ONLINE APPENDIX FOR

Energy Saving May Kill:

Evidence from the Fukushima Nuclear Accident

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Appendix A. Data Appendix

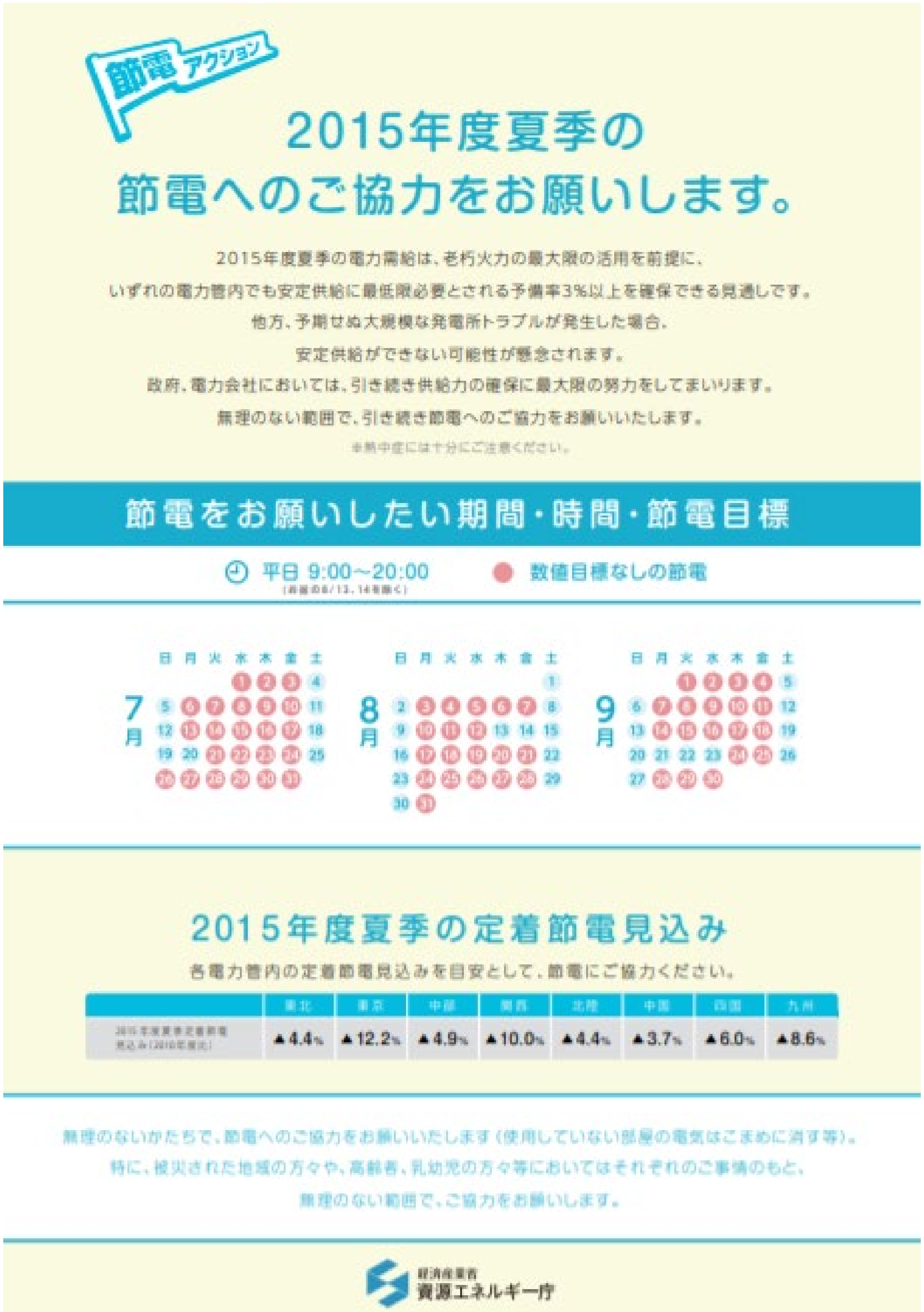
Electricity Data— Electricity consumption data are collected from the Federation of Electric Power Companies of Japan (FEPC). The FEPC reports regional-level monthly electricity consumption. We construct month-by-region level panel data on electricity consumption from 2004 to 2015. The regional-level average price is calculated by dividing the total electricity sales by the total consumption in each region. Data on total sales are obtained from the quarterly reports of each power company. The data on electricity generation from nuclear reactors are obtained from The Ministry of Economy, Trade, and Industry (Fig E1).

Socio-Economic Conditions—Data on prefectural population, GDP, and healthcare resources are obtained from the Statistical Observations of Prefectures (Table 4). The numbers of doctors and nurses are surveyed once every two years. Data on the quarterly unemployment rate are obtained from the Labor Force Survey provided by MIAC (Panels C and D in Figure 8). The monthly average household income is obtained from the Family Income and Expenditure Survey provided by MIAC (Panels C and D in Figure 8). The unemployment rate and household income are also collected at the regional level, and used in the regional-level analyses (Table 5 and Appendix F).

Air Pollution Data—Air pollution data are obtained from the National Institute for Environmental Studies. The concentrations of Suspended Particulate Matter ($PM_{7\sim8}$) and SO_2 are collected from around 1,900 monitoring stations covering all of Japan. We calculate the prefectural air pollution by averaging the readings from all the monitoring stations within a prefecture.

Appendix B. Background: Poster about Electricity-saving Policy

Figure B1. Poster for Electricity-Saving Campaign in Summer 2015: Page 1



Source: Setsuden.go.jp (節電.go.jp)

Poster for Electricity-saving Campaign in Summer 2015: Page 2

Source: Setsuden.go.jp (節電.go.jp)

Poster for Electricity-Saving Campaign in Summer 2015

Translation: page 1

We Appreciate Your Cooperation in the Electricity-saving Campaign in Summer 2015

It is expected that in the summer of 2015, we need to reserve 3% of the power capacity (the minimum requirement) to ensure a stable and safe electricity supply, with the assumption that some of the old thermal power plants will be utilized.

However, there is a risk that unforeseen problems with the power plants may jeopardize the electricity supply. The government and power companies will make the best efforts to strengthen the power supply capabilities.

Given this, we appreciate your cooperation in saving electricity.

* Meanwhile please take care of the risks of heatstroke

Period, Time and Goals for the Electricity-savings

Time	**9:00 ~ 20:00 on weekdays**
Period	**July, August, and September**
Goals	There is **no mandatory** electricity-saving goal

Expected Electricity-savings Targets

It will be appreciated if you refer to this guide and respond accordingly.

Tohoku	Tokyo	Chubu	Kansai	Hokuriku	Chugoku	Shikoku	Kyushu
4.4%	12.2%	4.9%	10.0%	4.4%	3.7%	6.0%	8.6%

It would be appreciated if you could cooperate and save electricity.
However, please manage the degree of electricity-saving and take care of yourself.
In particular, the elderly, children, and those living in areas that suffered from the earthquake should be cautious.

Ministry of Economy, Trade, and Industry

Agency for Natural Resource and Energy

Poster for Electricity-Saving Campaign in Summer 2015

Translation: page 2

For Households

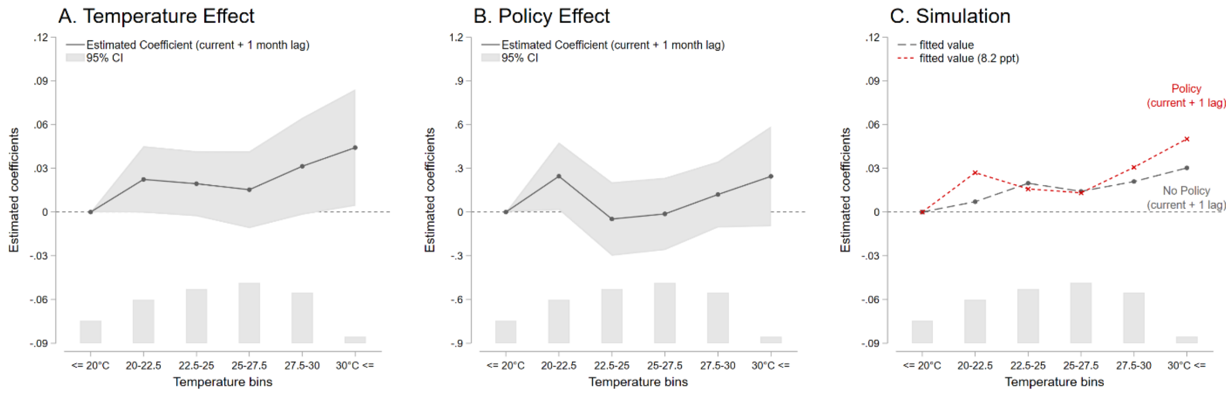
We would really appreciate it if you refer to **the expected percentage of electricity-savings in each region** and try to reduce your electricity consumption. The following action plan is provided for your reference.

Electricity-saving Menu and Expected Saving Percentages			
Air Conditioner	1	Set temperature at 28℃	**10%**
	2	Block sunlight with curtains	**10%**
	3	Turn off the air conditioner and use fans if possible	**50%**
Refrigerator	4	Change temperature setting from "strong" to "middle." Close the door of the refrigerator as soon as possible. Try not to put too many foods in the refrigerator.	**2%**
Light	5	Turn off the light when it is unnecessary	**5%**
TV	6	Set the TV at "energy-saving mode" and lower the brightness of its display. Turn off the TV when it is not used	**2%**
Electric Toilets	7	Set the toilets at "energy-saving mode."	**1%**
	8	Unplug the toilet when it is not used	
Rice Cooker	9	Cook a large volume of rice at once in the morning and keep it in the refrigerator for the rest of the day	**2%**
Standby Power	10	Turn off and unplug home appliances when they are not used.	**2%**

Meanwhile, please avoid using home appliances consuming much electricity during the daytime (**from 13:00 to 16:00**), such as electric kettle, electric griddle, toaster, dishwasher, and washing/drying machine.

Appendix C. Energy-Saving and Heatstroke

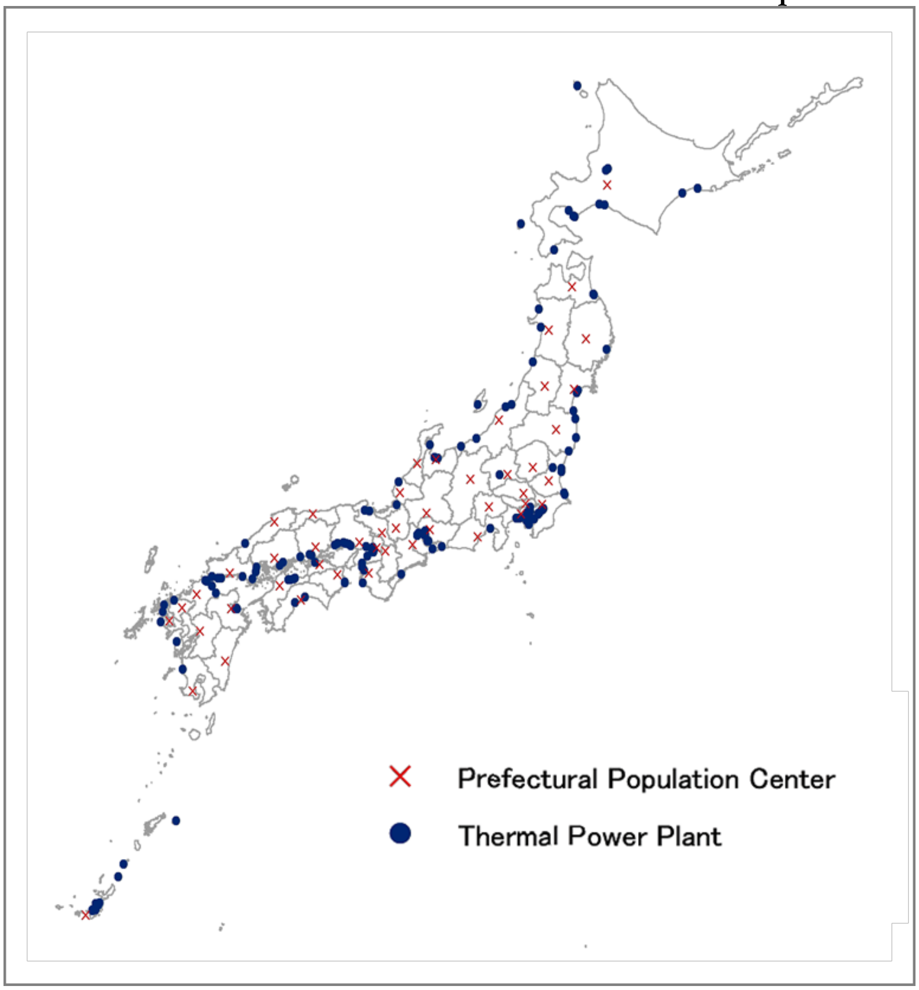
Figure C1. Energy Saving and Google Search Index for "Heatstroke"



Notes: Panel A plots the cumulative effects of temperature on the Google search index for "Heatstroke (熱中症)" during our study period (2008–2015). We use data from June to September, in which we have data on ambulance use by heatstroke. The dependent variable is the Google search index for "Heatstroke," and we use a 2-month (current month and 1-month lag) temperature window for this analysis. The temperature bin below 20°C is omitted. Panel B plots the estimates on the interaction terms between different temperature bins and region-year-specific saving targets (per 100 ppts). The interaction term between the saving target and the temperature bin below 20°C is omitted. Panel C plots the predicted impacts when the saving target is 0% (no policy) or 8.2% (actual population-weighted mean value). 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 policy. All the regressions include prefecture-by-month fixed effects, prefecture-by-year fixed effects, and year-by-month fixed effects, weather controls (precipitation, and wind), and share of people aged 0–19, 20–64, and above 65. Three prefectures heavily damaged by the earthquake are dropped. The number of observations is 1,320. The regressions are weighted by population, and standard errors are clustered at the prefecture level. In each panel, the gray bars represent the distribution of daily mean temperatures across different temperature bins.

Appendix D. The Energy-Saving Policy and Air Pollution

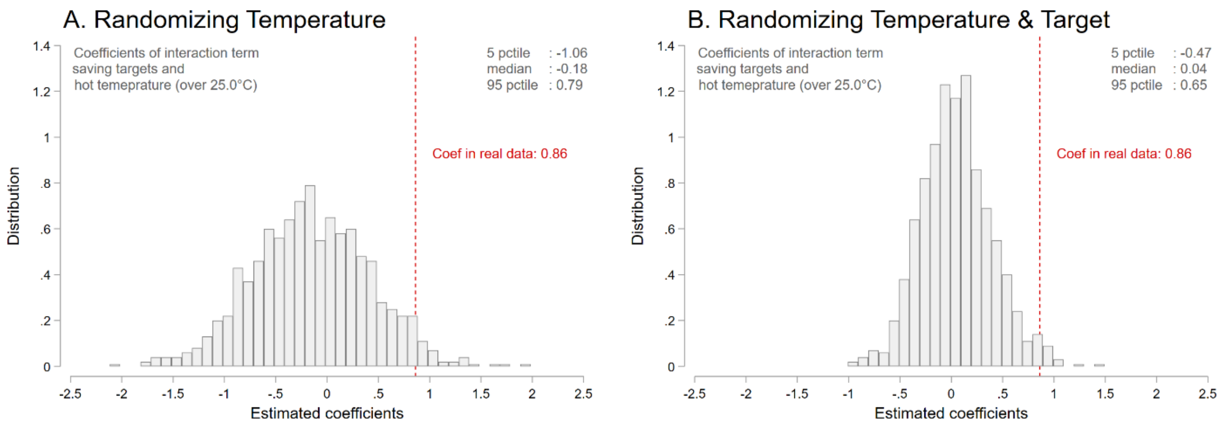
Figure D1. Locations of Thermal Power Plants and Prefectural Population Centers



Notes: This map shows the locations of thermal power plants and different prefectures' population centers. Power plants tend to locate in 1) big cities' neighborhoods to supply electricity and 2) distant from the population centers to reduce environmental externalities. On average, each plant is at least 48 km away from the closest prefectural population center.

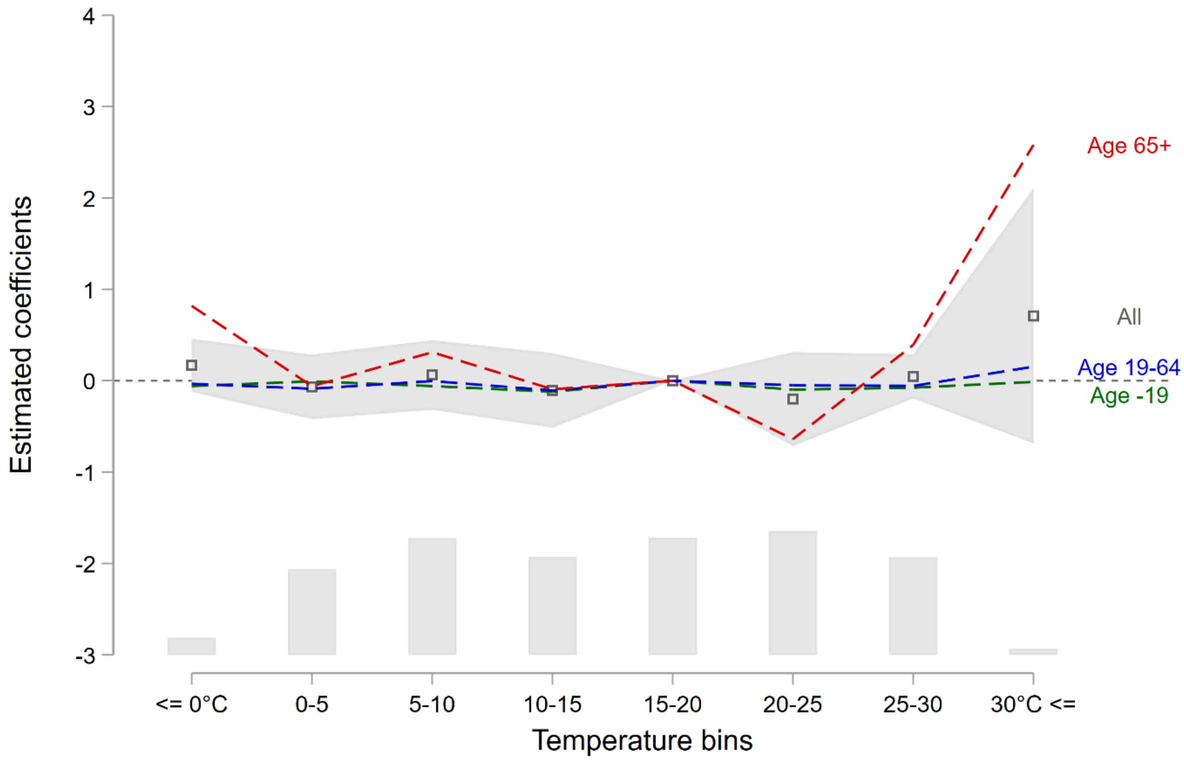
Appendix E. Additional Checks

Figure E1. Additional Randomization Inferences



Notes: These figures plot the distributions of 1,000 estimated coefficients of the interaction terms between the energy-saving targets (per 100 ppts) and hot temperature bins (above 25°C) obtained from two randomization inference procedures. The outcome variable is year by month mortality rate for different age groups. Panel A shuffled the temperature distributions (we shuffled prefecture-by-day temperature and summed them up to get shuffled prefecture-by-month data), and Panel B shuffled both the energy-saving targets and temperatures. 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.

Figure E2. Effects of Nuclear Shutdown on Mortality



Notes: The figure plots the estimates on the interaction terms between different temperature bins and the share of non-utilized nuclear power in a prefecture's power-generating process. If nuclear power plants had supplied 30% of the total electricity before the accident (2008-2010), and all of them were shut down after the accident, then we define the share of non-utilized nuclear as 30%. The positive coefficient implies that the temperature damages will increase when the region shuts down more nuclear reactors. In the regression, 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 summed up all the coefficients. The temperature bin between 15-20°C is omitted. 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), which are interacted by 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. In each panel, the gray bars represent the distribution of daily mean temperatures across 8 bins.

Appendix F. Pecuniary and Non-pecuniary Incentives on Electricity Consumption

APPENDIX TABLE F1—PRICE ELASTICITY OF ELECTRICITY CONSUMPTION PER CAPITA

Independent variable:	log (Electricity Consumption per capita)		
log (Average Price)	(1)	(2)	(3)
Panel A. Using All Seasons			
Baseline	-0.16	-0.26	-0.28
	(0.06)	(0.12)	(0.14)
Panel B. Subsample Analysis by Season			
Summer	-0.14	-0.16	-0.14
	(0.20)	(0.20)	(0.20)
Winter	-0.36	-0.33	-0.41
	(0.06)	(0.15)	(0.18)
Other seasons	-0.10	-0.18	-0.24
	(0.07)	(0.13)	(0.12)
Region FE	Y	Y	N
Year FE	Y	N	N
Month FE	Y	N	N
Year-by-Month FE	N	Y	Y
Region-by-Month FE	N	N	Y

Notes: The regressions use pre-Fukushima-accident data to estimate the price elasticities. We use regional data (10 regions in Japan) from Jan 2004 to Feb 2011. Regions that were heavily damaged by the Fukushima accident (Tohoku and Tokyo regions in March and April 2011) are dropped. Panel A uses data from all seasons, while Panel B uses observations separately for different seasons. The summer season corresponds to months from July to September and the winter season from December to February. Controls include temperature bins (7 bins), monthly precipitation (log), income (log), the employment rate (log), and the share of the working population. The numbers of observations are respectively 860 (all), 210 (summer), and 300 (winter). All regressions are weighted by population. Standard errors are clustered at the regional level.

F1. Machine Learning and Factors Driving Electricity Saving

To understand whether individuals' behavioral changes were driven by the price increase or the nonpecuniary incentives, we complement our main analyses by using machine learning techniques to construct a plausible counterfactual, following Jarvis et al. (2022) and Burlig et al. (2021). Machine learning allows us to maximize the predicting power (See Choi and Varian, 2012; Mullainathan and Spiess, 2017 for recent reviews). [1]

Specifically, we first train a region-specific prediction model using pre-accident data (monthly data from 2004 to 2011) and three machine learning algorithms: Random Forest (RM), Least Absolute Shrinkage and Selection Operator (LASSO), and Artificial Neural Network (ANN). In each machine learning model, electricity consumption per capita (log) is a function of electricity price (log), weather, socio-economic status, and month fixed effects.

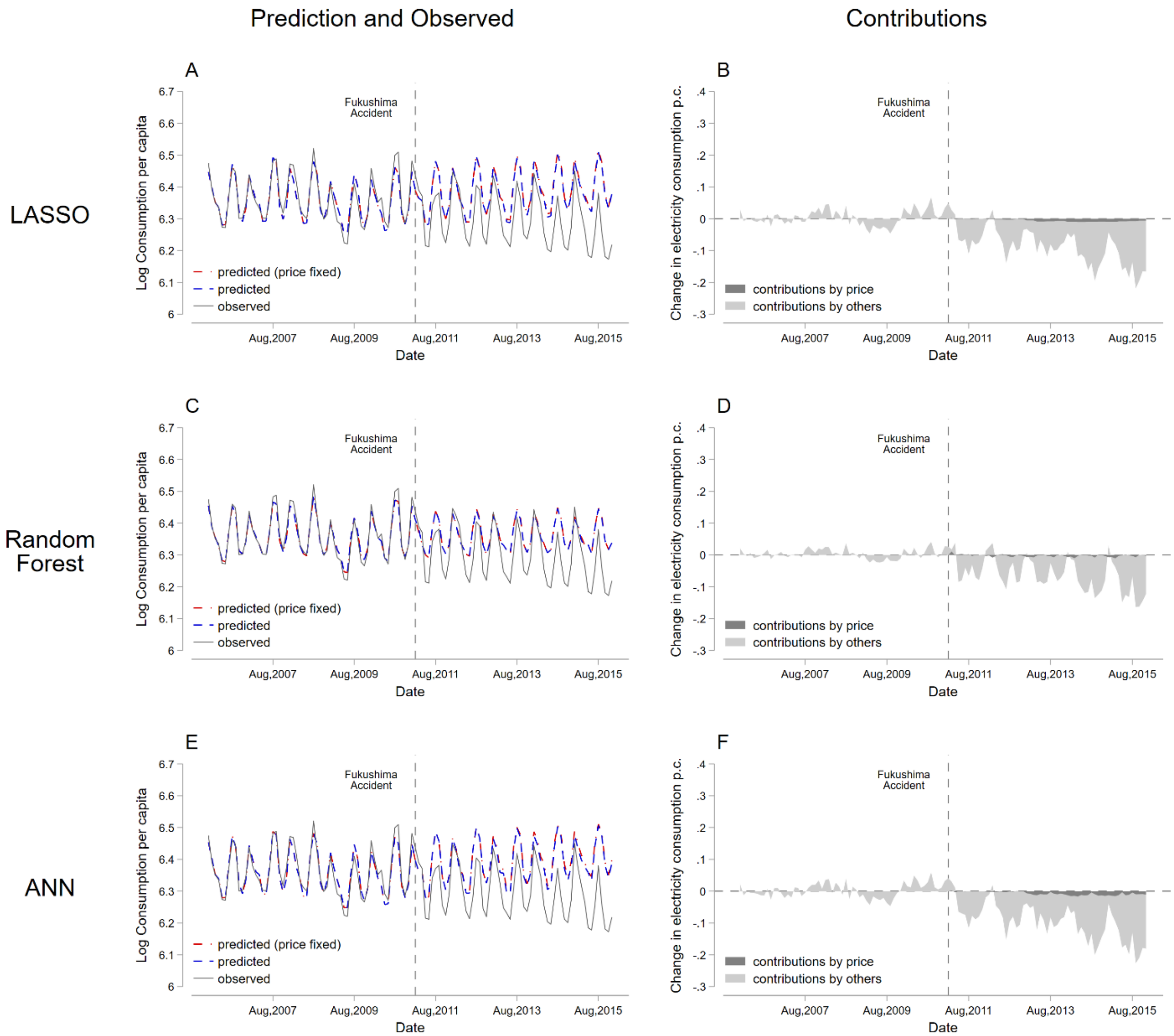
In the second step, using the trained models, we generate two out-of-sample predictions. The first prediction uses post-accident electricity prices and post-accident weather and socio-economic variables as inputs. The second out-of-sample prediction uses pre-accident electricity prices, and post-accident weather and socio-economic variables as inputs. The difference between these two tells us to what extent the rise in post-accident electricity prices can decrease electricity consumption. If we further compare the predicted values with the actual post-accident consumption, we can infer how much electricity-saving can/cannot be explained by price changes.

Appendix Figure F1 plots the two counterfactual predictions from LASSO (Panel A), Random Forest (C), and ANN (E), and the real consumption data over time. The blue dot line and red dash line represent the first and second predictions, while the solid black line represents the actual consumption. The difference between the red and blue lines approximates the effect of the increased price, while the difference between the blue and black lines measures the effect of non-pecuniary incentives (i.e., any incentives other than price) on electricity-saving. These differences are summarized in Panel B, D, and F, with dark gray denoting the price contributions. The price change can only induce a modest decline in electricity consumption, while the non-pecuniary incentives make an enormous contribution. The graph also shows that the effects of non-pecuniary incentives are more substantial in summer.

[1] Machine learning is becoming increasingly popular in economics and other social science studies. For example, it has been used to predict elderly mortality (Einav et al., 2018), poverty (Blumenstock et al., 2015), hygiene inspections (Glaesler et al., 2016), and judges' decisions (Kleinberg et al., 2018).

We then calculate population-weighted national estimates and report them in Appendix Table F2. Overall, electricity per capita declined by 7.8–13.2% in summer (Column (1)). Higher electricity prices can explain 4.0~4.7% of its reduction (Column (3)). In winter, the electricity consumption declined by 1.3–4.7%, and the price change contributed to 12.7–32.9% of the reduction. These results are qualitatively consistent with our "price elasticity approach," implying non-pecuniary incentives play a vital role in shaping people's energy conservation behaviors.

Figure F1. Prediction Results of LASSO, Random Forest and ANN



Notes: Using month-by-region data from 2004 to 2011, we train region-specific machine learning models of log (consumption per capita). Panels A and B summarize the results from LASSO, C and D from Random Forest, and E and F from ANN. Panels A, C and E show the predicted and actual electricity consumption per capita over the years. In each panel, the red dot line represents the counterfactual when using the price measured in the pre-accident period and other variables in the post-accident period, while the blue line uses the prices and other variables in the post-accident period. The black line represents the actual log (consumption per capita). The difference between the red and blue lines shows the effects of price changes while the difference between the blue and black lines shows the effects of the saving campaigns. In Panels B, D, and F, the former is described as the dark grey area, while the latter is described as the light grey area.

APPENDIX TABLE F2— DECOMPOSE THE REDUCTION IN ELECTRICITY CONSUMPTION USING MACHINE LEARNING

	Reduction in Electricity Consumption		
	Total	Explained by Price Change	Contributions to the Reduction in Electricity by Price Change
	(1)	(2)	(3)
Panel A. LASSO			
Summer	-12.5%	-0.6%	4.7%
Winter	-3.9%	-0.5%	12.7%
Others	-10.2%	-0.5%	5.4%
Panel B. Random Forest			
Summer	-7.8%	-0.3%	4.3%
Winter	-1.3%	-0.4%	32.9%
Others	-9.0%	0.0%	-0.2%
Panel C. ANN			
Summer	-13.2%	-0.6%	4.5%
Winter	-4.7%	-0.8%	18.1%
Others	-11.1%	-0.8%	7.0%

We use various machine learning algorithms to calculate how much the price change can explain the reduction in electricity consumption. Column (1) represents the reduced electricity consumption, which is calculated by taking the difference between real consumption and predicted consumption. Column (2) compares two counterfactuals: one with price change and one without price change. Column (3) shows the contribution of electricity prices to explain the reduction in electricity prices. See the main text in Appendix F1 for details.

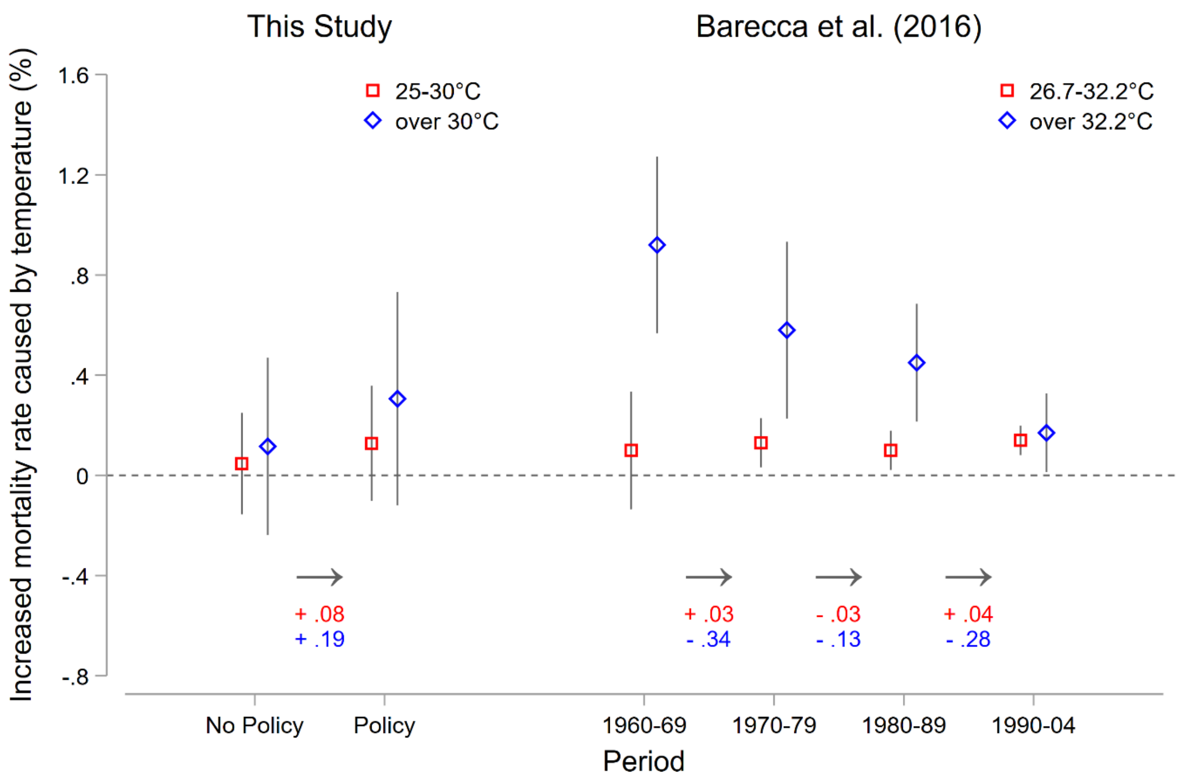
APPENDIX TABLE F3— THE IMPACT OF ENERGY-SAVING TARGETS ON ELECTRICITY CONSUMPTION

	Log (Electricity Consumption p.c.)		
	(1)	(2)	(3)
Panel A. Using All Seasons			
Saving Target (100 ppts)	-0.56	-0.50	-0.38
	(0.14)	(0.11)	(0.09)
log (Average Electricity Price)			-0.28
			(0.04)
Panel B. Summer			
Saving Target (100 ppts)	-0.65	-0.63	-0.52
	(0.15)	(0.15)	(0.13)
log (Average Electricity Price)			-0.25
			(0.04)
Panel C. Winter			
Saving Target (100 ppts)	-0.39	-0.28	-0.15
	(0.12)	(0.08)	(0.07)
log (Average Electricity Price)			-0.32
			(0.05)
Region-by-month FE	Y	Y	Y
Year-by-month FE	Y	Y	Y
Weather	Y	Y	Y
Controls	N	Y	Y

Notes: The regressions use regional data (10 regions in Japan) from 2008 to 2015. Regions that were heavily damaged by the Fukushima accident (Tohoku and Tokyo regions in March and April 2011) are dropped. The saving target implies that households and firms are encouraged to reduce electricity consumption relative to 2010. Panel A uses data from all seasons, while Panel B uses observations separately for different seasons. The summer corresponds to months from July to September and the winter season from December to February. Controls include temperature bins (7 bins), monthly precipitation (log), income (log), the employment rate (log), and the share of the working population. The numbers of observations are 960 (all), 240 (summer), and 320 (winter). All regressions are weighted by population. Standard errors are clustered at the prefecture level.

Appendix G. Interpretations

Figure G1: Comparison with Barreca et al., (2016)



Notes: This figure compares the temperature-mortality relationship between our study and Barreca et al. (2016). In our study, we plot the predicted temperature-mortality relationship with and without the energy-saving policy on the left side of the figure. After the Fukushima accident, the excess mortality risk caused by an additional day in temperature between 25–30°C will increase from 0.05% to 0.13% (difference: 0.08 ppts) due to energy saving, and the excess mortality risk caused by an additional day in temperature greater than 30°C will increase from 0.12% to 0.31% (difference: 0.19 ppts). The right side of the figure replicates the temperature-mortality relationships in the U.S in different periods from 1960 to 2004. During the 40+ years, the increase in monthly mortality rate caused by an additional day in the above 32.2°C (above 90°F) bin decreased dramatically from 0.92% to 0.18% (difference: 0.74 ppts). For example, from 1980s to 1990s, the temperature effect for an additional day in the above 32.2°C (above 90°F) bin decreased by 0.28 ppts.

Appendix H: Full Tables

APPENDIX TABLE H1—EFFECTS OF SAVING ELECTRICITY ON MORTALITY

	Monthly Mortality Rate (per 100,000)					
	Contemporaneous effect		Current + 1 month lag		Current + 2 months lags	
	(1)	(2)	(3)	(4)	(5)	(6)
# of days below 0°C	0.49	0.45	0.53	0.48	0.45	0.31
	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.06)
# of days 0–5°C	0.35	0.34	0.45	0.44	0.35	0.29
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
# of days 5–10°C	0.25	0.24	0.36	0.36	0.32	0.30
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
# of days 10–15°C	0.13	0.13	0.19	0.18	0.18	0.16
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)
# of days 20–25°C	-0.05	-0.04	-0.04	-0.02	0.00	0.04
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)
# of days 25–30°C	-0.04	-0.04	-0.02	-0.01	0.03	0.04
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)
# of days above 30°C	0.10	0.07	0.11	0.08	0.11	0.09
	(0.03)	(0.03)	(0.05)	(0.05)	(0.08)	(0.07)
# of days below 0°C * Saving Target		0.55		0.68		0.54
(100 ppts)		(0.17)		(0.22)		(0.22)
# of days 0–5°C * Saving Target		0.14		0.09		0.47
(100 ppts)		(0.14)		(0.22)		(0.25)
# of days 5–10°C * Saving Target		0.23		-0.06		0.02
(100 ppts)		(0.07)		(0.11)		(0.22)
# of days 10–15°C * Saving Target		-0.02		-0.03		-0.25
(100 ppts)		(0.15)		(0.23)		(0.40)
# of days 20–25°C * Saving Target		-0.03		-0.29		-0.47
(100 ppts)		(0.11)		(0.20)		(0.29)
# of days 25–30°C * Saving Target		0.05		0.17		0.79
(100 ppts)		(0.10)		(0.12)		(0.20)
# of days above 30°C * Saving Target		0.94		1.29		1.85
(100 ppts)		(0.36)		(0.44)		(0.70)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44
Obs.	12,672	12,672	12,540	12,540	12,408	12,408

Notes: We first estimate the age-specific temperature-mortality relationship. Then, we obtain a single age-adjusted estimate by taking its population-weighted average across age groups. The temperature bin between 15–20°C and its interaction with the energy-saving target is omitted. All the fixed effects are interacted with the age-group dummies. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

APPENDIX TABLE H2— THE EFFECTS OF SAVING ELECTRICITY ON MORTALITY BY AGE GROUPS

	Monthly Mortality Rate (per 100,000)					
	Age 0-19		Age 20-64		Age above 65	
	(1)	(2)	(3)	(4)	(5)	(6)
# of days below 0°C	-0.01	-0.01	0.05	0.05	1.74	1.19
	(0.07)	(0.07)	(0.09)	(0.10)	(0.17)	(0.19)
# of days 0–5°C	-0.00	-0.00	0.03	0.04	1.37	1.12
	(0.04)	(0.04)	(0.04)	(0.06)	(0.08)	(0.08)
# of days 5–10°C	0.01	0.03	0.00	-0.00	1.31	1.23
	(0.04)	(0.04)	(0.03)	(0.05)	(0.06)	(0.06)
# of days 10–15°C	-0.00	0.01	-0.00	-0.00	0.75	0.65
	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)
# of days 20–25°C	0.01	0.02	0.01	0.01	-0.01	0.14
	(0.03)	(0.04)	(0.03)	(0.04)	(0.07)	(0.08)
# of days 25–30°C	0.02	0.03	-0.01	-0.02	0.13	0.18
	(0.03)	(0.05)	(0.05)	(0.05)	(0.07)	(0.08)
# of days above 30°C	0.03	0.04	0.01	-0.00	0.42	0.36
	(0.08)	(0.09)	(0.09)	(0.09)	(0.18)	(0.18)
# of days below 0°C * Saving Target		-0.27		-0.14		2.79
(100 ppts)		(0.41)		(0.33)		(0.54)
# of days 0–5°C * Saving Target		-0.02		-0.06		2.12
(100 ppts)		(0.33)		(0.40)		(0.49)
# of days 5–10°C * Saving Target		-0.26		0.11		0.01
(100 ppts)		(0.39)		(0.35)		(0.48)
# of days 10–15°C * Saving Target		-0.15		-0.04		-0.83
(100 ppts)		(0.52)		(0.53)		(0.92)
# of days 20–25°C * Saving Target		-0.31		0.10		-1.98
(100 ppts)		(0.53)		(0.44)		(0.59)
# of days 25–30°C * Saving Target		-0.28		0.16		3.08
(100 ppts)		(0.30)		(0.35)		(0.37)
# of days above 30°C * Saving Target		-0.05		0.76		5.88
(100 ppts)		(0.94)		(1.06)		(1.54)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44
Obs.	12,408	12,408	12,408	12,408	12,408	12,408

Notes: 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 15-20°C and its interaction term with energy-saving target variable is omitted. All the fixed effects are interacted with age-group dummies. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

Appendix Table H3— The Effects of Saving Electricity on Ambulance Use by Heatstroke

	Ambulance Use by Heatstroke (per 100,000)							
	All		Age 0-19		Age 20-64		Age above 65	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# of days 20–22.5°C	0.07	0.06	-0.09	-0.02	0.05	0.03	0.23	0.20
	(0.05)	(0.05)	(0.06)	(0.07)	(0.05)	(0.05)	(0.08)	(0.07)
# of days 22.5–25°C	0.03	0.00	-0.13	-0.21	0.01	-0.01	0.21	0.19
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.09)	(0.08)
# of days 25–27.5°C	0.23	0.17	-0.07	-0.07	0.13	0.08	0.68	0.59
	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.13)	(0.12)
# of days 27.5–30°C	0.40	0.35	0.04	0.01	0.27	0.24	0.98	0.86
	(0.09)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.13)	(0.12)
# of days above 30°C	0.80	0.65	0.14	0.10	0.58	0.47	1.80	1.49
	(0.13)	(0.12)	(0.13)	(0.13)	(0.11)	(0.11)	(0.19)	(0.17)
# of days 20–22.5°C * Saving Target (100 ppts)		-0.38		-1.34		-0.16		-0.23
		(0.62)		(0.73)		(0.58)		(0.83)
# of days 22.5–25°C * Saving Target (100 ppts)		0.45		1.46		0.26		0.17
		(0.57)		(0.54)		(0.65)		(0.90)
# of days 25–27.5°C * Saving Target (100 ppts)		0.75		-0.54		0.89		1.36
		(0.47)		(0.62)		(0.48)		(0.85)
# of days 27.5–30°C * Saving Target (100 ppts)		1.00		0.09		0.74		2.30
		(0.59)		(0.56)		(0.59)		(0.97)
# of days above 30°C * Saving Target (100 ppts)		3.85		0.40		2.97		8.50
		(0.92)		(1.30)		(1.01)		(1.88)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44	44	44
Obs.	3,960	3,960	3,960	3,960	3,960	3,960	3,960	3,960

Notes: To capture the dynamic impact, we include current month and one-month lagged temperature bins in the regression and report the total impacts. The temperature below 20°C and its interaction term with the energy-saving target variable is omitted. All the fixed effects are interacted with age-group dummies. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

APPENDIX TABLE H4— HETEROGENEOUS EFFECTS BY BASELINE SUMMER TEMPERATURE

	Monthly Mortality Rate (per 100,000)					
	Age 0-19		Age 20-64		Age above 65	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. High Summer Temperature Group (Low < Median; High > Median, measured in 2008-2010)						
# of days below 5°C	0.01	0.02	-0.02	-0.04	0.34	0.39
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)
# of days 5–10°C	0.01	0.02	-0.02	-0.04	0.34	0.39
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)
# of days 10–15°C	-0.01	-0.02	0.01	0.01	0.43	0.35
	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.07)
# of days 20–25°C	0.02	0.02	-0.02	-0.04	-0.28	-0.03
	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)	(0.07)
# of days above 25°C	0.03	0.04	-0.04	-0.04	0.08	0.09
	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.08)
# of days below 5°C * Saving Target		-0.19		0.27		-1.20
(100 ppts)		(0.22)		(0.35)		(0.41)
# of days 5–10°C * Saving Target		-0.19		0.27		-1.20
(100 ppts)		(0.22)		(0.35)		(0.41)
# of days 10–15°C * Saving Target		0.01		0.14		-0.52
(100 ppts)		(0.41)		(0.39)		(0.69)
# of days 20–25°C * Saving Target		-0.19		0.40		-3.67
(100 ppts)		(0.32)		(0.31)		(0.43)
# of days above 25°C * Saving Target		-0.20		0.24		3.21
(100 ppts)		(0.21)		(0.28)		(0.40)
Panel B. Low Summer Temperature Group (Low < Median; High > Median, measured in 2008-2010)						
# of days below 5°C	0.01	0.02	-0.01	-0.02	0.42	0.53
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.07)
# of days 5–10°C	0.01	0.02	-0.01	-0.02	0.42	0.53
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.07)
# of days 10–15°C	-0.00	0.01	-0.04	-0.05	0.17	0.45
	(0.04)	(0.03)	(0.05)	(0.05)	(0.06)	(0.07)
# of days 20–25°C	-0.00	0.00	0.03	0.04	0.15	0.32
	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)	(0.07)
# of days above 25°C	-0.01	0.01	0.03	0.03	0.24	0.38
	(0.04)	(0.06)	(0.04)	(0.06)	(0.07)	(0.09)
# of days below 5°C * Saving Target		0.11		0.02		0.12
(100 ppts)		(0.48)		(0.55)		(0.63)
# of days 5–10°C * Saving Target		0.11		0.02		0.12
(100 ppts)		(0.48)		(0.55)		(0.63)
# of days 10–15°C * Saving Target		0.04		0.19		-4.78
(100 ppts)		(0.35)		(0.48)		(0.84)
# of days 20–25°C * Saving Target		-0.17		-0.05		-2.41
(100 ppts)		(0.36)		(0.44)		(0.66)
# of days above 25°C * Saving Target		-0.30		0.50		0.64
(100 ppts)		(0.25)		(0.36)		(0.45)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44
Obs.	12,408	12,408	12,408	12,408	12,408	12,408

Notes: 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 15–20°C and its interaction term with the energy-saving target variable is omitted. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

APPENDIX TABLE H5— HETEROGENEOUS EFFECTS BY INCOME

	Monthly Mortality Rate (per 100,000)					
	Age 0-19		Age 20-64		Age above 65	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. High Income Group (Low < Median; High > Median, measured in 2008-2010)						
# of days below 5°C	0.02	0.03	-0.01	-0.03	0.17	0.29
	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)
# of days 5–10°C	0.02	0.03	-0.01	-0.03	0.17	0.29
	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)
# of days 10–15°C	-0.02	-0.01	-0.03	-0.05	-0.17	-0.18
	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)
# of days 20–25°C	0.01	0.03	0.01	0.01	-0.19	0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.08)	(0.08)
# of days above 25°C	0.01	0.04	-0.00	-0.02	-0.10	0.02
	(0.04)	(0.05)	(0.05)	(0.06)	(0.08)	(0.09)
# of days below 5°C * Saving Target		-0.14		0.04		-2.10
(100 ppts)		(0.29)		(0.34)		(0.45)
# of days 5–10°C * Saving Target		-0.14		0.04		-2.10
(100 ppts)		(0.29)		(0.34)		(0.45)
# of days 10–15°C * Saving Target		-0.15		0.25		0.29
(100 ppts)		(0.41)		(0.40)		(0.75)
# of days 20–25°C * Saving Target		-0.24		0.03		-3.17
(100 ppts)		(0.36)		(0.41)		(0.59)
# of days above 25°C * Saving Target		-0.24		0.39		1.82
(100 ppts)		(0.20)		(0.29)		(0.41)
Panel B. Low Income Group (Low < Median; High > Median, measured in 2008-2010)						
# of days below 5°C	-0.01	-0.00	-0.05	-0.09	0.76	0.62
	(0.03)	(0.06)	(0.03)	(0.06)	(0.05)	(0.06)
# of days 5–10°C	-0.01	-0.00	-0.05	-0.09	0.76	0.62
	(0.03)	(0.06)	(0.03)	(0.06)	(0.05)	(0.06)
# of days 10–15°C	0.00	0.01	-0.01	0.01	0.91	0.96
	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
# of days 20–25°C	0.01	0.02	0.01	-0.01	0.08	0.32
	(0.04)	(0.05)	(0.04)	(0.05)	(0.08)	(0.08)
# of days above 25°C	0.02	0.03	-0.00	-0.01	0.57	0.62
	(0.04)	(0.06)	(0.05)	(0.05)	(0.08)	(0.09)
# of days below 5°C * Saving Target		-0.20		0.70		2.26
(100 ppts)		(0.29)		(0.60)		(0.47)
# of days 5–10°C * Saving Target		-0.20		0.70		2.26
(100 ppts)		(0.29)		(0.60)		(0.47)
# of days 10–15°C * Saving Target		0.04		-0.29		-5.60
(100 ppts)		(0.39)		(0.54)		(1.00)
# of days 20–25°C * Saving Target		-0.36		0.62		-4.38
(100 ppts)		(0.39)		(0.51)		(0.55)
# of days above 25°C * Saving Target		-0.20		0.05		5.77
(100 ppts)		(0.32)		(0.57)		(0.57)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44
Obs.	12,408	12,408	12,408	12,408	12,408	12,408

Notes: 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 15–20°C and its interaction term with the energy-saving target variable is omitted. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

APPENDIX TABLE H6—THE EFFECTS OF ENERGY-SAVING TARGETS ON CAUSE-SPECIFIC MORTALITY

	Cause-specific Mortality Rate (per 100,000)											
	Cardiovascular		Respiratory		Infectious Diseases		Neoplasms		Accident		Other Causes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
# days below 0°C	0.21	0.15	0.16	0.14	0.02	0.01	0.03	0.05	0.02	0.02	0.13	0.10
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)	(0.03)	(0.05)
# days 0–5°C	0.15	0.12	0.12	0.11	0.02	0.02	0.03	0.06	0.00	-0.00	0.10	0.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
# days 5–10°C	0.13	0.11	0.09	0.08	0.02	0.01	0.01	0.04	0.01	-0.01	0.09	0.10
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
# days 10–15°C	0.07	0.05	0.07	0.05	0.00	-0.00	0.01	0.05	-0.00	-0.01	0.05	0.05
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
# days 20–25°C	-0.01	-0.00	-0.00	-0.01	0.01	0.00	-0.02	0.01	-0.01	-0.01	0.04	0.05
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
# days above 25°C	0.03	0.03	-0.02	-0.03	0.01	0.00	0.02	0.04	-0.01	-0.01	0.04	0.04
	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
# days below 0°C * Saving Target		0.60		0.31		0.13		-0.36		0.04		0.03
(100 ppts)		(0.25)		(0.11)		(0.04)		(0.10)		(0.05)		(0.20)
# days 0–5°C * Saving Target		0.26		0.21		0.07		-0.52		0.02		0.32
(100 ppts)		(0.13)		(0.05)		(0.02)		(0.13)		(0.04)		(0.15)
# days 5–10°C * Saving Target		0.19		0.22		0.10		-0.54		0.17		-0.14
(100 ppts)		(0.14)		(0.09)		(0.03)		(0.13)		(0.05)		(0.13)
# days 10–15°C * Saving Target		0.24		0.21		0.03		-0.88		0.02		0.21
(100 ppts)		(0.17)		(0.13)		(0.03)		(0.18)		(0.06)		(0.23)
# days 20–25°C * Saving Target		-0.09		0.23		0.04		-0.59		0.09		0.07
(100 ppts)		(0.14)		(0.09)		(0.04)		(0.17)		(0.06)		(0.13)
# days above 25°C * Saving Target		0.31		0.34		0.13		-0.46		0.08		0.37
(100 ppts)		(0.15)		(0.07)		(0.03)		(0.12)		(0.03)		(0.13)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44	44	44	44	44	44	44
Obs.	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088

Notes: 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 15–20°C and its interaction term with the energy-saving target variable is omitted. All the fixed effects are interacted with age-group dummies. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

APPENDIX TABLE H7—THE EFFECTS OF ENERGY-SAVING TARGETS ON CAUSE-SPECIFIC MORTALITY AMONG THE ELDERLY

	Cause-specific Mortality Rate (per 100,000)											
	Cardiovascular		Respiratory		Infectious Diseases		Neoplasms		Accident		Other Causes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
# days below 0°C	0.82	0.59	0.61	0.50	0.08	0.04	0.10	0.16	0.09	0.08	0.43	0.27
	(0.07)	(0.05)	(0.04)	(0.05)	(0.02)	(0.02)	(0.06)	(0.06)	(0.02)	(0.02)	(0.08)	(0.09)
# days 0–5°C	0.60	0.48	0.45	0.41	0.08	0.06	0.13	0.25	0.03	-0.00	0.33	0.28
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)	(0.04)	(0.04)
# days 5–10°C	0.50	0.44	0.36	0.29	0.08	0.05	0.11	0.22	0.04	-0.00	0.32	0.36
	(0.03)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)	(0.04)	(0.05)
# days 10–15°C	0.29	0.19	0.26	0.19	0.02	-0.00	0.07	0.25	-0.03	-0.04	0.23	0.18
	(0.03)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)	(0.04)	(0.03)
# days 20–25°C	-0.05	-0.01	-0.02	-0.07	0.02	0.01	-0.08	0.03	-0.04	-0.06	0.20	0.20
	(0.02)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.04)	(0.04)
# days above 25°C	0.13	0.12	-0.08	-0.12	0.01	0.00	0.08	0.16	-0.03	-0.04	0.18	0.17
	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)
# days below 0°C * Saving Target		2.34		1.36		0.51		-1.68		0.02		0.99
(100 ppts)		(0.31)		(0.18)		(0.06)		(0.22)		(0.11)		(0.34)
# days 0–5°C * Saving Target		1.17		0.92		0.27		-2.18		0.02		1.45
(100 ppts)		(0.24)		(0.11)		(0.07)		(0.21)		(0.09)		(0.31)
# days 5–10°C * Saving Target		0.53		1.03		0.38		-2.12		0.43		-0.21
(100 ppts)		(0.26)		(0.16)		(0.08)		(0.23)		(0.15)		(0.32)
# days 10–15°C * Saving Target		1.26		1.04		0.13		-4.24		0.05		1.30
(100 ppts)		(0.43)		(0.25)		(0.09)		(0.41)		(0.17)		(0.56)
# days 20–25°C * Saving Target		-0.28		1.07		0.12		-2.63		0.29		0.41
(100 ppts)		(0.25)		(0.19)		(0.08)		(0.30)		(0.16)		(0.30)
# days above 25°C * Saving Target		1.35		1.45		0.49		-2.39		0.17		1.91
(100 ppts)		(0.20)		(0.15)		(0.06)		(0.22)		(0.10)		(0.19)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44	44	44	44	44	44	44
Obs.	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088	11,088

Notes: 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 15–20°C and its interaction term with the energy-saving target variable is omitted. All the fixed effects are interacted with age-group dummies. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

APPENDIX TABLE H8—EVENT STUDY ESTIMATES

	Monthly Mortality Rate (per 100,000)			
	All	Age 0-19	Age 20-64	Age above 65
	(1)	(2)	(3)	(4)
2008	0.07	-0.14	-0.56	1.73
	(0.93)	(0.97)	(1.23)	(1.55)
2009	0.43	-1.15	0.13	2.33
	(0.59)	(0.65)	(0.89)	(1.07)
2011	0.78	-0.71	0.40	2.80
	(0.61)	(0.73)	(0.82)	(1.18)
2012	0.65	-0.85	0.64	1.79
	(0.75)	(0.78)	(1.03)	(1.64)
2013	0.81	-0.99	-0.56	5.47
	(0.66)	(0.73)	(1.00)	(1.08)
2014	0.95	-1.01	0.20	4.22
	(0.66)	(1.04)	(1.00)	(1.75)
2015	1.81	-0.37	0.46	6.68
	(0.74)	(0.88)	(1.00)	(1.59)
Prefecture-by-month FE	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
# Prefectures	44	44	44	44
Obs.	12,408	12,408	12,408	12,408

Notes: 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 15–20°C and its interaction term with energy-saving target variable is omitted. All the fixed effects are interacted with age-group dummies. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

APPENDIX TABLE H9— ROBUSTNESS CHECKS

Dependent Variable Monthly Mortality Rate (per 100,000)	Including Prefecture Quadratic Trend		Including Local Economic Conditions		Controlling for Air Pollution		Using All Samples		Using Revised Target
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# of days below 0°C	0.56	0.44	0.44	0.31	0.45	0.32	0.42	0.29	0.31
	(0.16)	(0.09)	(0.06)	(0.06)	(0.05)	(0.06)	(0.04)	(0.05)	(0.06)
# of days 0–5°C	0.40	0.34	0.35	0.28	0.35	0.29	0.38	0.34	0.29
	(0.12)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
# of days 5–10°C	0.29	0.27	0.32	0.30	0.31	0.30	0.35	0.33	0.30
	(0.09)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
# of days 10–15°C	0.18	0.20	0.18	0.16	0.17	0.15	0.19	0.18	0.16
	(0.05)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
# of days 20–25°C	-0.03	-0.01	0.00	0.04	0.01	0.04	0.00	0.04	0.04
	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
# of days 25–30°C	0.09	0.07	0.03	0.04	0.04	0.05	0.06	0.07	0.04
	(0.10)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
# of days above 30°C	0.17	0.12	0.12	0.09	0.12	0.10	0.14	0.12	0.10
	(0.13)	(0.07)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
# of days below 0°C * Saving Target		0.17		0.52		0.48		0.58	0.40
(100 ppts)		(0.43)		(0.23)		(0.23)		(0.22)	(0.21)
# of days 0–5°C * Saving Target		0.30		0.48		0.40		0.30	0.40
(100 ppts)		(0.38)		(0.26)		(0.27)		(0.24)	(0.25)
# of days 5–10°C * Saving Target		-0.14		-0.03		-0.05		0.06	0.01
(100 ppts)		(0.55)		(0.21)		(0.24)		(0.21)	(0.22)
# of days 10–15°C * Saving Target		-0.71		-0.24		-0.23		-0.28	-0.34
(100 ppts)		(0.54)		(0.42)		(0.41)		(0.40)	(0.40)
# of days 20–25°C * Saving Target		-0.08		-0.46		-0.43		-0.49	-0.49
(100 ppts)		(0.56)		(0.34)		(0.31)		(0.31)	(0.30)
# of days 25–30°C * Saving Target		0.51		0.79		0.75		0.62	0.76
(100 ppts)		(0.43)		(0.21)		(0.21)		(0.20)	(0.19)
# of days above 30°C * Saving Target		2.09		2.01		1.85		1.93	1.76
(100 ppts)		(1.04)		(0.85)		(0.75)		(0.70)	(0.71)
Prefecture-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Prefecture-by-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Prefectures	44	44	44	44	44	44	47	47	44
Obs.	12,408	12,408	12,408	12,408	12,408	12,408	13,236	13,236	12,408

Notes: 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 15–20°C and its interaction term with the energy-saving target variable is omitted. All the fixed effects are interacted with age-group dummies. The regressions are weighted by population, and standard errors are clustered at the prefecture-by-age group level.

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