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Energy Saving Can Kill: Evidence from the Fukushima Nuclear Accident*

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Energy Saving Can Kill:

Evidence from the Fukushima Nuclear Accident

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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 campaigns that aimed to reduce summer electricity consumption by as much as 15% in some regions. Because electricity use plays a key role in mitigating climate impacts, such policies could potentially damage the population's health. Exploiting the different electricity-saving targets set by different regions, we show that the reduction in electricity consumption indeed increased heat-related mortality, particularly during extremely hot days. This unintended consequence suggests that there exists a tradeoff between climate adaptation and energy saving.

Keywords: Electricity saving, Climate Change Adaptation, Fukushima Accident, Extreme Weather

JEL: Q48; Q54; O12; I1

I. Introduction

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.¹ Among these damages, excess mortality caused by extreme weather is considered as one of the most devastating consequences: it is estimated the mortality cost alone could account for about 70% of the total damages in the U.S. by the end of the 21st century (e.g., Hsiang et al., 2017).

Facing such threats, human society has developed 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, which will benefit the climate in the long run. In particular, many countries adopt aggressive policies encouraging households to reduce energy consumption, as the residential sector alone accounts for 13% of the world's energy consumption, and it is expected to grow by 48% until 2040.² Not surprisingly, such policies are often recognized as a “win-win” opportunity, in which they not only help people save money but also reduce the negative externality of energy use (see Allcott and Greenstone (2012) for a recent review). Governments around the world thus provide costly support to promote energy saving (e.g., Boomhower and Davis, 2014; Davis et al. 2014; Ito, 2015; Fowlie et al. 2018). For example, from 2007 to 2012, the U.S. government alone spent around \$25 billion in subsidies for energy-saving programs.³

A separate line of literature has devoted effort to find effective ways to adapt to climate change. The society has adopted various forms of adaptive measures with the use of existing technologies,

¹ See Dell et al. (2014), IPCC (2014), Carleton and Hsiang (2016) and Auffhammer (2018b) for recent reviews.

² Electricity consumption from transportation uses is excluded.

Source: International Energy Outlook (2016): <https://www.eia.gov/outlooks/ieo/pdf/buildings.pdf>.

³ Source: U.S. Energy Information (2018): Electric Power Annual 2017.

and its power is evidently remarkable.⁴ For example, in the U.S., the chance of dying on extremely hot days has fallen by 75% 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 mortality risk that is more than 10 times that of urban dwellers (Burgess et al., 2017). As a result, identifying effective measures to mitigate the health damage from climate change is recognized as a global research priority for the 21st century (WHO, 2009; NIEHS, 2010).

A dilemma immediately emerges from these two lines of literature. To mitigate climate change, reducing energy consumption is considered as a priority. However, if energy consumption is so critical for people to adapt to climate changes, would policies discouraging people to consume energy have any negative consequences? This paper sheds light on this issue by investigating large-scale energy-saving campaigns in Japan and highlights the potential tradeoff between energy saving and climate adaptation.

Our empirical strategy exploits the dramatic changes in Japan's energy policies caused by the Fukushima Daiichi nuclear disaster. Following the epic magnitude-9.0 Tōhoku earthquake on 11 March 2011, a 13-to-15-meter (43 to 49 ft)-high 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 country-wide concerns about nuclear safety. The government, therefore, decided to stop the operation of *all* nuclear power plants, which resulted in a severe 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, which required different prefectures to reduce summer electricity usage by as much as 15%. The government paid particular attention to reducing the usage of air conditioning because it is

⁴ To adapt to climate, when exposed to extremely hot temperature, people tend to stay indoors (e.g. Zivin and Neidell, 2014), use more air conditioning (e.g. Davis and Gertler, 2015; Barreca et al., 2016), consume more electricity (e.g. Deschenes and Greenstone, 2011; Auffhammer, 2018a), and migrate to more pleasant environments (e.g. Deschenes and Moretti, 2009; Bohra-Mishra et al., 2014).

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 adaptive opportunities and make them more vulnerable to extreme weather shocks.

Analyzing the variation in electricity-saving targets set by different regions after the Fukushima accident, we explore the health consequences of policy-driven energy savings. Our analyses proceed in four steps. In the first step, we exploit how electricity-saving affects heat-related mortality and how it reshapes the temperature-mortality relationship. The results show that a higher electricity-saving target caused more people to die from heat strokes. The total number of excess heat-related deaths caused by a 10 percentage point change in the electricity-saving target is estimated to be around 1.57 per 1,000,000 people each summer. A back-of-the-envelope calculation reveals that the campaigns could lead to 800~836 additional deaths from 2011 to 2015. Additionally, almost all the extra deaths caused by electricity-saving occurred on very hot days (mean daily temperature above 27.5 °C), suggesting that electricity-saving makes people more vulnerable to extreme heat.

The second component of our analysis aims to uncover the mechanism. We show that the effect is likely to be driven by households' behavioral changes: people use less air conditioning (AC) and buy more non-AC cooling appliances (such as fans), as recommended by the central government during the energy-saving campaigns. In contrast, there is no evidence that energy saving induces more heat-related deaths by degrading the quality of healthcare services, air quality, or socio-economic conditions.

In the third step, we investigate the impact heterogeneity. The analysis reveals that formerly well-adapted areas are disproportionately affected by the electricity-saving policy. Specifically, hotter and richer areas that were more successful in mitigating the heat damage tended to suffer most from the electricity-saving policy, likely because they were discouraged from using air conditioners they already owned.

Finally, we investigate whether pecuniary or non-pecuniary incentives are more important in encouraging people to reduce electricity consumption, which eventually worsened their health outcomes. We train three different machine-learning models (LASSO, Random Forest, and Artificial Neural Network) and predict the counterfactual electricity consumption in the absence of the energy-saving campaigns for the post-accident periods. Our analysis shows that price change can only explain 10%~25% of the total consumption decline. In contrast, moral suasion seems to play a crucial role in encouraging Japanese people to save energy. This finding also holds when we use a simpler but more transparent “price elasticity approach” to predict the post-accident electricity consumption.

Our study contributes to the literature in four ways. First, this paper contributes to a vast body of climate-health relationships by providing one of the first quasi-experimental evidence on the effects of adaptation. Previously, many studies have documented temperature-health relationship and the role of adaptation in the U.S. (e.g., Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011; Barreca et al., 2016; Heutel et al., 2017), Germany (Karlson and Ziebarth, 2018), India (e.g., Burgess et al., 2017), China (e.g., Yu et al., 2019) and multiple countries (Gasparrini et al. 2015; Carleton et al., 2018; and Geruso and Spears, 2018). However, a key limitation in these studies is that there often lacks exogenous variation in the adaptive measures (i.e., use of air conditioner or electricity consumption).⁵ 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 on the impacts of adaptation.⁶ In our empirical set-up, because

⁵ Existing evidence often estimates the benefits of adaptation by measuring the sensitivity of economic outcomes to climate factors. 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. (2018) on mortality, Lobell et al. (2011) for agricultural output, and Dell et al. (2012) for income.

⁶ 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 to have healthier life styles, 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.

the Fukushima accident and the subsequent electricity-saving policies were totally unanticipated, and the degree of the savings largely depends on a region's former-reliance on nuclear power, they exogenously changed people's adaptive opportunities. This unique setting allows us to credibly estimate the impact of electricity saving on the temperature-mortality relationship, which helps identify the causal impact of adaptation on population health.

Second, this paper also speaks to the literature on welfare consequences from energy use. In developing countries, multiple studies show that the access to electricity has important implications on education (e.g., Lipscomb et al., 2013), non-agricultural productivity and income (e.g., Chakravorty et al., 2014), and employment (e.g., Dinkelman, 2011; and Rud, 2012), while a few other studies find such developmental effects are negligible (e.g., Burlig and Louis, 2016; and Lee et al., 2019). In comparison, in developed countries, as the energy supply is already guaranteed, researchers focus on the consequences of volatile energy prices. Two concurrent working papers are particularly relevant to ours: Chirakijia et al. (2019) show that cheaper heating reduces winter mortality in the U.S. and Neidell et al. (2019) show that more expensive electricity increases winter mortality in Japan. We differ from in Neidell et al. (2019) in that we focus on Japan's large-scale energy saving campaigns during the summer for identification and try to pin down the exact channels through which energy consumption affects heat-related deaths.

Relatedly, this paper also adds to the emerging literature on how to incentivize people to save energy (e.g., Reiss and White, 2008; Ito et al., 2018; Costa and Gerard, 2018). In particular, our finding is closely related to Ito et al. (2018), who conducted a field experiment in Japan and find that economic incentives induce greater electricity saving than moral suasion. Our results contrast to Ito et al. (2018) in that we find price changes can only explain a small portion of the overall electricity consumption reduction after the Fukushima accident. This inconsistency is likely to be driven by the fact that real-life electricity prices cannot be dramatically raised to a level that is comparable to Ito et al. (2018)'s field experiment, yet the moral suasion component is greatly intensified during the government's energy-saving campaigns.

Finally, our findings also contribute to the literature on the consequences of the Fukushima accident. The catastrophic experience of Fukushima generated far-reaching consequences for

nuclear policies around the world. Many countries, such as Germany, Italy, and Switzerland, made a sharp U-turn on nuclear development immediately after the accident and determined to rely less on nuclear power.⁷ Existing evidence on the Fukushima accident often focuses on the direct consequences of the disaster on the damaged areas, such as its impacts on local land prices (e.g., Kawaguchi and Yukutake, 2017) and health outcomes and subjective well-being of the locally affected population (e.g., Rehdanz et al., 2015; Hasegawa et al., 2015). This study highlights the unexpected consequence of reducing reliance on nuclear power in Japan and has broader relevance to other countries' nuclear policies.

Our findings have important implications for designing better energy-saving policies. Here, we want to emphasize that different approaches to encourage people to save energy may have different welfare consequences. As shown in this study, policies that directly restrict people's adaptive opportunities will make people less resilient to climate shocks. It is possible that many other programs, which share similar features to Japan's, can also incur non-negligible health costs; such programs may include increasing price during peak hours (e.g., Wolak, 2011; Jessoe and Rapson, 2014), energy conservation subsidy (e.g., Boomhower and Davis, 2014; Ito, 2015), nudging (e.g., Allcott and Rogers, 2014), and moral suasion (e.g., Reiss and White, 2008; Ito et al., 2018). In comparison, policies that allow people to enjoy the same level of functionality at a lower cost, notably energy efficiency programs, may bring about additional health benefits. Existing studies on energy-efficiency programs often find that they cannot achieve the expected level of savings because people tend to use electronic appliances more intensively when they become more energy-efficient (e.g., Davis et al. 2014). Our findings imply that this higher-than-expected electricity consumption may bring about additional benefits to the households (e.g., health improvement) and that previous literature might have understated energy efficiency programs' welfare implications (e.g., Dubin et al., 1986; Davis et al., 2014; Levinson, 2016; Fowle et al. 2018).

The rest of this paper is structured as follows. Section II provides the background of the Fukushima accident and the electricity-saving campaigns in Japan. Section III describes our data

⁷ For example, Germany shut down its eight oldest nuclear power plants within three months after the accident.

and provides the summary statistics of the key variables. Section IV discusses the empirical strategy. Section V reports our findings and explores the mechanisms. Section VI explores what drives people's electricity consumption patterns. Section VII concludes.

II. Background

The Fukushima nuclear accident is recognized as one of the worst catastrophes in the civil use of nuclear power 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.⁸

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 subsequently 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 also gradually suspended the operations of other reactors located in low-risk locations, as the public became more concerned about nuclear safety. Eventually, by May 2012, all nuclear reactors were taken off the grid. 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% 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

⁸ Source: https://www-ns.iaea.org/downloads/iec/ines_flyer.pdf

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. For instance, in the Tokyo region, where the Fukushima power plant supplied electricity, the government set a saving target of 15% in 2011. By contrast, in the Okinawa islands, no saving target was set because they do not use nuclear power. Figure 2 illustrates the summer electricity-saving targets across different regions from 2011 to 2014.⁹

The electricity-saving campaigns were collective efforts, in that local government, 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. Local governments were required to raise public awareness and advocate the importance and necessity of saving energy. The power companies need to provide real-time information on their demand and supply capacity and issue warnings when there was a risk of a blackout.¹⁰

Among these efforts, an essential component of the electricity-saving campaigns was to encourage households to reduce air conditioner usage, since air conditioning accounted for nearly 50% of residential electricity consumption.¹¹ For example, it was suggested by the government that households should use electric fans instead of air conditioners if possible and should set the air conditioner at 28°C if such equipment had to be used.

In addition to asking households to reduce air conditioner usage, the government also encouraged households to restrict the use of other electronic appliances. For example, people were

⁹ 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 assign the saving target adopted by the power company with the larger market share to the prefecture. The results are similar when we use the weighted average saving targets.

¹⁰ The central government provided guidelines for eight distinct industries. These are commercial buildings, retail stores, supermarkets, healthcare facilities, hotels, restaurants, schools, and manufacturing.

¹¹ Agency for Natural Resource and Energy, Ministry of Economy, Trade and Industry (2011):

http://www.kantei.go.jp/jp/singi/electricity_supply/0513_electricity_supply_02_08.pdf

asked to set their refrigerators to “medium” rather than “high” and to turn off 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 about only 1% of households’ electricity consumption. These behaviors were encouraged from 9:00 am to 8:00 pm from Monday to Friday. Appendix B shows a government advertising poster for the electricity-saving campaigns, with a detailed action list for households.

Although none of the above measures was mandatory, the campaigns indeed shaped households’ electricity consumption patterns. For example, according to Tanaka and Ida (2013), in the Tokyo area in 2011, where the government set a saving target of 15%, 95.2% of survey respondents were aware of the electricity conservation campaigns, which resulted in remarkable changes in their behaviors: 71.0% set a higher temperature when using air conditioners, 45.4% changed their refrigerator setting, and 81.0% reduced their standby power consumption. Fujimi et al. (2016) also find that Japanese people were very responsive to these campaigns: 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.

Note that, hospitals and clinics were excused from many of the electricity-saving actions to avoid degrading healthcare quality.¹² 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 the electricity supply is stable. This is important for our research design, as it helps to rule out the possibility that changes in healthcare quality caused additional deaths.

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 re-utilize old thermal plants to generate electricity (which are more costly). They thus negotiated with

¹² Healthcare facilities were allowed to set their own saving targets.

Source: http://www.kantei.go.jp/jp/singi/electricity_supply/20120518/taisaku.pdf

the government and requested to increase the electricity prices.¹³ However, as the power sector is heavily regulated and the government concerned that raising prices might trigger public dissent, such adjustments were not easy. For example, even though the Tokyo region faced a severe electricity shortage in the summer of 2011 and 2012 (because it lost the electricity supply from the Fukushima nuclear reactors), household electricity prices remained largely the same during this period. After rounds of discussions and negotiations with the government, eventually, eight out of ten power companies raised electricity prices, with the annual average price increasing by about 5 to 8 percent. Presumably, the increased electricity price also helped reduce the total consumption.

As such, the energy-saving campaigns are, in fact, a bundle of policy treatments that include both pecuniary and non-pecuniary incentives. Figure 3 summarizes the changes in electricity consumption per capita (Panel A) and electricity prices (Panel B). From the figure, we can observe that electricity consumption patterns are very different between summer and winter seasons: summer electricity consumption declined more than winter consumption, even though the price changes between winter and summer seasons were mostly the same. These patterns seem to suggest that the non-pecuniary incentives from the summer energy-saving campaigns could induce additional electricity saving.

In Figure 4, we further plot the changes in summertime electricity consumption between 2010 and 2015 against the summer electricity-saving targets for different regions in Japan. We observe a strong correlation between the saving targets and changes in actual electricity consumption. In regions with high saving targets, the total electricity consumption was brought down by more than 20% in just five years. Later in the results section, we will formally estimate how the saving targets (and electricity prices) affect real consumption.

These large-scale energy-saving campaigns offer a rare opportunity to investigate the role of energy use on climate adaptation. Because the Fukushima accident was unexpected, and because

¹³ Electricity price in Japan is determined by three components: the demand charge (block pricing), energy charge, and Renewable Energy Power Promotion Surcharge (REPPS). The energy charge and the REPPS automatically reflect fuel cost and exchange rate, and subsidy on renewable energy. The power company cannot change the demand charge without the approval of the central government. The demand charge consists of the largest share of electricity price.

the resulting plant shutdowns varied from place to place for reasons unrelated to local climate or the local population’s heat sensitivity, it creates plausibly exogenous variations in the 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, as measured by heat-related mortality? Second, if electricity saving indeed leads to heat-related deaths, is it because the policy limits people’s ability (or strongly discourages their willingness) to mitigate the heat damage? 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.

III. Data and Summary Statistics

A. Data Sources

1. 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.¹⁴ The Ministry of Economy, Trade, and Industry (METI) was responsible for advocating, promoting, and implementing the campaigns.¹⁵ 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% of its electricity, faced a saving target of 10% on average, while the Chubu area, where nuclear power had generated 9.44%, faced a target of about 3.4%.

¹⁴ Website: http://www.kantei.go.jp/jp/singi/electricity_supply/

¹⁵ For example, METI manages “Setsuden.go.jp (Setsuden means energy-saving)” and targets and related guidelines are published on this website from 2013.

Note that there is a concern that households or firms could purchase electricity from neighboring regions, which might affect our identification strategy. In practice, however, this is rare. As noted above, each of the 10 main power companies nearly monopolizes the provision of electricity in its region. According to METI (2017), in 2015, less than 5% of electricity was purchased from the PPS (Power Producer and Supplier), i.e., purchased outside the 10 companies.¹⁶ Therefore, the majority of the residents and firms didn't purchase electricity from other power companies.

2. Heat-Related Mortality Data

We construct annual prefecture-level heat-related mortality from the Vital Statistics of the Ministry of Health, Labour, and Welfare (MHLW) between 1999 and 2015. Cause-specific deaths are based on the International Statistical Classification of Diseases, 10th Revision, 2013 (ICD 10) classification, in which heat-related deaths are defined by “exposure to excessive natural heat” in code X30. Population data are collected from the Statistical Observations of Prefectures from the Ministry of Internal Affairs and Communications (MIAC)

3. Heat-Related Ambulance Transports

We use heat-related ambulance transports as an alternative measure of population health. The data are provided by the National Institute for Environmental Studies and are available at the district level from 2004 to 2015. We have information on the number of ambulance transports in 215 districts from 20 main cities across Japan, which cover over 35 million people (about 30% of the entire Japanese population).

4. 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 Trend for “energy-savings (*Setsuden* in Japanese),” AC penetration rate, and spending on other cooling appliances (such as fans).

¹⁶ METI (2017): <https://www.enecho.meti.go.jp/about/special/tokushu/denryokugaskaikaku/denryokujiyuka.html>

The keyword search for “energy saving” is collected from Google Trend. It represents the intensity of the online search of the keyword in a prefecture during a specific period. To compare the search indices across different prefectures and periods, we normalize the search indices from 0 to 100, with 100 representing the maximum number during our study period and other numbers representing the proportion of the maximum. For example, in Tokyo prefecture, the Google search index is 0.4 in 2010 and 90.0 in 2011, suggesting that the search intensity is as much as 0.4% and 90.0% of the highest search rate in our dataset. We aggregate the Google search index from May to September, including two months before the hottest season since the campaigns were announced before the summer. The Google Trend data are only available from 2004.

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. Non-single households from all regions in Japan are randomly chosen to answer the questionnaires. The survey collects data on households’ spending on different 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, so the sample size for this variable is significantly smaller. The government publishes the aggregated summary statistics for the capital cities online.

5. 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.¹⁷

B. Summary Statistics and Balance Checks

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. There is also a concern that 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.¹⁸ According to the Emergency Disaster Countermeasures Headquarters of National Police Agency of Japan (2019), more than 95% of the total number of deaths and missing people were from Iwate, Miyagi, and Fukushima.¹⁹

Table 1 reports the summary statistics of the key variables. Column (1) shows the means and standard deviations from 1999 to 2015. The mean per capita monthly electricity consumption during summer is about 1,794 kWh. On average, 4.67 per 1,000,000 people died of heat-related illnesses each summer, while 217 people per 1,000,000 were transported by ambulance due to heat-related illness. In terms of air conditioning, the mean penetration rate is 88.5%. On average, there were 27.9 “hot” days per summer (mean daily temperature 25.0 ~ 27.5°C) and 26.7 very hot days (mean daily temperature higher than 27.5°C).

Columns (2) and (3) summarize the means and standard deviations of key variables before the Fukushima accident (2006-2010) and afterward (2011-2015). Column (4) reports percentage changes in the key variables between those periods. Results in Panel A show that, on average, electricity consumption dropped by 8.8% after the Fukushima accident. In contrast, in Panel B, we see a substantial increase in heat-related mortality and ambulance transportation (11% and 93%) over the same period. Panel C shows that people are significantly more likely to search for

¹⁷ We also try a different weighting method to aggregate the station-level weather data. Instead of using the squared inverse distances as weights, we use the inverse distances as weights. We find similar results.

¹⁸ The results including the three prefectures are presented in one of the robustness checks.

¹⁹ Source: https://www.npa.go.jp/news/other/earthquake2011/pdf/higaijokyo_e.pdf

“energy saving” after the nuclear accident and that there is a modest increase in the AC penetration rate (2.0%) and a significant increase in the purchase of non-AC cooling appliances (28%). These trends are consistent with the governments’ efforts providing massive information for energy-savings and encouraging households to rely more on electric fans rather than AC during the electricity-saving campaigns. Finally, Panel D reveals that the number of hot days slightly increased over the years, but the difference is not substantial.

In Column (6), we estimate the correlations between average saving targets *after* the accident and the key variables *before* the accident. The results show that none of the coefficients is statistically significant at the 5% level, indicating that the targets are unlikely to be correlated with the pre-accident heat-related mortality rate or with the main factors affecting the mortality rate.

IV. Empirical Strategy

We examine the impact of the electricity-saving policy and temperature on health outcomes using the following model:

$$Y_{it} = \alpha_0 + \alpha_1 STarget_{it} + \sum_k TBin_{itk} * \beta_k + X_{it}\delta + \pi_t + \mu_i + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the heat-related mortality rate in prefecture i in summer t .²⁰ $STarget_{it}$ is the electricity-saving target in prefecture i in summer t . $TBin_{itk}$ denotes the number of days in prefecture i in summer t that fall into the k -th temperature bins. X_{it} denotes a vector of control variables including the log mean monthly precipitation, log mean monthly wind speed, log prefectural GDP per capita, and population share of four age groups: 0–4, 5–19, 20–64, and 65+. π_t is a time effect common to all prefectures in summer t , and μ_i is a time-invariant effect unique to each prefecture i .

We define three temperature bins: below 25°C, 25°C ~ 27.5°C, and above 27.5°C. The below ~25°C bin serves as the baseline group and is omitted in the regression. Thus the coefficients of 25°C~27.5°C and 27.5°C+ bins measure the health risks of higher temperatures relative to the

²⁰ We use the annual heat-related mortality rate as the dependent variable since we do not have monthly data. According to the Vital Statistics of Japan, 91.3% of heat-related deaths occurred from July to September over the period from 2007 to 2015.

baseline temperature.²¹ The heat effect is identified by temperature variations within the same prefecture. Intuitively, it is estimated by the deviation in the heat-related mortality rate between an average summer in a given prefecture and a hotter-than-average summer in the same prefecture, conditional on the set of fixed effects and controls. Since whether a prefecture will have several hotter or cooler days in summer (relative to the average) is largely random and thus independent from other covariates, the estimates of β_k can be interpreted as a causal relationship.

The coefficient α_1 is a variable of our primary interest, which estimates the impact of electricity-saving targets on heat-related mortality rate. We expect the sign will be positive, since higher saving targets hamper people's capability to adapt, and this could lead to more deaths from the heatstroke. Here, we use the electricity-saving targets as the primary explanatory variable for three reasons. First, recall that the electricity-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. Second, since the central government directly set the targets in a top-down manner, the targets are unlikely to be correlated with factors in local communities that may affect people's health status. Third, by focusing on a comprehensive measure, we can generate intuitive interpretations of the estimates and calculate policy-relevant counterfactuals.

Equation (1) estimates the overall effect of electricity-saving targets on heat-related mortality rates. To test whether the effect is indeed driven by restricting people's capacity to mitigate climate damage, we estimate the following equation:

$$Y_{it} = STarget_{it} * \alpha + \sum_k TBin_{itk} * STarget_{it} * \gamma_k + \sum_k TBin_{itk} * \beta_k + X_{it} * \delta + \pi_t + \mu_i + \varepsilon_{it} \quad (2)$$

where $\sum_k TBin_{itk} * STarget_{it}$ indicate the interactions between the temperature bins and the electricity-saving target. The interactions tell us whether the saving target can amplify the heat

²¹ We also estimated the baseline specification using different temperature bins (below 20°C is omitted). We find very similar results.

damage when the number of hot days changes. Again, we omit the below 25°C bin, so the estimated temperature effect is relative to the below 25°C group.

We conjecture that the coefficients of the interaction terms will be positive for high-temperature bins. That is, the impact of hot temperature on population health will be even greater if people face higher saving targets, presumably because saving energy may restrict their resilience to temperature shocks.

We cluster standard errors at the prefectural level to allow arbitrary correlation over time within the same prefecture. All the regressions are weighted by population in 2010 so that prefectures with larger populations are given greater weights. Intuitively, these weights help to estimate the impact of the policy on an average person instead of on an average prefecture.²²

V. Results

A. Main Results

We report our main findings in Table 2. Columns (1) and (2) summarize the results from estimating Equation (1). We find that the electricity-saving target increases the heat-related mortality rate, and this effect is statistically significant at the 5% level. A 10 percentage point increase in the saving target is associated with a 1.57~1.64 per 1,000,000 (about 33.6~35.1%) increase in the heat-related mortality rate. Given that the average saving target during the policy period is around 8.1%, the policy could have increased the number of heat-related deaths by 25~30% each summer.

For temperature, we find that extreme heat (temperature over 27.5°C) causes more people to die, and this effect is statistically significant at 5 or 10%. Compared with the baseline group (temperature below 25°C), one additional day in the hottest temperature bin (over 27.5°C) can lead to a 0.07 per 1,000,000 (about 1.5%) increase in heat-related mortality rate. On average, a prefecture has about 26.7 very hot days in summer, which would raise heat-related mortality by

²² We alternatively use population in the first (1999) and last (2015) year of our sample period rather than population in 2010 as weights. We find similar results.

roughly 40%. Relatively mild temperature (25~27.5°C), however, does not have a meaningful effect on heat-related mortality. These results imply that hot weather has a nonlinear impact on human health, and the marginal damage becomes more severe when the temperature is higher.

Comparing Column (1) with Column (2), we see that the estimated coefficient of the electricity-saving target is remarkably robust to the inclusion of a rich set of time-varying control variables. This finding implies that the saving target is unlikely to be correlated with local weather or socio-economic conditions.

Columns (3) and (4) of Table 2 report the results from estimating Equation (2). Several interesting patterns emerge. First, when the temperature is low, the saving target alone does not have any statistically significant effect on heat-related mortality (i.e., the coefficient of “Saving Target”). Second, high temperature causes more people to die (the coefficient of “Number of days above 27.5°C”), which is consistent with the results in Columns (1) and (2). Third, electricity-saving amplifies the heat damage: the interaction between “saving target” and “high temperature” (number above 27.5 °C) is positive and statistically significant in both regressions. The size of the effect is also economically meaningful: if we put 26.7 days above 27.5°C into the equation, which represents the average, the estimated coefficient of the interaction term will be $1.60 \sim 1.87$ ($0.06 \sim 0.07 * 26.7$ from Column (3) and (4)), which is nearly identical to the policy effect (1.64 from column (1)). In other words, almost the entire policy effect can be attributed to excess heat-related deaths on extremely hot days, revealing that electricity-saving kills people primarily because people cannot mitigate the heat damage through using sufficient electricity.

To visualize the health damages of the electricity-saving policy, we estimate the predicted excess mortality by fitting the observed temperature distribution in each prefecture over the period from 2011 to 2015 into the equation. Figure 5 plots the predicted health damage based on two different scenarios: one without an electricity-saving target and one with a 10% saving target. The difference between these two scenarios measures the policy effect. On the graph, the y-axis reports the change in the heat-related mortality rate (per 1,000,000) in a specific prefecture, compared to the case of the same prefecture always having a daily mean temperature below 25°C during the summer. The x-axis ranks all the prefectures in Japan from low to high based on the number of very hot days

(over 27.5°C) in summer. Each bubble represents a prefecture, and the bubble size is proportional to the population size. We observe that the electricity-saving policy amplifies the heat damage in most prefectures, and the effect becomes even more extensive in prefectures with more very hot days.

Applying our estimates to all the prefectures in Japan, we can calculate the number of additional deaths caused by the energy-saving campaigns. Roughly speaking, 150 ~ 179 additional deaths could be caused by energy-saving campaigns each summer from 2011 to 2015, respectively. Summing these numbers up, the energy-saving campaigns could have caused more than 800 ~ 836 additional heat-related deaths.²³

B. Alternative Explanations

In this section, to rule out alternative explanations of the baseline findings, we examine the impact of saving targets on three different outcomes: healthcare quality, air pollution, and socio-economic characteristics.

The first alternative explanation is that a deterioration in healthcare quality can drive the excess deaths caused by electricity-saving during the extremely hot days. If higher saving targets somehow jeopardized the quality of medical services, more people would die. This observed effect in our regression may not be driven by people becoming more vulnerable, but by fewer people being saved.

Conceptually, we think this is highly unlikely, as the healthcare facilities are exempted from many electricity-saving actions. Nevertheless, to address this concern, in Columns (1) to (3) of Table 3, we examine how the electricity-saving policy affects the number of heat-related ambulance transports and the number of doctors and nurses.

We first look at ambulance usage as an alternative outcome. People are transported by ambulances only when they call for help and when the hospital responds to the emergency. Thus,

²³ The mean saving target is about 8.0% in a typical summer. To calculate the number of additional heat-related deaths caused by the policy, we multiply this number by the estimated coefficient in Table 2 and then times the total population of Japan (127 million).

an increase in heat-related ambulance usage not only suggests that more people are suffering from exposure to heat but also implies that hospitals can execute their job.²⁴ The result in Column (1) shows that the electricity-saving policy indeed increased the number of heat-related ambulance transports. A 10% rise in the saving target can lead to a 24.2 (per 1,000,000) rise in heat-related ambulance use. This finding is consistent with our argument that the electricity-saving policy makes people more vulnerable to heat shocks.²⁵

In Columns (2) and (3), we examine whether the electricity-saving policy affects health care conditions. We focus on the number of doctors per capita and the number of nurses per capita. We find that these indicators for healthcare quality were not affected by the electricity-saving target. Thus, there is no evidence that the health care conditions deteriorated after the electricity-saving policy was implemented.

The second alternative explanation is 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 re-utilize thermal power plants, which might cause more air pollution. If air pollution can somehow increase deaths from heat (which is conceptually unlikely), our observed impacts can be confounded. To examine such possibility, in Columns (4) to (6), we estimate the impact of saving targets on air pollution. It turns out that the effects of the saving targets on different pollutants are small in size and statistically insignificant. One potential reason for the null result is the thermal power plants are located relatively far away from the population centers and their emissions would not be able to significantly change the air pollution levels in the urban areas (Appendix C 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 and all the power plants have to use clean coal for production. For whatever reason, this test shows that air pollution cannot possibly drive the health consequences of saving energy.

²⁴ In Japan, ambulance use is common because ambulance transportation is free of charge.

²⁵ If we further interact the temperature bins with the saving target, we find similar results: electricity-saving increased heat-related ambulance use during the very hot days.

Finally, in Columns (7) and (8), we investigate whether electricity-saving affects two basic socio-economic variables: per capita GDP and share of the old population. The first concern is that if the electricity-saving policy negatively affects the economy, it can also lead to undesirable health consequences. In Column (7), 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 the incentive to migrate across regions to mitigate climate damage. In Column (8), we cannot find that electricity-saving affects the share of older adults (above 65 years old) in the population.

C. Mechanisms

In this section, to better understand the channels through which the electricity-saving policy affects heat-related mortality, we investigate how the energy-saving policy shapes people's behaviors, and how it limits the people's resilience to extreme temperature.

We first examine whether people search more online on how to save energy when they are exposed to intensive energy-saving campaigns. We use Google Trend for “energy-saving” (in Japanese) to measure search behavior and report the finding in Column (1) in Table 4. We see that a 10 percentage point increase in the electricity-saving target increases the search by around 33.6%.

We then examine the effects on air conditioner (AC) ownership and the purchase behaviors on non-AC cooling appliances. As the campaigns repeatedly encouraged households to substitute ACs by other cooling devices (such as fans), we expect that air conditioner penetration could reduce, and the purchase of non-AC cooling appliances could increase. Column (2) and (3) support our expectations. We find that a 10 percentage point increase in the target reduces air conditioner penetration by around 14.7% and increases purchases of non-AC cooling appliances by about 13.0%.

These results are suggestive evidence that governments' actions during energy-saving campaigns were indeed useful: people paid attention to the campaigns and followed the guidelines. As air conditioning plays a crucial role in mitigating climate impact, reducing air conditioner use is a likely channel through which electricity-saving increases heat-related mortality rate.

D. Heterogeneous Effects

In this section, we investigate the heterogeneous impacts of electricity-saving on heat-related mortality across different subsamples. The results are summarized in Table 5. We first examine heterogeneity based on the number of days with extreme heat (over 27.5°C). Existing evidence also shows that areas facing extreme heat more frequently have smaller heat damages, presumably because they are well adapted to the climate and have succeeded in diminishing its risk (Barreca et al., 2016; Carleton et al., 2018). We find similar results that areas with hot weather have much smaller temperature effects (Panel A). One more hot day (above 27.5°C) can lead to a 0.16 (per 1,000,000) increase in the heat-related mortality rate in cooler areas (Column (1)), contrasting to a 0.03 change in warmer areas (Column (3)).

Turning from the impact of hot days to the impact of electricity-saving, we find the opposite pattern. Electricity-saving has a smaller effect on heat-related deaths (0.51 in Column (1)) in areas with less exposure to extreme heat. In sharp contrast, in areas experiencing extreme heat more frequently, the electricity-saving target has a statistically significant impact on heat-related mortality (2.31 in column (2)). These results imply that the health cost of electricity-saving is primarily driven by the warmer areas, possibly by discouraging the use of existing air conditioners.

Next, we examine income heterogeneity. Existing evidence suggests that the temperature-health relationship can be moderated by income levels (e.g., Burgess et al., 2017; Carleton et al., 2018) because higher income loosens households' budget constraints and helps people adopt defensive behaviors. Panel B reports our findings. Column (1) shows that, in low-income areas, extreme heat (above 27.5°C) has a significant impact on heat-related mortality, while Column (3) reveals that the effect is smaller and statistically non-significant in high-income area. The electricity-saving policy, however, has the opposite effect. Wealthier regions suffer more from electricity-saving than poor regions, as measured by heat-related mortality. A plausible explanation is that wealthier

regions, like warmer regions, had a relatively large number of air conditioners, but were discouraged from using them by the saving targets.²⁶

To summarize, climate damage tends to be smaller in richer and warmer regions. Our interpretation is that people in these regions can better adapt to climate shocks. When an electricity-saving policy is implemented, however, richer and warmer regions will be more severely affected and experience more considerable health damages since electricity-saving reduces their ability to mitigate the climate damage.

E. Robustness Checks

In this section, we conduct a variety of placebo tests and robustness checks, which together lend additional credibility to our findings. In Table 6, we focus on deaths from other causes that are less likely to be affected by extremely hot weather and air conditioning: infectious diseases, congenital malformations, and accidents. We find that hot temperature does not affect infectious diseases and congenital malformations, but can slightly increase the number of deaths from accidents. For the energy-saving variable, it does not affect any outcome.

Table 7 checks the robustness of our main findings in several different ways. First, we examine whether the results are sensitive to slight revisions of the electricity-saving targets. Recall that the saving targets were calculated based on the deviation between expected supply and demand for electricity, and the government announced these saving targets for different regions before the summer electricity-saving campaigns. At the same time, however, there were also heated debates on whether the government should re-utilize some nuclear power plants. In July 2012, during the national campaign period, the Oi Nuclear Reactors located in the Kansai region were re-started, after being approved by the central government. The increased supply capacity resulted in a reduction in the saving target in Kansai and nearby areas, and the government thus slightly revised

²⁶ In Appendix D, we also provide results on heterogeneity using the entire sample with interaction terms between saving target and the number of days with extreme heat or income level. The results remain the same using the alternative econometric model.

the saving targets in these areas.²⁷ Using the revised electricity-saving targets as the explanatory variable, we re-estimate Equations (1) and (2).²⁸ As reported in Panel A of Table 7, the new estimates become slightly smaller but are still quantitatively similar to the baseline estimates, suggesting that modification of the saving targets have negligible impacts on our findings.

Panel B uses a wider exposure window to estimate the policy impact, as the electricity-saving campaigns could somehow affect behavior even when it is not in effect. For example, households' behaviors might have been changed before the campaigns were initiated, as they were well aware of the electricity shortage. Alternatively, people's energy-saving habits might persist after the campaigns. In Panel B, we construct an alternative temperature variable, which counts the number of days in different temperature bins from June to October, including one month before and after the summer, as the primary explanatory variables. The findings remain the same.

In Panel C, we control for lagged effects of temperature and electricity-saving policy. A concern is that the effects of heat and energy-saving may be cumulative over time. Thus, we estimate the main specifications with additional controls for lagged variables on temperature bins, saving targets, and interaction between temperature and saving target in the previous year. We find that adding these controls does not affect our estimation.

We conduct several other robustness checks in Panels D to H. First, controlling for air pollution does not affect our findings (Panel D). Second, we use a slightly different temperature bin ($< 20^{\circ}\text{C}$) as the reference group and reach the same conclusion (Panel E). Third, in Panel F, we use the entire sample of Japanese prefectures, which include the three prefectures severely damaged by the earthquake, in the regressions. Again, we find similar results. In Panels G and H, we use two alternative outcome measures – the logarithm of heat-related mortality rate and the logarithm of the number of heat-related deaths – as the outcome variables. The results remain similar.

²⁷ Source: <https://www.bbc.com/news/world-asia-18662892>

²⁸ For the explanatory variable, we take the mean saving target in each region during the campaigns. For example, if the target is revised on August 1st, we use 31 days (before revision, July 1st to 31st) and 61 days (after revision, August 1st to September 30th) to obtain a weighted average.

Finally, in Appendix Table E, we use the share of nuclear power plants that were suspended over the total electricity supply in the pre-accident period as the explanatory variable.²⁹ Recall that the saving targets are computed from the deviation between the expected electricity demand and supply, there is a concern that saving targets may reflect demand-side factors that could be correlated with health outcomes (although it is difficult for us to come up with such factors). By focusing on the share of nuclear power plants that were shut down, which only captures the supply-side factors, we can alleviate such a concern. The results in Appendix Table E show that the effects of the nuclear suspension are quantitatively similar to our baseline estimates, suggesting that the demand-side elements not driving our main findings.³⁰

VI. What Incentivizes People to Save Electricity?

A. Decompose the Energy Saving using Machine Learning Algorithms

Now that we have established the fact that the energy-saving campaigns in Japan unintendedly caused more people to die. An important question naturally arises: what policy incentives – price increase or moral suasion – changed people’s behaviors, which eventually led to additional deaths? The answer to this question can not only help us better understand how to attribute the negative consequences of energy-saving to different components of the campaigns but also sheds light on the broader issue on how to design effective energy-saving policy.

Our first solution to the above question is to use machine learning. Intuitively, we can train machine learning models using the pre-accident data and fit electricity consumption by price, weather, and socio-economic conditions; then, we can use the trained models to predict the post-accident electricity consumption using post-accident price, weather, and socio-economic variables. Here, our purpose is to maximize the predicting power rather than drawing a causal inference, so

²⁹ For example, if the nuclear power had supplied 30% of the total electricity before the accident (3 years average) and all nuclear reactors were shutdown after the accident, the indicator is measured as -30%.

³⁰ As a placebo test, we also adopt the percentage changes in hydropower electricity supply. The results find statistically insignificant effects.

we rely on machine learning methods (See Varian, 2014; Kleinberg et al., 2015; Mullainathan and Spiess, 2017 for recent reviews).³¹

Specifically, in the first step, we train a region-specific prediction model using pre-accident data (monthly data from 2002 to 2011). Three machine learning methods are adopted to check the robustness of results: Random Forest (RM), Least Absolute Shrinkage and Selection Operator (LASSO), and Artificial Neural Network (ANN).³² In each machine learning model, electricity consumption per capita (log) is a function of electricity price (log), weather, and socio-economic status. For the electricity price, we use the regional level average electricity price. For weather variables, we include the mean precipitation (log) and different temperature bins similar to the baseline model. For socio-economic variables, we include household income (log), unemployment rate, and share of the working population (from age 15 to 64). These data are all measured at the monthly or quarterly level. We also include month fixed effects, and interact them with all the input variables.

For illustrative purposes, we summarize the prediction results from the RM model in Figure 6. Panel A plots the actual and predicted electricity consumption per capita during the pre-accident period. Panel B plots the scatter dots of actual consumption against predicted consumption. We can observe that the RM model can predict the consumption levels with high accuracy. LASSO and ANN generate quantitatively similar results (as summarized in Appendix F-1). If we regress the actual consumption on the predicted value using the pre-accident data, we obtain well-fitted regressions with R^2 equal to 0.98 for RM predictions, 0.94 for LASSO prediction, and 0.94 for ANN prediction.³³

³¹ 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; Jean et al., 2016), hygiene inspections (Glaesler et al., 2016), perceived safety (Naik et al., 2015), and judge's decisions (Kleinberg et al., 2018).

³² In recently developed literature in environment and energy economics, Lasso is used by Burlig et al. (2019), and the random forest is adopted by Cicala (2017) for out-of-sample prediction.

³³ One of the major empirical threat of the machine learning prediction is overfitting: the model is precise for the in-sample prediction, but inadequate for the out-of-sample prediction. For this issue, we randomly split the pre-accident data into the training sample with the 75% of periods and the testing sample with the remaining 25%, and examine

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 (the year right before the accident), and post-accident weather and socio-economic variables as inputs. The difference between the 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.

Figure 7 plots the two counterfactual predictions from the RM model and the real consumption data over time. The blue dot line and red dash line represent the first and the second predictions, while the solid black line represents the actual consumption. The difference between the red and the blue line approximates the effect of the increased price while the difference between the blue and the black line measures the effect of non-pecuniary incentives (i.e., any incentives other than price) on electricity-saving. These differences are summarized in the bottom graph. 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. When using alternative machine learning models, we also find similar results (Appendix F-2 summarizes the results from LASSO and ANN).

We then calculate population-weighted national estimates and report them in Panel A of Table 8. Overall, electricity per capita declined by 8.5%~12% from the 2011 summer to 2015 summer (column (3)). Higher electricity prices reduced electricity consumption, but the effect was modest (0.9%~3.0%). The lion share of the reduction (7.5%~9.4%) could not be attributed to price changes. Put the numbers in another way: the machine learning models suggest pecuniary incentives can only explain 10%~25% of the entire reduction in electricity consumption, implying non-pecuniary incentives play a vital role in shaping people's energy conservation behaviors.

whether the trained model can accurately predict the real value in testing sample. We conduct this process 10 times, and find that even though the out-of-sample prediction is slightly noisier than the in-sample prediction, the prediction is still well-fitted with median R^2 is equal to 0.86 for RM, 0.90 for LASSO, and 0.89 for ANN.

B. Predictions Based on Price Elasticity

To complement the above analyses, in Panel B in Table 8, we use a simpler but more transparent way to predict the price-driven changes in electricity consumption. Specifically, we first estimate the price elasticity using the pre-accident data, then apply the estimated elasticities to predict post-accident electricity consumption. We find that summer price elasticity in the pre-accident period is around -0.10 to -0.11, and the increase in electricity price after the Fukushima accident is able to decrease total electricity consumption by around 1.4% to 2.8%. Given that the summer electricity consumption actually dropped by 12.4%, we also conclude that the price change cannot explain a large portion of the electricity consumption reduction, which is consistent with the results from machine learning models. In Appendix Table G, we further provide our price elasticity estimates for other seasons (-0.15 to -0.30).

We can reach the same conclusion if we use price elasticity estimates from previous studies. Existing literature suggests that the price elasticity ranges from -0.39 to 0.04 (Reiss and White, 2005; Ito, 2014; Neidell et al., 2019; and Deryugina et al., 2018).³⁴ Even using the largest estimate (-0.39) from these studies, nearly half of the reduction in Japan's electricity consumption still cannot be explained by price increase. In fact, the price elasticity has to be as large as -0.71 to be able to explain the entire reduction in electricity consumption after the Fukushima accident.

C. Why Pecuniary Incentives Had Economically Modest Effects

Policymakers have historically favored non-pecuniary incentives, such as campaigns and advertisements, rather than raising prices, to encourage people to reduce electricity consumption.³⁵ The reason is that raising the price is often politically difficult because it can impose significant

³⁴ The four studies we cited here all use quasi-experimental approaches to estimate the price elasticity of electricity consumption. While there are many associational studies that also estimated the elasticities, they tend to suffer from the endogeneity problem and we thus do not include them in this analysis.

³⁵ See Borenstein (2002) and Reiss and White (2008) for the California Electricity Crisis, and Costa and Gerard (2018) for the Brazil Energy Crisis.

hardship on low-income households (Borenstein, 2012; Levinson and Silva, 2019). Our analyses suggest that these non-pecuniary incentives could indeed change people's behaviors.

However, this finding contrasts starkly with Ito et al. (2018), who designed a field experiment in Japan and show that price changes induce more electricity saving than moral suasion both in the short and long run. This inconsistency may be caused by the systematic differences between the well-designed field experiment and real-life policies. Specifically, in Ito et al. (2018)'s experiment, the researchers were able to raise electricity prices by 160%~320% during peak hours, while in reality the Japanese government increased electricity prices by only 5% to 10% each year. In addition, the moral suasion treatment in Ito et al. (2018) did not carry significant stake in peoples' real life, as there will be no severe consequence if people do not respond; but in Japan's energy-saving campaigns, the government repeatedly highlighted the significant risk of blackout and provided detailed instructions to households on how to reduce electricity consumption.

Finally, in the appendix, we provide two sets of additional results relevant to this discussion. First, we estimate the effects of saving targets and electricity prices on actual electricity consumption. The results are represented in Appendix Table H-1. We find that a 10 percentage point change in the saving target is associated with a decline in actual consumption per capita by around 7.4 ~ 11.2%. Notably, controlling for electricity prices only slightly attenuates the effect of saving targets. Second, we re-estimate the baseline model after controlling for electricity price and report the results in Appendix Table H-2. In this exercise, we find that electricity price does not have a statistically significant impact on heat-related mortality, and controlling for electricity price does not change our conclusion.

VII. Conclusion

Energy consumption plays a central role in mitigating climate damage. Therefore, energy-saving policies that limit people's adaptation opportunities may cause significant health damages. Such damages will be amplified when energy-saving is interacted with extreme weather, as people depend critically on energy consumption to avoid exposure to extreme weather.

This paper provides an empirical investigation of how saving energy affects population health using data from Japan. We exploit the electricity-saving targets in different regions following the Fukushima accident and show that electricity-saving significantly increased heat-mortality rates. This effect can be entirely attributable to excess deaths on extremely hot days. We also find that electricity-saving discourages people from using air conditioners and encourages people to buy non-AC cooling appliances. The negative impact of electricity-saving is particularly large in rich and warmer regions, which had higher AC penetration before the disaster but made less use of their AC afterward because of the electricity-saving target.

Our findings highlight the non-negligible 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). Future research is needed to understand better how to balance the tradeoff between climate adaptation and energy saving.

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Figure 1. Nuclear Power Utilization Rate

Notes: This figure shows the utilization rate of nuclear reactors in Japan. The vertical dashed line represents the timing of the Fukushima accident. The blue circles represent utilization rate before the accident, while the red squares represent utilization after the accident.

Source: Federation of Electric Power Companies of Japan (FEPC, 2018)

https://www.fepec.or.jp/library/data/infobase/pdf/08_d.pdf

Figure 2. Electricity-saving Targets in Different Years

Notes: This figure shows saving targets over the period from 2011 to 2014. In 2011, only three regions had electricity-saving targets. In 2012, almost all areas in Japan had saving targets, and this trend continued. The mean and standard deviation are weighted by the population each year.

Figure 3. Trends in Japan's Electricity Consumption and Price

Panel A: Trend of Electricity Consumption per capita (2010 = 1.00)

Panel B: Trend of Average Electricity Price (2010 = 1.00)

Notes: This figure shows the trends in electricity consumption per capita and prices. In both Panel A and B, the X-axis represents the period in which 0 denotes one year before the Fukushima Accident. The black dash line represents the annual averages. The blue line with a diamond marker shows the data in summer seasons (from July to September each year), while the red line with a circle marker shows the data in winter seasons (from December to February each year). We standardize the data, with 1 representing the data measured one year before the accident.

Figure 4. Electricity-Saving Targets and Changes in Actual Consumption

Notes: This figure shows the relationship between the average saving target and electricity consumption reductions (%) in all 10 regions in Japan from 2011 to 2015. The size of each circle represents the population in each region. The downward dashed line has a slope of -1.

Figure 5. Predicted Damage of Electricity-Saving Policy

Notes: Using mean temperature distribution in each prefecture from 2011 to 2015, we calculate the predicted damages of 10% electricity saving target in different prefectures. The red circles predict the heat-related mortality rate when the saving policy is in effect, while the blue circles estimate the damage without the saving policy. The size of the circle represents the size of the population. The damages are calculated based on the estimates in column (4) of Table 2.

Figure 6. The Predicted Consumption of Random Forest

Panel A: Predicted and Actual Electricity Consumption per capita

Panel B: Scatter Plot

Notes: Using month-by-region data from 2000 to 2011, we train region-specific random forest models of log (consumption per capita). Panel A shows the prediction and actual value over the years. In Panel B, the scatter plot shows the actual consumption per capita on the y-axis and the prediction on the x-axis. The black line represents the fitted value. The results show that the model precisely predicts the actual value in the pre-accident period.

Figure 7. The Predicted Counterfactual and the Actual Consumption

Notes: The above graph shows the predicted counterfactuals and the actual log (consumption per capita) in the post-accident period. 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. The blue dash line represents the predicted counterfactual when using 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 line shows the effects of price changes while the difference between the blue and the black line shows the effects of the saving campaigns. These differences are summarized in the bottom graph. The red area represents the effects of price change, and the blue represents the effects of moral suasion. The results from LASSO and ANN are described in Appendix F

TABLE 1—SUMMARY STATISTICS OF THE KEY VARIABLES AND BALANCE CHECKS

	Summary Statistics				Balance Checks
	Entire Sample (1)	2006-2010 (2)	2011-2015 (3)	% Change (4)	Saving Target (per 10pps) (5)
<i>Panel A. Energy-saving Policy</i>					
Monthly Electricity Consumption per capita	1,794	1,873	1,708	-8.8%	-152
(summer, kwh)	(204)	(189)	(200)		(105)
<i>Panel B. Health Outcomes</i>					
Heat-Related Mortality Rate	4.67	5.96	6.63	11%	0.26
(per 1,000,000)	(4.11)	(5.25)	(3.46)		(1.36)
Heat-Related Ambulance Use	217	161	310	93%	-18.0
(per 1,000,000)	(162)	(142)	(150)		(16.0)
<i>Panel C. Adaptation Technology</i>					
Google Search for “Energy Saving”	8.23	0.95	18.4	1838%	-0.45
(Index)	(19.1)	(1.00)	(26.3)		(0.27)
Air Conditioner Penetration	88.5	89.1	90.9	2.0%	10.9
(%)	(18.1)	(17.8)	(15.4)		(7.72)
# of purchases of non-AC Cooling Appliances	13.3	12.0	15.3	28%	-1.89*
(per 100 household)	(4.96)	(3.97)	(5.88)		(1.12)
<i>Panel D. Weather</i>					
# of days below 25°C	37.4	38.1	38.2	0.3%	-4.51
(in summer)	(19.5)	(20)	(18.5)		(7.71)
# of days from 25°C to 27.5°C	27.9	26.9	26.4	-1.9%	2.77
(in summer)	(10.6)	(9.79)	(10.2)		(3.24)
# of days exceeding 27.5°C	26.7	27.0	27.4	1.5%	1.74
(in summer)	(15.5)	(17.2)	(14.2)		(5.93)
Monthly Precipitation	187	177	199	12%	-19.9
(mm)	(68.2)	(59.8)	(73.1)		(14.3)
Mean Monthly Wind Speed	2.14	2.06	2.21	7.3%	-0.15
(m/s)	(0.581)	(0.546)	(0.545)		(0.34)

Notes: Columns (1) to (3) report the means and standard deviations of the key variables using different samples. Column (4) reports percentage differences between (2) and (3) for the key variables. In Column (5), we test how these variables before the Fukushima accident are correlated with the electricity-saving targets announced after the Fukushima accident. Each cell represents a separate regression in which the average energy-saving target is the explanatory variable, and the dependent variable is each key variable. We use data between 2008 and 2010, and year dummies are included in each regression. Robust standard errors are reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

TABLE 2—TEMPERATURE, ELECTRICITY SAVING, AND HEAT-RELATED MORTALITY

	Heat-Related Mortality Rate (per 1,000,000)			
	(1)	(2)	(3)	(4)
Saving Target (per 10 pps)	1.64** (0.69)	1.57** (0.59)	-1.60 (1.08)	-1.04 (1.23)
# of days between 25°C ~ 27.5°C		-0.00 (0.04)	-0.01 (0.03)	-0.00 (0.03)
# of days above 27.5°C		0.07** (0.03)	0.06* (0.03)	0.07** (0.03)
# of days between 25°C ~ 27.5°C * Saving Target (per 10 pps)			0.03 (0.03)	0.03 (0.02)
# of days above 27.5°C * Saving Target (per 10 pps)			0.07** (0.03)	0.06* (0.03)
Log (Monthly Precipitation)		0.57 (0.37)	0.52 (0.35)	0.50 (0.35)
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Obs.	748	748	748	748
R-Squared	0.66	0.69	0.68	0.69

Notes: The omitted group is # of days below 25°C. Controls include log wind speed, log prefectural GDP per capita, and population shares of age groups 0 to 4, 5 to 19, and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

TABLE 3— RULING OUT ALTERNATIVE EXPLANATIONS

	Health Status & Healthcare Quality			Air Pollution			Socio-economic Characteristics	
	Heat-Related Ambulance Use (per 1,000,000)	Log (# doctors per capita)	Log (# nurses per capita)	Log (PM)	Log (SO ₂)	Log (O ₃)	Log (Prefectural GDP per capita)	Share of Age 65+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Saving Target (per 10 pps)	24.197*** (8.699)	0.014 (0.011)	-0.004 (0.015)	-0.036 (0.027)	0.012 (0.076)	-0.030 (0.023)	0.013 (0.012)	0.004 (0.004)
# of days between 25°C ~ 27.5°C	-0.468 (0.496)	0.000 (0.000)	0.000 (0.000)	0.001* (0.001)	-0.003 (0.003)	0.002** (0.001)	0.000 (0.000)	0.000 (0.000)
# of days above 27.5°C	3.073*** (0.597)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.001)	-0.003 (0.003)	0.002*** (0.001)	0.001* (0.000)	0.000 (0.000)
Prefecture FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	2,689	352	352	748	745	748	748	748
R-Squared	0.71	0.95	0.99	0.81	0.67	0.63	0.49	0.97

Notes: In column (4), we use SPM (Suspended Particulate Matter) for PM. The omitted group is # of days below 25°C. Controls include monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), population shares of age groups 0 to 4, 5 to 19, and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

TABLE 4—MECHANISMS

	Behaviors for Adaptation		
	Log (Google Search Rate “Energy- saving”) (1)	Log (AC Penetration) (2)	Log (# Purchase of non-AC Cooling Appliances) (3)
Saving Target (per 10 pps)	0.336*** (0.083)	-0.147* (0.077)	0.130** (0.051)
# of days between 25°C ~ 27.5°C	-0.004 (0.004)	0.003 (0.003)	-0.001 (0.003)
# of days above 27.5°C	-0.002 (0.004)	0.002 (0.002)	0.001 (0.003)
Prefecture FE	Y	Y	Y
Year FE	Y	Y	Y
Controls	Y	Y	Y
Obs.	528	176	704
R-Squared	0.89	0.40	0.27

Notes: In column (1) to (3), we use data from May to September, including two months before the summer campaigns since households may change behaviors before the hottest season. The omitted group is # of days below 25°C. Controls include monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), population shares of age groups 0 to 4, 5 to 19, and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

TABLE 5—HETEROGENEOUS EFFECTS OF ELECTRICITY SAVING ON HEAT-RELATED MORTALITY

	Heat-Related Mortality Rate (per 1,000,000)			
	Low		High	
	(1)	(2)	(3)	(4)
<i>Panel A. The number of days above 27.5 °C (Low < Median; High > Median)</i>				
Saving Target (per 10 pps)	0.51 (0.60)	-1.13 (1.35)	2.31** (0.87)	-2.82 (3.43)
# of days between 25°C ~ 27.5°C	0.02 (0.04)	0.02 (0.04)	-0.02 (0.06)	-0.01 (0.05)
# of days above 27.5°C	0.16*** (0.03)	0.16*** (0.04)	0.03 (0.05)	0.03 (0.05)
# of days between 25°C ~ 27.5°C *		0.05		0.04
Saving Target (per 10 pps)		(0.03)		(0.06)
# of days above 27.5°C		0.01		0.11*
* Saving Target (per 10 pps)		(0.04)		(0.06)
Obs.	374	374	374	374
R-Square	0.67	0.67	0.72	0.73
<i>Panel B. GDP per capita (Low < Median; High > Median)</i>				
Saving Target (per 10 pps)	1.14 (0.73)	-0.16 (1.35)	1.75* (0.88)	-2.67 (1.70)
# of days between 25°C ~ 27.5°C	0.01 (0.04)	0.01 (0.04)	-0.03 (0.04)	-0.02 (0.04)
# of days above 27.5°C	0.11*** (0.02)	0.11*** (0.02)	0.01 (0.05)	0.01 (0.04)
# of days between 25°C ~ 27.5°C *		0.05		0.03
Saving Target (per 10 pps)		(0.03)		(0.05)
# of days above 27.5°C		-0.01		0.11***
* Saving Target (per 10 pps)		(0.03)		(0.03)
Obs.	374	374	374	374
R-Square	0.62	0.62	0.74	0.75
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y

Notes: Subsamples are based on the number of days above 27.5°C and prefectural GDP per capita from 2010, before the Fukushima accident. The omitted group is # of days below 25°C. Controls include monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), and population shares of age groups 0 to 4, 5 to 19, and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

TABLE 6—PLACEBO TEST

	Infectious Diseases			Congenital	
	All	Tubercu losis	Viral Hepatitis	Malforma tions	Accident
	(1)	(2)	(3)	(4)	(5)
<u>Mean</u>	<u>43.4</u>	<u>4.2</u>	<u>9.6</u>	<u>4.2</u>	<u>51.5</u>
<u>S.D</u>	<u>(9.33)</u>	<u>(1.6)</u>	<u>(3.03)</u>	<u>(1.38)</u>	<u>(14.9)</u>
Saving Target (per 10 pps)	0.00 (0.94)	-0.21 (0.29)	0.03 (0.43)	-0.07 (0.22)	1.41 (1.00)
# of days between 25°C ~ 27.5°C	-0.05 (0.05)	-0.02 (0.01)	-0.00 (0.02)	0.00 (0.01)	0.01 (0.05)
# of days above 27.5°C	-0.01 (0.05)	-0.02* (0.01)	-0.01 (0.01)	0.01 (0.01)	0.09** (0.04)
Prefecture FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Obs.	748	748	748	748	748
R-Squared	0.52	0.11	0.13	0.12	0.28

Notes: The cause-specific mortality rate is adjusted to per 1,000,000. Data on cause-specific mortality is collected from July to September. In column (5), accidents mainly include deaths from traffic, falling, drowning, and choking. The omitted group is # of days below 25°C. Controls include monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), and population shares of age groups 0 to 4, 5 to 19, and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

TABLE 7— ROBUSTNESS CHECKS

	Impact on Heat-Related Mortality Rate (per 1,000,000)			Obs.	R ²
	Saving Target (10 pps)	# of days between 25~27.5°C* Saving Target (10 pps)	# of days over 27.5°C * Saving Target (10 pps)		
A. Using Saving Target After Revision	1.37** (0.56)			748	0.69
	-1.16 (1.21)	0.02 (0.02)	0.06* (0.03)	748	0.69
B. Different Temperature Window	1.60*** (0.58)			748	0.69
	-1.02 (1.37)	0.03 (0.02)	0.05* (0.03)	748	0.69
C. Controlling for Lagged Effects	1.55** (0.58)			704	0.69
	-0.68 (1.33)	0.02 (0.03)	0.05* (0.03)	704	0.69
D. Controlling for Air Pollution and Ozon	1.61*** (0.55)			745	0.70
	-1.07 (1.21)	0.03 (0.02)	0.06* (0.03)	745	0.71
E. Using < 20°C Bin as the Reference Group	1.57** (0.59)			748	0.69
	-2.93 (2.55)	0.04 (0.03)	0.08* (0.04)	748	0.69
F. Using all samples	1.45** (0.58)			799	0.68
	-0.90 (1.03)	0.03 (0.02)	0.06* (0.03)	799	0.69
G. Using Log (Heat-Related Mortality Rate)	0.246** (0.115)			728	0.69
	0.028 (0.226)	-0.001 (0.005)	0.007* (0.004)	728	0.69
H. Using Log (Heat-Related Deaths)	0.274** (0.120)			728	0.69
	0.045 (0.229)	-0.001 (0.005)	0.008* (0.004)	728	0.70

Notes: All regressions include prefecture fixed-effects, year fixed-effects, and the set of controls. Controls include # of days between 25°C ~ 27.5°C, # of days above 27.5°C, log monthly precipitation, log wind speed, log prefectural GDP per capita, and population shares of age groups 0 to 4, 5 to 19 and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. Panel B uses temperature from June to October, while our main specification uses temperature from July to September. Panel C includes lagged saving targets as a control variable. Panel D adds a logarithm of three air pollutants; SPM (Suspended Particulate Matter), NOx and SO2, and a specific kind of ozone; Ox (photochemical oxidant). Panel E adds the number of days between 20°C~25°C and its interaction with the saving target. Panel E adds four different precipitation bins indicating the relative amount of precipitation given the same prefecture instead of log monthly precipitation. For all models, standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

TABLE 8—DECOMPOSE THE REDUCTION IN ELECTRICITY CONSUMPTION IN SUMMER

	Reduction in Summer Consumption				Price Elasticity
	Price Effects	Effects of Moral Suasion	Total	% Explained by Price Effects	
	(1)	(2)	(3)	(4)	
<i>Panel A. Predictions based on Machine Learning</i>					
LASSO	-2.5%	-9.2%	-11.7%	23%	-
Random Forest	-0.9%	-7.5%	-8.4%	10%	-
ANN	-3.0%	-9.1%	-12.2%	25%	-
<i>Panel B. Predictions based on Price Elasticity</i>					
OLS	-1.8~-1.9%	-		14~16%	-0.10~-0.11
Deryugina et al. (2018)	-1.6~-4.7%	-		13~38%	-0.09~-0.27
Ito (2014)	-1.6%	-	-12.4%	13%	- 0.09
Neidell et al. (2019)	0.7~-3.15%	-		0~25%	0.04~-0.18
Reiss and White (2005)	-6.8%	-		55%	-0.39

Notes: Panel A shows the aggregated effect of energy-saving campaigns (moral suasion) and price changes on the log (electricity consumption per capita) from July to September. The effects of the moral suasion and price correspond to the effects described in Figure 7. In Panel B, price effects are calculated from multiplying average price change with the price elasticity. Our estimation of price elasticity estimation is summarized in Appendix G. Total consumption reduction (-12.4% in column (3)) comes from the difference between the average consumption level after the accident relative to the level one year before the accident.

Energy Saving Can Kill:

Evidence from the Fukushima Nuclear Accident

ONLINE APPENDIX

Appendix A. Data Sources

1. Electricity Consumption and Electricity Prices

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 1999 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. When quarterly data are not available, we use semi-annual or annual level data to calculate the average price.

2. Cause-Specific Deaths

Cause-specific deaths data are collected from the Vital Statistics reported by the Ministry of Health, Labour, and Welfare (MHLW). We conduct placebo tests using several causes that are arguably not related to energy consumption: infectious diseases (tuberculosis and viral hepatitis), congenital malformations, and accident. We count all the cause-specific deaths appearing from July to September, during which the electricity-saving policy was implemented.

The classification of the cause-specific deaths follows the International Statistical Classification of Diseases, 10th Revision (ICD 10, 2013). Infectious diseases correspond to codes A00 ~ B99, tuberculosis to A15 ~ A19, viral hepatitis to B15 ~ B19, congenital malformations to Q00 ~ Q99, and accident to V00 ~ V99 and W00 ~ W84. Accidents mainly include those from traffic, falling, drowning, and choking.

3. Prefectural Socio-Economic Conditions

Population data are collected from the Ministry of Internal Affairs and Communications. Prefectural GDP data is collected from the Cabinet Office and other socio-economic data from the Statistical Observations of Prefectures reported by the Ministry of Internal Affairs and Communications (MIAC). The numbers of doctors and nurses are surveyed once every two years.

We use region-by-month or region-by-quarter level data and quarterly data in section VI. Data on the quarterly unemployment rate and share of the working population are obtained from the Labor Force Survey provided by MIAC. Monthly average household income is obtained from the Family Income and Expenditure Survey provided by MIAC.

4. Air Pollution Data

Air pollution data are obtained from the National Institute for Environmental Studies. The concentrations of Suspended Particulate Matter (PM_{7-8}), NO_x , and SO_2 and Ox (Photochemical Oxidants) are collected from around 1,900 monitoring stations covering entire Japan. We calculate the prefectural air pollution by averaging the readings from all the monitoring stations within a prefecture.

Appendix B. Electricity-saving Policy and Electricity Consumption

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

2015年度夏季の 節電へのご協力をお願いします。

2015年度夏季の電力需給は、老朽火力の最大限の活用を前提に、
 いずれの電力管内でも安定供給に最低限必要とされる予備率3%以上を確保できる見通しです。
 他方、予期せぬ大規模な発電所トラブルが発生した場合、
 安定供給ができない可能性が懸念されます。
 政府、電力会社においては、引き続き供給力の確保に最大限の努力をまいります。
 無理のない範囲で、引き続き節電へのご協力をお願いいたします。
※期中症には十分ご注意ください。

節電をお願いしたい期間・時間・節電目標

平日 9:00～20:00
(前夜の8/12、14を除く)

数値目標なしの節電

7月

8月

9月

2015年度夏季の定着節電見込み

各電力管内の定着節電見込みを目安として、節電にご協力ください。

	東北	関東	中部	関西	北陸	中部	四国	九州
2015年度夏季定着節電見込み率(2015年度比)	▲4.4%	▲12.2%	▲4.9%	▲10.0%	▲4.4%	▲3.7%	▲6.0%	▲8.6%

無理のないかたちで、節電へのご協力をお願いします(使用していない部屋の電気はこまめに消す等)。
 特に、被災された地域の方々や、高齢者、乳幼児の方々等においてはそれぞれのご事情のもと、
 無理のない範囲で、ご協力をお願いします。

**経済産業省
資源エネルギー庁**

Source: https://www.enecho.meti.go.jp/category/electricity_and_gas/setsuden/

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

ご家庭のみなさま

お住まいの電力管内の**定着節電見込み**を目安に、
下記の節電メニュー等で、
節電へのご協力をお願いします。

5つの基本メニュー		節電効果
1 エアコン 室温を28℃にする。(＋2℃の場合)	10%
	2 “すだれ”や“よしず”などで窓からの日差しを和らげる。	10%
	3 無理のない範囲でエアコンを消し、扇風機を使用する。	50%
4 冷蔵庫 設定温度を「強」から「中」に変え、扉を開ける時間をできるだけ減らし、食品を詰め込みすぎないようにする。(食品の傷みにご注意ください。)	2%
5 照明 日中は不要な照明を消す。	5%
6 テレビ 省エネモードに設定する。画面の輝度を下げ、必要な時以外は消す。	2%
7 温水洗浄便座(温水洗浄) 温水のオフ機能、タイマー節電機能を利用する。	いずれかで 1%未満
	8 上記の機能がない場合、使わない時はコンセントからプラグを抜く。
9 ジャー炊飯 早朝にタイマー機能で1日分まとめて炊いて、冷蔵庫や冷凍庫に保存する。	2%
10 待機電力 リモコンの電源ではなく、本体の主電源を切る。長時間使わない機器はコンセントからプラグを抜く。	2%

その他にも、消費電力が大きい電気製品は、特に日中(13時～16時)を避けて使用していただくなど、ご協力をお願いいたします。

アイロン

電気ポット

電気洗濯機

ネットプレーン

ドライヤー

トースター

IHクッキングヒーター

掃除機

浴室乾燥機

換気扇・乾燥機

※各電気製品のピーク時の消費電力(約1200W)を以てする節電率の目安。※電源をオフするに限り、

Source: https://www.enecho.meti.go.jp/category/electricity_and_gas/setsuden/

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 summer in 2015, we need to reserve 3% of the power capacity (the minimum requirement) to ensure 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 such, 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 can 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°C 10%
	2	Block sunlight with curtain 10%
	3	Turn off the air conditioner and use fans if possible 50%
Refrigerator		Change temperature setting from “strong” to “middle.”
	4	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		Set the TV at “energy-saving mode” and lower the brightness of its display. Turn off the TV when it is not used
	6	2%
Electric Toilets	7	Set the toilets at “energy-saving mode.”
	8	Unplug the toilet when it is not used 1%
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. The Effects of The Saving Policy on Air Pollution

Locations of Thermal Power Plants and Prefectural Population Centers

Notes: This map shows the locations of thermal power plants and prefectural 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 D. Heterogeneity

APPENDIX TABLE D— HETEROGENEITY USING THE ENTIRE SAMPLE

	Heat-Related Mortality Rate (per 1,000,000)			
	(1)	(2)	(3)	(4)
Saving Target (per 10 pps)	-1.629 (1.058)	-1.180 (1.279)	-1.269 (0.765)	-1.061 (1.456)
Saving Target (per 10 pps) *	0.063**	0.057*		-0.16 (0.17)
# of Extreme Hot Days	(0.026)	(0.028)		
Saving Target (per 10 pps) * log (Prefectural GDP per capita)			0.001*** (0.000)	0.001* (0.000)
* # of days between 25°C ~ 27.5°C	-0.003 (0.031)	0.003 (0.032)	-0.008 (0.032)	-0.003 (0.034)
* # of days over 27.5°C	0.068** (0.031)	0.076** (0.029)	0.062* (0.033)	0.072** (0.030)
<i>The Joint Effects (Saving Target = 10%)</i>				
25 percentile	0.751 (0.508)	0.973* (0.490)	0.627 (0.527)	0.731 (0.581)
75 percentile	1.628** (0.649)	1.767*** (0.567)	1.111** (0.488)	1.188** (0.457)
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Obs.	748	748	748	748
R-Squared	0.683	0.692	0.686	0.692

Notes: # of extremely hot days and prefectural GDP per capita are measured in 2010, which is one year before the accident. # of extremely hot days corresponds to the number of days with mean temperature over 27.5°C. The joint effects measure the effects of saving target when # of extremely hot days or prefectural GDP per capita is 25% or 75% given saving target is equal to 10%. The omitted group is # of days below 25°C. Controls include monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), population shares of age groups 0 to 4, 5 to 19, and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

Appendix E. Robustness Check

APPENDIX TABLE E— THE IMPACT OF SHUTDOWN ON HEAT-RELATED MORTALITY RATE

Heat-Related Mortality Rate (per 1,000,000)	Nuclear		Hydro	
	(1)	(2)	(3)	(4)
	<u>Mean</u>	<u>-0.280</u>	<u>0.003</u>	
	<u>S.D.</u>	<u>0.123</u>	<u>0.013</u>	
Nuclear Share Change (10 ppt)	-0.578** (0.217)	-0.071 (0.262)		
Hydro Share Change (10 ppt)			-1.018 (1.943)	1.328 (1.193)
# of days between 25°C ~ 27.5°C	-0.000 (0.035)	0.007 (0.031)	-0.003 (0.035)	0.002 (0.033)
# of days above 27.5°C	0.082*** (0.029)	0.079** (0.030)	0.076** (0.031)	0.077** (0.030)
# of days between 25°C ~ 27.5°C * Nuclear Share Change (10 ppt)		-0.004 (0.005)		
# of days above 27.5°C * Nuclear Share Change (10 ppt)		-0.014* (0.008)		
# of days between 25°C ~ 27.5°C * Hydro Share Change (10 ppt)				-0.182 (0.121)
# of days above 27.5°C * Hydro Share Change (10 ppt)				0.101 (0.138)
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Obs.	748	748	748	748
R-Squared	0.69	0.69	0.68	0.68

Notes: The omitted group is # of days below 25°C. Controls include # of days between 25°C ~ 27.5°C, # of days above 27.5°C, log monthly precipitation, log wind speed, log prefectural GDP per capita, population shares of age groups 0 to 4, 5 to 19 and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

Appendix F. Machine Learning Results of LASSO and Artificial Neural Network (ANN)

F-1. Prediction Results of LASSO and ANN

Notes: Using month-by-region data from 2000 to 2011, we train region-specific machine learning models of log (consumption per capita). Panels A and B summarize the results from LASSO, while Panels C and D show the results from ANN. Panels A and C show the prediction and actual value over the years. In Panels B and D, we plot actual consumption per capita on the y-axis against the prediction on the x-axis. The black line represents the fitted value. The results show that the model precisely predicts the actual value in the pre-accident period.

F-2. Prediction Results of LASSO and ANN

Panel A: Results from LASSO

Panel B: Results from ANN

Notes: This graph shows the predicted counterfactuals and the actual log (consumption per capita) in the post-accident period. Prediction in Panel A uses the LASSO, and Panel B uses ANN. 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. The blue dash line represents the predicted counterfactual when using 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 line shows the effects of price changes while the difference between the blue and the black line shows the effects of the saving campaigns.

Appendix G. Price Elasticity of Electricity Consumption

APPENDIX TABLE G—PRICE ELASTICITY OF ELECTRICITY CONSUMPTION PER CAPITA

Log (Average Price)	Log (Total Electricity Consumption per capita)		
	(1)	(2)	(3)
Panel A. Using All Seasons			
Baseline	-0.15** (0.06)	-0.30** (0.12)	-0.27* (0.14)
Panel B. Subsample Analysis by Season			
Summer	-0.10 (0.22)	-0.11 (0.22)	-0.10 (0.22)
Winter	-0.27*** (0.07)	-0.39** (0.14)	-0.40** (0.15)
Region FE	Y	Y	Y
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: We control for weather and socio-economic conditions in all regression. Weather controls include monthly average temperature bins (7bins) and log precipitation. Socio-economic conditions include household income (log), unemployment rate, and share of the working population (from age 15 to 64). In panel B, summer uses observations from July to September, and winter uses from December to February. All regressions are weighted by population in 2010. Standard errors are clustered at the region level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%

Appendix H. Results after Accounting for Price Change

H-1. The Impact of Saving Targets on Electricity Consumption

APPENDIX TABLE H-1—THE IMPACT OF SAVING TARGETS ON ELECTRICITY CONSUMPTION

	Log (Electricity Consumption per capita)			
	(1)	(2)	(3)	(4)
Saving Target (per 10 pps)	-0.112*** (0.026)	-0.111*** (0.022)	-0.092*** (0.014)	-0.074*** (0.014)
Log (Average Price)				-0.400*** (0.087)
# of days between 25°C ~ 27.5°C		0.018 (0.012)	0.016** (0.006)	0.009* (0.004)
# of days above 27.5°C		0.057** (0.023)	0.042*** (0.012)	0.024*** (0.007)
Log (Monthly Precipitation)		0.010 (0.017)	0.009 (0.009)	-0.013 (0.012)
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	N	N	Y	Y
Obs.	170	170	170	170
R-Squared	0.73	0.76	0.76	0.9

Notes: The omitted group is # of days below 25°C. Controls include prefectural GDP per capita (log), population shares of age groups 0 to 4, 5 to 19, and over age 65. We use monthly average temperature and precipitation since the daily average temperature is likely to be very different within the same region. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%.

H-2. The Impact of Electricity Prices and Saving Targets on Heat-related Mortality

APPENDIX TABLE H-2— ADDITIONAL CHECKS CONTROLLING FOR PRICE CHANGES

	Heat-Related Mortality Rate (per 1,000,000)			
	(1)	(2)	(3)	(4)
Saving Target (per 10 pps)	1.57** (0.59)		1.63*** (0.55)	-0.99 (1.13)
Ln (Average Price)		1.75 (4.44)	-1.05 (4.12)	-0.44 (4.17)
# of days between 25°C ~ 27.5°C	-0.00 (0.04)	-0.00 (0.03)	-0.00 (0.03)	0.00 (0.03)
# of days above 27.5°C	0.07** (0.03)	0.08** (0.03)	0.07** (0.03)	0.07** (0.03)
# of days between 25°C ~ 27.5°C * Saving Target (per 10 pps)				0.03 (0.02)
# of days above 27.5°C * Saving Target (per 10 pps)				0.06* (0.03)
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Obs.	748	748	748	748
R-Squared	0.69	0.68	0.69	0.69

Notes: The omitted group is # of days below 25°C. Controls include # of days between 25°C ~ 27.5°C, # of days above 27.5°C, monthly precipitation (log), wind speed (log), prefectural GDP per capita (log), and population shares of age groups 0 to 4, 5 to 19 and over age 65. Three prefectures that were heavily damaged by the earthquake are excluded from the regressions. All regressions are weighted by population in 2010. Standard errors are clustered at the prefecture level and reported below the coefficients. * significant at 10% ** significant at 5%. *** significant at 1%