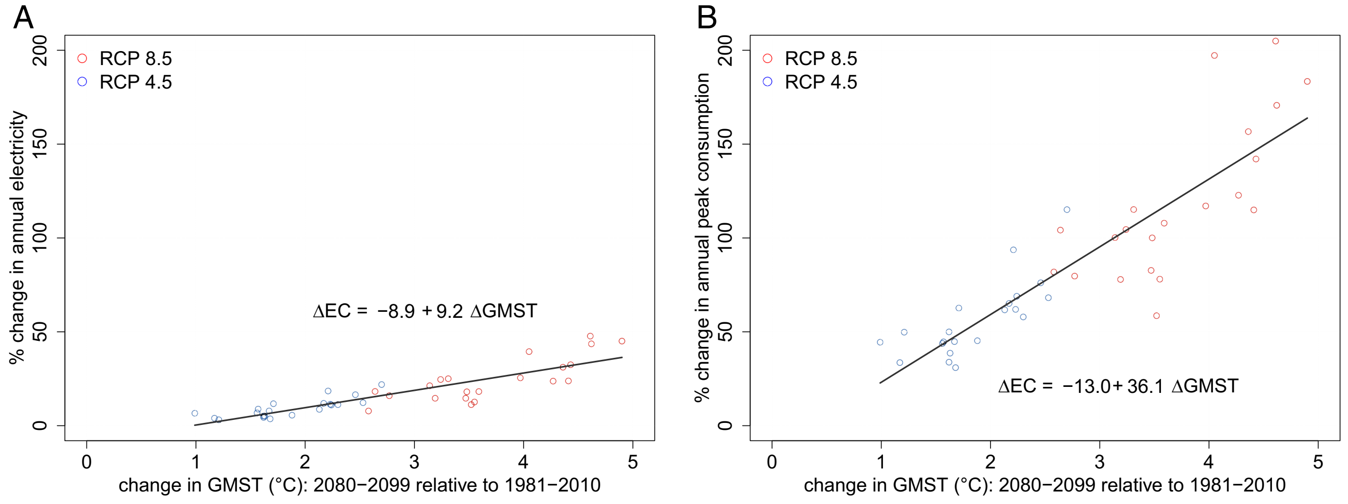

Fig. 5. Damage function. (*A*) The *y* axis shows the predicted change in annual electricity, a weighted aggregation of daily changes using electricity consumption in 2015 as the consumption pattern across a year. (*B*) The *y* axis shows the predicted change in annual preak electricity, defined as the maximum of the daily electricity change across the year. The GMST data are from tables 2 and 4 in ref. 24, matched by the model scenario. Detailed calculation process for the change in electricity is described in *SI Appendix*.

why the effect averaged over the year is much smaller than the peak effect. Note that the daily pattern of predicted consumption changes across the summer varies significantly over the 21 models but the average is relatively flat.

Conclusion and Future Efforts

Consistent with previous studies in the United States and Mexico, we find a U-shaped relationship between residential electricity consumption and daily temperature in Shanghai, China. Studies across diverse climate zones, such as the United States, find more symmetric U-shaped curves. Our study in Shanghai is steeper for hot days and flatter for cold. Mexico, by comparison, is very responsive at high temperatures even with relatively low air-conditioner penetration rate, while the response for cold days is not significantly different from zero.

These observed differences could be attributed to a combination of factors, including insulation features, appliance stock and efficiency, and use patterns. In winter, households have a wide range of choices, including electric heaters, heat pumps, and gas-fueled furnaces, leading to different impacts on electricity consumption for a given temperature change depending on regional culture, markets, and infrastructure. Alternatively, differences in the flat portion of the U-shaped curves may hint at different tolerance levels for heat and cold. Shanghai residents may have a larger comfort zone—in which they do not engage in significant space conditioning—compared with their US counterparts.

Combining our estimated response curves with downscaled projections of climate change, we estimate that each 1 °C increase in GMST leads to a 9.2% increase in annual electricity consumption. Of equal interest, we highlight the difference between the impact on annual average electricity consumption and the impact on annual peak electricity consumption. If the global climate warms by 1 °C, the annual peak electricity consumption increases by 36.1%. As peak demand drives investment in electricity generation, our result suggests that the economy-wide impact could be underestimated based on the average annual response.

Our data do not capture enough persistent weather variation to identify changes in housing characteristics and appliance ownership in response to different climates. In this way, our estimation speaks largely to the intensive margin and illustrates the relationship between household electricity use and temperature given a fixed capital stock. On the one hand, the estimates exclude long-term adaptation, such as upgrading insulation, moving to more energy-efficient dwellings, or even migrating to cooler cities (26). Thus, our results may overstate impacts. On the other hand, some households may adopt more space-conditioning appliances as temperatures persistently change. In Shanghai, this factor is less important given the already high penetration rate of air conditioners. However, the estimates could underestimate the response in other cooler or less-developed regions of China.

In contrast to developed countries, we expect climate change to occur concurrently with economic development in China and other developing countries. In this context, it is necessary to consider both climate change and income as two long-term drivers of electricity consumption to understand climate impacts and consumption growth. Previous work found that income would lead to 85–143% growth in electricity consumption in China from 2010 to 2025 (15). As shown in Fig. 5*A*, climate change will lead to an ∼50% increase in electricity consumption in the most extreme scenario by the end of the century, which is

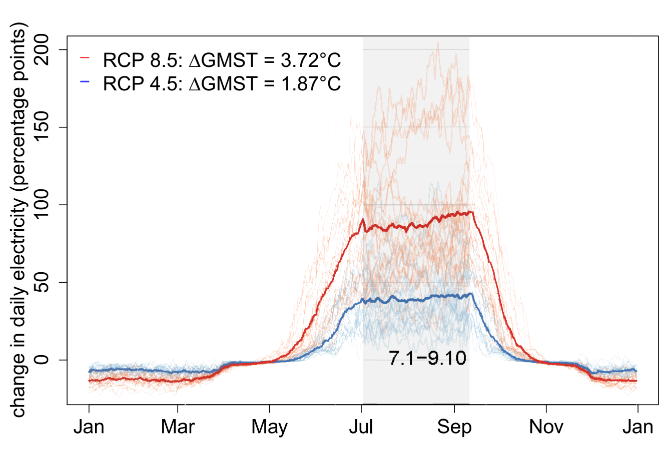

Fig. 6. Daily electricity change under climate change. Blue is RCP4.5; red is RCP8.5. Light lines show each of the 21 models individually, while the dark lines show the average. The gray area highlights the period during which the increase in daily electricity is the highest due to climate change.

important but considerably smaller than the increase due to income growth.

This work also examines the potential interaction between income and climate by estimating the response function by income groups. We found some differences in climate sensitivity across income groups at lower temperatures, but our estimates were limited by the relatively high income levels in our sample compared with China more generally. These estimates are more relevant for our interest in the climate impacts in a richer China and less informative about impacts in poorer regions.

While our work is an important addition to the limited work on climate change impacts on energy consumption in developing countries, it also points to the importance of further work in at least three dimensions. First, we need to consider more diversity in terms of housing stock as well as heating and cooling services relative to our current sample. We would expect that impacts differ by the type of residential construction and use of different heating and cooling technologies and fuels. Second, we need to examine the relationship between income and climate impacts more closely using households with more widely varying income. We should also recognize that the lack of response among the lowest-income households might indicate even higher nonmarket costs, such as discomfort, morbidity, and even mortality. Finally, we need to consider the longer-term, extensive margin when capital stocks adjust in ways that could both raise and lower energy impacts and when migration and public infrastructure investment emerge and interact. One approach would be to include greater regional and climate zone diversity. As highlighted by Hsiang, a panel dataset across diverse climate zones can be used to capture impacts net of longer-term adjustments (23). Such research is an important input toward decisions about both energy-sector planning and adaption in the future, as well as efforts to balance mitigation costs and benefits today.

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