American Economic Journal: Applied Economics 2023, 15(2): 377–414
https://doi.org/10.1257/app.20200505

Energy Saving May Kill: Evidence from the Fukushima Nuclear Accident†

By Guojun He and Takanao Tanaka*

Following the Fukushima nuclear accident, Japan gradually shut down all its nuclear power plants, causing a countrywide power shortage. In response the government launched large-scale energy-saving campaigns to reduce electricity consumption. Exploiting the electricity-saving targets across regions and over time, we show that the campaigns significantly increased mortality, particularly during extremely hot days. The impact is primarily driven by people using less air conditioning, as encouraged by the government. Nonpecuniary incentives can explain most of the reduction in electricity consumption. Our findings suggest there exists a trade-off between climate change mitigation and climate change adaptation. (*JEL* I12, L94, L98, Q48, Q54, Q58)

Understanding the consequences of climate change is of tremendous scientific and policy relevance. Decades of research have shown that climate change can threaten freshwater supply, reduce food and agriculture production, endanger coastal areas, damage human health, and deteriorate the ecosystems (see Dell, Jones, and Olken 2014; IPCC 2014; Carleton and Hsiang 2016; and Auffhammer 2018 for recent reviews). Among these damages, excess mortality caused by extreme weather is considered as one of the most devastating consequences. It is estimated that the mortality cost alone could account for about 70 percent of the total damages in the US by the end of the twenty-first century (e.g., Hsiang et al. 2017).

There are two cornerstone strategies to reduce and manage the growing risks of climate change (IPCC 2014). In one line of literature, researchers focus on how to reduce greenhouse gas emissions associated with the generation and consumption of energy. In particular, many countries have adopted aggressive policies to reduce energy consumption, as the energy sector alone accounts for about 35 percent of

* He: Faculty of Business and Economics, The University of Hong Kong (email: gjhe@hku.hk); Tanaka: Department of Agricultural and Resource Economics, University of California, Berkeley (email: takanao.tanaka.0323@gmail.com). Neale Mahoney was coeditor for this article. We appreciate suggestions and comments from seminar and conference participants at the University of Chicago, Shanghai Jiao Tong University, Renmin University of China, Waseda University, the Occasional Workshop, the 27th Annual Conference of the European Association of Environmental and Resource Economists, CEMPA-USC Joint Workshop on Environmental Economics, UTokyo-GRIPS fourth Empirical Microeconomics Workshop, second AWEHE, GARESC, and the 2019 International Symposium on Contemporary Labor Economics. We thank Xi Lan and Yucheng Quan for excellent research assistance. We also appreciate our former colleagues' help in this project when both authors were working at the Hong Kong University of Science and Technology. Any remaining errors are the authors'.

† Go to https://doi.org/10.1257/app.20200505 to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

greenhouse gas emissions and is expected to grow steadily for the next several decades (IPCC 2014).

A separate line of literature has tried to find effective ways to adapt to climate change. Measures to mitigate exposure to extreme weather have been remarkably successful.[1] For instance, in the United States the chance of dying on extremely hot days has fallen by 75 percent over the past half century, and this decline can be almost entirely attributed to the diffusion of residential air conditioning (Barreca et al. 2016). In India people in rural areas, who cannot easily adapt to hot temperatures due to financial constraints, face a substantially higher mortality risk than urban dwellers (Burgess et al. 2017). As a result, identifying effective measures to mitigate the health damage from climate change is recognized to be crucial in addressing future climate risks (WHO 2009; NIEHS 2010).

A dilemma immediately emerges from these two lines of literature. To mitigate climate change, reducing energy consumption is considered a priority. However, if energy consumption is so critical for people to adapt to climate change, do policies discouraging people from consuming energy induce significant health costs? In this paper we study Japan's large-scale energy-saving campaigns following the Fukushima nuclear accident. We document the existence, and discuss the implications, of the grand trade-off between climate adaptation and energy saving.

Our empirical strategy exploits the dramatic changes in Japan's energy policies caused by the Fukushima Daiichi nuclear disaster. Following the magnitude 9.0 Tohoku earthquake on March 11, 2011, a 13- to 15-meter-high (43–49 ft) tsunami struck the nuclear power plant in Fukushima and eventually led to a meltdown of the nuclear reactors. A massive quantity of radioactive substances leaked from the reactors, and within days the accident raised countrywide concerns about nuclear safety. The government, therefore, decided to stop the operation of *all* nuclear power plants, which resulted in a countrywide electricity shortage. To address the challenge, the central government launched ambitious electricity-saving campaigns, intending to reduce the demand for electricity consumption within a short period. Energy-saving targets were set that required different regions to reduce summer electricity usage by as much as 15 percent. The government paid particular attention to reducing the usage of air conditioning because it is the largest contributor to residential electricity consumption in Japan. For example, it was recommended to set the air conditioner at 28°C on hot days, and people were encouraged to substitute fans for air conditioning if possible. Electricity prices were also raised to further discourage consumption. Arguably, these measures could significantly limit people's capacity to take adaptive actions and make them more vulnerable to extreme weather shocks.

Analyzing the changes in electricity-saving targets set by different regions after the Fukushima accident, we examine the health impacts of Japan's energy-saving campaigns. Our analyses proceed in three steps. First, we estimate the

[1] To adapt to climate, when exposed to extremely hot temperature, people tend to stay indoors (e.g., Graff Zivin and Neidell 2014), use more air conditioning (e.g., Davis and Gertler 2015; Barreca et al. 2016), consume more electricity (e.g., Deschênes and Greenstone 2011), and migrate to more pleasant environments (e.g., Deschênes and Moretti 2009; Bohra-Mishra, Oppenheimer, and Hsiang 2014).

temperature-mortality relationship by exploiting quasi-random year-to-year fluctuations in temperature distribution within a prefecture-by-month and investigate how the energy-saving targets can change the temperature-mortality relationship. We find that exposure to extreme temperatures leads to more premature deaths and that the weather effects become greater in prefectures with higher electricity-saving targets. The mortality risk caused by electricity saving is particularly high in the summer, during which the energy-saving campaigns are intensively promoted. To account for the potential "harvesting effect" or "delayed effect," we also estimate distributed lag models on the impacts of temperature and the energy-saving policy. If we take into account this dynamic impact, we estimate that the energy-saving campaigns could have led to nearly 7,710 premature deaths annually in Japan.

The second component of our analysis examines how individuals responded to the energy-saving campaigns. We show that the Japanese people actively searched for strategies to reduce electricity consumption following the energy-saving campaigns; they used less air conditioning (AC) and bought more non-AC cooling appliances (such as fans), as recommended by the central government. Because the use of AC is a critical instrument to mitigate climate damages (Barreca et al. 2016), these behavioral responses could help explain the significant changes in the temperature-mortality relationship during the energy-saving campaigns.

The third part of the paper analyzes whether it is the pecuniary incentives or nonpecuniary incentives that changed the Japanese people's energy consumption patterns. Facing a severe electricity shortage, the power companies across the country raised electricity prices. However, due to public opposition and heavy regulation in the power sector, the electricity price adjustment was very limited. The annual electricity price growth was only 5 to 6 percent each year after the Fukushima accident. As a result, we find that the price increase can only explain about 10 to 30 percent of the total decline in Japan's electricity consumption. Instead, nonfinancial incentives, such as moral suasion, information campaigns, and social pressures, seemed to play a more crucial role.

This study contributes to the literature in several ways. First, this paper adds to the literature on the effects of adaptation on the climate-health relationship. Many studies have investigated the temperature-health relationship and discussed the role of adaptation (e.g., Deschênes and Moretti 2009; Deschênes and Greenstone 2011; Barreca et al. 2016; Heutel, Miller, and Molitor 2021; Burgess et al. 2017; Carleton et al. 2020; Geruso and Spears 2018). However, they often lack exogenous variation in the adaptive measures (i.e., use of air conditioner or electricity consumption), and the benefits of adaptation are measured as the sensitivity of economic or health outcomes to climate factors.[2] Since people's avoidance and adaptive behaviors are fundamentally endogenous, failure to account for such selection in adaptation precludes one from drawing credible causal inferences.[3] In our empirical setup because

[2] For example, if the probability of people dying on extremely hot days in one area is larger than in another area, the difference is regarded as the benefit of adaptation. This approach is used by Barreca et al. (2016) and Carleton et al. (2020) for mortality; Lobell, Schlenker, and Costa-Roberts (2011) for agricultural output; and Dell, Jones, and Olken (2012) for income.

[3] For instance, rich and educated people tend to act more aggressively to mitigate climate damage because they are better informed about the potential harm and have more resources. At the same time, these people also tend

the Fukushima accident and the subsequent electricity-saving policies were unanticipated, and the energy-saving intensity largely depends on a region's former reliance on nuclear power, these factors exogenously discouraged people from taking adaptive measures against extreme heat. This unique setting allows us to credibly estimate the impact of electricity saving on the temperature-mortality relationship, which helps identify the true impact of adaptation on population health.

Second, this paper also speaks to the literature on the welfare consequences of energy use. In developing countries multiple studies document that access to electricity can improve education (e.g., Lipscomb, Mobarak, and Barham 2013) and labor outcomes (e.g., Dinkelman 2011), while a few other studies find such developmental effects are negligible (e.g., Burlig and Preonas 2021; Lee, Miguel, and Wolfram 2020). In developed countries because the energy supply is stable, researchers instead focus on the effects of volatile energy prices. Two recent studies are relevant to ours: Chirakijja, Jayachandran, and Ong (2019) show that inexpensive heating in the US reduces winter mortality, and Neidell, Uchida, and Veronesi (2021) show that high electricity prices after the Fukushima accident increase winter mortality but not summer mortality.

We differ from Neidell, Uchida, and Veronesi (2021) in several ways, with the most noteworthy distinction being that we focus on the overall impacts of Japan's energy-saving campaigns, while Neidell, Uchida, and Veronesi (2021) focus only on prices. As discussed in the paper, changes in electricity prices can explain only a small portion of electricity consumption after the Fukushima accident, so it is important to take into account overall behavioral responses when assessing the relationship between energy usage and climate adaptation. This difference may help to explain why Neidell, Uchida, and Veronesi (2021) find a null effect of electricity price on heat-related mortality. In this regard this paper is also related to the emerging literature on how to incentivize people to save energy (e.g., Reiss and White 2008; Leighty and Meier 2011; Ito, Ida, and Tanaka 2018; Costa and Gerard 2021). Notably, our findings differ from Ito, Ida, and Tanaka (2018), whose field experiment in Japan found that economic incentives induced greater electricity saving than moral suasion. As discussed in Section V, electricity prices increased much less during the Fukushima crisis than in Ito, Ida, and Tanaka's (2018) experiment, and that experiment did not include the risk of a power blackout, which Japan was facing after the nuclear accident.

Finally, our research contributes to the literature on the consequences of nuclear disasters. Existing evidence often focuses on the direct consequences of nuclear accidents, such as Chernobyl (Almond, Edlund, and Palme 2009) and Fukushima (e.g., Kawaguchi and Yukutake 2017; Rehdanz et al. 2015). In contrast, this study highlights an unexpected consequence of reducing reliance on nuclear power in Japan, which is relevant to nuclear policies in other countries, such as Germany (Jarvis, Deschenes, and Jha 2022).

to have healthier lifestyles, better nutrition, and high-quality medical services. The observed correlation between mitigation behaviors and health outcomes thus may overstate the true effect of climate adaptation. Alternatively, if the adaptation decision is driven by latent health vulnerabilities to extreme weather and the more sensitive population adapts more aggressively, the effect of adaptation can be understated.

I. Background

The Fukushima nuclear accident was one of the worst nuclear power catastrophes in history. It is rated at Grade 7 on the International Nuclear and Radiological Event Scale, which is the maximum value used to assess nuclear accidents. Before Fukushima, only the Chernobyl disaster was rated as a level 7 accident.

On March 11, 2011, the Great East Japan Earthquake, the strongest earthquake in Japan's history since the new measurement of earthquakes was employed, triggered a gigantic tsunami that struck the Fukushima Nuclear Power Plants. This disabled the power supply used for cooling the nuclear reactors and resulted in the meltdown of the cores of several reactors. Within a couple of days, immense quantities of radioactive substances were released into the environment, raising public concerns about nuclear safety.

After the accident, the Japanese government ordered urgent shutdowns of nuclear reactors located in all areas with high risks of earthquakes. Within the next several months, the government gradually suspended the operations of other reactors located in low-risk locations, as the public became more concerned about nuclear safety. By May 2012, all nuclear reactors were taken off the grid. Panel A of Figure 1 illustrates the sharp reduction in the utilization rate of nuclear power plants after the Fukushima accident.

Because Japan had relied heavily on nuclear power (about 30 percent before the accident), the shutdowns of the nuclear power plants caused a nationwide electricity shortage. The electricity shortage was particularly severe during the summer, as the peak use of air conditioning imposed significant challenges to the stability of the grid. Thus, to avoid costly power blackouts, from July to September, the government set ambitious electricity-saving targets for different regions and initiated massive campaigns to encourage people to reduce electricity consumption. Since the reliance on nuclear power and the timing of the shutdowns differed across regions, the electricity-saving target also varied across regions and over time (Figure 2). For instance, in the Tokyo region, where the Fukushima power plant supplied electricity, the government set a saving target of 15 percent in 2011. By contrast, in the Okinawa Islands no saving target was set because they do not use nuclear power.

The electricity-saving campaigns were collective efforts, in that local governments, utility companies, households, industries, and schools were all involved in achieving the targets. For example, the central government directly released guidelines to these parties to encourage them to save energy. These guidelines were widely advocated through TV channels, news media, and various levels of governments' websites. Local governments were required to raise public awareness and advocate the importance and necessity of saving energy. The power companies needed to provide real-time information on their demand and supply capacity and issue warnings when there was a risk of a blackout.

Among these efforts, an essential component of the electricity-saving campaigns was to encourage households to reduce air conditioner usage because air conditioning accounted for nearly 50 percent of summer residential electricity consumption. For example, it was suggested by the government that households should use electric fans instead of air conditioners if possible and should set the

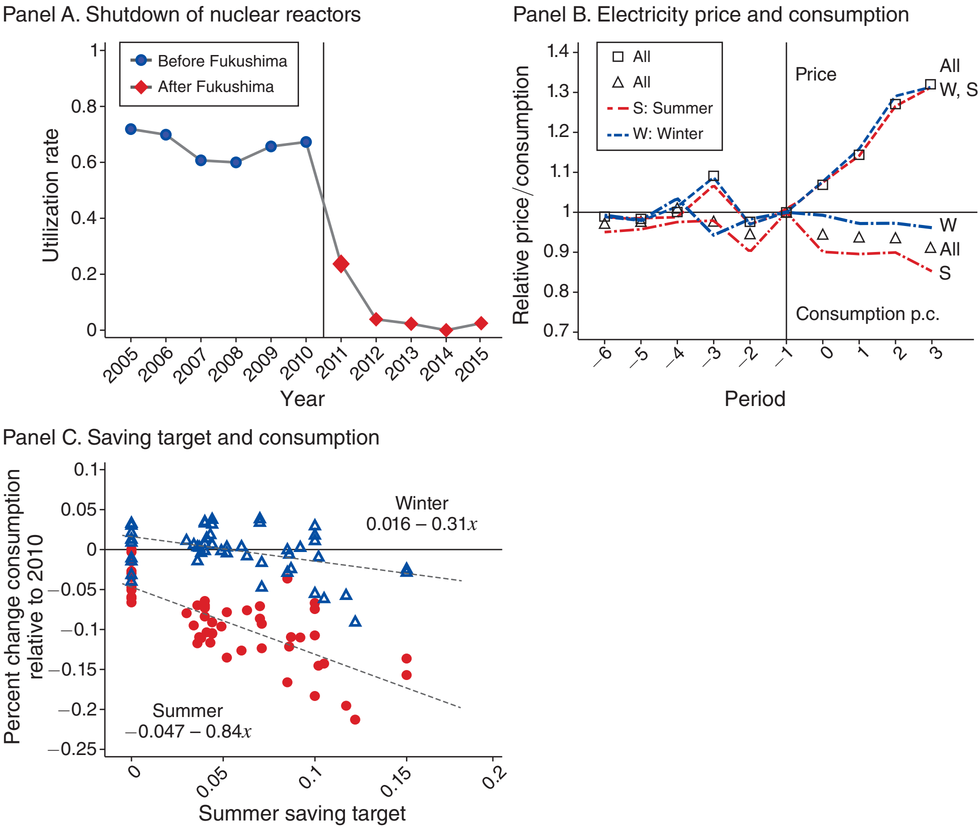


Figure 1. Nuclear Shutdown, Electricity Price, and Consumption

Notes: Panel A shows the utilization rate of nuclear reactors in Japan. The vertical line represents the timing of the Fukushima nuclear accident. The blue circles represent the utilization rate before the accident, while the red squares represent utilization after the accident. Panel B shows the trends in electricity consumption per capita and prices. The red line shows the data in summer (from July to September each year), while the blue line shows the data in winter seasons (from December to March). The triangles and rectangles correspond to prices and per capita consumption using data in all the seasons. We normalize the data, with 1 representing the prices and the consumption per capita measured one year before the accident. Panel C shows the relationship between the electricity-saving targets and electricity consumption reductions (percent) in all ten regions in Japan. Each dot represents a region-year observation (ten regions from 2011 to 2015 in total), the x-axis indicates the energy-saving target in a given region and year, and the y-axis indicates the corresponding reduction in electricity consumption relative to the 2010 level (one year before the Fukushima accident). We plot changes in electricity consumption separately for summer and winter.

Source: Panel A: Federation of Electric Power Companies of Japan, 2018, https://www.fepc.or.jp/library/data/infobase/pdf/08_d.pdf

air conditioner at 28°C if such equipment had to be used. Air conditioner usage also was limited in various facilities, including schools, manufacturing plants, restaurants, and shops.

In addition to discouraging air conditioner usage, the government encouraged households to restrict the use of other electronic appliances. For example, people were asked to set their refrigerators to "medium" rather than "high" and to turn off

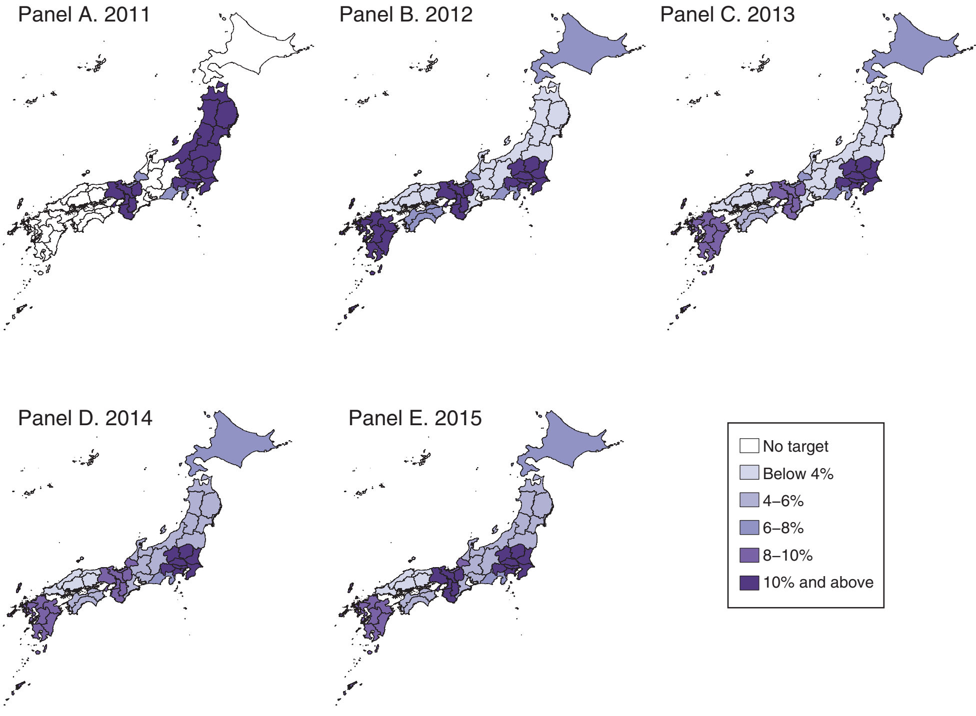


Figure 2. Changes in Electricity-Saving Targets

Notes: This figure shows saving targets over the period from 2011 to 2015. In 2011 only three regions had electricity-saving targets. In 2012 almost all areas in Japan had saving targets after the Japanese government shut down almost all the nuclear reactors. The population-weighted mean of the saving targets from 2011 to 2015 is 8.2 percent.

the lights during the daytime. Even for electronic toilet seat covers, the government suggested households set them on "energy-saving" mode, which was expected to reduce only about 1 percent of households' electricity consumption. These behaviors were encouraged from 9 AM to 8 PM from Monday to Friday. Online Appendix B shows a government advertising poster for the electricity-saving campaigns, with a detailed action list for households. Similar posters were also distributed by the government to schools, plants, restaurants, and public facilities.

Although none of the above measures was mandatory, the campaigns successfully shaped households' electricity consumption patterns. For example, in the Tokyo area in 2011, where the government set a saving target of 15 percent, 95.2 percent of survey respondents were aware of the electricity conservation campaigns (Tanaka and Ida 2013). This resulted in remarkable changes in their behaviors: 71.0 percent set a higher temperature when using air conditioners, 45.4 percent changed their refrigerator setting, and 81.0 percent reduced their standby power consumption. Fujimi, Kajitani, and Chang (2016) also find that the Japanese people were very responsive to these campaigns; for example, the average setting of air conditioners increased from 24.1°C to 26.4°C in the Tokyo and Tohoku areas during the first summer after the Fukushima accident.

Following the Fukushima accident, electricity prices were also raised. After shutting down the nuclear reactors, the power companies faced severe financial difficulties because they had to reutilize old and costly thermal plants. They therefore negotiated with the government to obtain approval to increase electricity prices. However, since the government was concerned that raising prices might trigger public dissent, such adjustments were not easy. After rounds of discussions and negotiations with the government, it took about two years to alter the regulated part of electricity prices (other parts increased during this period). Eventually, 8 out of 10 power companies raised electricity prices, with the annual average price increasing by about 5 to 6 percent. Presumably, the increased electricity price also helped reduce the total consumption.

Energy-saving campaigns are a bundle of policy treatments that include both pecuniary and nonpecuniary incentives. Panel B of Figure 1 summarizes the changes in electricity prices and electricity consumption per capita. From the figure, we can observe that electricity usage patterns are very different between summer and winter seasons; summer electricity consumption declined more than winter consumption, even though the price changes between the two seasons were mostly the same. These patterns suggest that the nonpecuniary incentives from the summer energy-saving campaigns induced additional electricity savings.

In panel C of Figure 1, we further plot the relationship between the electricity-saving targets and electricity consumption reductions (percent) in all ten regions in Japan. Each dot represents a region-year observation (ten regions from 2011 to 2015 in total), the x-axis indicates the energy-saving target in a given region and year, and the y-axis indicates the reduction in electricity consumption relative to the 2010 level (one year before the Fukushima Accident). We observe a strong correlation between the energy-saving targets and changes in electricity consumption in summer, with the estimated slope being -0.84, implying that a 1 percentage point increase in target is associated with a 0.84 percent decline in consumption. Winter electricity consumption also was slightly affected, suggesting that the summer campaigns might have a persistent impact. In Section V we will formally estimate how the saving targets (and electricity prices) affect consumption.

These large-scale energy-saving campaigns offer a rare opportunity to investigate the role of energy use, a critical instrument for climate adaptation, in protecting health outcomes. Because the Fukushima accident was unexpected, and because the resulting plant shutdowns varied from place to place for reasons unrelated to local climate or the local population's heat sensitivity, these circumstances create plausibly exogenous variations in electricity saving. Exploiting the energy-saving targets across different prefectures in Japan, we try to answer the following questions. First, does electricity conservation cause health damages by amplifying extreme temperature damages? Second, if electricity saving indeed does so, what are the driving mechanisms? Third, can we rule out alternative explanations that may confound our interpretations? Below, we use systematic data to address these questions and explore the channels through which electricity saving damages population health.

II. Data and Summary Statistics

A. *Data Sources*

Electricity-Saving Target Data.—We collect region-specific electricity-saving targets from 2011 to 2015 from the Electricity Supply-Demand Verification Subcommittee in each summer season. The Ministry of Economy, Trade, and Industry (METI) was responsible for advocating, promoting, and implementing the campaigns. The targets were calculated based on the deviation between expected demand and supply. The government tried to ensure sufficient backup capacity to avoid power blackouts. While other factors could affect the saving target (e.g., weather, regional electricity demand forecast, and the electricity-generating capacity of other power plants), the primary determinant of the saving target was a region's dependence on nuclear power before the accident. For example, the Kansai area, where nuclear power had generated 51 percent of its electricity, faced saving targets of 10 percent on average, while the Chubu area, where nuclear power had generated only 9.44 percent, faced a target of 3.4 percent. There are ten major power companies in Japan, and each of them nearly monopolized the provision of electricity in their service regions. As a result, households and firms within a prefecture were not likely to purchase electricity from other prefectures, implying little spillover of the electricity-saving targets.[4]

Mortality Data.—Mortality data are collected from the Vital Statistics reported by the Ministry of Health, Labor, and Welfare (MHLW), covering the deaths based on the whole Japanese population. Matching with population data, we construct prefecture-year-month mortality data (per 100,000) from 2008 to 2015. The mortality data in each age cohort are also collected. The classification of the cause-specific deaths follows the International Statistical Classification of Diseases, tenth Revision (ICD 10, 2013). Infectious diseases correspond to codes A00–B99, Neoplasms to C00–D48, Cardiovascular disease to I00–I99, Respiratory disease to J00–J99, and Accident to V01–V99 (traffic accident), W00–W84 (falling, drowning, and suffocation), X00–09 (fire accident), and X40–49 (exposure to hazardous substance). Others include deaths due to all the other causes.

Ambulance Use Due to Heatstroke.—We use ambulance transports due to heatstroke, a disease directly caused by heat stress. Ambulance use is common in Japan because it is free of charge. The data are provided by the Fire and Disaster Management Agency. The data cover all the ambulance use caused by heatstroke from June to September since 2008 and collected at the prefecture-year-month level. The data also include the ambulance use by age cohorts.

[4] There are a few prefectures in which two different power companies supply the electricity. In those cases two different regional saving targets were announced within the same prefecture. For example, in Shizuoka prefecture, about one-third of the electricity was supplied by Tokyo Electric Power Co. and the remaining two-thirds by Chubu Electric Power Co. In such cases we use the weighted average saving targets with the population as weights.

Climate Damage Mitigation Measures.—We collect three different variables on climate mitigation measures that are likely to be affected by the energy-saving policy. These three variables are Google Trends for "energy-saving (*Setsuden* in Japanese)," AC penetration rate, and spending on other cooling appliances (such as fans).

The keyword search for "energy-saving" is collected from Google Trends. It represents the intensity of the online search of the keyword in a prefecture during a specific period. To compare the search indexes across different prefectures and periods, we normalize the search indexes from 0 to 100, with 100 representing the maximum value during our study period and other values representing the proportion of the maximum. For example, in Tokyo prefecture the Google search index for energy-saving was 1.2 in 2010 and became 81.3 in 2011, suggesting that people's search intensities in Tokyo 2010 and 2011 were, respectively, 1.2 percent and 81.3 percent of the highest Google search index in our dataset. We aggregate the Google search index from May to September, including two months before the hottest season, because the campaigns were announced before the summer.

We collect data on air conditioner penetration rate and spending on other cooling appliances from the Family Income and Expenditure Survey. The survey is conducted by the Ministry of Internal Affairs and Communications (MIAC), and the data include detailed information about household income, expenditure, and ownership of different facilities and appliances. Nonsingle households from all regions in Japan are randomly chosen to answer the questionnaires. The survey collects data on households' spending on various appliances at the monthly level, and we use data from May to September to construct people's purchases of cooling appliances. We include data two months before the campaigns since households might buy cooling appliances before the hottest season. For air conditioner penetration, the survey only collects such data every five years. The government publishes the aggregated summary statistics for the capital cities online.

Weather Data.—The weather data are obtained from the Meteorological Agency of Japan. The micro weather information is collected by the Automated Meteorological Data Acquisition System, which consists of 1,300 real-time weather stations covering all of Japan. We collect data on temperature and precipitation from all the weather stations and calculate the prefectural temperature and precipitation by aggregating the station-level data. We use the inverse of the distance from the population center as the weights in aggregating the station-level data so that the closer stations are given greater weights. The weights are inversely proportional to squared distance.

B. *Summary Statistics*

We exclude three prefectures (Iwate, Miyagi, and Fukushima) from our primary analyses because these regions were directly damaged by the earthquake and tsunami and may not be readily comparable to other prefectures. Survivors in these prefectures might be different from people in other prefectures in terms of age structure, mental and physical health status, and access to medical resources. According to the Emergency Disaster Countermeasures Headquarters of the National Police

Agency of Japan (2019), more than 95 percent of the total number of deaths and missing people were from these three prefectures.[5]

Table 1 reports the summary statistics of the key variables. Column 1 shows the means and standard deviations using the entire sample. The mean per capita monthly electricity consumption is about 591 kWh in summer and winter. On average, the monthly mortality rate per 100,000 is 2.1 for those aged 0–19, 12 for those aged 20–64, and 302 for those aged above 65. The elderly account for more than 95 percent of all deaths. Nearly 9 people per 100,000 were transported by ambulance due to heatstroke each month from June to September. The mean air conditioner penetration rate is high (89 percent). An average Japanese person was exposed to 4.6 "hot" days (14.8 percent, mean daily temperature 25–30°C) and 0.27 "extremely hot" days (0.87 percent, mean daily temperature higher than 30°C) in each month.

Columns 2 and 3 summarize the means and standard deviations of key variables before and after the Fukushima accident. Column 4 reports percentage changes in the key variables between those periods. Results in panel A show that, on average, electricity consumption in summer dropped by 8.5 percent after the Fukushima accident, while winter consumption did not change much (−0.89 percent). In panel B we see a substantial increase in ambulance use caused by heatstroke (32 percent) after the Fukushima accident. Panel C shows that people were significantly more likely to search for "energy-saving" after the nuclear accident and that there is only a modest increase in the AC penetration rate (3.6 percent) and a significant increase in the purchase of non-AC cooling appliances (28 percent). These trends are consistent with the governments' efforts to provide massive information on energy savings and encourage households to rely more on electric fans rather than AC during the electricity-saving campaigns.

III. Empirical Strategy

Japan's large-scale energy-saving campaigns could bring about significant health damages because they restricted individuals' capacity to adapt to extreme weather. To investigate the impacts, we start by quantifying the temperature-mortality response function following Barreca et al. (2016) and Carleton et al. (2020). Specifically, we estimate

$$(1) \quad Y_{aiym} = \sum_l \sum_k TBin_{iymkl} \times \beta_{akl} + X_{iym} \times \pi_a + \delta_{aim} + \theta_{aym} + \mu_{aiy} + \varepsilon_{aiym},$$

where Y_{aiym} denotes the mortality rate for age group a in prefecture i in year month ym. We estimate the age-specific temperature-mortality relationship for three age groups (0–19, 20–64, above 65). $TBin_{iymk}$ denotes the number of days in prefecture i in year-month ym that fall into the kth temperature bins. X_{iym} is a vector of control variables, including the mean monthly precipitation, wind speed, and snow depth, that are classified into ten quantile groups, and their interactions with the age groups. ε_{iyma} represents the error term.

[5] Source: https://www.npa.go.jp/news/other/earthquake2011/pdf/higaijokyo_e.pdf

Table 1—Summary Statistics of the Key Variables

	Entire sample	By year		Percent change (2) to (3)
		2008–2010	2011–2015	
	(1)	(2)	(3)	(4)
Panel A. Energy consumption				
Monthly electricity use p.c., summer	591	623	571	−8.5%
(kWh)	(76)	(71)	(72)	
Monthly electricity use p.c., winter	591	594	589	−0.89%
(kWh)	(75)	(67)	(80)	
Monthly electricity use p.c., others	522	543	509	−6.3%
(kWh)	(60)	(52)	(61)	
Panel B. Health outcomes				
Mortality rate age 0–19	2.1	2.2	2.0	−10%
(per 100,000)	(0.71)	(0.72)	(0.69)	
Mortality rate age 20–64	12	14	11	−26%
(per 100,000)	(3.3)	(4.0)	(1.6)	
Mortality rate age over 65	302	297	304	2.3%
(per 100,000)	(37)	(34)	(39)	
Ambulance use due to heatstroke	8.8	7.3	9.6	32%
(per 100,000)	(10)	(9.0)	(10)	
Panel C. Adaptation technology				
Google Search for "energy-saving"	11	1.4	17	1,068%
(index)	(21)	(1.4)	(24)	
Air conditioner penetration rate	89	88	91	3.6%
(%)	(18)	(19)	(15)	
Number of purchases of non-AC cooling appliances	2.8	2.4	3.0	28%
(per 100 household)	(1.1)	(0.75)	(1.2)	
Panel D. Temperature				
Percent of days below 0°C	0.79	0.70	0.84	19%
(month, days)	(4.0)	(3.8)	(4.2)	
Percent of days between 0 and 5°C	4.0	3.6	4.3	21%
(month, days)	(7.3)	(6.7)	(7.6)	
Percent of days between 25 and 30°C	4.6	4.6	4.5	−1.8%
(month, days)	(8.7)	(8.8)	(8.7)	
Percent of days above 30°C	0.27	0.27	0.27	−0.72%
(month, days)	(1.4)	(1.6)	(1.3)	

Notes: Columns 1 to 3 report the means and standard deviations of the key variables using different samples. These statistics are weighted by population. Column 4 reports percentage differences between columns 2 and 3 in key variables. We use data from 2008 to 2015 except for AC penetration rate, which uses four waves in 1999, 2004, 2009, and 2014.

The equation includes three sets of fixed effects, prefecture-by-month fixed effects (δ_{im}), year-by-month fixed effects (θ_{ym}), and prefecture-by-year fixed effects (μ_{iy}). Prefecture-by-month fixed effects δ_{im} account for permanent unobserved prefecture-by-month determinants of mortality rates, particularly seasonal mortality rate. Year-by-month fixed effects absorb shocks unique to each time period but common to all prefectures (e.g., nationwide health policy and macroeconomic conditions), and prefecture-by-year fixed effects control for shocks unique to each prefecture each year (e.g., local economic conditions). These fixed effects are interacted with the age groups so that all the fixed effects can absorb flexible shocks unique to the age-specific mortality rates.

We define eight temperature bins in $TBin_{iymk}$: below 0°C, 0–5°C, 5–10°C, 10–15°C, 15–20°C, 20–25°C, 25–30°C, and above 30°C. The 15–20°C bin serves as the baseline group and is omitted in the regression. Thus, the coefficient for each temperature bin k (β_{ak}) measures the age-specific mortality risk of adding one day in this temperature bin k relative to a day in the 15–20°C bin. Because our regression includes prefecture-by-month fixed effects (δ_{im}), the temperature effect is identified using day-to-day temperature variations within the same prefecture in the same month. Intuitively, the model is estimated by the deviation in the mortality rate between an average month and a hotter or colder than average month in the same prefecture-month, conditional on the set of other fixed effects and controls. Whether a prefecture will have several hotter or colder days in a specific month (relative to the average) from year to year is likely random; therefore, the estimate of β_{ak} can have a causal interpretation.

Accurately estimating the temperature-mortality relationships also requires accounting for the intertemporal dynamics. On the one hand, a contemporaneous association between extreme temperature and mortality rate may be driven by the "harvesting effect," in which extreme temperature causes deaths that would soon occur anyway even in the absence of the event. If this were the case, the extreme temperature could increase mortality without significantly affecting overall population health, thus overstating the true health impacts. On the other hand, the effect of extreme temperature can accumulate over time. Failure to account for this "delayed effect" can result in understating the total health impacts. Regardless of which effect dominates, to account for the dynamic impacts, we include lagged temperature bins ($TBin_{iymkl}$) in l months prior to month m ($l \leq 2$) in Model (1) and then sum the estimated parameters in the current and previous two months ($\sum_l \beta_{akl}$) to compute the cumulative effects. In essence, we allow the temperature in month $l = 2$ (for example, July), $l = 1$ (August), and $l = 0$ (September) to affect the mortality rate in month $l = 0$ (September).[6]

Next, to test whether the energy-saving campaigns affect the temperature-mortality relationship, we augment equation (1) and estimate the following model:

$$(2) \qquad Y_{aiym} = \sum_l \sum_k TBin_{iymkl} \times STarget_{iyml} \times \gamma_{akl} + \sum_l \sum_k TBin_{iymkl} \times \beta_{akl} + \sum_l STarget_{iyml} \times \alpha_{al} + X_{iym} \times \pi_a + \delta_{aim} + \theta_{aym} + \mu_{aiy} + \varepsilon_{aiym},$$

where $STarget_{iym}$ is the energy-saving target in prefecture i in year month ym. We interact $STarget_{iym}$ with temperature bins ($\sum_k TBin_{iymk} \times STarget_{iym}$). The interactions tell us whether energy saving can reshape the temperature-mortality response function by reducing people's resilience to temperature shocks.[7]

[6] We include up to two months of lags because the hot (or cold) seasons in Japan last for at most three months each year.

[7] Regions are not administrative units, so there are few regional-level laws and regulations. While there are a few region-based infrastructure companies, such as power companies (Tokyo Gas Co., Osaka Gas Co.) and transportation companies (Japan Railway Hokkaido, Japan Railway East Japan), we are not aware of any concurrent policies that focused on individuals' energy consumption.

Recall that the energy-saving campaigns are a bundle of treatments, including both pecuniary and nonpecuniary incentives. So, any single element of the campaign, such as the intensity of media advocacy or electricity price, cannot precisely capture the intensity of the entire campaign. In contrast, the energy-saving target is a comprehensive measure that the central government directly sets in a top-down manner. Therefore, by focusing on this omnibus indicator, we can generate more intuitive interpretations of the policy by constructing reasonable policy-relevant counterfactuals.

Energy-saving targets were announced in the summer, but they might change energy-saving behaviors throughout the year. In fact, we observe that a larger energy-saving target indeed reduces winter electricity consumption, albeit on a smaller scale (Section V). Therefore, we assign the same value to the saving target ($STarget_{iym}$) throughout a campaign year, i.e., the target remains the same from each May (in which the summer target was announced) to the next April (a month before the target was renewed). We conjecture that the coefficients (γ_{ak}) of the interaction terms $(TBin_{iymk} \times STarget_{iym})$ will be positive for extremely hot or cold temperature bins. That is, the impact of extreme temperature on population health will be manifested, likely because saving energy can restrict individuals' resilience to heat or cold shocks. In addition, because the energy-saving campaigns only slightly reduced winter electricity consumption, we expect the impact of the campaigns on cold-related mortality to be weaker.

Similarly to equation (1), the regression omits the interaction term between the energy-saving target and the 15–20°C bin, so the coefficients measure how the energy-saving target alters the mortality risk in each temperature bin relative to the omitted group. We also investigate the intertemporal dynamics by including the lags of the interaction terms, in which we allow the policy's effects to diminish or accumulate over periods. Specifically, the policy's total effects are computed by summing up the estimates of the current and previous two months' effects, as denoted by $\sum_l \gamma_{akl} \left(where\ 0 \le l \le 2\right)$.

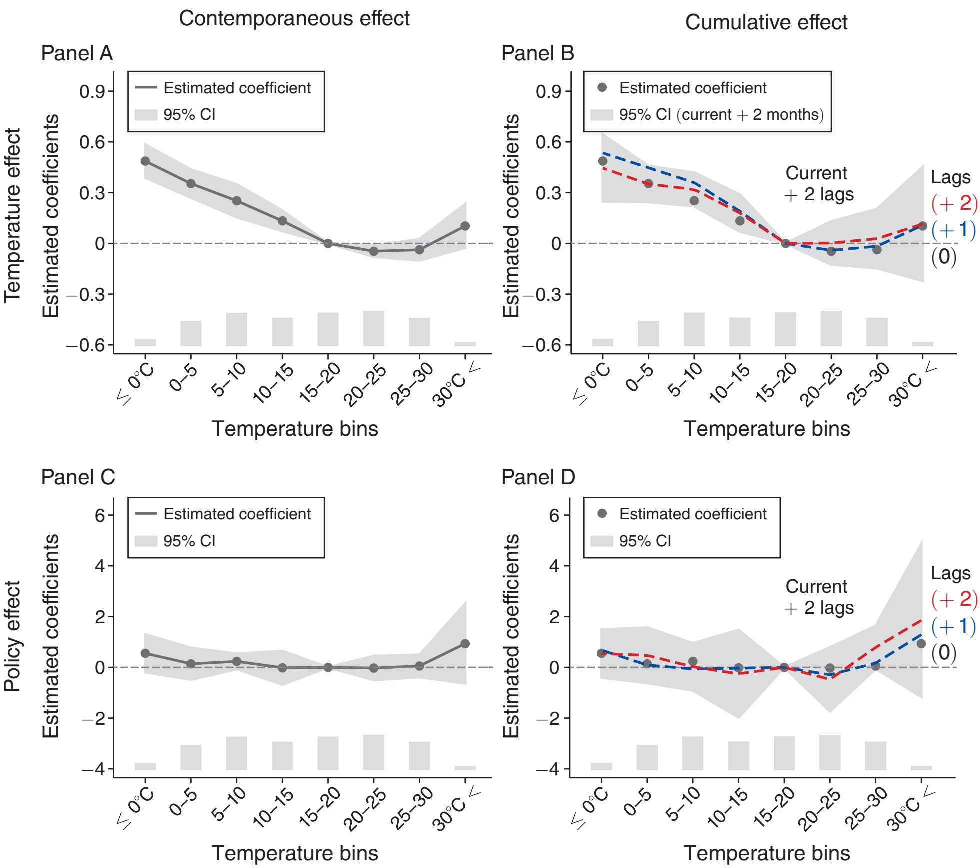
We cluster standard errors at the prefecture-by-age-group level to allow arbitrary correlation over time within the same age group in the same prefecture. All the regressions are weighted by population so that prefectures with larger populations are given greater weights. Intuitively, these weights help us estimate the impact of the policy on an average person instead of on an average prefecture.

IV. Results

A. *Main Results*

Temperature-Mortality Response Function.—We first fit equation (1) using data from 2008 to 2015 and summarize the age-adjusted temperature-mortality relationship in panels A and B of Figure 3 and panel A of Table 2. The age-adjusted mortality is calculated by taking the weighted average of age-specific mortality across three age groups with each group's corresponding population share as the weight.

In panel A of Figure 3, we find that the contemporaneous temperature-mortality relationship is U-shaped, with a steeper slope in the cold temperature bins. An



(*continued*)

Figure 3. The Effects of Saving Electricity on Mortality

average Japanese person has about four to five times higher mortality risk during cold days than hot days. Replacing a day in the 15–20°C bin by a day in the bins below 0°C and between 0–5°C will increase the monthly mortality rate by 0.49 and 0.35 per 100,000 people, respectively. In comparison, 1 day increase in the above-30°C range increases the mortality rate by 0.10.

In panel B we account for the dynamic impacts by including lagged temperature bins in the regression and summing up the estimates for the current month and the two lagged terms. The figure shows that adding lags does not shift the curve substantially, implying that temperature does not have significant harvesting effects or delayed effects at the monthly level. These results are consistent with previous studies that also documented the U-shaped temperature-mortality relationship. One minor difference is that an average Japanese is more susceptible to cold weather than an average American; Japan has a warmer climate than the United States, so people are less equipped to adapt to cold temperatures (Deschênes and Greenstone 2011; Barreca et al. 2016).

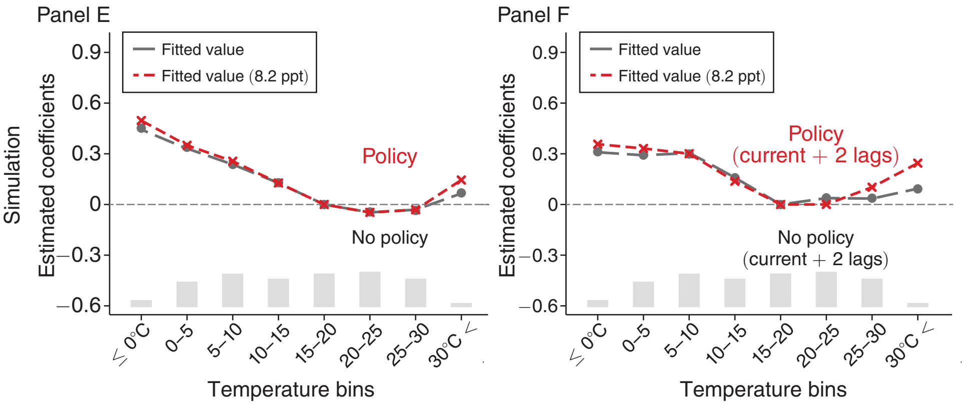


Figure 3. The Effects of Saving Electricity on Mortality (*continued*)

Notes: Panels A and B plot the temperature-mortality relationship during our study period (2008–2015), which is obtained by fitting equation (1). The dependent variable is the mortality rate (per 100,000). We first estimate the age-specific temperature-mortality relationship, and then we calculate the age-adjusted estimate by taking the population-weighted average across different age groups. The temperature bin between 15 and 20°C is omitted. Panels C and D plot the estimates on the interaction terms between each temperature bin and region-year-specific saving target (per 100 ppts) by fitting equation (2). The interaction term between the saving target and temperature bin between 15 and 20°C is omitted. Panels E and F plot the predicted temperature-mortality relationships when the saving target is 0 percent (no policy) or 8.2 percent (population-weighted mean). Panels A, C, and E report the contemporaneous effects (one-month temperature window), and panels B, D, and F report the accumulative effects (current month, one-month lag, and two-month lag). All the regressions include prefecture-by-month fixed effects, prefecture-by-year fixed effects, year-by-month fixed effects, and weather controls (precipitation, wind, and snow), and their interactions with age group dummies. Three prefectures heavily damaged by the earthquake are dropped. The number of observations is 12,672. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level. In each panel the gray bar represents the distribution of daily mean temperatures across eight bins. The full regression results are reported in online Appendix Table H1.

The Effects of the Energy-Saving Campaigns on Temperature-Mortality Response Function.—We fit equation (2) and summarize the estimated coefficients on the interaction terms between temperature bins and the energy-saving targets in panels C and D of Figure 3 (also in panel B of Table 2). These estimates indicate how the energy-saving targets reshape the temperature-mortality response function: a positive coefficient implies that energy saving amplifies the temperature damages in each bin.

We find that the energy-saving campaigns increase the mortality risks when the weather is extremely hot and extremely cold, and the effect is especially large during the hottest days (above 30°C). In panel C of Figure 3, when we estimate the contemporaneous impact, a 10 percentage point (ppt) increase in the saving target leads to a 0.094 increase in the mortality risk associated with an additional day above 30°C. This means that the average saving target (8.2 percent) will increase the impact of hot weather on the monthly mortality rate (per 100,000) by 0.077. Because the energy-saving campaigns also slightly reduced winter electricity consumption, we see a corresponding slight increase in cold-related mortality risk in the below-0°C bin. We observe a 0.055 increase in mortality for a 10 ppt increase in the saving target.

Table 2—Temperature-Mortality Relationship Modified by Electricity-Saving Policy

	Current month	Current + 1 month lag	Current + 1-month lag + 2-months lag			
Dependent variable	All	All	All	Age 0–19	Age 20–64	Age 65+
Mortality rate (per 100,000)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Temperature-mortality relationship						
Number of days below 0°C	0.49	0.53	0.45	−0.01	0.05	1.74
	(0.02)	(0.02)	(0.05)	(0.07)	(0.09)	(0.17)
Number of days 0–5°C	0.35	0.45	0.35	−0.00	0.03	1.37
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.08)
Number of days 25–30°C	−0.04	−0.02	0.03	0.02	−0.01	0.13
	(0.01)	(0.02)	(0.04)	(0.03)	(0.05)	(0.07)
Number of days above 30°C	0.10	0.11	0.11	0.03	0.01	0.42
	(0.03)	(0.05)	(0.08)	(0.08)	(0.09)	(0.18)
Number of prefectures	44	44	44	44	44	44
Observations	12,672	12,540	12,408	12,408	12,408	12,408
Panel B. Energy-savings and temperature-mortality relationship						
Number of days below 0°C	0.55	0.68	0.54	−0.27	−0.14	2.79
× Saving Target (100 ppts)	(0.17)	(0.22)	(0.22)	(0.41)	(0.33)	(0.54)
Number of days 0–5°C	0.14	0.09	0.47	−0.02	−0.06	2.12
× Saving Target (100 ppts)	(0.14)	(0.22)	(0.25)	(0.33)	(0.40)	(0.49)
Number of days 25–30°C	0.05	0.17	0.79	−0.28	0.16	3.08
× Saving Target (100 ppts)	(0.10)	(0.12)	(0.20)	(0.30)	(0.35)	(0.37)
Number of days above 30°C	0.94	1.29	1.85	−0.05	0.76	5.88
× Saving Target (100 ppts)	(0.36)	(0.44)	(0.70)	(0.94)	(1.06)	(1.54)
Number of prefectures	44	44	44	44	44	44
Observations	12,672	12,540	12,408	12,408	12,408	12,408
Prefecture-by-month fixed effects	Y	Y	Y	Y	Y	Y
Prefecture-by-year fixed effects	Y	Y	Y	Y	Y	Y
Year-by-month fixed effects	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y

Notes: Panel A shows the temperature-mortality relationship during our study period (2008–2015), which is obtained by fitting equation (1). We first estimate the age-specific temperature-mortality relationship and then calculate the age-adjusted estimate by taking the population-weighted average across different age groups in columns 1–3. The temperature bin between 15 and 20°C is omitted. Panel B shows the estimates on the interaction terms between different temperature bins and region-year-specific saving targets by fitting equation (2). The interaction term between the saving target and temperature bin between 15 and 20°C is omitted. Column 1 estimates the contemporaneous effect of temperature, column 2 includes one-month lag, and columns 3–6 include two-month lags. Weather controls include precipitation, wind, and snow. Three prefectures heavily damaged by the earthquake are dropped. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age groups. The full regression results are reported in online Appendix Tables H1 and H2.

Panel D suggests that the adverse policy effect can accumulate over time, especially during the hot months. We find that the cumulative impact (red and blue lines) is more substantial than the contemporaneous impact (gray dots) for temperatures above 25°C. When we use the three-month temperature window (red line), a 10 ppt increase in the saving target leads to a 0.079 and 0.185 increase in the cumulative mortality effects in the 25–30°C range and the above-30°C range. This, in turn, implies that an average Japanese, who faces the saving target of 8.2 percent, faces 0.064 and 0.152 higher mortality impact (per 100,000 people) from an additional day in each temperature bin, relative to the no-energy-saving scenario.

Based on the estimates from equation (2), we plot the temperature-mortality response functions with and without the average energy-saving targets (8.2 percent) in panels E and F of Figure 3. We observe that the energy-saving campaigns made the right side of the U-shaped curve steeper, indicating that people became less resilient to extremely hot weather. When accounting for the cumulative effect (panel F), the mortality risk caused by an additional day in the 25–30°C bin shifted from 0.038 to 0.102 (difference: 0.064). For the above-30°C bin, the risk increased from 0.093 to 0.245 (difference: 0.152). That is, the heat-related mortality risks increased about threefold after the large-scale energy-saving campaigns. For cold-related mortality, we observe only a modest increase due to electricity saving.

Estimates by Age Groups.—Existing studies have documented that elderly people are particularly vulnerable to extreme climate shocks (Deschênes and Greenstone 2011; Carleton et al. 2020). In Figure 4 (or columns 4–6 in Table 2) we investigate age-specific temperature-mortality relationships for three different age groups (0–19, 20–64, and 65+) and how they are reshaped by electricity savings. Here, we also account for the dynamic impacts by including both current and lagged temperature variables and estimate the impacts.

Panel A of Figure 4 shows that the temperature-mortality response function is almost flat for children and adolescents (those aged 0–19). Panel B also finds that the energy-saving policy does not alter the response function meaningfully in this group. Consequently, in panel C we observe that the predicted temperature-mortality relationships with and without policy interventions are almost identical. We find similar patterns among those aged 20–64: the temperature and policy effects are both close to zero in panels D–F.

In stark contrast, the mortality risk among the elderly (those older than 65) rises substantially when they are exposed to extremely cold or hot weather (panel G), and the energy-saving campaigns further make this U-shaped curve steeper on both sides (panel H). We observe that higher saving targets lead to a sizable increase in the mortality rate during the hot days (between 25–30°C and above 30°C) but a relatively moderate increase for cold temperatures (below 0°C and 0–5°C). The coefficients for both hot and cold temperature bins are statistically significant at the 5 percent or 10 percent level, even though some temperature bins have a very small share (e.g., only 0.87 percent of days have a mean temperature above 30°C in our data). Panel I also confirms that the impact of extreme temperature on mortality becomes significantly larger after the energy-saving campaigns. We thus conclude that the elderly population is most adversely affected by the energy-saving campaigns, which drives the baseline results.

B. *Mechanisms*

In this section to better understand the channels, we investigate how the energy-saving campaigns shape people's adaptive behaviors. Because we observe that electricity saving has a strong negative impact on individuals' health during the summer campaign time, in this subsection we focus on their behaviors during the summer season.

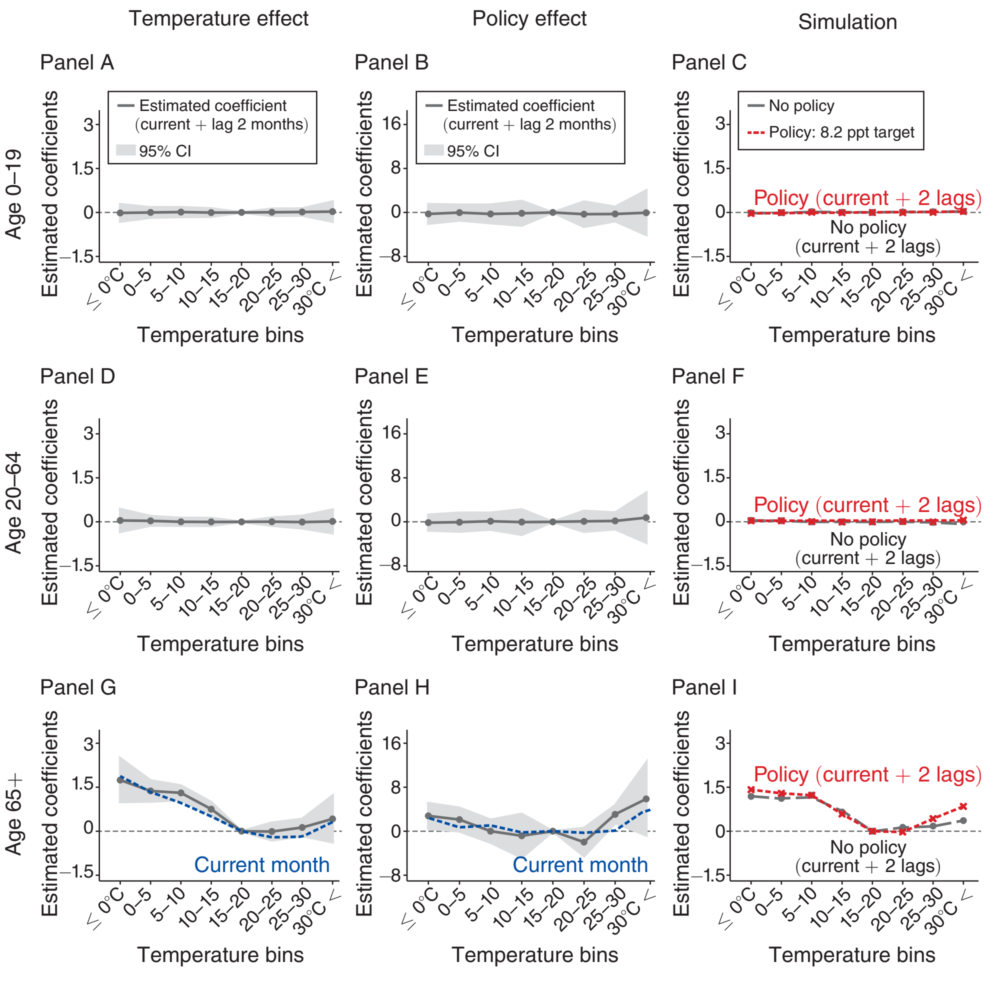


Figure 4. The Effects of Saving Electricity on Mortality by Age Groups

Notes: Panels A, D, and G plot the cumulative age-specific temperature-mortality relationship during our study period (2008–2015), which is obtained by fitting equation (1). The dependent variable is the mortality rate (per 100,000). The temperature bin between 15 and 20°C is omitted. To capture the dynamic impact, we include current month, one-month lagged, and two-month lagged temperature bins in the regression and report the total impacts. Panels B, E, and H plot the estimates on the interaction terms between each temperature bin and region-by-year-specific electricity saving target (per 100 ppts) by fitting equation (2). The interaction term between the saving target and the temperature bin between 15 and 20°C is omitted. Panels C, F, and I plot the predicted temperature-mortality relationships when the saving target is 0 percent (no policy) or 8.2 percent (population-weighted mean). The former is a gray dot line, while the latter is a red dot line, with the difference representing the effect of the energy-saving campaigns. All the regressions include prefecture-by-month fixed effects, prefecture-by-year fixed effects, year-by-month fixed effects, and weather controls (precipitation, wind, and snow). Three prefectures heavily damaged by the earthquake are dropped. The number of observations is 12,408. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age groups. The full regression results are reported in online Appendix Table H2.

In Table 3 we examine how people respond to the electricity-saving campaigns. In column 1 we investigate whether people seek more information online regarding how to save energy. The results show that a 10 ppt increase in the electricity-saving target increases the Google Trends search index for “energy-saving (in Japanese)”

Table 3—Energy Saving and Behavioral Responses

	Behaviors for adaptation		
	Google Search "energy-saving" (index) (1)	log (AC penetration rates) (2)	log (purchase of non-AC cooling appliances) (3)
Saving target (100 ppts)	160.61	−0.77	1.96
	(48.51)	(0.26)	(0.81)
Mean	11.10		
Predicted effect (8.2 ppts)	13.16	−6.3%	16.0%
Prefecture fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Controls	Y	Y	Y
Number of prefectures	44	44	44
Observations	352	176	352

Notes: These regressions report how the energy-saving targets affect people's behaviors. The analyses only focus on summer seasons. A 1 percentage point increase in the saving target implies that households and firms are encouraged to reduce electricity consumption by 1 percent relative to 2010 summer. The predicted effect size tells us how large the effect is when the saving target is 8.2 percent, which is the mean energy-saving target during our study period. Controls include four temperature bins (below 20, 20–25, 25–30, above 30°C), monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), population shares of age groups 0 to 19 and 20 to 64. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population. Standard errors are clustered at the prefectural level. Columns 1 and 3 use data from 2008 to 2015, and column 2 uses data from 1999, 2004, 2009, and 2014.

by about 16.06.[8] Given that the mean energy-saving target was 8.2 percent, we estimate that the energy-saving campaigns increased the search index by 13.16, a significant increase relative to the mean (11.0).

We then examine air conditioner (AC) ownership and the purchasing behaviors of non-AC cooling appliances. Existing empirical papers suggest the diffusion of air conditioners plays a crucial role in mitigating climate impact (Barreca et al. 2016). When AC usage is restricted, people will be exposed to higher indoor temperatures. Meanwhile, people also may reduce time spent indoors, which leads to increased exposure to high outdoor temperatures. Therefore, restriction on AC usage can result in a lower resilience to extreme heat and increased heat-related deaths during summer.

During Japan's energy-saving campaigns, because air conditioning accounted for nearly 50 percent of residential electricity consumption in summer, the government repeatedly encouraged households to substitute ACs with other cooling devices, such as fans, which consume less electricity. Thus, we expect that the AC penetration rate could decline, and the purchase of non-AC cooling appliances could increase. Columns 2 and 3 of Table 3 confirm that energy-saving campaigns indeed reduced the AC penetration rate and increased purchases of non-AC cooling

[8] There are some caveats of using Google Search as a measure of adaptive behaviors. First, people may use other Internet search platforms rather than Google, even though Google has the largest market share in Japan (around 70 percent in 2015). Second, people may search other words instead of "Setsuden (energy-saving)" when they try to figure out how to save electricity. Third, it is difficult to interpret the exact magnitude of the changes in search volume, as Google Trends is a composite index rather than a linear function of search volume.

appliances.[9] These results suggest that the energy-saving campaigns were highly effective; people paid attention to the campaigns and followed the guidelines to reduce conditioner usage.

Next, we examine ambulance use caused by heatstroke. The ambulance data are available from June to September each year, so we restrict our sample to the hot temperature bins in this analysis. The results are plotted in Figure 5.[10] Panel A confirms that the risk of heatstroke rises during high-temperature days. Compared to a day below 20°C, an additional day in the 27.5–30°C bin increases heat-related ambulance use by 0.40 per 100,000 people, and an additional day above 30°C does so by 0.80 per 100,000 people. Panel B of Figure 5 shows that the coefficients for the interactions between saving targets and hot temperature bins are all positive. We find that the risk of getting heatstroke during extreme heat days becomes more significant when people are encouraged to save electricity. As a result, the predicted temperature-ambulance response function becomes steeper after the policy implementation (panel C of Figure 5). The ambulance usage for the entire population increased from 0.35 to 0.43 (24 percent increase) per 100,000 people for the 27.5–30°C bin, and this number changed from 0.65 to 0.97 (49 percent increase) per 100,000 for the above-30°C bin.

The energy-saving campaigns increase the incidence of heatstroke (measured by ambulance use) in both the young (those aged 20–64) and old adult groups (those aged above 65), so both groups are affected by extreme heat. However, the younger adults who are affected can often recover from heat-related diseases, so we do not observe increased mortality for this group. In comparison, for the elderly population, many of them could die from extreme heat due to reducing electricity consumption.

C. *Alternative Explanations*

To rule out alternative explanations of the baseline findings, we examine the impact of saving targets on three different outcomes: health care quality, air pollution, and socioeconomic characteristics.

The first alternative explanation is that a deterioration in health care quality can drive the excess deaths caused by electricity saving during sweltering summer days. If higher saving targets somehow jeopardized the quality of medical services, more people would die. In that case the observed effect in our baseline model might not be driven by people becoming more vulnerable to extreme heat but by fewer people being saved. We think this is highly unlikely because the health care facilities were exempted from many electricity-saving actions.[11] In

[9] The result on AC penetration rate is based on a difference-in-difference setting, so the reduction in AC penetration comes from comparing the high-energy-saving group with the low-energy-saving group. Because the AC penetration rate is increasing over time, the result implies that fewer people buy and install AC in prefectures with higher saving targets. Our results do not necessarily mean that people got rid of their AC.

[10] In online Appendix C we also use Google Search for "Heatstroke." The results are very similar. During hot days, people look up the word more online, and energy-saving campaigns lead to increased search during very hot days.

[11] Hospitals and clinics were excused from many of the electricity-saving actions to avoid degrading health care quality. For example, to prevent blackout of the entire grid, the government planned to disconnect specific districts when the risk was high; health facilities were exempted from such planning to ensure a stable electricity supply. Source: http://www.kantei.go.jp/jp/singi/electricity_supply/20120518/taisaku.pdf

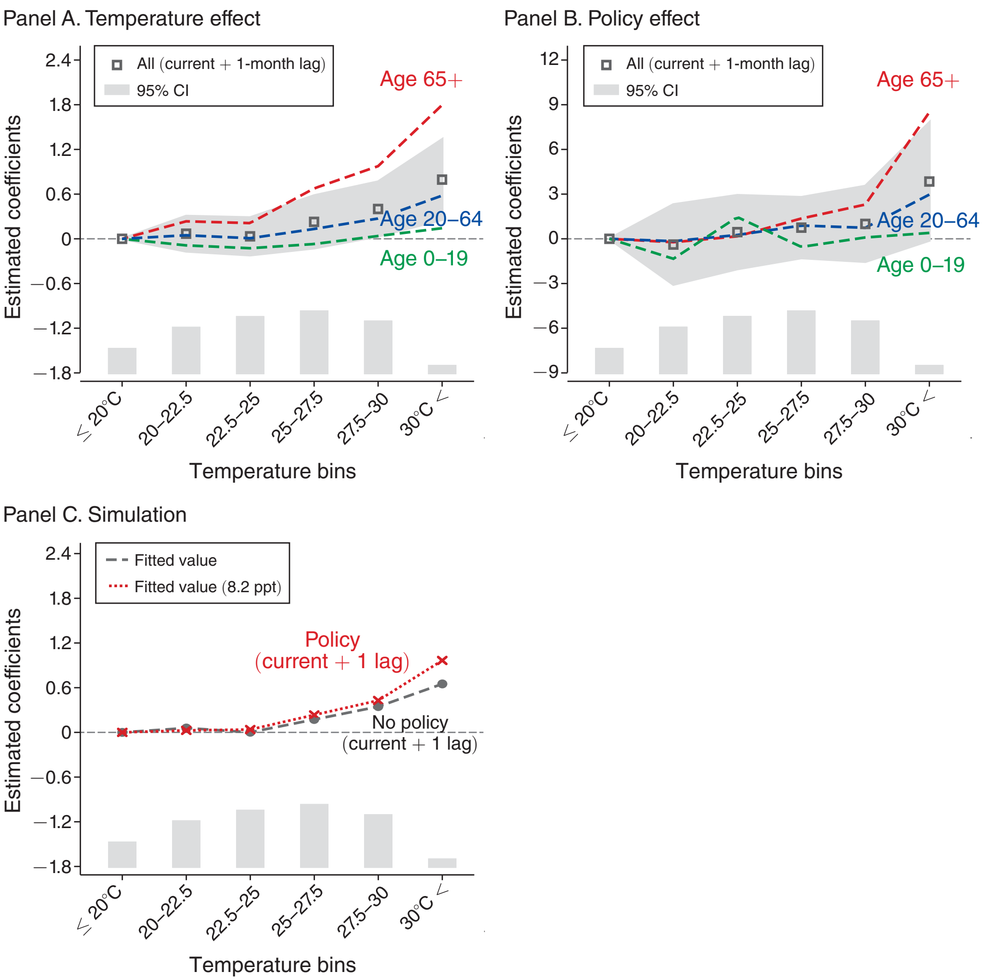


Figure 5. The Effects of Saving Electricity on Ambulance Use by Heatstroke

Notes: Panel A plots the cumulative effects of temperature on emergency ambulance use caused by heatstroke during our study period (2008–2015). The data are only available from June to September each year. The dependent variable is the number of ambulance services caused by heatstroke (per 100,000), and we estimate the cumulative effect by including both current and one-month lagged temperature as the explanatory variables and report the total impacts. We first estimate the age-specific temperature-ambulance relationship (green, blue, and red lines), and then we calculate the age-adjusted estimate (gray rectangles and shaded area) by taking the population-weighted average across different age groups. The temperature bin below 20°C is omitted. Panel B plots the estimates on the interaction terms between different temperature bins and the energy-saving targets (per 100 ppts). The interaction term between the saving target and temperature bin below 20°C is omitted. Panel C plots the predicted relationship when the saving target is 0 percent (no policy) or 8.2 percent (population-weighted mean). The former is a gray dotted line, while the latter is a red dotted line, with the difference representing the effect of the energy-saving campaigns. All the regressions include prefecture-by-month fixed effects, prefecture-by-year fixed effects, year-by-month fixed effects, weather controls (precipitation and wind), and their interactions with age group dummies. Three prefectures heavily damaged by the earthquake are dropped. The number of observations is 3,960. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age groups. In each panel the gray bar represents the distribution of daily mean temperatures across six bins. The full regression results are reported in online Appendix Table H3.

addition, in columns 1–2 of Table 4, we show that the numbers of doctors and nurses were not affected by the electricity-saving target. So the quality of health care was not likely dramatically changed by the electricity-saving campaigns. Also, Figure 5

TABLE 4—RULING OUT ALTERNATIVE EXPLANATIONS

	Health care resources		Air pollution		Socioeconomic variables	
	log (doctors per capita)	log (nurses per capita)	log (PM)	log (SO_2)	log (prefectural GDP p.c.)	Share of age 65+ (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Saving target (100 ppts)	0.027	−0.084	−0.265	0.116	−0.053	−0.003
	(0.057)	(0.130)	(0.705)	(0.241)	(0.033)	(0.019)
Predicted effect (8.2 ppts)	0.22%	−0.69%	−2.20%	0.95%	−0.43%	−0.03%
Prefecture fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Number of prefectures	44	44	44	44	44	44
Observations	176	176	350	352	352	352

Notes: These regressions report how the energy-saving targets affect health care quality, air pollution, and socioeconomic conditions. The analyses only focus on summer seasons from 2008 to 2015. A 1 percentage point increase in the saving target implies that households and firms are encouraged to reduce electricity consumption by 1 percent relative to the 2010 summer. The predicted effect size tells us how large the effect is when the saving target is 8.2 percent, which is the mean energy-saving target during our study period. Controls include four temperature bins (below 20, 20–25, 25–30, above 30°C), monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), population shares of age groups 0 to 19 and 20 to 64. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population. Standard errors are clustered at the prefectural level.

shows that the energy-saving campaigns significantly increased emergency ambulance use, implying that the hospitals' emergency departments were able to do their jobs during this period.

The second alternative explanation is that the deterioration in air quality could cause excess heat-related deaths. The argument is the following: after nuclear power was suspended, power companies had to reutilize old thermal power plants, which might have worsened air quality. If air pollution can somehow increase deaths from heat (which is conceptually unlikely), our observed impacts could be confounded. To examine such a possibility, in columns 3–4 of Table 4, we estimate the impact of saving targets on air pollution. It turns out that the effects on various pollutants are small and statistically insignificant. One potential reason for the null result is that the thermal power plants are located far away from the population centers, and their emissions would not significantly change the air pollution levels in the urban areas (online Appendix D shows the map of power plants and urban population centers). It is also possible that thermal power plants in Japan are simply not generating large amounts of pollutants, as the country has very tight air quality standards. For whatever reason, this test shows that air pollution is unlikely to drive the temperature-related mortality of saving energy.

Finally, in columns 5–6 we investigate whether electricity saving affects two basic socioeconomic variables: per capita GDP and share of the elderly population. The first concern is that, if the electricity-saving policy negatively affected the economy, this could lead to undesirable health consequences. In column 5 we find that the saving target does not affect per capita GDP. The second concern is migration. Because older adults are particularly vulnerable to heat shocks, they may have an incentive to migrate across regions to mitigate climate damage. In column 6 we cannot find that electricity saving affects the share of older adults (above 65 years old) in the population.

D. *Regional Heterogeneity and Cause of Deaths*

Regional Heterogeneity by Climate and Income.—In Figure 6 we investigate the heterogeneous impacts of electricity saving on heat-related mortality across different subgroups. Here we combine the two hottest temperature bins (25–30°C and above-30°C bin) into one group (above 25°C) to have sufficient variation in each subsample. In our sample only 0.87 percent of days have a mean temperature above 30°C, while 14.6 percent of days have a daily mean temperature between 25 and 30°C.[12]

We first examine heterogeneity based on the baseline summer temperature. Existing evidence shows that warmer regions are usually more able to mitigate heat damages because they are well adapted to the climate (Heutel, Miller, and Molitor 2021; Carleton et al. 2020). We find similar results: hot days (above 25°C) have no health effects in warmer prefectures, but they lead to increased health damages in colder prefectures (panel A of Figure 6). When we examine the impacts of electricity saving, we find the opposite: electricity saving increased heat-related mortality in hotter prefectures but not in cooler prefectures (panel B of Figure 6). Supposedly, people dwelling in warmer prefectures could be better adapted to the climate. However, once the government announced the electricity-saving policy, warmer regions were more severely affected and incurred more health damage because electricity saving reduces people's capacity to mitigate climate damage.

Next, we examine income heterogeneity. Previous literature suggests that higher income can mitigate negative temperature impacts (e.g., Burgess et al. 2017; Carleton et al. 2020) because it loosens households' budget constraints and allows them to buy ACs. The results in panel C of Figure 6 show that hot temperature (above 25°C) has a more significant impact on mortality in poorer prefectures, which is consistent with previous studies. In terms of policy impact, however, we have no prior knowledge of whether poorer or richer households should be more affected by the energy-saving campaigns. Poor households are generally more vulnerable to negative policy shocks, but they also own fewer electronic appliances, which reduces the adverse impacts of the electricity-saving policy. In panel D of Figure 6, we find that Japan's electricity-saving campaigns led to more substantial temperature damages in the less wealthy prefectures.

Temperature, *Energy Savings*, *and Cause-Specific Mortality*.—Existing evidence in epidemiology shows that high ambient temperature can place a burden on cardiovascular and respiratory systems. Higher body temperature can accelerate blood circulation, leading to higher blood pressure and increased heart and respiratory rates (Basu and Samet 2002). Therefore, we expect extreme hot temperatures to cause more deaths from cardiovascular and respiratory diseases than from other diseases.

[12] In practice, we estimate heterogeneity by including two interaction terms between temperature and saving targets that are specific to each group ($\sum_j \sum_k TBin_{iymk} \times STarget_{iym} \times Group_j$, $where\, Group_j = \{High, Low\}$). The temperature bin between 15 and 20°C is omitted, so the effects are relative to this omitted range.

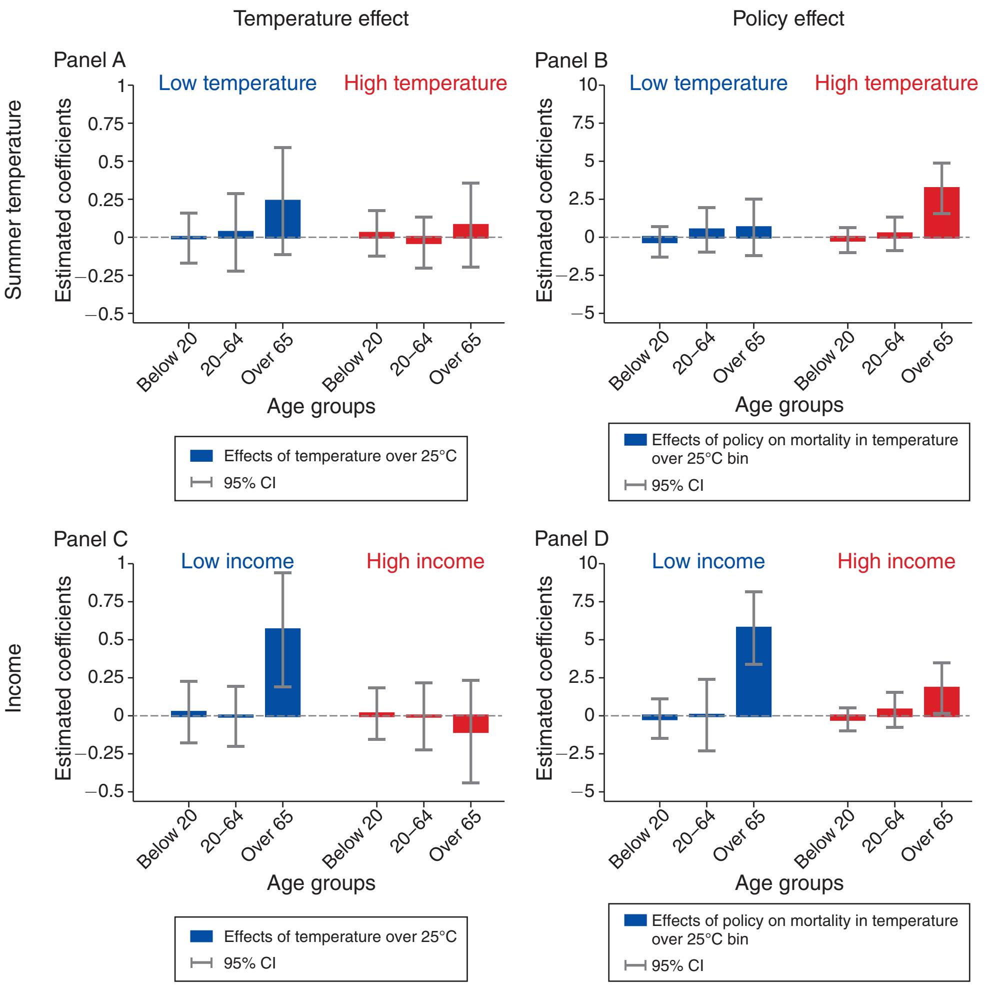


Figure 6. Heterogeneous Effects by Baseline Summer Temperature and Income

Notes: Each panel represents a separate regression. If a prefecture's mean summer temperature (or income) measured in 2008–2010 is below the median, we classify it as a low-temperature (or low-income) prefecture. In each regression we estimate group-specific estimates on the temperature effect or the energy-saving effect. The dependent variable is the mortality rate (per 100,000). To capture the dynamic impact, we include current month, one-month lagged, and two-month lagged temperature bins in the regression and report the total impacts. Panels A and C plot the age-specific effects of an additional hot day (above 25°C) on the mortality rate in each heterogeneous group. In the regression the temperature bin between 15 and 20°C is omitted. Panels B and D plot the age-specific estimates on the interaction terms between different temperature bins and the energy-saving targets (per 100 ppts) in each heterogeneous group. All the regressions include prefecture-by-month fixed effects, prefecture-by-year fixed effects, year-by-month fixed effects, weather controls (precipitation, wind, and snow), and their interactions with age group dummies. Three prefectures heavily damaged by the earthquake are dropped. The number of observations is 12,408. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age groups. The full regression results are reported in online Appendix Tables H4 and H5.

Figure 7 summarizes how hot temperature (above 25°C) affects cause-specific mortality rates and how the energy-saving campaigns alter the temperature-mortality relationships. In panel A we find that hot temperature indeed increases cardiovascular mortality. Panel B shows that electricity saving increases both cardiovascular and

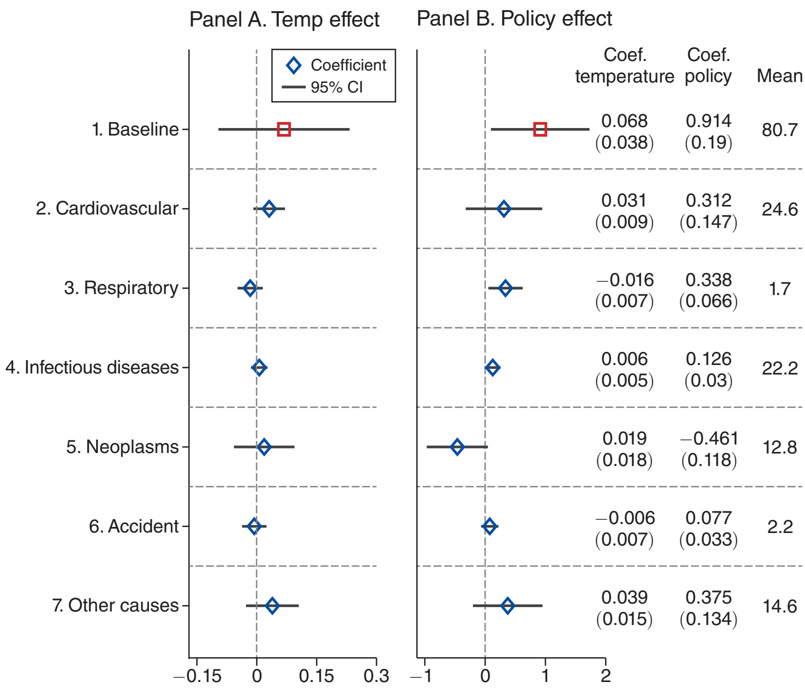


Figure 7. The Effects of Saving Electricity on Cause-Specific Mortality

Notes: Panel A plots the age-adjusted cumulative temperature-mortality relationship during our study period (2009–2015), which is obtained by fitting equation (1). The dependent variable is the cause-specific mortality rate (per 100,000). To capture the dynamic impact, we include current month, one-month lagged, and two-month lagged temperature bins in the regression and report the total impacts. The temperature bin between 15 and 20°C is omitted. The regression model uses 8 temperature bins, and here we only display the effects of the hottest 2 bins (above 25°C). Panel B plots the estimates on the interaction terms between different temperature bins and region-year-specific saving targets (per 100 ppts) by fitting equation (2). The interaction term between the saving target and temperature bin below 20°C is omitted. All the regressions include prefecture-by-month fixed effects, prefecture-by-year fixed effects, year-by-month fixed effects, weather controls (precipitation, wind, and snow), and their interactions with age group dummies. Three prefectures heavily damaged by the earthquake are dropped. The number of observations is 11,088. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age groups. The full regression results are described in online Appendix Tables H6 and H7.

respiratory mortality in the hot temperature bin, which accounts for about 70 percent of the total mortality impacts. Although some of these age-adjusted results are only marginally significant because they lack statistical power, all the coefficients for elderly populations are statistically significant at the conventional level (online Appendix Table H7).

Meanwhile, the effects of extreme temperature and the energy-saving campaigns on deaths caused by cancers (neoplasms), infectious diseases, accidents, and other causes are somewhat mixed. For example, deaths from infectious diseases are slightly increased by the policy. This could be because more people went outside for social interaction when their homes were too hot, which increased their risk of getting infectious diseases. Or it could be that hot indoor temperature makes people who have infectious diseases more vulnerable. We also see that the energy-saving campaigns slightly increased deaths due to "other causes" (statistically nonsignificant), which is consistent with the reality that it is often difficult to attribute certain deaths to heat directly (even when autopsies are performed). It is possible that some heat-related deaths are classified into other categories.

E. *Additional Checks*

Event Study.—The identifying assumption for the interacted model (equation (2)) is that the temperature-mortality relationship between high- and low-energy-saving regions should follow a similar trend in the absence of the energy-saving policy. Because the energy-saving policy primarily affects the temperature-mortality relationship during the hot seasons, we plot the dynamic changes in the interacted effects between "temperature>25°C" and "mean energy-saving targets" in panel A of Figure 8. The interacted effect one year before the Fukushima accident (i.e., 2010) was set to zero, so the estimated coefficients in other years indicate the interacted effects relative to 2010. We observe that the interacted effects become larger after the Fukushima accident, with the magnitude especially large for those aged above 65 from 2013 to 2015. In contrast, the estimated interacted effects before the Fukushima accident are all close to zero and statistically insignificant. We thus conclude that our baseline findings are not driven by systematic differences in heat-related mortality risks across different regions but by the energy-saving campaigns.

Randomization Inference.—To verify our results are not driven by spurious correlations, we compare the baseline estimates with those obtained from a randomization inference procedure. Specifically, we shuffle and reassign the observed saving targets using all the prefecture-by-month data 1,000 times. Then, we estimate the coefficients of the interaction terms between the shuffled saving targets and temperature, analogously to equation (2). We plot the distribution of these placebo coefficients for the interaction terms between the shuffled saving targets and temperature bins above 25°C in panel B of Figure 8. We find that 95 percent of the placebo coefficients are smaller than 0.65, while the real estimate is 0.86 (p-value: 0.01). In online Appendix Figure E1, we implement two other randomization inferences by shuffling temperature distributions only (panel A) and shuffling both the saving targets and temperature distributions (panel B). In both exercises we find that the real estimate lies above the 95 percentiles of the placebo estimates' distributions. We thus conclude that our finding that the energy-saving campaigns increased heat-related mortality is not driven by chance.

Robustness Checks.—Panels C and D of Figure 8 check the robustness of our main findings in several different ways. We start by including prefecture-specific quadratic time trends into the regression and find similar results. We then include income and employment data as additional controls and reach the same conclusion.[13] Third, we add air pollution (particulate matter and SO_2), and the results are again

[13] Because there is no official prefectural-level monthly income data, the regression uses prefecture-by-quarter-level unemployment rate and survey-based income level in prefectural capital cities as controls.

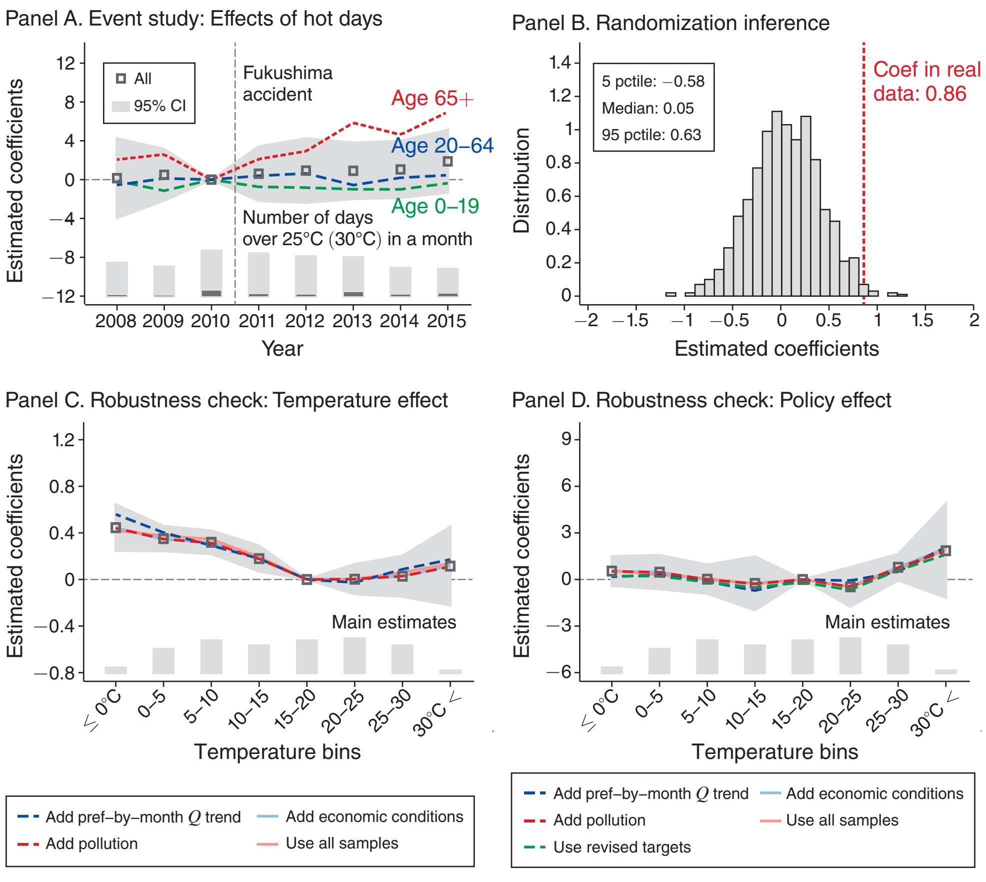


Figure 8. Event Study, Randomization Inference, and Robustness Checks

Notes: Panel A plots the event study estimates on the interaction terms between hot temperature bin (above 25°C) and region-specific saving targets (per 100 ppts) from 2008 to 2015. The interaction term between the energy-saving target and temperature bin between 15 and 20°C is omitted. The interaction term a year before the Fukushima accident (2010) is also omitted so that the estimates in each year can present the relative differences in a specific year to those in the omitted year. The gray bar denotes the frequency of the hot days, with a light gray bar representing 25–30°C and a dark gray bar representing above 30°C. Panel B reports the distribution of 1,000 age-adjusted coefficients of the interaction term between saving targets and hot temperature bins (above 25°C) obtained from the randomization inference procedure. In each iteration we use the reshuffled saving targets and estimate the main model (equation (2)). Panel C fits equation (1), and panel D fits equation (2) with different model specifications. More details of each robustness check can be found in the main text. In all the regressions the dependent variable is the mortality rate (per 100,000). To capture the dynamic impact, we include current month, one-month lagged, and two-month lagged temperature bins in the regression and report the total impacts. All the regressions include prefecture-by-month fixed effects, prefecture-by-year fixed effects, year-by-month fixed effects, weather controls (precipitation, wind, and snow), and their interactions with age group dummies. The number of observations is 12,408. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age groups. In panels C and D, the gray bar represents the distribution of daily mean temperatures across eight different bins. The full regression results are reported in online Appendix Tables H8 and H9.

quantitatively similar. The fourth robustness check uses all the prefectures' data. Recall that our main analyses exclude three prefectures that were heavily damaged by the earthquake and nuclear accident. The robustness regression includes samples in these three prefectures (but still excludes the first two months after the nuclear accident, i.e., March and April in 2011). The results remain very similar to the baseline estimates. We further examine whether the results are sensitive to slight revisions of the electricity-saving targets. In July 2012 the Kansai power company restarted one of the main nuclear reactors (Oi Nuclear Reactors), which eased the electricity shortage in the region. As a result, the saving targets were revised. Using the revised target as the explanatory variable does not affect our findings meaningfully.

In online Appendix Figure E2, as an alternative indicator for the energy-saving targets, we use the share of nuclear power plants that were shut down as the explanatory variable. As mentioned, a prefecture's saving target was calculated based on the difference between the expected electricity demand and supply, so a lower utilization rate of nuclear reactors would result in a more severe electricity shortage and a higher demand for electricity saving. We find that low utilization of nuclear reactors indeed significantly raised the mortality risk in hot temperature bins.

V. What Incentivizes People to Save Electricity?

Now that we have established that the energy-saving campaigns unintentionally increased mortality, an important question arises. What incentivizes individuals to change their behaviors? Is it because of price increases or nonpecuniary incentives that eventually lead to additional deaths?

Table 5 answers this question by using the classic price elasticity approach. In column 1 of panel A of Table 5, we first show that, after the nuclear accident, per capita electricity consumption fell by 14.3 percent in the summer seasons, compared to the scenario without the energy-saving campaigns.[14] Given that Japan's summer electricity price rose by 16.8 percent relative to the pre-accident period, for this reduction to be entirely explained by electricity price changes, the price elasticity would have to be as high as −0.85. However, various quasi-experimental studies suggest this is highly unlikely. Most price elasticity estimates range from −0.09 to −0.39 (e.g., Reiss and White 2005; Ito 2014; Ito, Ida, and Tanaka 2018; Neidell, Uchida, and Veronesi 2021; and Deryugina, MacKay, and Reif 2020).[15] To put this question differently, existing literature suggests that only 10–30 percent of the total reduction in summer electricity consumption can be explained by price changes, implying that the nonpecuniary incentives played a major role in encouraging electricity savings during the crisis. We further investigate electricity consumption in other seasons. We observe that the electricity consumption in winter and other seasons (spring and fall) was also reduced by about 5.9 percent for winter (panel B of Table 5) and 11.0 percent for spring and fall. The increase in electricity price can only explain about 40–70 percent of Japan's electricity consumption change in the winter and 20–40 percent in other seasons.

[14] This is computed by taking the difference between the actual electricity consumption and the predicted value in the absence of energy-saving policies, which is estimated using the pre-accident data. The prediction uses regional-by-month fixed effects, temperature (eight bins), precipitation, regional income, employment rate, and working populations. The predicted consumption serves as the counterfactual in the absence of the countrywide energy-saving campaigns.

[15] In online Appendix Table F1, we also estimate the price elasticity using our data. It is −0.14 to −0.16 in summer and is −0.41 to −0.33 in winter. These are slightly more elastic but similar to Neidell, Uchida, and Veronesi (2021).

Table 5—Decompose the Reduction in Electricity Consumption

	Reduction in electricity consumption			
	Total	Explained by price change	Contributions to the reduction in electricity by price change	Price elasticity
	(1)	(2)	(3)	(4)
Panel A. Summer				
Deryugina, MacKay, and Reif (2020)	−14.3%	−1.5% to −4.5%	11% to 33%	−0.27 to −0.09
Ito (2014)		−1.5%	11%	−0.09
Ito, Ida, and Tanaka (2018)		−2.3%	16%	−0.14
Neidell, Uchida, and Veronesi (2021)		0% to −3.0%	0% to 21%	−0.18 to 0.04 (summer)
Reiss and White (2005)		−6.5%	46%	−0.39
Panel B. Winter				
Deryugina, MacKay, and Reif (2020)	−5.9%	−1.5% to −4.4%	25% to 75%	−0.27 to −0.09
Ito (2014)		−1.5%	25%	−0.09
Ito, Ida, and Tanaka (2018)		−2.3%	39%	−0.14
Neidell, Uchida, and Veronesi (2021)		−2.0%	33% to 70%	−0.25 to −0.12 (winter)
Reiss and White (2005)		−6.4%	100%	−0.39

Notes: This table reports to what extent the electricity price change can explain the reduction in electricity consumption after the Fukushima accident. Column 1 reports electricity reduction relative to the counterfactual without the Fukushima accident. Column 2 shows the reduction in electricity consumption that can be explained by price change, and column 3 shows the percent of its contributions. We compute column 2 using the price elasticities in column 4 that are estimated by previous studies. Each panel corresponds to a different season.

Our findings contrast starkly with Ito, Ida, and Tanaka (2018), whose field experiment in Japan showed that price changes induce more electricity saving than moral suasion. The inconsistency could be attributable to differences between their research setting and ours. Ito, Ida, and Tanaka's (2018) experiment raised electricity prices by 160–320 percent during peak hours, while the Japanese government increased prices by only 5–6 percent each year after the Fukushima crisis.[16] Additionally, Ito, Ida, and Tanaka's (2018) moral suasion treatment did not accompany a credible risk of a blackout, but Japan indeed faced a severe risk of a power blackout during our study period.

The findings also help us explain the seemingly contradictory results between Neidell, Uchida, and Veronesi (2021) and ours. Neidell, Uchida, and Veronesi (2021) find that higher electricity prices increased cold-related winter mortality but not heat-related summer mortality after the Fukushima accident. This conflict is likely because the change in electricity prices can explain only a small portion of electricity-saving behaviors during Japan's energy-saving campaigns. Indeed, the number of premature deaths estimated by Neidell, Uchida, and Veronesi (2021) is an order of magnitude smaller than ours. They estimate that about 1,100 annual premature deaths are due to the increased electricity prices, while we estimate that the entire energy-saving campaigns could have led to nearly 7,710 premature deaths

[16] During past electricity crises, some governments raised electricity prices drastically to reduce demand. In the California electricity crisis, the electricity price was raised by 130 percent (from 10 cents to 23 cents per kWh) at the beginning; the state then used information campaigns to encourage saving electricity. Both interventions reduced electricity consumption significantly (Reiss and White 2008). In the Juneau (Alaska) electricity crisis, electricity price increased 500 percent for 45 days (Leighty and Meier 2011), which led to a large reduction in electricity consumption.

each year (see next section).[17] Therefore, focusing on electricity price changes after the Fukushima accident would understate the importance of electricity consumption in protecting people from extreme weather.

To augment these analyses, we provide two sets of additional results in online Appendix F. First, in online Appendix F1 we introduce a machine learning technique to decompose the factors driving electricity reductions. We predict electricity consumption in various scenarios with/without price change and the overall electricity-saving policies using machine learning algorithms. Then, by comparing them, we can derive which factors contributed to the reduction in electricity consumption. These analyses also show that the price change explains less than 20 percent of summer electricity saving (online Appendix Table F2). Second, in online Appendix Table F3, we directly regress electricity consumption on saving targets and electricity prices. The results show that a 1 percentage point change in the saving target is associated with a decline in consumption by 0.52–0.65 percent in summer and 0.15–0.39 percent in winter. Notably, controlling for electricity prices only slightly attenuates the effect of saving targets.

Why did price changes play a limited role in inducing electricity-saving behaviors? One potential explanation is that the electricity price changes were too modest to induce meaningful behavioral changes. The government was concerned that raising prices might trigger public dissent and was reluctant to allow the power companies to adjust the electricity price dramatically.[18] In fact, although some regions (such as Tohoku and Tokyo) faced severe power shortages after the Fukushima accident, it took nearly two years for the power companies to alter the electricity tariff. During our study period, eight out of ten power companies eventually raised electricity tariffs, but all the increases were modest in magnitude (usually a 5–6 percent increase in a year).[19] Given this, the only feasible option for the policymakers in Japan to significantly reduce individuals' electricity consumption was to exploit individuals' nonpecuniary incentives, which they did through the energy-saving campaigns.

VI. Interpretations

Back-of-the-Envelope Calculation.—To understand the welfare consequences of Japan's energy-saving campaigns, we conduct a back-of-the-envelope calculation and discuss its interpretations. To start with, we estimate annual premature deaths due to the energy-saving campaigns. Using the age-specific impact estimates (columns 4 to 6 of Table 2), the number of days in different temperature bins, the population in

[17] Neidell, Uchida, and Veronesi (2021) use data from capital cities. We adjust the population size to calculate the averted number of deaths.

[18] In many countries raising the electricity price is politically challenging. One reason is that nonlinear pricing could disproportionately affect the poor and exacerbate inequality (e.g., Borenstein 2012; Levinson and Silva 2022).

[19] Electricity prices in Japan are determined by three components: block pricing, energy surcharge, and Renewable Energy Power Promotion Surcharge (REPPS). The energy surcharge reflects changes in fuel cost and exchange rate, and the REPPS reflects subsidies for renewable energy. About 45 percent of the price increase during the post-Fukushima period can be explained by changes in block pricing, 35 percent by the increased cost of imported fuel, and 20 percent by the REPPS. Changes in REPPS and imported fuel price are highly unlikely to have been affected by the Fukushima accident.

different age groups, and the average electricity-saving targets (8.2 percent), we can derive the number of premature deaths caused by the electricity-saving campaigns, assuming constant impacts across locations and over time. Because we found null effects among those aged below 19 and 20–64, we focus on those aged older than 65. We find that approximately 7,710 premature deaths each year, which account for 0.7 percent of total mortality, could be caused by energy-saving policies. Notably, around 60 percent (about 4,500–5,000) of the excess deaths occurred during the summer.[20]

To better understand the magnitude of these impacts, in online Appendix G we compare our results with Barreca et al. (2016), who studied the historical temperature-mortality relationship in the United States. They find that the diffusion of air conditioners remarkably reduced the temperature-related mortality risk throughout the entire twentieth century. In particular, from 1960 to 2004, the mortality rate associated with an additional extremely hot day (above 90°F, 32.2°C) declined by about 0.20–0.25 percentage points every 10 years. In comparison, Japan's energy-saving campaigns led to an increased temperature-related mortality risk by 0.19 percentage points for an additional extreme heat day (above 30°C).[21] In other words, the reduction in a representative Japanese person's capacity to adapt to extreme climate caused by energy-saving behaviors is nearly equivalent to sending a representative American back ten years ago by a time machine.

The mortality effects can also be translated into economically meaningful monetary value using the concept of value of statistical life (VSL). Because most of the excess deaths were among people aged above 65, we use a discounted VSL for this elderly group. Based on the mortality statistics of different age groups in Japan, an average Japanese older than 65 has 13.88 years (16.72 percent) of expected life expectancy. We assume that people who died prematurely from the energy-saving campaigns would have had a similar life expectancy in the absence of such policies. Adopting the value of statistical life of US$(2010)8.0 million used by the US EPA, and assuming individuals have a constant willingness to pay for an additional year of life, we estimate that the energy-saving policy led to a loss in life years that is equivalent to US$10.31 billion annually from 2011 to 2015.[22]

In addition to the health cost, the reduction in electricity consumption could be another source of welfare loss; i.e., individuals could not consume the amount that they would like to due to either moral suasion or higher electricity price. Although estimating the welfare change is challenging,[23] it is informative to note that, during

[20] The energy-saving policy also led to additional ambulance transportation among those aged 20–64 by 3,232 and older than 65 by 3,047, which corresponds to a 21.2 percent increase in total, respectively.

[21] After the Fukushima accident, the monthly mortality rate associated with a day in a temperature bin above 30°C shifted from 0.12 percent to 0.31 percent in Japan. Barreca et al. (2016) finds that an additional day in a temperature bin above 32.2°C (above 90°F) increased monthly mortality rate by 0.92 percent from 1960 to 1970 but 0.18 percent from 1990 to 2004 in the United States.

[22] Ashenfelter and Greenstone (2004) estimated VSL is about US$1.54 million, and Rohlfs, Sullivan, and Kniesner (2015) and Lee and Taylor (2019) obtained US$9–11 million and US$8–10 million, respectively. We use US$8.0 million and assume that people who died prematurely from saving electricity had the same willingness to pay to add a year of life.

[23] Welfare calculation requires estimating the changes in consumer surplus and producer surplus associated with the reduction in electricity consumption (e.g., Barreca et al. 2016; Ito, Ida, and Tanaka 2018; Costa and Gerard 2021). Additionally, if households had a bias in optimizing the consumption level and energy-saving policy corrected it, this

the energy-saving campaigns, the entire nation's total electricity consumption was reduced by 84.09 billion kWh annually (based on Table 5), which is equivalent to US$15.70 billion (measured by 2010 US dollars) each year.

The benefits of the energy-saving campaigns are much more difficult to monetize because the main purpose of reducing electricity consumption is to avoid blackouts (which didn't happen). For example, if no one had saved energy, Japan could have experienced multiple blackouts that would have resulted in larger social damages. Alternatively, if the government had restarted the nuclear reactors to avoid blackouts, the decision could have triggered political distrust or instability. These benefits are difficult to measure. The only benefit that we can quantify is the reduction in carbon emissions associated with the reduction in total energy consumption. Based on the relationship between power generation and greenhouse gas emissions, we estimate that the energy-saving campaigns reduced CO_2 emissions by 0.043 billion tons annually, corresponding to about 3.4 percent of the nation's total carbon emissions. If we use US$(2010)44.2/ton as the social cost of carbon (US EPA 2021),[24] the monetized benefit is equivalent to US$(2010)1.91 billion. If we adopt a more aggressive estimate of the social cost of carbon, US$(2010)108.7/ton, recommended by Carleton and Greenstone (2021), the estimated climate benefit could be as much as US$(2010)4.70 billion.

If we make a simple comparison between the climate benefit from reducing energy consumption and the health cost, we see that the cost is substantially higher than the benefit. While this comparison is overly simplified and relies on many underlying assumptions on the costs and benefits calculations,[25] it does reveal that the health cost of reducing electricity consumption is substantial.

Policy Implications.—While Japan's energy-saving campaigns were designed to reduce the risk of power outages, they provided a rare opportunity for us to understand the welfare consequences of large-scale energy-saving policies. Across the globe, energy-saving policies have been widely used as a key strategy to mitigate climate change. So our findings could provide important insights on how to better design climate policies and manage climate risks.

First, our results imply that there is a trade-off between climate change mitigation and climate change adaptation. Climate mitigation policies (such as energy-saving policies) can reduce future climate disasters and thus save future lives. However, our study shows that such policies can kill people living now because they reduce individuals' capacity to adapt to extreme climate events. In reality, this dilemma has not been fully recognized by researchers and policymakers. For example, the

can bring marginal (dis)utility to households (e.g., Allcott and Taubinsky 2015). The energy-saving policy may also induce other types of social incentives, such as peer pressures or altruism, which can generate (dis)utility (e.g., Allcott and Kessler 2019). Estimating the welfare change by taking these into account is beyond the scope of our analysis.

[24] https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html (accessed July 4, 2021).

[25] First, the value of statistical life and the social cost of carbon can vary substantially depending on what assumptions are used for the calculation. Second, we do not account for several aspects of the costs and benefits, such as the morbidity and productivity cost of the limited AC usage and the benefits from the reduced risk of blackouts. Finally, we do not consider behavioral changes from energy-saving policies. For example, when indoor air conditioner usage is restricted, people may have utility gains from changing activities from indoor to outdoor (Leard and Roth 2019).

IPCC Fifth Assessment Report (AR5) states that "Adaptation and mitigation are complementary strategies for reducing and managing the risks of climate change (Summary for Policymakers 3)." However, at least in the short run, we show that there are scenarios where these two strategies can be incompatible. Policymakers, thus, should carefully consider the underlying trade-off before designing the climate policies, even in developed countries similar to Japan.

Second, given this "mitigation-adaptation" trade-off, we expect that low- and middle-income countries will face big challenges in dealing with climate change. On the one hand, in the next several decades, the developing countries are predicted to account for almost all the growth in energy demand and associated greenhouse gas emissions. Specifically, the emissions from these countries are predicted to grow by 5 gigatons (Gt) over the next two decades, while they will fall by only 2 Gt in developed countries and China (IEA 2021). If energy consumption follows an S-shaped curve, i.e., if people growing out of poverty rapidly increase energy consumption over the next few decades, the actual total energy demand and associated emissions will be even higher (Wolfram, Shelef, and Gertler 2012). So, whether the globe can successfully mitigate climate change will rely critically on whether developing countries can control their greenhouse gas emissions. On the other hand, these countries also face the highest temperature-related health risks. Today, the heat-related mortality risk for a representative Indian is still about 20 times higher than that for a representative American (Burgess et al. 2017), and the weather-driven mortality risk in the poorest countries is equivalent to that in the US during 1930–1959 (Geruso and Spears 2018). These imply that low- and middle-income countries need to substantially increase their energy consumption to better adapt to climate change. The second dilemma that we face is, therefore, that the future major emitters also will be the ones that need to rely most on energy consumption. This issue cannot be easily resolved without global coordination and the invention of disruptive technologies.

Third, our findings also imply that some widely used energy-saving policies might unexpectedly impose nonnegligible health costs; such policies include dynamic pricing (e.g., Wolak 2011; Jessoe and Rapson 2014), moral suasion (e.g., Reiss and White 2008; Ito, Ida, and Tanaka 2018), subsidies for energy conservation (e.g., Boomhower and Davis 2014; Ito 2015), and nudging (e.g., Allcott and Rogers 2014). In those studies the health impacts caused by energy savings are largely neglected. Future research is warranted to better assess the benefits and costs of these policies.

Finally, rather than focusing on reducing energy consumption, we believe a better way to address the climate change challenge is to adopt more energy-efficient appliances and promote clean energy. Energy-efficient technology enables individuals to enjoy the same level of functionality at a lower cost and with lower greenhouse gas emissions, while clean energy allows individuals to use electricity without emitting greenhouse gases. Although some studies suggest that, with current technology and policy schemes, these investments do not always deliver positive net societal benefits (Levinson 2016; Fowlie, Greenstone, and Wolfram 2018; Greenstone and Nath 2020), we believe this will change in the future when it becomes significantly cheaper to produce energy-efficient appliances and use clean energy.

VII. Conclusion

Energy consumption plays a central role in mitigating climate damage. Therefore, energy-saving policies that limit adaptation capacity may cause significant health damages. Such damages will be amplified when energy saving interacts with extreme weather because people depend critically on energy consumption to avoid exposure to extreme weather. This paper studies Japan's large-scale energy-saving campaigns following the Fukushima nuclear accident and documents three main findings.

First, we show that reducing electricity consumption indeed causes more people to die from extreme temperatures. We estimate that each year about 7,710 people could have died prematurely due to reducing electricity consumption. Most of the deaths were from the elderly population (aged above 65). Younger people also were more likely to get heatstroke and use more emergency ambulance services. Additionally, the energy-saving campaigns reduced the use of air conditioning and substituted air conditioners with alternative cooling appliances, such as fans. Because air conditioning plays a critical role in mitigating extreme climate damages (Barreca et al. 2016), reducing its usage is likely the key factor that increases the mortality risk associated with extreme temperature. Further, nonpecuniary incentives seem to be very effective in reducing individuals' electricity consumption during Japan's energy-saving campaigns, which eventually worsened the health outcomes. We estimate that only a small share of the reduction in electricity consumption can be explained by the increased electricity price, and most of the reduction is driven by nonpecuniary incentives.

Overall, our findings highlight the nonnegligible cost of saving energy, which is largely neglected in climate discussions and policy implementation. We believe what is captured in this study is just a small portion of the overall cost of energy saving, as the same logic can also be applied to other scenarios (such as air filtering and heating). Further, Japan's lessons can be more policy relevant in low- and middle-income countries, where people lack access to technology such as air conditioners and are more vulnerable to adverse climate shocks. Future research is needed to better understand how to balance the trade-off between climate adaptation and energy saving.

REFERENCES

- **Allcott, Hunt, and Judd B. Kessler.** 2019. "The Welfare Effects of Nudges: A Case Study of Energy Use Social Comparisons." *American Economic Journal: Applied Economics* 11 (1): 236–76.
- **Allcott, Hunt, and Todd Rogers.** 2014. "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation." *American Economic Review* 104 (1): 3003–37.
- **Allcott, Hunt, and Dmitry Taubinsky.** 2015. "Evaluating Behaviorally Motivated Policy: Experimental Evidence from the Lightbulb Market." *American Economic Review* 105 (8): 2501–38.
- **Almond, Douglas, Lena Edlund, and Mårten Palme.** 2009. "Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden." *Quarterly Journal of Economics* 124 (4): 1729–72.
- **Ashenfelter, Orley, and Michael Greenstone.** 2004. "Using Mandated Speed Limits to Measure the Value of a Statistical Life." *Journal of Political Economy* 112 (1): S226–S267.
- **Auffhammer, Maximilian.** 2018. "Quantifying Economic Damages from Climate Change." *Journal of Economic Perspectives* 32 (4): 33–52.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy* 124 (1): 105–59.

Basu, Rupa, and Jonathan M. Samet. 2002. "Relation between Elevated Ambient Temperature and Mortality: A Review of the Epidemiologic Evidence." *Epidemiologic Reviews* 24 (2): 190–202.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang. 2014. "Nonlinear Permanent Migration Response to Climatic Variations but Minimal Response to Disasters." *PNAS* 111 (27): 9780–85.

Boomhower, Judson, and Lucas W. Davis. 2014. "A Credible Approach for Measuring Inframarginal Participation in Energy Efficiency Programs." *Journal of Public Economics* 113: 67–79.

Borenstein, Severin. 2012. "The Redistributional Impact of Nonlinear Electricity Pricing." *American Economic Journal: Economic Policy* 4 (3): 56–90.

Burgess, Robin, Olivier Deschênes, Dave Donaldson, and Michael Greenstone. 2017. "Weather, Climate Change, and Death in India." LSE Working Paper.

Burlig, Fiona, and Louis Preonas. 2021. "Out of the Darkness and Into the Light? Development Effects of Rural Electrification, Energy Institute at Haas." Unpublished.

Carleton, Tamma, and Michael Greenstone. 2021. "Updating the United States Government's Social Cost of Carbon." Unpublished.

Carleton, Tamma A., and Solomon M. Hsiang. 2016. "Social and Economic Impacts of Climate." *Science* 353 (6304).

Carleton, Tamma A., Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon M. Hsiang, Andrew Hultgren, et al. 2020. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." NBER Working Paper No. 27599.

Chirakijja, Janjala, Seema Jayachandran, and Pinchuan Ong. 2019. "Inexpensive Heating Reduces Winter Mortality." NBER Working Paper No. 25681.

Costa, Francisco, and François Gerard. 2021. "Hysteresis and the Welfare Effect of Corrective Policies: Theory and Evidence from an Energy-Saving Program." *Journal of Political Economy* 129 (5): 1705–43.

Davis, Lucas W., and Paul J. Gertler. 2015. "Contribution of Air Conditioning Adoption to Future Energy Use under Global Warming." *PNAS* 112 (12): 5962–67.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4 (3): 66–95.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3): 740–98.

Deryugina, Tatyana, Alexander MacKay, and Julian Reif. 2020. "The Long-Run Dynamics of Electricity Demand: Evidence from Municipal Aggregation." *American Economic Journal: Applied Economics* 12 (1): 86–114.

Deschênes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics* 3 (4): 152–85.

Deschênes, Olivier, and Enrico Moretti. 2009. "Extreme Weather Events, Mortality, and Migration." *Review of Economics and Statistics* 91 (4): 659–81.

Dinkelman, Taryn. 2011. "The Effects of Rural Electrification on Employment." *American Economic Review* 101 (7): 3078–3108.

Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram. 2018. "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program." *Quarterly Journal of Economics* 133 (3): 1597–1644.

Fujimi, Toshio, Yoshio Kajitani, and Stephanie E. Chang. 2016. "Effective and Persistent Changes in Household Energy-Saving Behaviors: Evidence from Post-Tsunami Japan." *Applied Energy* 167: 93–106.

Geruso, Michael, and Dean Spears. 2018. "Heat, Humidity, and Infant Mortality in the Developing World." NBER Working Paper No. 24870.

Google Trends. 2021. "Setsuden and heatstroke". https://www.google.com/trends (accessed March 2021).

Graff Zivin, Joshua, and Matthew Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics* 32 (1): 1–26.

Greenstone, Michael, and Ishan Nath. 2020. "Do Renewable Portfolio Standards Deliver Cost-Effective Carbon Abatement?" https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3374942.

He, Guojun, and Takanao Tanaka. 2023. "Replication data for: Energy Saving May Kill: Evidence from the Fukushima Nuclear Accident." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/E170502V1.

Heutel, Garth, Nolan H. Miller, and David Molitor. 2021. "Adaptation and the Mortality Effects of Temperature across US Climate Regions." *Review of Economics and Statistics* 103 (4): 740–53.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D.J. Rasmussen, et al. 2017. "Estimating Economic Damage from Climate Change in the United States." *Science* 356 (6345): 1362–69.

IEA. 2021. *Financing Clean Energy Transitions in Emerging and Developing Economies*. Paris, France: IEA.

IPCC. 2014. *IPCC Fifth Assessment Synthesis Report-Climate Change 2014 Synthesis Report*. Geneva, Switzerland: IPCC.

Ito, Koichiro. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review* 104 (2): 537–63.

Ito, Koichiro. 2015. "Asymmetric Incentives in Subsidies: Evidence from a Large-Scale Electricity Rebate Program." *American Economic Journal: Economic Policy* 7 (3): 209–37.

Ito, Koichiro, Takanori Ida, and Makoto Tanaka. 2018. "Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand." *American Economic Journal: Economic Policy* 10 (1): 240–67.

Jarvis, Stephen, Olivier Deschenes, and Akshaya Jha. 2022. "The Private and External Costs of Germany's Nuclear Phase-Out." *Journal of the European Economic Association* 20 (3): 1311–46.

Jessoe, Katrina, and David Rapson. 2014. "Knowledge is (Less) Power: Experimental Evidence from Residential Energy Use." *American Economic Review* 104 (4): 1417–38.

Kawaguchi, Daiji, and Norifumi Yukutake. 2017. "Estimating the Residential Land Damage of the Fukushima Nuclear Accident." *Journal of Urban Economics* 99: 148–60.

Leard, Benjamin, and Kevin Roth. 2019. "Voluntary Exposure Benefits and the Costs of Climate Change." *Journal of the Association of Environmental and Resource Economists* 6 (1): 151–85.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020. "Experimental Evidence on the Economics of Rural Electrification." *Journal of Political Economy* 128 (4): 1523–65.

Lee, Jonathan M., and Laura O. Taylor. 2019. "Randomized Safety Inspections and Risk Exposure on the Job: Quasi-experimental Estimates of the Value of a Statistical Life." *American Economic Journal: Economic Policy* 11 (4): 350–74.

Leighty, Wayne, and Alan Meier. 2011. "Accelerated Electricity Conservation in Juneau, Alaska: A Study of Household Activities that Reduced Demand 25%." *Energy Policy* 39 (5): 2299–2309.

Levinson, Arik. 2016. "How Much Energy Do Building Energy Codes Save? Evidence from California Houses." *American Economic Review* 106 (1): 2867–94.

Levinson Arik, and Emilson Silva. 2022. "The Electric Gini: Income Redistribution through Energy Prices." *American Economic Journal: Economic Policy* 14 (2): 341–65.

Lipscomb, Molly, A. Mushfiq Mobarak, and Tania Barham. 2013. "Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil." *American Economic Journal: Applied Economics* 5 (2): 200–31.

Lobell, David B., Wolfram Schlenker, and Justin Costa-Roberts. 2011. "Climate Trends and Global Crop Production since 1980." *Science* 333 (6042): 616–20.

Ministry of Health, Labor, and Welfare. 2008–2021. "Vital Statistics." https://www.mhlw.go.jp/toukei/list/81-1.html (accessed April 2021).

Ministry of Internal Affairs and Communications, Fire, and Disaster Management Agency. 1999–2021. "Information about Heatstroke." https://www.fdma.go.jp/disaster/heatstroke/post3.html (accessed January 2021).

Ministry of Internal Affairs and Communications, Statistics Bureau of Japan. 1999–2021. "Family Income and Expenditure Survey." https://www.stat.go.jp/data/kakei/index.html (accessed April 2021).

Ministry of Land, Infrastructure, Transport, and Tourism, Japan Meteorological Agency. 2008–2021. "Historical Weather Data." https://www.data.jma.go.jp/gmd/risk/obsdl/ (accessed September 2021).

National Institute of Environmental Health Sciences. 2010. A Human Health Perspective on Climate Change. Durham, NC: National Institute of Environmental Health Sciences.

Neidell, Matthew, Shinsuke Uchida, and Marcella Veronesi. 2021. "The Unintended Effects from Halting Nuclear Power Production: Evidence from Fukushima Daiichi Accident." *Journal of Health Economics* 79: 102507.

Prime Minister of Japan and His Cabinet, Electricity Supply-Demand Verification Subcommittee. 2008–2021. http://www.kantei.go.jp/jp/singi/electricity_supply/ (accessed 2020).

Rehdanz, Katrin, Heinz Welsch, Daiju Narita, and Toshihiro Okubo. 2015. "Well-Being Effects of a Major Natural Disaster: The Case of Fukushima." *Journal of Economic Behavior and Organization* 116: 500–17.

Reiss, Peter C., and Matthew W. White. 2005. "Household Electricity Demand, Revisited." *Review of Economic Studies* 72 (3): 853–83.

Reiss, Peter C., and Matthew W. White. 2008. "What Changes Energy Consumption? Prices and Public Pressures." *RAND Journal of Economics* 39 (3): 636–63.

Rohlfs, Chris, Ryan Sullivan, and Thomas Kniesner. 2015. "New Estimates of the Value of a Statistical Life Using Air Bag Regulations as a Quasi-experiment." *American Economic Journal: Economic Policy* 7 (1): 331–59.

Tanaka, Makoto, and Takanori Ida. 2013. "Voluntary Electricity Conservation of Households after the Great East Japan Earthquake: A Stated Preference Analysis." *Energy Economics* 39: 296–304.

WHO. 2009. *Protecting Health from Climate Change: Global Research Priorities*. Geneva, Switzerland: WHO.

Wolak, Frank A. 2011. "Do Residential Customers Respond to Hourly Prices? Evidence from a Dynamic Pricing Experiment." *American Economic Review* 101 (3): 83–87.

Wolfram, Catherine, Orie Shelef, and Paul Gertler. 2012. "How Will Energy Demand Develop in the Developing World?" *Journal of Economic Perspectives* 26 (1): 119–38.