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BE CAUTIOUS WITH THE PRECAUTIONARY PRINCIPLE: EVIDENCE FROM FUKUSHIMA DAIICHI NUCLEAR ACCIDENT

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Be Cautious with the Precautionary Principle: Evidence from Fukushima Daiichi Nuclear Accident
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ABSTRACT

This paper provides a large scale, empirical evaluation of unintended effects from invoking the precautionary principle after the Fukushima Daiichi nuclear accident. After the accident, all nuclear power stations ceased operation and nuclear power was replaced by fossil fuels, causing an exogenous increase in electricity prices. This increase led to a reduction in energy consumption, which caused an increase in mortality during very cold temperatures. We estimate that the increase in mortality from higher electricity prices outnumbers the mortality from the accident itself, suggesting the decision to cease nuclear production has contributed to more deaths than the accident itself.

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As a regulatory tool, the precautionary principle has been met with mixed reactions. While many variants exist, a generally accepted definition of the principle is that activities should not proceed when the threats of damage are not fully understood.[1] A major concern with this principle is that by focusing solely on the risk from action, it fails to consider the risk from the alternative action. Something abandoned out of precaution is replaced by something else, which may also carry risk. From an economic perspective, it fails to consider the tradeoffs inherent in policy decisions.

In this paper, we provide a large scale, empirical evaluation of the tradeoff from invoking the precautionary principle using the nuclear power plant shutdowns resulting from the accident at Fukushima, Japan.[2] The accident, which resulted from a Tsunami caused by the 4th largest earthquake in recorded history, led to a nuclear meltdown at the Fukushima Daiichi nuclear power plant. Driven by long-standing concerns over the unknown effects from radiation risk, this rejuvenated the anti-nuclear movement.[3] Within 14 months of the accident, nuclear power production came to a complete halt in Japan.[4]

The decrease in nuclear energy production did not come without a cost: higher electricity prices. To meet electricity demands, the reduction in nuclear energy production was offset by increased importation of fossil fuels, which increased the price of electricity by as much as 38 percent in some regions. These higher electricity prices led to a decrease in electricity

[1] E.g., World Charter for Nature (1983); Rio Declaration on Environment and Development (1992, principle 15).
[2] While there are several case studies that evaluate this tradeoff (see, for example, those described in Adler 2000; Sunstein 2003), we are unaware, to the best of our knowledge, of large scale, systematic evidence.
[3] While there may be many reasons behind the anti-nuclear movement, nearly all are rooted in the precautionary principle. The main damages from nuclear power include risk from an accident, risk from nuclear waste and routine radioactive releases, all of which raise concerns with risks from radiation exposure. Additional concerns include increased nuclear proliferation and threats of terrorism, both of which also relate to unknown risks and damages, and thus relate to the precautionary principle.
[4] The accident also triggered opposition to nuclear production around the globe, with several nations ceasing nuclear operations shortly after the Fukushima accident.

consumption, particularly during times of the year with greater heating demand. Given the role that climate control plays in providing protection from extreme weather events, we find that the reduced electricity consumption caused an increase in mortality. Our estimated increase in mortality from higher electricity prices significantly outweighs the mortality from the accident itself, suggesting the decision to cease nuclear production caused more harm than good.

We produce these results using the following strategy. First, we document that the shutdown of nuclear power plants increased electricity prices, with strong variation throughout the country depending on the initial energy mix within a region. For example, regions with almost no nuclear energy before the accident experienced electricity prices increases around 10 percent, whereas regions with higher dependence on nuclear experienced prices increases up to 40 percent. The highly regulated nature of residential electricity markets in Japan means that supply factors contributed to these price changes, suggesting the price changes are exogenous to consumer demand for electricity.

Second, we explore how the price changes affected electricity consumption, estimating models that include multiple fixed effects to control for many possible sources of confounding. For example, in our richest specification we compare electricity consumption in Tokyo in January, 2012 to electricity consumption in Tokyo in January, 2011. We find that electricity consumption decreased roughly 1-2 months after price changes occur, a finding consistent with models of rational inattention (e.g., Salee 2013, Auffhammer and Rubin 2018). The decreases in electricity consumption are more pronounced during the winter[5], suggesting less protection during the coldest times of the year.

[5] Most sources of heating and cooling in Japan rely on energy from the grid except for Northern Japan.

Third, we explore the consequences from the reduced electricity consumption by estimating how it moderates the temperature-mortality relationship. We estimate fixed effect models with flexible temperature bins to relate exogenous changes in monthly temperature to mortality. Similar to previous research, we find that extreme temperatures affect mortality (e.g., Deschenes and Moretti 2009, Deschenes and Greenstone 2011, Barreca et al. 2016, Karlsson and Ziebarth 2018), in particular during very cold temperatures, though the effects from higher temperatures are small given high rates of air conditioning penetration, comparable to more recent estimates in the US. We then interact temperature with electricity prices to explore how electricity prices moderate the relationship between temperature and mortality. We find increased mortality effects from extreme cold weather, suggesting the decreased consumption of electricity that resulted from higher electricity prices increased mortality.[6] Our findings are robust to a wide variety of specification tests.

To put these estimates in context, we calculate that the higher electricity prices resulted in at least an additional 1,280 deaths during 2011-2014. Since our data only covers the 21 largest cities in Japan, which represents 28 percent of the total population, the total effects for the entire nation are even larger. Meanwhile, the number of deaths due to the Fukushima Daiichi nuclear accident is much lower. No deaths have yet to be directly attributable to radiation exposure, though projections estimate a cumulative 130 deaths (Ten Hoeve and Jacobson 2012). An estimated 1,232 deaths occurred as a result of the evacuation after the accident.[7] Therefore, the deaths from the higher electricity prices likely outnumber the deaths from the accident in only

[6] This finding is consistent with the evidence from Chirakijja et al. (2019), who find that lower energy prices in the US as a result of natural gas expansion decreased mortality rates, and Bhattacharya et al. (2003), who find that cold shocks lead to decreased nutrition.

[7] These estimates we gathered from interviews conducted in local municipalities in Fukushima in March 2015 by the Tokyo Shimbun Newspaper (Tokyo Shimbun 2016).

four years if we extrapolate our estimates to the entire country, and almost certainly outnumber the deaths over a longer time period given that the higher electricity prices persisted beyond the end of our study. This suggests that ceasing nuclear energy production has contributed to more deaths than the accident itself.

Electricity markets in Japan

For the period of our analysis, 2007-2014, the electricity market in Japan was heavily regulated.[8] The market consisted of ten regions (Figure 1). In each region, there was only one electric power company where households can purchase their electricity. Household electricity bills consist of nonlinear price schedules: a basic delivery charge and 3-tier energy charges based on consumption in the previous month (1-120kWh, 121-300kWh and over 300kWh).[9] To change the rate of the basic charge and/or 3-tier energy charges for residential electricity, electricity companies were required to apply to the Ministry of Economy, Trade and Industry (METI) for permission. Any request for a price change must relate to the electric power company's operating costs, the level of investment, and the dependence on fossil-fuel based power generation (coal, liquefied natural gas, and oil).

As shown in Figure 2, prices were relatively steady and quite comparable across the regions before the Fukushima accident in 2011. In fact, during this time, applications for a price change were approved almost simultaneously for the ten electricity companies. Between 2007

[8] The residential electricity market in Japan has been deregulated since April 2016.
[9] Six regions (Hokkaido, Tohoku, Tokyo, Hokuriku, Chubu and Kyushu) and the remaining four regions (Kansai, Chugoku, Shikoku and Okinawa) have slightly different pricing systems; the first group of regions applies the monthly basic charge per 10A and the latter a minimum charge of 1-15kWh.

and 2011, each region underwent just one approved price change (in 2008), due to the surge in world oil prices.[10]

Shortly after the Fukushima disaster, all nuclear power reactors ceased production in Japan.[11] Shortage of power generation from these shutdowns was mostly offset by increasing the importation of fossil fuels. The electricity power companies resumed operations of old, often idle coal, gas, and oil-fired power generators to convert the fuel into energy. The share of power generation from fossil fuels rose from 62 to 88 percent in the four years after the earthquake, while the share of nuclear power generation declined from over 30 percent to zero (U.S. Energy Information Administration, 2015). This led to significant increases in energy prices.

Furthermore, the dependence on nuclear power prior to Fukushima varied across regions, ranging from zero to 44 percent. Therefore, the replacement of nuclear power with fossil fuels also differed regionally after the shutdowns (Table 1). This resulted in a non-uniform increase in electricity prices across regions after 2011 (Figure 2).[12]

The size of the increase in electricity prices depended on the initial proportion of nuclear-powered generation as well as the choice of how to replace it. As shown in Figure 2, some regions (e.g., Hokkaido, Kansai, and Tokyo) underwent a sharp increase in electricity prices while other regions (e.g., Chugoku and Okinawa) experienced a smaller increase. For instance, comparing the average price index of residential electricity in January 2011 and December 2014, there was an increase of 33 percent in the Hokkaido region, 29 percent in the

[10] Changes in imported oil prices explain the smaller price shifts across years in Figure 2.

[11] At the time of the Fukushima accident, 37 of the 54 reactors were in operation (The Independent Investigation Commission on the Fukushima Nuclear Accident 2014). After the accident, all reactors were shutdown until one reactor, in Kyushu, was allowed to restart in August 2015.

[12] In addition, the oil price peaked at more than $100/barrel in 2012 due to political instability in the Middle East (Iran, Syria, Egypt, Libya, and Iraq). In general, per unit, the operation cost of coal/gas/oil-fired power stations is much higher than in nuclear power stations, so the net effect of the replacement of nuclear by fossil fuels is negative. According to METI (2015), the average annual cost of replacement was about 3.1 trillion yen (0.65 percent of GDP) in 2011-2014.

Kansai region, and 38 percent in the Tokyo region. Table 1 shows that, before 2011, the energy dependence of these three regions on nuclear power was considerable (44 percent in Hokkaido and Kansai; 28 percent in Tokyo). In contrast, the price schedule did not increase as much in the Chugoku and Okinawa regions (15 percent and 14 percent, respectively) where the share of electricity generated by nuclear power stations was very small before 2011 (three percent in Chugoku and zero in Okinawa).[13] We exploit this regional variation in prices over time to identify the causal effects of interest.

Data

We collected monthly data in the 21 largest municipalities in Japan from 2007 to 2014 on residential electricity prices, electricity expenditure, mortality rates, population, and weather. The 21 largest municipalities consist of the special wards of Tokyo and 20 so-called "designated cities" (see Figure A1 of the Appendix). A municipality with a population greater than 500,000 can be designated by government ordinance. These cities are located in seven of the ten electricity regions: Hokkaido, Tohoku, Tokyo, Chubu, Kansai, Chugoku, and Kyushu.

A. Residential Electricity Price Data

The monthly average price (per kWh) of electricity, obtained from the Japanese statistical office, is computed as the weighted average of the unit price paid by five groups of households in each region, where the groups are defined by the consumption level and contract.[14] Given the

[13] The price schedule in Hokuriku and Shikoku regions did not increase much despite high nuclear dependence. This is because of a smaller population (and industrial size) than other regions that required a smaller production of the *absolute* amount of electricity. Also, they replaced nuclear mostly by coal, which was relatively cheap. Hokkaido, on the other hand, experienced higher price increase than Shikoku despite having similar nuclear dependence and economy size. This arose from greater dependence on oil, which was more expensive than coal, after the shutdown.
[14] The five groups are those who consume 160kWh electricity per month with a 20A contract, 250kWh (30A), 330kWh (40A), 440kWh (50A), and 720kWh (60A). The number of households in each group is used as a weight.

regulated nature of electricity markets, these prices are uniform for cities within the same electricity region.

B. Electricity expenditure

Given the lack of access to electricity consumption data we instead collected publicly available data on household electricity expenditure at the municipality level. These data are obtained from the Ministry of Internal Affairs and Communications, which conducts a monthly survey to collect information from sample households regarding monthly household expenditure on various goods including electricity. Households are randomly selected from the stratified census in each municipality, and asked to record their expenditures for six consecutive months. In each month, one-sixth of the sample households are replaced by new observations. Because the collected number of single-member households is very limited at the municipality level, data are only available for the subgroup of households with two or more members. This monthly average electricity expenditure is then used to examine electricity consumption by estimating the price elasticity of demand in the 21 cities during our sample period.

It is important to note that the vast majority of heating and cooling devices in Japan rely on electricity for power. For example, air conditioners, which rely on grid electricity, are the primary source of both cooling and heating, which differs from places like the US. Kerosene and gas stoves are used at much lower rates, though they are more prevalent in the northern regions of Hokkaido and Tohoku. As a robustness check, we estimate models that exclude these two regions (Sapporo, Sendai, and Niigata cities).

C. Mortality and Population Data

Monthly mortality data at the municipality level are from the Survey on Population Dynamics by the Ministry of Health, Labor and Welfare of Japan. Mortality data are combined with age-specific city population data to compute age-adjusted mortality rates (per 100,000 population). The annual population of the designated cities by age groups is available from the Statistics Bureau of the Ministry of Internal Affairs and Communications. We also use information on cause of mortality to evaluate the robustness of our results.

D. Weather Data

We use hourly weather information from the Meteorological Agency of Japan. All but five designated cities have weather stations in the city center. For those five cities (Kawasaki, Kitakyushu, Saitama, Sagamihara, and Sakai) data are replaced by the nearest stations in neighboring municipalities (ranging from 9 to 28 km away). A key variable for our analysis is hourly average temperature. We follow Deschenes and Greenstone (2011) and Barreca et al. (2016) to construct temperature bins to approximate the distribution of temperatures. Figure 3 illustrates the annual average distribution of hourly average temperature over eight temperature bins (<0, 0-4, 5-9, 10-14, 15-19, 20-24, 25-29, >30°C). Each bar represents the weighted average number of hours per year in each temperature bin, using the total population in a city-year as weights. Table 2 shows the annual average mortality rates and temperature distributions by region. Regional variations in hourly temperature are mainly observed in both tails of the temperature distribution.

Other meteorological elements and air pollution are potential confounders in the relationship between temperature and mortality. To address this, we also collected data on precipitation and average wind speed from the Japanese Meteorological Agency, and air

pollution data (Suspended Particulate Matter, SPM; Photochemical Oxidant, Ox) from the National Institute for Environmental Studies.

Econometric Models

In this section, we describe the two econometric models we estimate. First, we estimate the effect of electricity prices on consumption. Second, we estimate the effect of temperature on mortality, and explore whether energy prices shift this relationship.

A. Electricity prices and demand

To explore the relationship between residential electricity prices and electricity demand, we follow the empirical model developed by Auffhammer and Rubin (2018). Specifically, we estimate the following equation:

$$(1)\ \log(EXP_{ct}) = \delta\log(P_{ct-k}) + X_{ct}\beta + \rho_{ct} + \varepsilon_{ct}$$

where EXP_{ct} is the average household expenditure of electricity in city c and month t, and P_{ct-k} is the average residential electricity price in month t-k. The parameter of interest is (δ-1), which represents the price elasticity of residential electricity demand.[15] As previously discussed, the regulated electricity market dictates that price changes are driven solely by supply-side factors, suggesting price changes are exogenous to demand-side factors, enabling identification of the

[15] Recall that we only observe electricity expenditure data. Since $\frac{\partial lnEXP_{ct}}{\partial lnp_{ct}} = \frac{\partial lnq_{ct}}{\partial lnp_{ct}} + 1$, the price elasticity is $\frac{\partial lnq_{ct}}{\partial lnp_{ct}} = \delta - 1$.

parameter δ. Based on the law of demand, we hypothesize that higher electricity prices reduces energy consumption (δ-1<0) (**hypothesis 1**).

Although energy prices change monthly, consumers may not respond immediately to price changes because of rational inattention (Salee 2013, Auffhammer and Rubin 2018). For example, households in Japan usually learn about residential electricity prices when they receive their electricity bill, which specifies the price during the previous period (i.e., the first price lag). The bill of the previous month arrives about ten days into the current billing period, with payment due within two weeks for automatic billing and within 30 days for cash payments. Given this billing structure, household decisions about electricity consumption may respond to electricity prices with a lag, as evidence within the US supports (Auffhammer and Rubin 2018). Therefore, we allow for a possible delayed effect of price changes on consumption by allowing price to enter equation (1) with a lag as denoted by t-k, where k = {0, 1, 2}. We also use the average price rather than the marginal price given previous evidence that suggests that consumers respond to the average electricity price and not to the marginal price because of the cognitive burden of understanding complex pricing (e.g., Shin 1985; Metcalf and Hassett 1999; Bushnell and Mansur 2005; Borenstein 2009; Ito 2014).

To control for other factors that may explain energy consumption, we include several additional variables in this model. The variable X_{ct} includes several time-varying covariates. First, we control for weather flexibly as the number of hours in city c and month t where hourly temperature is categorized in one of the seven temperature bins i < 0, 0-4, 5-9, 10-14, 20-24, 25-29, >30 degrees Celsius (the 15-19 degrees Celsius bin is the excluded category). Second, we control for unusually low or high precipitations by using two dummy variables equal to one if monthly precipitation is less than the 25th or more than the 75th percentile of the 2007-2014

average monthly precipitation in a given city-month, respectively. Third, we include a vector of household characteristics, such as the total number of household members, the percentage of children under 18 years of age, the percentage of the elderly (65 or above), the percentage of adults with a job, the age of the household head, the logarithm of total household expenditure, the percentage of home ownership, the size of the house, and the percentage of farm households. Fourth, we account for the destruction and reconstruction of power-supply lines in Sendai after the earthquake by including a dummy variable equal to one for Sendai city in March 2011.

This model also includes several fixed effects to account for various fixed characteristics, denoted by the term ρ_{ct}. We include city-by-month fixed effects to account for seasonality in electricity use by city, and year-by-month fixed effects to control for time-varying factors common to all cities (e.g., macro business cycles, national policies such as government information policy on energy use). We also account for the change in the awareness of energy saving behavior after the earthquake by including city-by-period fixed effects, where the period is defined equal to one after the March 2011 earthquake and zero before then. After the Fukushima accident, energy-saving campaigns were conducted at both national and region/city levels for several years. As a result, some households reduced electricity consumption and others replaced heating and cooling devices with more energy-efficient appliances regardless of the change in the electricity price. Finally, standard errors are clustered at the city level, and regressions are weighted by the number of households within a city.

B. Temperature and mortality

After exploring the relationship between energy prices and consumption, we next turn to how this affects the temperature-mortality relationship. We begin by estimating the temperature

mortality relationship, adhering to the specification by Barreca et al. (2016). Specifically, we estimate the following equation:

(2) $\log(M_{ct}) = \Sigma_i \alpha_i T_{cti} + X_{ct}\theta + \gamma_{ct} + \mu_{ct}$.

In this equation, M_{ct} is the monthly mortality rate (per 100,000) in city c and month t. As specified in Barreca et al. (2016), T_{cti} represents temperature values over the past two months to account for lagged physiological effects, with hourly temperature indicators as discussed above. Based on previous findings, we expect extreme temperatures to increase mortality (**hypothesis 2**).

The vector X_{ct} includes controls for precipitation as defined above and a dummy variable for the excess mortality from the earthquake and tsunami in Sendai city in March, 2011. A series of fixed effects are included in the vector γ_{ct}, which includes city-by-year to adjust for unobservable city-specific, dynamic determinants of mortality rates (e.g., age distribution, income distribution, and hospital quality),[16] year-by-month to control for time factors common to all the cities (e.g., national business cycles), and city-by-month fixed effects to account for unobservable city-specific, seasonal factors that may affect mortality (e.g., migration, seasonal employment, and epidemics such as influenza). Regressions are weighted by city-level population, and standard errors are clustered by city.

This model fits temperature semi-parametrically, with the only assumption that the impact of hourly temperature on the monthly mortality rate is constant within five-degree Celsius

[16] In this equation, we can include city-by-year (instead of city-by-period) fixed effects because there is considerable variation in temperature within cities over time, unlike electricity prices, which move slowly over time (see Figure 2).

intervals. Our use of fixed effects allows us to identify the causal effect of temperature on mortality rates by relying on random variations in the temperature distribution for a given city and month. This model builds on existing models of temperature and mortality (Deschenes and Greenstone 2011; Barreca et al. 2016) and the climate-economy literature more generally (Dell et al. 2014). An important deviation in our model is that we include hourly temperature to avoid having to distinguish between maximum, mean, and minimum temperatures.

C. Electricity prices, temperature and mortality

After exploring the dose-response relationship between temperature and mortality, we then investigate the effect of residential electricity prices on the temperature-mortality relationship. This model extends equation (2) by adding the residential electricity price and its interaction with temperature. Specifically, we estimate the following equation:

$$(3)\ \log(M_{ct}) = \Sigma_i \alpha'_i T_{cti} + \delta' \log(P_{ct-k}) + \Sigma_i \lambda_i T_{cti} * \log(P_{ct-k}) + X_{ct}\theta' + \gamma'_{ct} + v_{ct}.$$

where all variables are defined as in equations (1) and (2), with the prime superscript separating this equation from the previous one. Our main focus is on the interaction term of the temperature bins and lagged price, λ, which indicates whether price moderates the effect of temperature on mortality. Based on hypotheses 1 and 2 above, we hypothesize that mortality rates increase with the rise of the electricity price during extreme temperatures ($\lambda>0$) (**hypothesis 3**). That is, if higher electricity prices reduce the usage of heating and cooling devices, this increases exposure to extreme temperatures, and therefore the risk of dying. This is a strong hypothesis because we only expect the interaction terms (λ) to be significant for the temperature bins that affect

mortality, as uncovered from estimation of equation (2). During moderate temperatures, however, we expect $\lambda=0$ because, although electricity consumption may decline, moderate temperatures do not affect mortality. Given the same set of fixed effects as before, identification in this model follows from the exogeneity of temperature and prices as described above.

Results

A. Electricity prices and demand

We first provide graphical evidence before discussing estimation results of equation (1). Figure 4 plots annual average residential electricity consumption per capita by region and shows a sharp decline in electricity consumption after 2011.[17] Correlation between electricity consumption and prices is about -0.9 in every region in 2007-2014. This is also consistent with findings from household surveys conducted by the Japanese Ministry of the Environment in the winter and summer of 2012, which indicate that the average electricity consumption per household decreased from the previous year by about 1-8 percent, with larger reductions in regions that experienced large price increases, such as Tokyo and Kansai (Ministry of the Environment, 2012, 2013). These surveys also show that the annual reduction rates in electricity consumption are larger in winter (4.9 percent on average) than in summer (2.7 percent).

Panel A of Table 3 provides the price elasticity estimates of residential electricity demand, δ-1, obtained from fitting equation (1) with the different lagged prices to test **hypothesis 1**.[18] The estimates in columns 1-3 uses the second price lag, the first price lag, and

[17] Data on total residential electricity consumption at the regional level are from the Federation of Electric Power Companies of Japan. The consumption per region is divided by the size of the respective populations to calculate the annual average consumption per capita.
[18] Given the slow movements in prices, and therefore high degree of collinearity across lags, we include each lag separately in these models.

the contemporaneous price, respectively. We find that the second lag-based elasticity (-0.303) is significantly different from zero at the 5 percent level. This estimated elasticity accords with the recent estimate of -0.38 in Japan (Krishnamurthy and Kriström, 2015). Estimates using the first lag or contemporaneous price are smaller and less precise than the second lag, a pattern consistent with the billing and payment structure of residential electricity previously described, and in line with the findings by Auffhammer and Rubin (2018) who also find the largest household response to the second lag of energy prices.

To explore how this response varies by whether families are heating or cooling their homes, we follow Auffhamer and Rubin (2018) and Chirakijja et al. (2019) and estimate the price elasticity by season. Winter is a dummy variable equal to one during winter months (October through March) when electricity use is mostly for heating; summer is a dummy variable equal to one when energy is mostly used for cooling (June through August). Panel B of Table 3 shows that the price elasticity is significantly different from zero during the winter months (-0.249), and is more elastic than during the summer months (-0.180). This suggests that people are more sensitive to electricity price during winter months.[19] There are two possible explanations. One, heating requires more electricity and hence higher payments than cooling (for instance, increasing the temperature from 0°C to 20°C costs roughly twice as much as decreasing the temperature from 35°C to 25°C). Two, inexpensive substitutes are more abundant in the cold: people can wear warmer clothes and use blankets; on the other hand, there are few alternatives to the use of cooling devices for coping with heat.

[19] Our results are robust to alternative definitions of winter and summer. For instance, if we define winter as November to March the price elasticity is -0.241; if we define summer as June to September the price elasticity is -0.129.

Our results are robust to several different specifications as shown in Table 4. Column 1 presents our main specification including the full set of fixed effects. Columns 2-3 experiment with excluding different control variables and fixed effects. Column 4 applies the wild cluster bootstrap-t procedure suggested by Cameron et al. (2008) to account for the small number of clusters (21). Columns 5-6 exclude the northern regions of Hokkaido and Tohoku where kerosene or gas heaters are more often used rather than electricity. As shown in this table, our estimates are insensitive to these various changes.

B. Temperature and mortality

Figure 5 displays the temperature-mortality relationship from the estimation of equation (2) to test **hypothesis 2**. Following Barreca et al. (2016), our estimates account for lagged physiological effects of temperatures over the past 2 months.[20] Estimates for colder temperatures generally follow patterns from previous studies. The temperature effect generally decreases in temperatures, with estimates for the two coldest bins significantly different from zero. The point estimates indicate that the effect of an additional hour below 0°C or between 0°C and 4°C significantly increases the mortality rate by 0.028 percent compared to temperatures in the 15-19°C range. This implies that one day below 0°C increases mortality by 0.672 percent. For comparison purposes, Barreca et al. (2016) find that in US each day below 40°F, which translates to 4°C, increases mortality by 0.34 percent, though their estimate is based on average daily temperatures.[21]

[20] Each of the reported estimates represents the sum of the estimated coefficients for the respective temperature bin in the current and previous months.
[21] We use their estimate from Table 3 for the 1960-2004 period.

Estimates for warmer temperatures are small in magnitude and imprecisely estimated. Although this appears to diverge from previous studies, a likely explanation is the high rates of air conditioning penetration, which is close to 90 percent. For example, Barreca et al. (2016) find that temperatures above 90°F, which corresponds with 32°C, affect mortality during periods when AC penetration rates were low, but have much smaller effects as AC rates increased. During the 1990-2004 period, when AC penetrations rates in the US were comparable to those in Japan, the effect of a day over 90°F is small and statistically insignificant. In light of this, our estimates align quite closely with the previous literature. We also investigate the underlying cause of death in Table 5 (columns 1, 2).[22] Results indicate that the increase in mortality from cold temperatures is mainly due to cardiovascular disease. Cold temperatures are related to an increase in blood viscosity and vasoconstriction, harming elderly people in particular. A similar effect is found by Deschenes and Moretti (2009) in the US. On the other hand, we do not find any effect of temperature on mortality due to respiratory disease.

Finally, we perform a number of robustness checks in Table 5. Column 3 presents our baseline specification, which includes the full set of fixed effects. In column 4, we omit city-by-year fixed effects and find that the cold temperature effect is robust. We show that our results remain robust when we control for air pollution and windchill[23] (column 5), and also when we account for the small number of clusters (column 6).

C. Electricity prices, temperature and mortality

[22] For the sake of brevity, we report estimates for only the most extreme temperature bins (< 0°C, 0-4°C, 25-29°C, and ≥ 30°C).
[23] We use the Steadman index to measure windchill, which is a nonlinear combination of temperature and wind speed (Steadman 1984).

Given that we have found a relationship between price and electricity usage and a relationship between temperature and mortality, we next probe our main **hypothesis 3** that electricity prices affect the temperature-mortality relationship from fitting equation (3). Given that we only found effects on mortality from the coldest temperatures, our strong hypothesis is that we only expect prices to affect the temperature-mortality gradient at colder temperatures, but not to affect the temperature-mortality gradient at other temperatures. This is precisely the pattern we find.

We present the effect of electricity prices on the temperature-mortality relationship in Table 6. Our preferred specification focuses on the second price lag given that this had the largest effect on electricity usage, and is shown in column 1. Recall that we found statistically significant effects on mortality for temperatures below 0°C and between 0-4°C, making these the only bins where we might expect an interaction effect. We find a statistically significant interaction term for temperatures below 0°C, although we do not find one for temperatures 0-4°C. The positive coefficient on the interaction term suggests that higher temperatures have a larger effect on mortality when energy prices increase. A 10 percent increase in the residential electricity prices significantly increases mortality due to very cold hours by 0.01 percent. This is a sizeable effect on cold-related mortality, contributing about one third of the temperature-mortality relationship in Figure 5. Meanwhile, for all other temperatures, we do not find a statistically significant interaction term, which is the pattern we expect given that we did not find a level effect.[24]

Table 6 also shows results using the first price lag and contemporaneous price of electricity in columns 2 and 3, respectively. Consistent with our previous evidence, we find that

[24] Table 6 only shows results for the two highest and the two lowest temperature bins. Appendix Figure A2 shows the results for all temperature bins.

the second price lag has the largest impact, followed by the first price lag. These results are in line with the billing and payment schedule of residential electricity previously discussed and our analysis on the relationship between electricity prices and consumption.

We also perform a robustness analysis with alternative specifications and samples in Table 7. Column 1 reports the baseline estimates including the full set of fixed effects. Column 2 shows that the cold-price effect remains positive and significant when we exclude city-by-year fixed effects. Our results hold also when we control for air pollution and windchill (column 3), when we account for the small number of clusters by wild cluster bootstrap-t procedure as described by Cameron et al. (2008) with 1,000 replications (column 4, *p*-values in square brackets); or when the northern regions of Hokkaido or Tohoku are excluded, where households use kerosene or gas for heating more often than electricity (columns 5-6).

Welfare Impacts

We assess the welfare impacts of temperature and residential electricity price on mortality. We use the parameter estimates of the temperature variables (α's) from equation (2) and the interaction terms between electricity price and temperature (λ's) from equation (3) to compute the average annual number of deaths from temperatures below 0°C and the proportion of deaths due to the change in electricity price in our 21 sample cities after the disaster in 2011-2014. Table 8 shows that the average annual number of cold-related deaths is 1,683, of which 320 deaths are due to the annual average price increase of about 5.8 percent. Combining across the four years suggests a total of 1,280 deaths. This suggests that 19 percent of cold-related deaths are associated with the price increase due to the nuclear power shutdown.

To put these estimates in context, we compare the number of deaths from the replacement of nuclear power to those from the accident itself. Since our data only covers 28 percent of the population, the total death toll is likely to be much higher than 1,280 deaths. Assuming the same elasticity of electricity consumptions, temperature-mortality relationship, and temperature distribution, this estimate would imply over 4,500 deaths from 2011-2014 across the entire nation. Meanwhile, the number of deaths due to the Fukushima accident is much lower. No deaths have yet to be directly attributable to radiation exposure, though projections estimate a cumulative 130 deaths (Ten Hoeve and Jacobson, 2012). An estimated 1,232 deaths occurred as a result of the evacuation after the accident as of March 2015 (Tokyo Shimbun, 2016). The estimated number of deaths from the higher electricity prices outnumber the deaths from the accident in only four years, and a gap that is likely to grow with time given that the higher electricity prices have persisted since the end of our study period.[25] This suggests that ceasing nuclear energy production has contributed to more deaths than the accident itself.

Conclusion

In this paper, we evaluate the downstream effects from invoking the precautionary principle following the Fukushima Daiichi nuclear accident in which Japan ceased operation at all nuclear power plants throughout the country. In an effort to meet the energy demands, nuclear power was replaced by imported fossil fuels, which led to increases in electricity prices. The price increases led to a reduction in electricity consumption but only during the coldest times of the year. Given its protective effects from extreme weather, the reduced electricity consumption led to an increase in mortality during very cold temperatures. We estimate that the increased

[25] Electricity prices in all years after 2014 remain at least 10 percent higher than pre-2011 prices (authors' calculations using residential electricity data described in the Data section).

mortality resulting from the higher energy prices outnumbered the mortality from the accident itself, suggesting that applying the precautionary principle caused more harm than good.

Another potential welfare impact from replacing nuclear power with fossil fuels is the health effects from local air quality. In addition to the lower marginal costs of energy production, nuclear power has minimal impacts on local air quality. Fossil fuels, on the other hand, emit a wide range of pollutants that deteriorate local air quality and have significant effects on morbidity and mortality (see, for example, Graff Zivin and Neidell 2013, and references within). Indeed, estimates from the US show that closure of nuclear power plants after the Three Mile Island accident led to increased particle pollution and higher infant mortality (Severnini 2017).[26] Therefore, the total welfare effects from ceasing nuclear production in Japan are likely to be even larger than what we estimate, and represents a fruitful line for future research.

Given this surprising result, why do governments invoke this principle? One possible explanation is that salient events, such as a nuclear disaster, affect perceived risk, which is often based more on emotions and instincts than on reason and rationality (Ropeik 2011). For example, after the Fukushima accident, housing prices were affected in places as far away as the US despite no change in underlying risk (Tanaka and Zabel 2018).[27] Meanwhile, deaths from higher energy prices are largely unnoticed; we cannot attribute any particular death to the higher energy prices, but can only estimate population level impacts. Although the public and policy makers place greater fears on the deaths directly attributable to the accident, the two are equivalent from a cost-benefit perspective, and should be treated accordingly. The precautionary principle

[26] Although replacing nuclear with renewable resources, such as wind and solar, would not worsen local air quality, renewables would likely have had higher price impacts, and therefore mortality impacts, given the higher marginal costs of production. For example, in 2014, wind and solar had 2-2.5 times higher power generation costs than nuclear (Advisory Committee for Natural Resources and Energy 2015).

[27] Interestingly, the price changes were limited to properties within 2 km of a nuclear plant, despite the fact that the radiation risk is much wider than 2 km, and rebounded roughly 1 year after the accident.

emphasizes salient events – the worst case scenario – and in doing so ignores the alternative, thereby encouraging inefficient policy-making.

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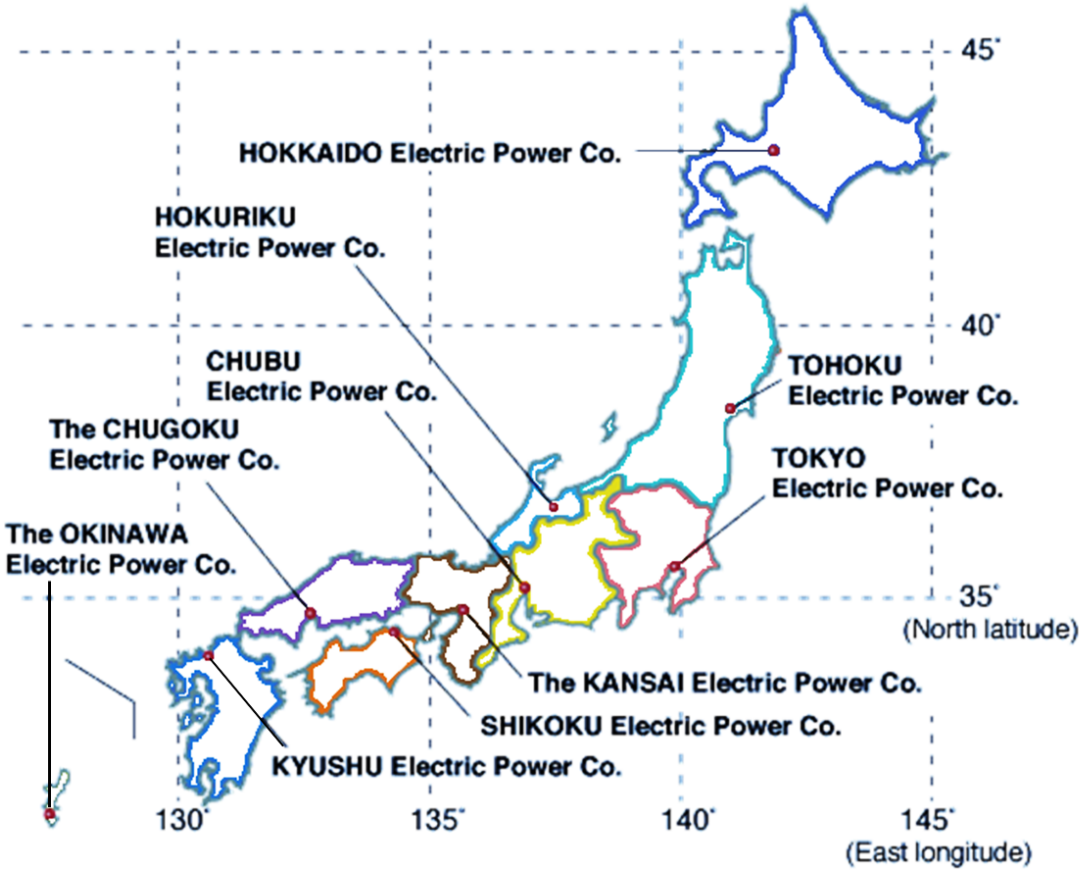

FIGURE 1. THE TEN REGIONS OF THE ELECTRICITY MARKET IN JAPAN

Source: The Federation of Electric Power Companies of Japan (FEPC)

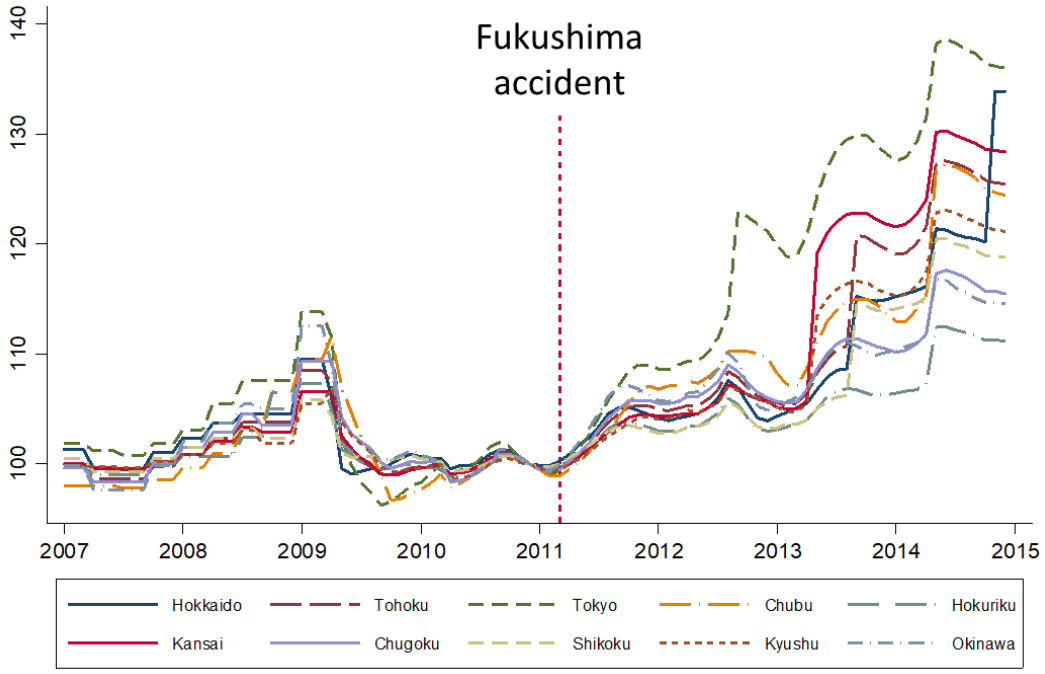

FIGURE 2. MONTHLY AVERAGE PRICE INDEX OF RESIDENTIAL ELECTRICITY BY REGION, 2007-2014 (2010 = 100)

Notes: The figure shows the average monthly price index of residential electricity in Japan by region for the period 2007-2014. The vertical dashed line indicates March 2011 when the Tohoku earthquake and tsunami triggered the Fukushima Daiichi nuclear disaster. Data are from the Retail Price Survey by the Ministry of Internal Affairs and Communications (https://www.stat.go.jp/english/data/kouri/index.html).

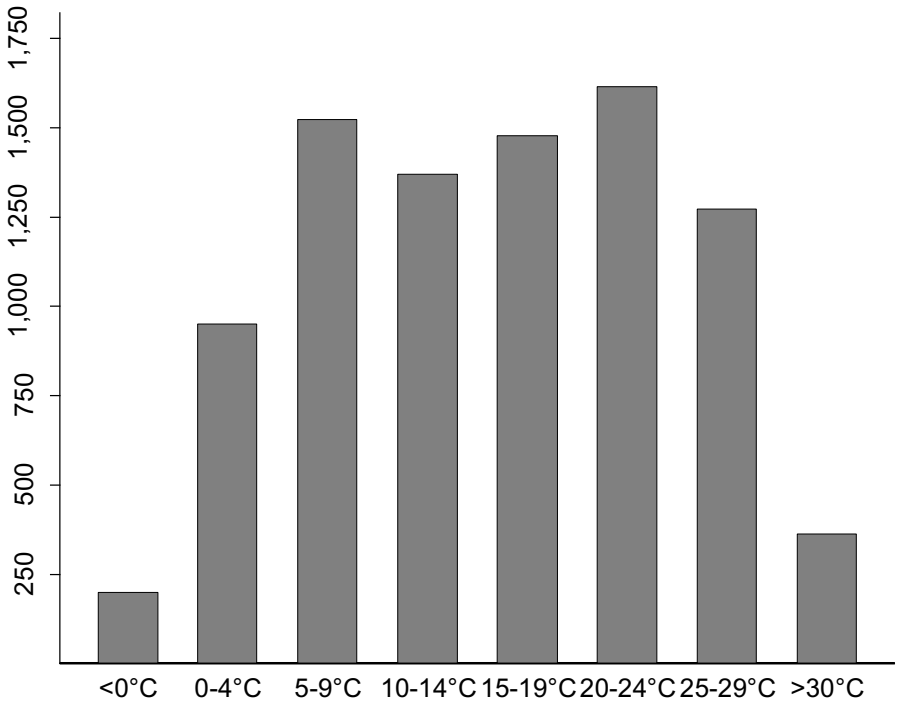

FIGURE 3. DISTRIBUTION OF HOURLY TEMPERATURES, 2007-2014

Notes: The figure represents the average number of hours per year in each temperature bin (< 0, 0-4, 5-9, 10-14, 15-19, 20-24, 25-29, and ≥ 30 degrees Celsius) weighted by the total population in a city-year. The figure refers to the seven electricity regions included in our analysis (Hokkaido, Tohoku, Tokyo, Chubu, Kansai, Chugoku, and Kyushu). Data are from the Meteorological Agency of Japan for years 2007-2014.

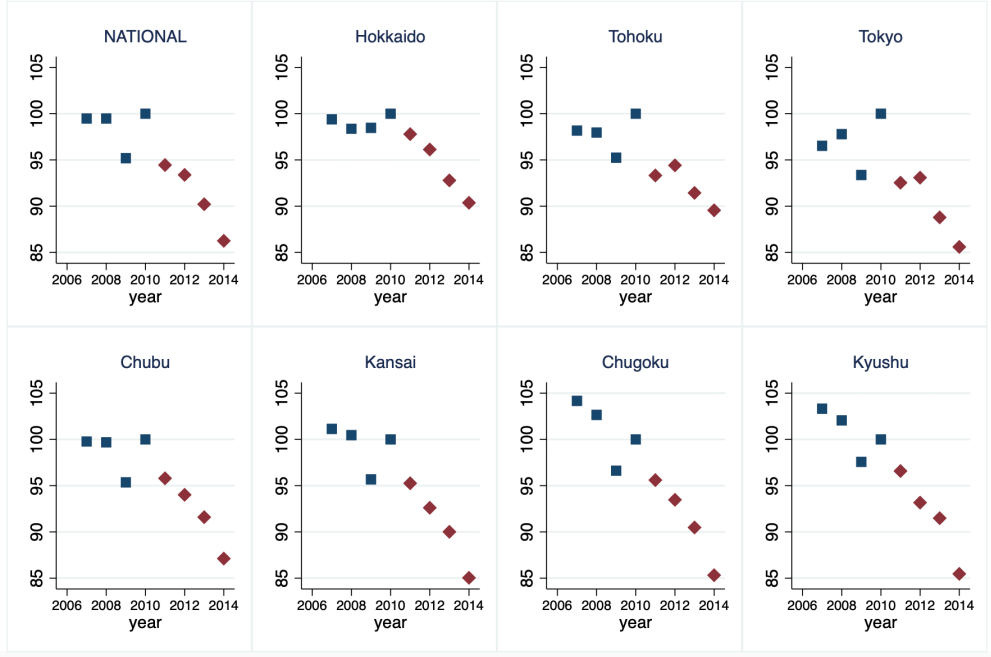

FIGURE 4. ANNUAL AVERAGE RESIDENTIAL ELECTRICITY CONSUMPTION PER CAPITA BY REGION, 2007-2014 (2010 = 100)

Notes: The figure represents average residential electricity consumption per capita by region before (blue squares) and after (red diamonds) the Fukushima Daiichi Nuclear Power Station accident in 2011 with electricity consumption in 2010 as baseline. The first figure refers to the national distribution of residential electricity consumption while the remaining figures refer to the seven electricity regions included in our analysis (Hokkaido, Tohoku, Tokyo, Chubu, Kansai, Chugoku, and Kyushu). Data are from the Electricity Statistics Information by the Federation of Electric Power Companies of Japan for years 2007-2014.

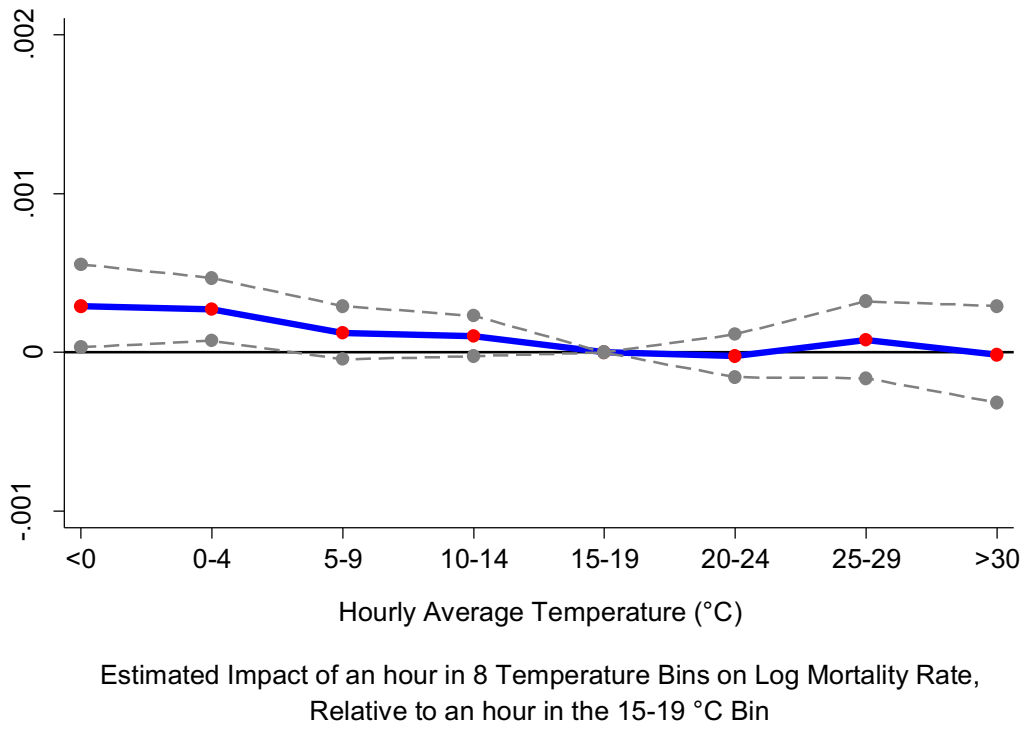

FIGURE 5. CUMULATIVE DYNAMIC ESTIMATES OF TEMPERATURE-MORTALITY RELATIONSHIP

Notes: The dependent variable is the logarithm of the monthly mortality rate. The figure plots the point estimates (dots in continuous line) and the 95 percent confidence intervals (dots in dashed line) of the temperature coefficients α_i obtained by fitting equation (2). The excluded category is a temperature in the 15°C-19°C range. Each of the plotted estimates is calculated by the sum of the coefficient estimates of each temperature bin α_i in the current and the previous months. Regressions are weighted by city population. Standard errors are clustered at the city level. Data refer to the period 2007-2014.

TABLE 1. COMPOSITION OF JAPAN ELECTRICITY PRODUCTION BY REGION (2010, 2014)

	Panel A				Panel B			
	Fuel types in 2010 (percentage)				Change in 2010-2014 (percentage point)			
	Nuclear	Coal	Oil	Gas	Nuclear	Coal	Oil	Gas
Hokkaido	44	31	8	0	-44	20	20	1
Tohoku	26	34	3	22	-26	6	5	12
Tokyo	28	10	10	45	-28	7	-3	23
Chubu	15	26	4	46	-15	0	-3	15
Hokuriku	28	44	3	0	-28	21	5	0
Kansai	44	21	5	20	-44	3	12	26
Chugoku	3	58	13	19	-3	-3	-4	6
Shikoku	43	36	6	5	-43	20	13	3
Kyushu	39	27	7	19	-39	5	8	20
Okinawa	0	77	21	0	0	-12	-8	18

Notes: Panel A shows the percentage of electricity production by fuel type and region in 2010. Panel B shows the change in percentage point of the electricity production by fuel type and region. We omit renewable energy (hydro and others) from the table to improve readability. Their share was small and changed little in 2010-2014. Source: Chan and Kiso (2018).

TABLE 2—DESCRIPTIVE STATISTICS ON AVERAGE MORTALITY RATE AND TEMPERATURE EXTREMES, 2007-2014

	All-age mortality rate			Number of hours per year		
	Total	Male	Female	< 0°C	0-4°C	≥ 30°C
Total	846.16	926.90	768.49	173	882	371
By electricity region						
01 Hokkaido	824.73	936.24	725.51	2,011	1,355	27
02 Tohoku	837.33	917.18	762.67	403	1,650	156
03 Tokyo	790.79	865.83	716.07	43	779	357
04 Chubu	905.08	979.58	832.12	68	878	403
05 Kansai	965.33	1,068.85	868.93	31	846	495
06 Chugoku	822.62	880.36	768.55	82	1,006	480
07 Kyushu	855.07	929.75	787.86	29	660	438

Notes: The mortality rate indicates the number of deaths per 100,000 weighted by the total population in a city-year. The number of hours per year is calculated as the average number of hours per year in each temperature bin (< 0°C, 0-4°C, and ≥ 30°C) weighted by the total population in a city-year in the 2007-2014 period. The table refers to the seven electricity regions included in our analysis (Hokkaido, Tohoku, Tokyo, Chubu, Kansai, Chugoku, and Kyushu). Data on temperature are from the Meteorological Agency of Japan. Data on mortality rate are from the Survey on Population Dynamics by the Ministry of Health, Labor and Welfare of Japan.

TABLE 3— PRICE ELASTICITY OF RESIDENTIAL ELECTRICITY DEMAND

Log(price)	2 lags	1 lag	Current
	(1)	(2)	(3)
Panel A. Baseline			
	-0.303**	-0.198	-0.163
	(0.108)	(0.122)	(0.135)
Panel B. Seasonality			
Winter	-0.249**	-0.155	-0.119
	(0.110)	(0.113)	(0.116)
Summer	-0.180	-0.004	0.039
	(0.184)	(0.218)	(0.220)

Notes: Each column denotes a separate regression with different lags of the average residential electricity price: column 1 uses the second lag of price, column 2 the first lag of price, and column 3 the contemporaneous price. Panel A shows price elasticities for the baseline model. They refer to the estimated coefficients δ-1 obtained by fitting equation (1) where the dependent variable is the logarithm of the average household expenditure of electricity in city *c* and month *t*. Panel B shows the price elasticity for winter months (October through March) and summer months (June through August). All regressions include city-by-month fixed effects, year-by-month fixed effects, city-by-period fixed effects, and other control variables, that is a dummy variable equal to one for Sendai city in March 2011; the number of hours where hourly temperature is categorized in one of the seven temperature bins < 0, 0-4, 5-9, 10-14, 20-24, 25-29, >30°C; two dummy variables equal to one if monthly precipitation is less than the 25th or more than the 75th percentile of the 2007-2014 average monthly precipitation in a given city-month, respectively; a vector of household characteristics, such as the total number of household members, the percentage of children under 18 years of age, the percentage of the elderly, the percentage of adults with a job, the age of the household head, the logarithm of total household expenditure, the percentage of home ownership, the size of the house, and the percentage of farm households. All regressions are weighted by the number of households, and standard errors clustered at the city level are presented in parentheses. Data refer to the period 2007-2014. ** indicates significance at the 5% level.

TABLE 4— PRICE ELASTICITY OF RESIDENTIAL ELECTRICITY DEMAND: ROBUSTNESS CHECKS

	(1)	(2)	(3)	(4)	(5)	(6)
Price elasticity	-0.303**	-0.292***	-0.338**	-0.303**	-0.242**	-0.277**
	(0.108)	(0.041)	(0.108)	[0.011]	(0.097)	(0.115)
City-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	No	Yes	Yes	Yes	Yes
Other controls	Yes	No	No	Yes	Yes	Yes

Notes: The price elasticity is computed by using the estimate of the logarithm of the average residential electricity price with two-month lagged from fitting equation (1). Column 1 shows our main specification with the full set of fixed effects and controls. Column 2 includes only city-by-month fixed effects and column 3 adds year-by-month fixed effects. Column 4 presents in square brackets *p*-value obtained by wild cluster bootstrap-t procedure as described by Cameron et al. (2008) with 10,000 replications to account for the small number of clusters. Column 5 excludes Hokkaido and column 6 excludes Tohoku. All regressions are weighted by the number of households, and standard errors clustered at the city level are presented in parentheses. Data refer to the period 2007-2014. ***, ** indicate significance at the 1% and 5% level, respectively.

TABLE 5— TEMPERATURE-MORTALITY RELATIONSHIP:
CAUSE OF DEATH AND ROBUSTNESS CHECKS

	Cardiovascular disease (1)	Respiratory disease (2)	Baseline (3)	No city-by-year fixed effects (4)	Air pollution and windchill (5)	Wild cluster bootstrap (6)
Number of hours						
< 0°C	0.058***	0.028	0.028**	0.040**	0.030**	0.028**
	(0.020)	(0.016)	(0.012)	(0.018)	(0.015)	[0.015]
0-4°C	0.062***	0.028	0.027***	0.024**	0.028**	0.027***
	(0.016)	(0.020)	(0.009)	(0.011)	(0.011)	[0.004]
25-29°C	0.003	0.010	0.008	0.013	0.006	0.008
	(0.016)	(0.025)	(0.011)	(0.010)	(0.010)	[0.428]
≥ 30°C	-0.009	-0.019	0.000	0.007	-0.003	0.000
	(0.030)	(0.040)	(0.014)	(0.010)	(0.012)	[1.000]
SPM					4.374	
					(56.350)	
Ox					57.883	
					(60.091)	
Windchill					0.094	
					(0.216)	
City-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City-by-year fixed effects	Yes	Yes	Yes	No	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Coefficients estimates are multiplied by 100 for readability. The dependent variable is the logarithm of the monthly mortality rate. Column 1 refers to mortality due to cardiovascular disease while column 2 due to respiratory disease. Column 3 reports our baseline estimates computed as the sum of the coefficient estimates for each temperature bin in the current and previous months by fitting equation (2). Column 4 excludes city-by-year fixed effects. In column 5, we report estimates where in equation (2) we control also for air pollution (Suspended Particulate Matter, SPM; Photochemical Oxidant, Ox) and windchill. Column 6 presents in square brackets *p*-values obtained by wild cluster bootstrap-t procedure as described by Cameron et al. (2008) with 1,000 replications to account for the small number of clusters. The excluded category is the hourly average temperature in the 15°C-19°C range. Regressions are weighted by city population. Standard errors clustered at the city level are presented in parentheses. Data refer to the period 2007-2014. ***, ** indicate significance at the 1% and 5% level, respectively.

TABLE 6— THE IMPACT OF RESIDENTIAL ELECTRICITY PRICES ON THE TEMPERATURE-MORTALITY RELATIONSHIP WITH ELECTRICITY PRICES AT DIFFERENT TIMES

	2 lags	1 lag	Current
	(1)	(2)	(3)
Number of hours			
< 0°C	0.108**	0.099**	0.044
	(0.038)	(0.042)	(0.034)
0-4°C	-0.049	-0.059	-0.065
	(0.045)	(0.047)	(0.051)
25-29°C	0.011	-0.001	-0.015
	(0.029)	(0.022)	(0.029)
≥ 30°C	-0.060	-0.075	-0.094
	(0.059)	(0.062)	(0.055)

Notes: Coefficients estimates are multiplied by 100 for readability. The dependent variable is the logarithm of the monthly mortality rate. The reported estimates are obtained by fitting equation (3) and computed by the sum of the coefficient estimates of each interaction term λ_i between the average residential electricity price and the temperature bins in the current and the previous months. Column 1 uses the second price lag of the average residential electricity price, column 2 the first price lag, and column 3 the contemporaneous price. The excluded category is the hourly average temperature in the 15°C-19°C range. Regressions are weighted by city population. Standard errors clustered at the city level are presented in parentheses. Data refer to the period 2007-2014. ** indicates significance at the 5% level.

TABLE 7— THE IMPACT OF RESIDENTIAL ELECTRICITY PRICES ON THE TEMPERATURE-MORTALITY RELATIONSHIP: ROBUSTNESS CHECKS

	Baseline	No city-by-year fixed effects	Air pollution and windchill	Wild cluster bootstrap	No Hokkaido	No Tohoku
	(1)	(2)	(3)	(4)	(5)	(6)
Number of hours						
< 0°C	0.108**	0.181***	0.106**	0.108***	0.148**	0.101**
	(0.038)	(0.028)	(0.039)	[0.002]	(0.072)	(0.040)
0-4°C	-0.049	-0.020	-0.052	-0.049	-0.054	-0.040
	(0.045)	(0.028)	(0.045)	[0.240]	(0.053)	(0.056)
25-29°C	0.011	-0.004	0.006	0.011	-0.001	0.002
	(0.029)	(0.025)	(0.030)	[0.698]	(0.003)	(0.003)
≥ 30°C	-0.060	-0.144	-0.063	-0.060	-0.089	-0.039
	(0.059)	(0.073)	(0.059)	[0.250]	(0.059)	(0.061)
SPM			34.753			
			(55.899)			
Ox			72.280			
			(58.817)			
Windchill			0.147			
			(0.204)			
City-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City-by-year fixed effects	Yes	No	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Coefficients estimates are multiplied by 100 for readability. The dependent variable is the logarithm of the monthly mortality rate. Column 1 reports our baseline estimates computed as the sum of the coefficient estimates for each temperature bin in the current and previous months by fitting equation (3). Column 2 excludes city-by-year fixed effects. In column 3, we report estimates where in equation (3) we control also for air pollution (Suspended Particulate Matter, SPM; Photochemical Oxidant, Ox) and windchill. Column 4 presents in square brackets *p*-values obtained by wild cluster bootstrap-t procedure as described by Cameron et al. (2008) with 1,000 replications to account for the small number of clusters. Column 5 excludes Hokkaido and column 6 excludes Tohoku. The excluded category is the hourly average temperature in the 15°C-19°C range. Regressions are weighted by city population. Standard errors clustered at the city level are presented in parentheses. Data refer to the period 2007-2014. ***, ** indicate significance at the 1% and 5% level, respectively.

TABLE 8—ANNUAL WELFARE IMPACTS OF
COLD TEMPERATURES AND ELECTRICITY PRICE INCREASES

Total population in 21 cities (million)	35.2
Total number of deaths (million)	0.31
Number of hours < 0°C	237
Average change in electricity prices	5.8%
Number of deaths < 0°C	1,683
Number of deaths < 0°C due to electricity price increase	320

Notes: We compute the annual average number of deaths in our 21 sample cities during the period of 2011-2014. The annual average number of deaths below 0°C are calculated by $\sum_j \sum_t \hat{\alpha}_j \times T_{ct} \times M_{ctj} \times POP_{cyj}$, where $\hat{\alpha}_j$ is the parameter estimate of the temperature below 0°C *in age group j (j = 0-4, 5-19, 20-44, 45-64, or above 65),* T_{ct} represents the number of hours in the temperature below 0°C *in city c and* month *t*; M_{ctj} and POP_{cyj} are the monthly mortality rate and the annual population, respectively, in city *c*, year *y*, month *t, and age group j*. We sum the average number of deaths across the 21 cities for each year, and then take the average across all years. The annual average number of deaths due to the electricity price increase when the temperature is below 0°C are calculated by $\sum_j \sum_t \hat{\lambda}_j \times T_{ct} \times \Delta P_{cy} \times M_{ctj} \times POP_{cyj}$, where $\hat{\lambda}_j$ is the parameter estimate of the electricity price for the temperature bin below 0°*C in age group j, and* Δp_{cy} represents the actual year-to-year percentage change in electricity prices in city *c* and year *y*. Estimates by age group are available upon request.

APPENDIX

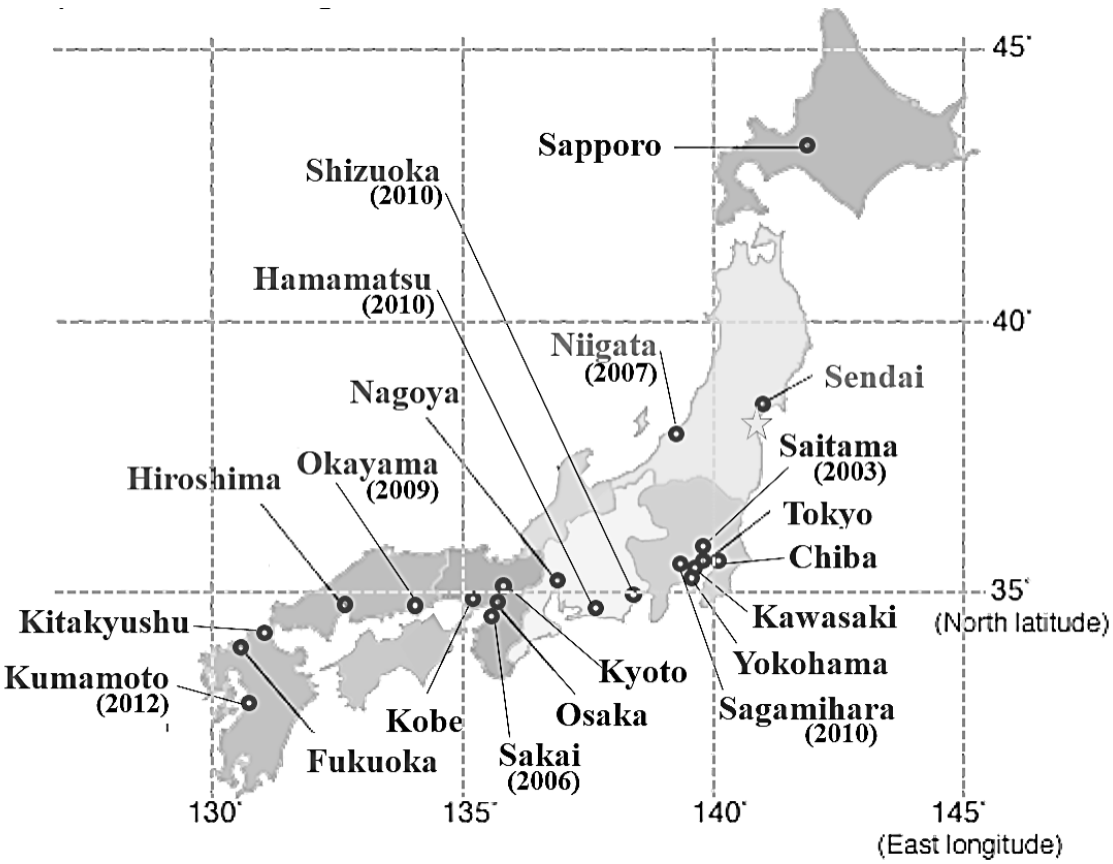

FIGURE A1. LOCATION OF 21 DESIGNATED CITIES

Source: Authors' drawing based on the Federation of Electric Power Companies of Japan map.

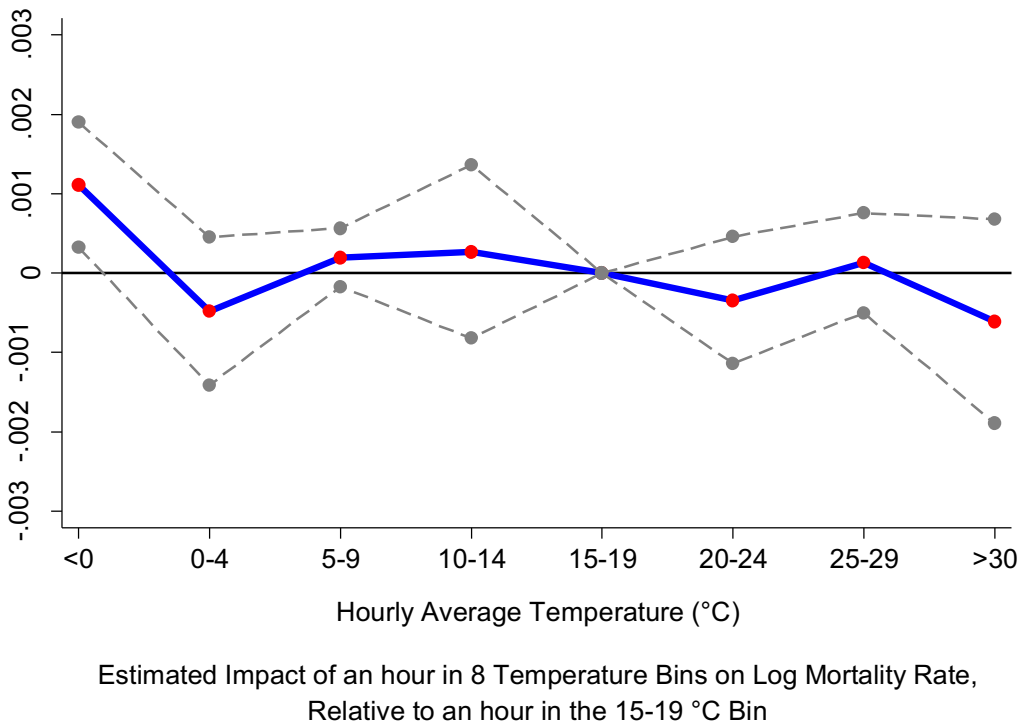

FIGURE A2. THE IMPACT OF RESIDENTIAL ELECTRICITY PRICES ON THE TEMPERATURE-MORTALITY RELATIONSHIP

Notes: The dependent variable is the logarithm of the monthly mortality rate. The figure plots the point estimates (dots in continuous line) and the 95 percent confidence intervals (dots in dashed line) of the coefficients λ_i associated with the interaction terms between the second lag of the average residential electricity price and the temperature bins. Each of the plotted estimates is obtained by fitting equation (3) and calculated by the sum of coefficient estimates of each interaction term λ_i in the current and the previous months. The excluded category is a temperature in the 15°C-19°C range. Regressions are weighted by city population. Standard errors are clustered at the city level. Data refer to the period 2007-2014.